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# PLATFORM AS A RULE-MAKER: EVIDENCE FROM AIRBNB'S CANCELLATION POLICIES

Jian Jia
Ginger Zhe Jin
Liad Wagman

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Cambridge, MA 02138
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We study a recent Airbnb rule that mandates guest reservations to be fully refundable within 48 hours of booking. Using data from ten US cities, we find (i) the rule leads to higher prices and higher occupancy for Airbnb listings, (ii) the number of active listings increases less on Airbnb than on VRBO, and (iii) some Airbnb hosts react by multi-homing on VRBO and lowering service quality on Airbnb. Platform competition attenuates the first effect but strengthens the third, suggesting that the nature of platform competition is more intricate than a stylized theory of positive network effects would predict. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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**ABSTRACT**

Digital platforms are not only match-making intermediaries but also establish internal rules that govern all users in their ecosystems. To better understand the governing role of platforms, we study two Airbnb pro-guest rules that pertain to guest and host cancellations, using data on Airbnb and VRBO listings in 10 US cities. We demonstrate that such pro-guest rules can drive demand and supply to and from the platform, as a function of the local platform competition between Airbnb and VRBO. Our results suggest that platform competition sometimes dampens a platform wide pro-guest rule and sometimes reinforces it, often with heterogeneous effects on different hosts. This implies that platform competition does not necessarily mitigate a platform's incentive to treat the two sides asymmetrically, and any public policy in platform competition must consider its implication on all sides.

Jian Jia
Illinois Institute of Technology
565 W Adams, 4th Flr
Chicago, IL 60661
jjia5@hawk.iit.edu

Ginger Zhe Jin
University of Maryland
Department of Economics
College Park, MD 20742-7211
and NBER
ginger@umd.edu

Liad Wagman
Illinois Institute of Technology
565 W Adams St, Suite 412
Chicago, IL 60661
lwagman@stuart.iit.edu

# 1 Introduction

Many digital platforms are not only matchmakers but also rule-makers. Whether it is matching buyers and sellers, riders and drivers, or guests and hosts, a platform must set rules to govern users on all sides. These rules include who can register, what information to provide, what behavior is allowed, and how a user may be awarded, punished or even kicked out based on their behavior on the platform. Unlike a government regulator that often acts as a third-party arbitrator between stakeholders, a for-profit platform is directly involved in the business: it earns commissions, fees, and other revenues from one or more sides. How to set rules to balance different interests of users is a fundamental question facing all platforms.

The classical literature on two-sided platforms emphasizes how different sides may *complement* each other (Rochet and Tirole 2003 and the followup studies). Take e-commerce as an example: because each side prefers a marketplace that attracts more users on the other side, a matchmaking platform has strong incentives to adopt rules that appeal to users on side A, which in turn brings more users on side B. In theory, the two sides reinforce each other through positive network effects, which could result in the overall increased desirability of the platform and even a monopoly. To push it further, it is of concern that positive network effects may constitute a barrier to entry for future platforms, even if they offer better services than the incumbent platform.[1] Indeed, this concern has triggered antitrust investigations and legislative efforts to regulate large platforms worldwide,[2] although empirical evidence on the anti-competitive aspect of the network effects remains scarce.

In reality, different sides of a platform often have *conflicting* interests, implying that a rule-making platform has to trade off positives on one side against negatives on the other, beyond nurturing the positive spillovers between sides. For example, at the onset of the COVID-19 pandemic, an Airbnb rule that required a full refund to all guests that had booked before March 14, 2020 triggered class-action lawsuits on behalf of thousands of Airbnb hosts.[3] A reverse rule that honors all pre-pandemic refund policies may please hosts

[1]See, for instance, the 2019 expert report to the UK government (Furman et al. 2019), the 2019 report to the European Commission (Crémer et al. 2019) and the 2019 Stigler report by over 30 experts (Stigler Committee 2019).

[2]See, for example, a number of efforts at the European Union, including the Digital Markets Act (DMA), https://ec.europa.eu/info/strategy/priorities-2019-2024/europe-fit-digital-age/digital-markets-act-ensuring-fair-and-open-digital-markets_en; the European Union's Digital Services Act (DSA), https://digital-strategy.ec.europa.eu/en/policies/digital-services-act-package; as well as a number of US Congressional and Senate bills, https://www.nytimes.com/2022/01/20/technology/big-tech-senate-bill.html.

[3]Source: https://www.cnbc.com/2020/11/06/airbnb-hit-with-proposed-class-action-lawsuit-from-host-

but upset guests. These types of conflicts are usually more immediate than indirect network effects and must be addressed by platform rule-making directly.

The prevalence of conflicting interests also implies that a regulatory focus on network effects may miss an integral part of platform economics. If the biggest concern is that an inefficient platform is too big to be competed away due to strong network effects, policy makers should have received most complaints from nascent platforms that try to compete with the incumbent. While such complaints do exist, many ongoing complaints come from *users on one side* of an incumbent platform despite the fact that users on the other side are highly satisfied. For example, merchants were concerned about high transaction fees and anti-steering clauses of major credit card companies but cardholders appreciate the convenience, cash back rewards, and full fraud protection from credit cards;[4] some app developers complained about the high commission fees on Apple's iOS ecosystem while most apps are free to download on Apple's App Store;[5] and some delivery workers reportedly felt squeezed by platform algorithms when demand for food and shopping deliveries grew quickly.[6] These examples suggest that the rules set by the platforms may have been friendly to the buyer side at the expense of the seller side. While such asymmetry is consistent with the "divide-and-conquer" strategy natural to platforms with positive network effects (Caillaud and Jullien 2003), it also highlights the conflicting interests that a platform has to address across sides. To identify whether these platform rules need further regulation, one must understand how a platform sets rules to balance conflicting interests, above and beyond the network effects.

Using a 2018 rule change on Airbnb, this paper highlights the role of conflicting interests and platform competition in platform rule-making. Short-term rentals provide an excellent setting to study this topic, not only because hosts and guests enjoy positive network effects on the same short-term rental platform, but also because the competition between the two largest short-term rental platforms (Airbnb and VRBO) allows us to define localized platform competition for each listing.

More importantly, Airbnb tends to be more pro-guest than VRBO. In May 2018, Airbnb adopted a new pro-guest rule that mandates all hosts provide a minimum level of flexibility in

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missing-payments.html, accessed on May 31, 2022.

[4]See, for instance, `https://www.justice.gov/file/485746/download` for the District Court decision in US vs. American Express, 2015.

[5]See, e.g., Spotify's complaint regarding Apple's "tax" on subscription payments, `https://rb.gy/ywyxpg`.

[6]As reported on NPR news in 2019; see, e.g., `https://rb.gy/dipgss`.

guest cancellation. In particular, all Airbnb listings are required to offer guests the option to cancel their reservations, with a full refund, inclusive of any platform fees, within 48 hours of their booking, provided their check-in dates are at least 14 days away (see Appendix Figure A1 for details of the Airbnb guest cancellation policy structure post the 48-hour rule). This guest-friendly grace period applies to all listings regardless of their hosts' chosen cancellation policies, and does not provide hosts with an ability to opt out. In comparison, as of yet, VRBO does not have a similar rule. Assuming the 48-hour rule is exogenous to individual hosts and guests, it allows us to document how individual hosts react to this pro-guest change, while facing network effects, competition, and conflicting interests with guests.

To study the impact of the 48-hour rule, we use AirDNA-collected data on Airbnb and VRBO listings in 10 major US cities (Atlanta, Austin, Boston, Chicago, Houston, Los Angeles, New Orleans, New York, Seattle, and Washington DC) between January 2017 and December 2019.

If we focus on price and quantity alone, the 48-hour rule does lead to higher prices and higher occupancy rates for Airbnb listings on average, as compared to VRBO-only listings in the same zipcode, suggesting that the rule boosts guest demand on Airbnb. In theory, these results could be part of a positive-network-effects story, to the extent that the 48-hour rule attracts more guests to Airbnb, more guests attract more hosts, more hosts attract more guests, etc.

However, a closer look suggests that some things are at odds with such a stylized network-effect story: for example, the effects on prices and occupancy rates are greater for Airbnb listings with flexible or moderate cancellation policies ("loose hosts"), who already allowed guest cancellations within 48 hours even before the 48-hour rule. If network effects are the dominant force at play, the original demand effect should come from listings with strict guest cancellation policies ("strict hosts"), as the 48-hour rule was most binding for them at the time of adoption.

Further analysis suggests that part of the supply side *moves away from* Airbnb post the 48-hour rule. In particular, the total number of active Airbnb listings per zipcode-month declined 2.55% after the 48-hour rule (relative to VRBO listings), and Airbnb hosts are more likely to also advertise their listings on VRBO ("co-list" or "cross-list") post the rule than vice versa. Within Airbnb, the hosts that were strict and thus more directly affected by the 48-hour rule tend to lower service quality by reducing guests' ability to book instantly (i.e., to "Instant Book," without first requesting host approval) and by increasing host cancellation of guest reservations. Most of these results are stronger if an Airbnb listing faced more competition from VRBO listings within a 0.3-mile radius before the 48-hour rule.

Altogether, these results suggest that some hosts defy the network power of Airbnb, although the 48-hour rule makes Airbnb more attractive to guests overall. One countervailing force is conflict of interest between users: post the 48-hour rule, strict Airbnb hosts can no longer retain half of the reservation payment if a guest cancels within 48 hours. Not only does this reduce the host's expected revenue, it could also lead to greater uncertainty and higher operation costs. These fundamental economics could explain why strict hosts tend to lower service quality more than loose hosts in response to the 48-hour rule.

The second countervailing force is platform competition. The presence of a widely accepted competing platform may enable some hosts to divert traffic away from Airbnb through less entry, more cross-listing, or quality downgrade on Airbnb. Consistent with that, our back-of-the-envelope calculation finds that Airbnb enjoys higher Gross Booking Value (GBV) from the 48-hour rule, but GBV growth is slower in the cities where Airbnb faces more VRBO competition. This suggests that viable platform competition could limit a platform's incentives to appeal to the demand side and squeeze the supply side, should Airbnb have the freedom to set the rule differently in different cities. Put it another way, platform competition could counter the positive network effects on a single rule-making platform and limit its incentives of asymmetric treatment, because the side that faces a less favorable treatment has an outside option in the competing platform.

This finding also presents a cautionary note to antitrust authorities: while promoting market competition is a laudable goal of antitrust enforcement, more platform competition between Airbnb and VRBO could lead to a welfare *decline* for guests even after Airbnb adopts an explicit pro-guest policy. This happens because platform competition allows some hosts to escape the economic pressure from Airbnb and lower service quality. Estimates from a structural model of guest utility suggest that guest welfare may have declined after the 48-hour rule in five of the ten cities that have seen more fierce competition between Airbnb and VRBO before the 48-hour rule. This intricate pattern of platform competition highlights a potential trade-off between the classical consumer welfare standard in antitrust enforcement and a more general goal of "promoting competition" in the recent policy discussion of antitrust reform.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 provides some background on Airbnb's cancellation policies. Section 4 provides a conceptual framework, highlighting how network effects, conflicting interests of users and platform competition may affect user response to the 48-hour rule. Section 5 describes the dataset and provides summary statistics. Section 6 reports our empirical findings. Section 7 discusses their implications and concludes.

# 2 Related Literature

Our work is closely related to the literature on two-sided platforms. Emphasizing positive network effects between sides, the earliest strand of the literature explores a platform's optimal pricing strategy. Cailaud and Jullien (2003) show that a platform may follow a "divide and conquer" strategy, subsidizing participation on one side and profiting from the other. Further research finds that the degree of asymmetric pricing depends on how much of a positive externality one side could generate for the other (Armstrong 2006), and to what extent users may switch away in response to a price hike (Rochet and Tirole 2003). According to Armstrong (2006), platform competition may result in lower prices, but when one side single-homes and the other side multi-homes, competition can push platforms to subsidize the side that is more likely to single-home.

Consistent with that, we observe asymmetric pricing on many multi-sided platforms, where individual consumers receive free services (e.g., search engines, social media services, and B2C e-commerce platforms), or even negative prices (e.g., cash-back referral websites and credit cards). To support such prices and subsidies, platforms usually earn revenue from the other sides (e.g., advertisers, sellers, and retail merchants). Empirically, Jin and Rysman (2015) examine the role of platform competition in Sportscard conventions, which were held offline and hence the degree of competition can be measured by geographic and timing distance. They find that Sportscard conventions do change their asymmetric pricing in response to platform competition, and the response depends on the ease of multi-homing and the difficulty to adopt a negative price.

A growing literature recognizes asymmetric treatment in a platform's non-pricing decisions as well. For example, Hermalin (2016) shows that a firm that taxes trade on its platform may have incentives to adopt minimum quality standards even if seller quality is observable to buyers and the standard is costly for sellers. Empirically, Hui et al. (2018) demonstrate the effect of eBay replacing the "Power Seller" badge with a more stringent "eBay Top Rated Seller" badge in 2009. They show that the higher bar motivates some sellers to incur costs for quality improvement while other sellers give up on the badge and reduce effort. In a different setting, Jin et al. (2022) study the effect of the 2015 China Food Safety Law on Taobao.com, where the law requires all package food sellers be licensed by local governments. They find that the new law improved the average quality of surviving sellers, though many small or non-reputable sellers exited, and market concentration increased. Notably, the badge upgrade on eBay constituted a platform effort to govern the two sides, whereas China's Food Safety Law was an external regulator trying to strike a new balance between buyers and sellers. Our study is more similar to the former, as Airbnb has full control over what cancellation policies to allow or disallow on its platform.

While quality standards are often touted as a way to help consumers (the actual effects may differ),[7] several studies demonstrate that platforms may have incentives to tilt towards the non-consumer side. For example, a quality certifier may offer few clues about product quality once a seller meets a minimum quality standard (Lizzeri 1999); a platform may prefer some noise in its user-rating system to avoid repelling too many sellers (Bouvard and Levy 2018); an online marketplace may shroud some product attributes because consumers are unlikely to deviate when they are already deep in the search process (Hossain and Morgan 2006; Blake et al. 2021) or because too much transparency would intensify seller competition and reduce the platform's profit from the trade (Ellison and Ellison 2009; Johnen and Somogyi 2019). As the founders of Google wrote, "advertising funded search engines will be inherently biased towards the advertisers and away from the news of the consumers" (Brin and Page 2012). Consistently, theories have shown that a search engine may be incentivized to lower the quality of its search results because that will discourage users' (product) search and soften seller competition (Chen and He 2011; Eliaz and Spieger 2011); and there is empirical evidence that hotel booking platforms may rank a hotel's listing in a worse position if the same hotel is priced lower on its own website or on other booking platforms (Hunold, Kesler, and Laitenberger 2020).

In short, many theories have explained why a platform may treat different sides asymmetrically because of positive network effects, and some empirical studies have demonstrated the existence of asymmetric treatment, in both pricing and non-pricing rules. However, this does not imply that positive network effects are the only, or even the main, reason for asym-

[7] Quality standards can also be used to mitigate negative spillovers among sellers on a platform. For example, Nosko and Tadelis (2015) show that buyers may draw conclusions about the quality of the platform from single transactions, causing a reputational externality across sellers.

metric rule-making. Our work highlights conflicting interests as another important factor: results suggest that a pro-guest rule may hurt some hosts and motivate them to lower quality, multi-home, or even avoid the platform, all of which could counteract the positive network effects between guests and hosts on that platform.

Our work also highlights the role of platform competition in a platform's rule-making incentives, especially with respect to non-price rules. Because short-term rental platforms compete in local markets, we are able to measure platform competition continuously and study hosts' cross-listing behavior across platforms. In comparison, the existing studies tend to rely on one-time change of platform competition in terms of merger or bifurcation.

Focusing on a merger between two pet-sitting platforms, Farronato, Fong, and Fradkin (2022) find that the merger benefited users of the acquiring platform because of network effects, but made users of the acquired platform worse off. Their results highlight the importance of platform differentiation besides network effects within each platform. Chen, Forman and Kummer (2022) study bifurcation of communities on Stack Overflow (a large programming question and answer platform), where users can create a spin-off community away from the home community. They find that the bifurcation decreases user contribution in the home community but the home and spin-off communities, in total, generate more user contribution and attract more new users than a single united community. This suggests that factors such as congestion and differentiation may counteract positive network effects on a single united community and limit its efficient size. Similarly, congestion and differentiation are present in our context[8], but we emphasize that conflicting interest between sides of a platform, and its interaction with platform competition, is another fundamental force driving platform and user incentives.

Policy-wise, our work contributes to the ongoing antitrust debate about two-sided platforms. In a theoretical review for competition policy, Jullien and Sand-Zantman (2021) show that, although positive network effects may cause inefficient tipping towards the incumbent platform, the inefficiency can be hampered by platform differentiation, multi-homing, within-platform congestion, and platform interoperability. As detailed below, all these features exist in our empirical setting and help explain why conflicting interests and platform competition are important factors in Airbnb's rule-making incentives, above and beyond positive network effects between guests and hosts. Our finding also highlights the possibility that more

[8]The differences between loose and strict hosts can be a result of congestion and differentiation on the same side of Airbnb, and the 48-hour rule is a form of differentiation between Airbnb and VRBO.

platform competition does not necessarily enhance consumer welfare if consumer welfare is limited to final consumers of the focal service (guests). As detailed in Section 7, this finding helps to inform the ongoing debate between the classical consumer welfare standard and the general aim of promoting competition in antitrust practice.

Finally, our paper contributes to the growing literature on Airbnb. Focusing on the competition between Airbnb and traditional hotels, Farronato and Fradkin (2022) find that Airbnb increases the welfare of individual guests and hosts, because Airbnb hosts are responsive to market conditions, expand supply as hotels fill up, and keep hotel prices down as a result. Zervas et al. (2016) indicate that Airbnb listings have higher average ratings compared to the hotel industry. Lee et al. (2015) point out that host reputation, including the number of reviews, host responsiveness, and host tenure, can impact a listing's price per night on Airbnb. Wang and Nicolau (2017) and Jia and Wagman (2020) confirm that host attributes are the most important price determinants of Airbnb listings. Huang (2021) demonstrates significant price frictions on Airbnb, and argues that sellers' price-setting costs and cognitive constraints are plausible drivers of these frictions. Zhang et al. (2021) find that only 22.5% of Airbnb properties in their sample adopted an Airbnb-recommended pricing algorithm, although adopters on average had a 8.6% revenue improvement and a 5.7% downward price correction. As detailed in Section 3, this pricing algorithm was introduced in November 2015, which is before the beginning of our sample period (2017). Our data do not indicate which hosts adopt the pricing algorithm but most of our analyses control for listing or host fixed effects, and therefore have accounted for the use of a pricing algorithm if a host had adopted it before 2017 for a particular listing. To the best of our knowledge, we are the first to study cancellation policies on short-term rental platforms and the first to use short-term rentals to shed light on platform competition and antitrust policy.

# 3 Background of Airbnb Governance Framework

Sellers regularly contract with buyers for transactions that will take place at some point in the future, including airlines, hotels, and suppliers. Sometimes, sellers fail to follow through on contracted obligations. For example, airlines oversell seats, hotels overbook rooms, suppliers under-deliver product units, and contractors in construction, consulting, carpentry, roof repair, among others, may fail to complete agreed-upon projects.

A platform such as Airbnb can influence user behavior through a reputation system[9], a standardized menu of policies for user choice, and a mandate on certain practices. Since a growing literature has examined the role of reputation on Airbnb, here our focus is on the choices that Airbnb offers and requirements that it sets as far as host and guest cancellation.

On Airbnb, guests have to follow a listing's cancellation policy (flexible, moderate, or strict by Airbnb's definition), as selected by the listing's host, and pay the corresponding cost stipulated by the listing's cancellation policy should they cancel a reservation. For example, if a listing has a strict cancellation policy, its guests would only receive 50% of the cost of their booking when cancelling a reservation that is at least one week away from arrival, and lose the full 100% if the cancellation is less than a week away. If a listing offers a flexible cancellation policy, guests could get a full refund if they cancel up to 24 hours before their trip, or up to 5 days before their trip for listings that offer a moderate cancellation policy. Under any of the three guest-facing cancellation policies—flexible, moderate or strict—a refund would not include the fee that guests paid to Airbnb.

Beginning on May 1, 2018, however, Airbnb started offering guests the option to cancel their reservations for a full refund—inclusive of the Airbnb service fees—within 48 hours of their booking, as long as their check-in dates are at least 14 days away. In Appendix Figure A1, we show a few Airbnb-provided examples of flexible, moderate, and strict cancellation policies after the introduction of the 48-hour rule.

We are not aware of any other major policy change on Airbnb around May 2018. Airbnb's commission structure (3% charged to hosts and ∼12% to guests) was stable throughout our sample period (2017-2019) until Airbnb started testing a simplified fee structure (0% on guests and ∼15% on hosts) in December 2020. Similarly, Airbnb remained a private company until its IPO in December 2020. Airbnb rolled out an algorithmic tool for price setting in 2013. Despite its subsequent update in November 2015 (Hill 2015), according to Gibbs et al. (2018) and Zhang et al. (2021), host adoption of algorithmic pricing has been limited.

Perhaps in part because some hosts complained about guest cancellations after the introduction of the 48-hour rule, Airbnb began allowing hosts to offer a no-refund option to guests on October 1, 2019.[10] This option offers a 10% discount to guests and is only avail-

[9]To foster trust, Airbnb's reciprocal reputation system enables hosts and guests to blindly review each other within 14 days after a guest's stay. If one side does not review the other, the other's review becomes visible after 14 days.

[10]See https://www.airbnb.com/resources/hosting-homes/a/airbnb-answers-protecting-you-from-guest-cancellations-124, accessed on May 14, 2021.

able to listings with flexible or moderate cancellation policies. Unfortunately, our data does not capture this feature and thus we do not know how many flexible or moderate listings incorporated this option after October 2019. Since this option was only available in the last three months of our sample period, we have rerun our analyses excluding these three months and found that our results are robust. Since this no-refund option is in some sense a partial dial back from the 48-hour rule, results reported in this paper (with data until December 2019) are likely more conservative than the true effects of the 48-hour rule.

On the host side, Airbnb provides an automated system review, which is added to the other, guest-provided reviews, for listings whose hosts cancel a confirmed reservation prior to the guest's arrival. Since they are system generated and posted only upon a confirmed cancellation by a host, these cancellation reviews have a pre-structured syntax, and can be readily distinguished from other, guest-written reviews.[11] Appendix Figure A2 provides an example. These automated reviews may signal to travelers that there could be a higher than usual probability that their lodging plans might fall through at some point prior to their arrival, a costly situation especially in locales of high demand for temporary accommodations. In addition to receiving automated cancellation reviews when cancelling guest reservations, hosts forfeit eligibility for the "Superhost" status on Airbnb for a year, a status badge related to metrics concerning a listing's performance.[12] Hosts may also incur direct monetary punishments from Airbnb in the form of a reduction in the amount of a future payout. Airbnb also blocks the host-cancelled calendar days on the listing from being re-booked, so the host cannot rent the listing out to another guest on Airbnb. However, if the listing is cross-listed on both Airbnb and VRBO, the host can still rent it out on VRBO after cancelling the

[11] The automated cancellation review format is: "The host canceled this reservation X days before arrival. This is an automated posting," where X $\geq$1 is as stated. For same-day cancellations, guests can still post a (non-automated) review. Prior to August 2015, the format was: "The reservation was canceled X days before arrival. This is an automated posting."

There are multiple benefits to looking at system-generated cancellation reviews as a measure of negative information about sellers' transaction reliability. First, they are credible, non-manipulable, and demonstrably negative. Second, while prior works that study user-generated reviews tend to focus on products such as goods, hotels or restaurants (including Mayzlin et al. 2014 and Luca and Zervas 2016), Airbnb reviews are much more personal and rate an experience in another individual's dwelling. As a result, reviews on Airbnb are overwhelmingly positive (Zervas et al. 2020), which may grant further weight to the negative information implied by automated cancellation reviews. Third, Airbnb does not show individual guest scoring of a listing but only averages, making it less clear-cut to objectively identify negative guest reviews in a data set — a non-issue for automated cancellation reviews.

[12] Hosts who meet the following criteria receive a Superhost designation: (i) Hosted at least 10 guests in the past year; (ii) maintained a high response rate and low response time; (iii) received primarily 5-star reviews; (iv) did not cancel guest reservations in the past year. VRBO has a similar feature called 'Premier' host.

booking on Airbnb.

Besides automated host cancellation reviews, another feature available on both Airbnb and VRBO is instant booking. Hosts that choose this feature allow guests to book immediately without the need to send a request to the host for approval. The 48-hour grace period of free guest cancellation could make instant booking even more convenient for guests, but generate more revenue and operation uncertainty for hosts.

As for competition, it is difficult to define the market for short-term rentals. A guest looking for short-term rentals may find supply in hotels, bed and breakfasts, and hostels, in addition to private-room and shared-space listings; a host that manages a residential property could put the property up for short-term rent, long-term rent, or other use. As a matchmaker, Airbnb brings together guests and hosts, as does VRBO, FlipKey, Booking.com, and traditional travel agencies, among others.

In this paper, we only consider the competition between Airbnb and VRBO because VRBO has a similar business model and is arguably the closest competitor to Airbnb in the US. In particular, VRBO offers similar features to hosts and guests but does not generate automated cancellation reviews for hosts who cancel a guest's reservation, or offer a 48-hour grace period for guests who seek a full refund after booking a reservation.[13] Moreover, as VRBO's original name (Vacation Rentals By Owners) implies, VRBO specializes in vacation rentals, and thus it tends to be more present in cities that attract tourism or in the touristic parts of a city. This generates natural variations in the extent of local competition between VRBO and Airbnb.

# 4 Conceptual Framework

In this section, we present a stylized framework to highlight the interplay between positive network effects and conflicting interests across different sides of a platform.

Consider a local short-term rental area where Airbnb matches potential guests and hosts. Following Rochet and Tirole (2006), we assume the probability of matching a user depends

[13] Airbnb's cancellation policies on both its guest and host sides are illustrative of the observation that peer-to-peer markets such as home sharing and ride sharing may also suffer from a reliability problem, more so than traditional similar markets. The reliability issue can pervade both sides: on the seller side, Airbnb hosts may cancel guests' confirmed reservations; on the buyer side, Airbnb guests may cancel their own reservations. More centralized traditional market operators, such as hotels and taxis, offer standardization and consistency, which may help improve reliability and align expectations. To foster reliability in a peer-to-peer setting, a platform can choose policies that incentivize more reliable behavior on both its seller and buyer sides, but those policies may also have other effects.

on the number of users on the other side, thanks to the positive network effects on Airbnb. More specifically, if the potential mass of users is 1 on both sides, the number of users on side $j$ ($N^j$) can be used as a proxy for the probability of a user on side $i$ matching with any users on side $j$. Conditional on a good match, we assume the benefit of trade is $b^i$ for a user on side $i$, and the price user $i$ needs to pay to Airbnb is $p^i$. For simplicity, we assume $p^i$ is a membership fee that does not depend on the number of trades in which user $i$ engages on the platform. Rochet and Tirole (2006) allow both membership fee and per-trade price in $p_i$, and find similar insights about network effects. We assume that each potential user on side $i$ chooses to use Airbnb, relative to an outside option with utility $\underline{U}^i$. We allow $b^i$ to have a component common to all users on side $i$ and a random component specific to each individual user. The common component depends on platform rules on side $i$, and the random component allows different users on side $i$ to choose to use or not use the platform even if they face the same outside option $\underline{U}^i$.

Overall, the Airbnb system can be written as:

$$\begin{cases} \text{Guest utility: } U^G = b^G \cdot N^H - p^G \\ \text{Number of guests: } N^G = Pr(U^G > \underline{U}^G) \\ \text{Host utility: } U^H = b^H \cdot N^G - p^H \\ \text{Number of hosts: } N^H = Pr(U^H > \underline{U}^H) \end{cases}$$

In the simplest abstract, our empirical exercise is examining how $N$ and $U$ change as the 48-hour rule changes the benefits of trade ($b$), while keeping price $p$ and the outside option $\underline{U}$ fixed on both sides.

Following Rochet and Tirole (2006), the demand function on side $i$ can be defined as:

$$N^i = Pr(b^i \cdot N^j - p^i > \underline{U}^i) \equiv D^i(b^i, N^j), \qquad i \in \{G, H\}.$$

Under regular conditions, we can solve the two equations for a unique set of $N$:

$$\begin{cases} N^G = n^H(b^G, b^H) \\ N^H = n^H(b^G, b^H) \end{cases}$$

If the 48-hour rule only increases $b^G$ while keeping $b^H$ unchanged, its impact on $N^G$ is:

$$\frac{\Delta N^G}{\Delta b^G} \text{ if } b^H \text{ is unchanged} = \underbrace{\frac{\partial D^G}{\partial b^G}}_{\substack{b^G attracts \\ guests}} \cdot \underbrace{\frac{1}{1-\frac{\partial D^G}{\partial N^H}\cdot\frac{\partial D^H}{\partial N^G}}}_{\substack{magnified\ by \\ positive\ network \\ effects}} \tag{1}$$

However, if the 48-hour rule not only increases $b^G$ but also decreases $b^H$ at the same time (assuming by the same magnitude), the policy's impact on $N^G$ will have an extra term that counters the initial positive effect of $b^G$:

$$\frac{\Delta N^G}{\Delta b^G} \text{ if } b^H \text{ drops} = (\underbrace{\frac{\partial D^G}{\partial b^G}}_{\substack{b^G\ attracts \\ guests}} - \underbrace{\frac{\partial D^H}{\partial b^H}\cdot\frac{\partial D^B}{\partial N^H}}_{\substack{drop\ of\ b^H \\ repels\ hosts}}) \cdot \underbrace{\frac{1}{1-\frac{\partial D^G}{\partial N^H}\cdot\frac{\partial D^H}{\partial N^G}}}_{\substack{magnified\ by \\ positive\ network \\ effects}} \tag{2}$$

Similarly, we can derive the relevant impacts of the 48-hour rule on $N^H$. If the rule changes $b^G$ without affecting $b^H$, its impact on $N^H$ is all positive:

$$\frac{\Delta N^H}{\Delta b^G} \text{ if } b^H \text{ unchanged} = \underbrace{\frac{\partial D^G}{\partial b^G}}_{\substack{b^G attracts \\ guests}} \cdot \underbrace{\frac{\partial D^H}{\partial N^G}}_{\substack{Guest \\ spillovers \\ to\ hosts}} \cdot \underbrace{\frac{1}{1-\frac{\partial D^G}{\partial N^H}\cdot\frac{\partial D^H}{\partial N^G}}}_{\substack{magnified\ by \\ positive\ network \\ effects}} \tag{3}$$

However, if the rule changes $b^G$ while decreasing $b^H$ by the same amount, we have a new negative term:

$$\frac{\Delta N^H}{\Delta b^G} \text{ if } b^H \text{ drops} = (\underbrace{\frac{-\partial D^H}{\partial b^H}}_{\substack{drop\ of\ b^H \\ repels\ hosts}} + \underbrace{\frac{\partial D^G}{\partial b^G}}_{\substack{b^G attracts \\ guests}} \cdot \underbrace{\frac{\partial D^H}{\partial N^G}}_{\substack{Guest \\ spillovers \\ to\ hosts}}) \cdot \underbrace{\frac{1}{1-\frac{\partial D^G}{\partial N^H}\cdot\frac{\partial D^H}{\partial N^G}}}_{\substack{magnified\ by \\ positive\ network \\ effects}} \tag{4}$$

We can readily derive how $U$ would change post the 48-hour rule because we have defined $U^i = b^i \cdot N^j - p^i$ and thus:

$$\frac{\Delta U^i}{\Delta b^G} = \frac{\partial b^i}{\partial b^G} \cdot N^j + b^i \cdot \frac{\Delta N^j}{\Delta b^G}.$$

This conceptual framework highlights four effects from the 48-hour rule:

The first is the rule's *direct effect on guest demand*, namely $\frac{\partial D^G}{\partial b^G} > 0$. This positive effect is larger for strict hosts than for loose hosts (as of the rule adoption time), because (a) the rule is only binding for strict hosts, and (b) Airbnb waives the platform's cancellation fee for all cancellations eligible for the 48-hour rule. In particular, (b) is a common benefit that should attract more guests to Airbnb and thus benefiting all hosts, while (a) is an extra effect only applicable to strict hosts. This alone implies that strict hosts should enjoy a larger, positive change from the 48-hour rule in terms of occupancy rate and revenue on Airbnb.

The second is *the positive network effects between guests and hosts*, which magnifies the direct effect on guest demand. Since the 48-hour rule boosts $b^G$ and keeps $b^H$ unchanged for loose hosts on Airbnb, the network effect magnifies the positive demand boost for loose hosts (Equation 1). As a result, loose hosts should be more likely to stay on Airbnb post the 48-hour rule (Equation 3). By the same logic, the positive network effects apply to strict hosts as well. As mentioned above, the direct positive demand effect is greater for strict hosts, hence that effect magnified by the network effects should be greater for strict hosts.

The third effect reflects *a conflicting interest between guests and strict hosts*. Because the 48-hour rule boosts $b^G$ but reduces $b^H$ for strict hosts, these hosts suffer an *extra* negative effect on top of the rule's positive, direct effect on guest demand. This negative effect is magnified by the network effects as well (Equations 2 and 4). In net, strict hosts may or may not enjoy higher revenues from Airbnb post the 48-hour rule, and may or may not stay on Airbnb, depending on whether the negative effect of conflicting interests dominates the rule's positive effect on guest demand. This ambiguous prediction on strict hosts is in a sharp contrast to the clear, positive prediction on loose hosts.

The fourth effect comes from *platform competition*. Though we do not model platform competition explicitly, it can impact Equations (1) to (4) via users' outside option ($\underline{U}^G$ and $\underline{U}^H$) in two channels. First, everything else being equal, lower $\underline{U}^G$ and $\underline{U}^H$ as implied by less platform competition would encourage more guests and hosts to join the focal platform. Because we assume that guest utility $U^G$ increases with $N^H$ and host utility $U^H$ increases with $N^G$, a platform facing less platform competition would enjoy stronger network effects, which in turn strengthen the three effects of the 48-hour rule as per the above.

The second channel is through the outside option's impact on the magnitude of the direct effect of the 48-hour rule on guest demand ($\frac{\partial D^G}{\partial b^G}$). In theory, this impact can be positive or negative depending on how the random component of $b^G$ is distributed across guests. If more VRBO competition implies a higher elasticity of guest response to the direct benefit from the 48-hour rule (i.e. greater $\frac{\partial D^G}{\partial b^G}$ as $\underline{U}^G$ increases), it can reinforce the rule's positive effect on guests and hosts. Similarly, if more VRBO competition implies a higher elasticity of strict hosts' response to the rule's direct harm on them (i.e. greater $\frac{\partial D^H}{\partial b^H}$ as $\underline{U}^H$ increases), it can exacerbate the rule's negative effect on strict hosts. Conversely, if more VRBO competition implies smaller elasticity on either side, competition may mitigate the rule's effect on guests and hosts. Altogether, competition with VRBO may have an ambiguous effect on the effectiveness of the 48-hour rule on Airbnb.

To summarize, the above framework highlights the basic intuition that a pro-guest rule like the 48-hour rule could boost guest demand and benefit host revenue because of the positive network effects, or hurt some hosts because it conflicts with the interests of these hosts. It does not incorporate more details on the supply side such as how loose and strict hosts operate on the same platform, how guests and hosts multi-home on Airbnb and VRBO, and how hosts may change the quality of the service they provide to guests.

These supply-side features may further blur the effect of the 48-hour rule: for example, when both loose and strict hosts compete on Airbnb in the same local area, the extra, negative effect of the 48-hour rule on strict hosts could hamper the positive effect on guests (through the network effects), which in turn hampers the positive effect on loose hosts.

There is also direct competition between loose and strict hosts. Some hosts own/manage more popular properties on Airbnb, and as a result, have more room to set less guest-friendly cancellation policies; we find that, unsurprisingly, strict hosts tend to own/manage more popular properties on Airbnb than loose hosts. Because the 48-hour rule has a direct, negative effect on strict hosts but strict hosts tend to have more popular properties on Airbnb than loose hosts, the 48-hour rule will alter their product differentiation and reshape their competition within the same platform.

In addition, as some guests and hosts change their multi-homing decision, the utility from the outside option could change endogenously, which will trigger more changes in entry, exit and multi-homing. We will keep the above complications in mind as we explore empirical results on the supply side.

# 5 Data

We use consumer-facing information on the complete set of hosts who had advertised their listings in the 10 US cities of Atlanta, Austin, Boston, Chicago, Houston, Los Angeles, New Orleans, New York, Seattle, and Washington DC, on Airbnb from January 2017 to December 2019. We also obtain such information for hosts who list their properties in these 10 cities on

VRBO during 2017-2019. The data was acquired from AirDNA, a company that specializes in collecting Airbnb and VRBO data.

Each listing is identified by a unique identifier and comes with time-invariant characteristics such as the host's unique identifier, listing zipcode, approximate locale,[14] and property type (entire home, private room, or shared space). Throughout the paper, we focus on entire-home listings, which are both more numerous[15] and more comparable with VRBO because VRBO does not allow private-room or shared-space listings.

Listing information also comprises time-variant characteristics, including an average monthly price,[16] the number of nights in a listing's calendar reserved by guests in a month, nights that had been blocked off in a month (i.e., nights that hosts chose not to offer to guests), the number of reservations reserved by guests in a month, the listing's number of reviews, its average overall review rating by guests (based on a 5 star rating system with 1/4 star intervals), the listing's guest-facing cancellation policy, its minimum nights per stay, its maximum number of guests, a measure of the host's experience (number of days since the host's first listing was created), review time gap (number of days since the latest review), whether the listing is offered for Instant Booking (i.e., without requiring host approval), the average response time in minutes (the time it takes the host to respond to an initial guest inquiry), response rate to guest inquiries (percentage of inquiries to which hosts respond within 24 hours), and whether a listing's host is a Superhost. Other listing-month information includes the listing's total number of reviews and average review ratings up to the study month.

Similar to Airbnb's three-tier structure, VRBO defines guest cancellation policy in five tiers: no refund, strict, firm, moderate and relaxed.[17] Throughout the paper, we treat no refund and strict as "strict" on VRBO, comparable to Airbnb's strict cancellation policy. The other three — firm, moderate and relaxed — are aggregated as "loose" on VRBO, comparable to flexible and moderate cancellation policies on Airbnb. Reclassifying VRBO's firm cancellation policy as "strict" generates similar results.

[14]To be exact, the data includes latitude and longitude positioning in a six-digit decimal format that indicates the approximate location of a listing.

[15]Private room and shared space average 1,248 and 150 per month per city on Airbnb, respectively.

[16]A listing's per-night price represents the most recent rate a host set for the night up until the night was either booked, blocked off the calendar, or remained unbooked/unblocked until it passed; these nightly prices are then averaged over the month to give an average monthly listing price — for brevity, we henceforth refer to these averages as the listing's price.

[17]Source: https://help.vrbo.com/articles/What-are-the-cancellation-policy-options, accessed on May 14, 2021.

We focus on listings that are offered for rent for less than 30 days. We also exclude observations with listing prices per night over $1000, because some hosts may set their rates prohibitively high in lieu of blocking their calendars. In total, our sample includes 1,198,017 listing-months.

To measure the occupancy rate of a listing, we divide the number of reserved days by the number of days available for reservations in a given month. We use two approaches for the number of days available in a month, one being the number of calendar days, and the other being the number of calendar days minus the number of days that had been blocked off the calendar by the host. Results under both approaches are similar and we report the latter.

To measure competition between Airbnb and VRBO, we use geographical mapping software to count the total number of listings on VRBO that are located in close proximity to each Airbnb listing. We define close proximity by forming a geographic circle with a radius of 0.3 miles around each Airbnb listing based on its approximate coordinates. We then define a competition index equal to the number of VRBO listings divided by the total number of both Airbnb and VRBO listings. If a listing appears on both platforms, it is counted as one on each. This calculation is repeated every month, so the competition index is listing-specific and time-varying. In most regression analyses, we use a listing's competition index as of April 2018 to avoid a potential change in the competition index because of the introduction of the 48-hour rule in May 2018. In some specifications, we split the sample by high and low competition areas, where a listing belongs to a high competition area if the listing's local competition index is above the city-median as of April 2018.

Across the 10 cities in our sample, New York City is the largest home-sharing market, with approximately 75,000 unique listing IDs. Airbnb listings in New York City and New Orleans tend to have higher competition from VRBO listings, compared to other cities. Zooming into the top 30 zipcodes in terms of the total number of listings, we find that areas with a higher number of Airbnb listings also face more competition from VRBO.

The next step is computing the number of host cancellations for each Airbnb listing.[18] To do so, we use the fixed format of the automated reviews, e.g., "The host canceled this reservation X days before arrival. This is an automated posting." (See Appendix Figure A2 for an example.) Searching for such a format in listing reviews, we count the cumulative number of cancellation reviews for each Airbnb listing up to each specific month.

Since VRBO targets touristic areas more than Airbnb, we use the annual Zipcode Busi-

[18]We do not know host cancellations for VRBO listings.

ness Patterns from the US Census to account for time-varying tourism attributes, including the number of hotel rooms, theme parks, national parks, restaurants, and tourism attractions per zipcode.

Table 1 summarizes our whole sample of 1,198,017 listing-months, of which 863,380 (72.07%) are listed on Airbnb only in the study month, 203,225 (16.96%) are VRBO only, and 131,412 (10.97%) are listed on both. Since a listing's cross-listing status can change over time, we label a listing ID "Airbnb first" if it first appeared on Airbnb, and "VRBO first" if it first appeared on VRBO.[19] Among all Airbnb-first listings, 11.77% have ever cross-listed on VRBO from 2017 to 2019; among all VRBO-first listings, 36.53% of VRBO have ever cross-listed on Airbnb. For listings that are cross-listed, we can track their total occupancy rate and average price per night, but we do not know whether the occupancy was booked through Airbnb or VRBO.

At the listing-month level, Table 1 presents summary statistics for Airbnb-only, VRBO-only, and cross-listings in three separate columns. On average, VRBO-only listings have a higher listing price [20] and a higher occupancy rate but a lower number of reservations per month than Airbnb-only listings. The average price of cross-listed listings is in between, likely because it is a mixture of Airbnb and VRBO bookings. Cross-listed listings have, on average, a higher number of reservations per month than both VRBO-only and Airbnb-only listings. The average occupancy rate of cross-listed listings is between that of Airbnb-only and VRBO-only listings.[21]

Since host cancellation is only available on Airbnb, we can only compare it for Airbnb-only and cross-listings. On average, cross-listed listings are more likely to have any host cancellation, suggesting that hosts of lower quality (at least in terms of cancelling guest reservations) may be more likely to multi-home on VRBO. Consistently, cross-listed listings are more likely than Airbnb-only listings to adopt a strict policy in guest cancellation; VRBO-only listings have an even higher probability of adopting strict cancellation than cross-listed listings. However, in other measures of host quality, cross-listed listings are more likely to have hosts with Superhost status and are more likely to allow Instant Booking than Airbnb-only listings. The equivalents of a Superhost badge ('Premier Host') and Instant

[19]Our data on Airbnb listings can go back to May 2015, which helps to define whether the listing is Airbnb first or VRBO first. Our VRBO data begins in 2017. We do not observe a listing in our sample that began as cross-listed at the outset.

[20]These prices do not include transaction fees that guests and hosts pay Airbnb and VRBO.

[21]Reservations and occupancy rate are not perfectly correlated because a reservation may have a longer or shorter occupancy.

Booking are also available on VRBO, where VRBO-only listings are more likely to be listed by Superhosts (Premier Hosts) and are more likely to offer Instant Booking than cross-listed listings. Both Airbnb-only and cross-listed listings have a larger number of reviews than VRBO-only listings, likely because Airbnb is overall a larger platform than VRBO, though the average review rating is similar across the three types of listings.

Cross-listed listings are also more likely than Airbnb-only listings to be located in an area with a higher VRBO competition index. This is understandable because VRBO tends to target areas with more theme parks, national parks, restaurants, and touristic attractions per zipcode, and these areas are attractive to cross-listed listings as well, given that touristic areas often have seasonality. This is also reflected in the fact that both cross-listed and VRBO-only listings are significantly larger than Airbnb-only listings in terms of the number of bedrooms and bathrooms.

Table 2 further distinguishes listing-months by the listing's loose and strict cancellation policies on Airbnb and VRBO. To facilitate a comparison, the loose/strict status in the column title is as of April 2018. To better compare the time-varying cross-listing rate between types of listings, Table 2 presents the statistics in two column blocks, one for "Airbnb first" and the other for "VRBO first." By definition, if an Airbnb listing has never been listed on VRBO, it is Airbnb-first. If a VRBO listing has never been listed on Airbnb, it is VRBO-first. If the listing has been cross-listed, it is classified as either Airbnb-first or VRBO-first depending on where the listing appeared first in the entire listing history we can observe. We report two panels: one before the 48-hour rule (Jan. 2017 to Apr. 2018) and the other after the 48-hour rule (May 2018 to Dec. 2019).

Overall, Table 2 suggests that strict listings are more popular: they tend to charge a higher price, enjoy a higher number of reservations and a higher occupancy rate per month, and are more likely to cross-list on the other platform. This pattern is similar across the two platforms and continues after Airbnb adopted the 48-hour rule. From Tables 1 and 2, we note that strict listings are of better quality than loose listings in some dimensions (property popularity, Instant Booking, Superhost status) but lower quality in other dimensions (stringency of guest cancellation policy, history of host cancellation). These multi-dimensional differences are important for us to understand how the 48-hour rule may affect the two types of listings differently.

A comparison before and after the 48-hour rule suggests that price, number of reservations, and occupancy rate all increase over time, but the increase is most evident for

Airbnb-first listings that offered loose cancellation as of April 2018, which is somewhat surprising given that the 48-hour rule is only binding for strict listings on Airbnb. In contrast, strict Airbnb-first listings have the highest increase in their cross-listing rate as compared to the other three columns, and these listings display a greater increase in monthly host cancellation reviews than loose Airbnb-first listings. These patterns suggest that the 48-hour rule has a different effect on strict and loose listings on Airbnb.

# 6 Empirical Analyses

In this section, we first document the impact of the 48-hour rule on listing-level market outcomes (price and occupancy), and then dive into changes in host behavior, guest welfare, and Airbnb GBV. Throughout the analysis, we allow the effects to differentiate by the degree of localized Airbnb-VRBO competition before the 48-hour rule.

## 6.1 Price, Quantity, and the Role of Platform Competition

According to our conceptual framework, the 48-hour rule brings a direct positive effect on the benefits of trade that guests may gain from Airbnb ($b^G$), but a potential negative effect on the benefits of trade that strict hosts may gain from Airbnb ($b^H$). Both of them influence a user's choice of Airbnb and therefore the amount of trade occurring via Airbnb. Empirically, we measure the amount of trade by the price and occupancy (quantity sold) of Airbnb listings.

More specifically, we use a difference-in-differences methodology (DID), which contrasts all listings on Airbnb (including Airbnb-only and cross-listings) with VRBO-only listings, before and after Airbnb introduced the 48-hour rule in May 2018.

Our baseline specification is:

$$Y_{izt} = \alpha_i + \alpha_t + \delta_1 X_{it} + \delta_2 X_{zt} + \beta_1 Airbnb_{it} + \beta_2 Airbnb_{it} \times \text{Post}_t + \varepsilon_{it}, \tag{5}$$

where $i$ denotes an individual listing, $z$ denotes zipcode, $t$ indexes month, $Airbnb_{it}$ is a dummy equal to 1 if the listing is listed on Airbnb at $t$, $Post_t$ is a dummy equal to 1 if $t$ is on or after May 2018. Depending on the specification, the dependent variable $Y_{it}$ is the log of the average listing price over the month, or log of the monthly occupancy rate.[22]

[22]Results on reservations are very similar to that of occupancy rate, so we only report the latter in the paper.

Year-month and listing fixed effects are denoted by $\alpha_t$ and $\alpha_i$, respectively. $X_{it}$ is listing-level controls, including the number of bedrooms and bathrooms, the number of minimum nights per stay, the number of maximum guests per stay, average review rating, number of reviews, Superhost status, instant booking status, response rate, response time, the number of months since the host created their first listing, as well as the number of cancellation reviews of the same listing up to period $t-1$. $X_{zt}$ denotes the zipcode's tourism attributes, including the number of hotel rooms, theme parks, national parks, restaurants and tourism attractions. These variables may change over time, and therefore are not completely absorbed by listing fixed effects. Stanford errors are clustered by zipcode.

The DID specification is built on the assumption that Airbnb listings and VRBO-only listings follow similar pre-treatment trends before May 2018. To check this assumption, Figure 1 plots the average price and occupancy rate per listing-month for the treated group (Airbnb listings) and control group (VRBO-only listings), with a vertical line indicating the month that Airbnb adopted the 48-hour rule. Figure 1 suggests parallel pre-treatment trends between the two groups, which are confirmed in statistical tests (shown in last row of Table 3). In an unreported table, we also performed a placebo test, examining a hypothetical treatment in the middle of the pre-treatment period. Results confirm the comparability between treatment and control groups before the 48-hour rule.

Post the 48-hour rule, Figure 1 shows that Airbnb listings narrowed their average price gap with VRBO-only listings, and the catch-up was more conspicuous in the later half of the post period than in the first half. In comparison, Airbnb listings began to narrow their occupancy gap with VRBO-only listings right after the 48-hour rule, suggesting that guest demand may have responded immediately to the new rule while hosts may have lagged behind in price response. This is consistent with the limited rationality that Huang (2021) and Zhang et al. (2021) demonstrated in the pricing behavior of Airbnb hosts.

Although Airbnb listings and VRBO-only listings follow a similar pre-treatment trend, a potential caveat of using VRBO-only as the control is that market demand may switch between the two platforms, implying that our DID results may have double-counted the true effect on Airbnb listings. However, from Airbnb's perspective, the estimated effects would all contribute to the platform's market position vis-à-vis VRBO, no matter whether they are driven by demand switching from VRBO or new demand for short-term rentals. Thus, our estimates should help examine Airbnb's rule-making incentives.

Another econometric challenge is that the dummy of whether listing $i$ is listed on Airbnb at month $t$ —$Airbnb_{it}$—can reflect a listing's endogenous response to the 48-hour rule. To address this concern, we use listing $i$'s Airbnb listing status as of April 2018 as an instrumental variable (IV) for $Airbnb_{it}$.

Table 3 reports the OLS DID estimates in Columns (1) and (2) and the DID estimates with IV in Columns (3) and (4). The two sets of results are similar, and both confirm the raw data patterns in Figure 1. According to the IV results, the 48-hour rule leads to a 2.69% higher price and a 2.11% higher occupancy rate for Airbnb listings than for VRBO-only listings. These are the average effects over the twenty months after the 48-hour rule. To understand how fast the effects take place, Columns 5 and 6 split the post period into halves. The IV estimates suggest that the price effect of the 48-hour rule almost doubled in the second half relative to the first half of the post period (3.45% vs. 1.81%, both significant). In comparison, the effect on the occupancy rate is similar across the two halves of the post period (2.01% vs. 2.19%).

Although our DID analysis includes many time-varying listing attributes, Table 3 only reports the coefficient of one such attribute – the number of host cancellation reviews on Airbnb up to time $t-1$.[23] This coefficient turns out negative and highly significant, suggesting that Airbnb guests view host cancellation as a strong negative attribute.[24] This also confirms the assumption that Airbnb automatically posts host cancellation reviews in order to provide useful information to Airbnb guests.

As detailed in our conceptual framework, the 48-hour rule may have different effects on Airbnb loose or strict listings because loose listings had offered free guest cancellation within 48 hours of booking even before Airbnb adopted that rule. To capture these differential effects, Table 4 reports the DID results for the subsample of Airbnb loose listings vs. VRBO-only loose listings (Columns 1 and 2), and Airbnb strict listings vs. VRBO-only strict listings (Columns 3 and 4). The loose or strict status of listings are all as of April 2018, the month before the 48-hour rule. In all columns, we use a listing's Airbnb status as of April 2018 as an instrument for its contemporaneous listing status.

All columns of Table 4 suggest that the positive effects of the 48-hour rule on price and occupancy rate are significantly larger for Airbnb loose hosts than for strict hosts. This supports two predictions in Section 4: first, the 48-hour rule increases guests' marginal

[23]This variable is coded as zero for VRBO-only listings because VRBO does not offer any information on host cancellation.

[24]In unreported tables, we have used historical bad weather as instruments for the cumulative count of host cancellation reviews and found similar negative coefficients.

benefit of trade ($b^G$) and therefore boosts guest demand for Airbnb relative to VRBO; second, although the 48-hour rule generates a greater increase in $b^G$ for strict hosts, it also creates a conflict of interest and decreases the benefit of trade for them ($b^H$). Results suggest that the conflict of interest between guests and strict hosts are significant but do not completely cancel out the direct positive effect of the 48-hour rule on guest demand.

Our data tracks listings by listing ID; hence, if a listing is cross-listed on both platforms in month $t$, we cannot tell which of its month-$t$ bookings are from Airbnb. This implies that the comparison of Airbnb vs. VRBO-only listings in Tables 3 and 4 may misrepresent the true effect of the 48-hour rule because cross-listings are only partially treated by the 48-hour rule. To address this concern, Appendix Table A1 restricts the sample to Airbnb-only and VRBO-only listings, and reruns the DID analysis (with IV). The estimates are of slightly lower magnitude than Table 3 (2.41% vs. 2.69% on price and 1.96% vs. 2.11% on occupancy). For the subsamples of loose and strict hosts, the estimates are also smaller but the overall patterns remain the same as in the baseline. Appendix Table A2 repeats the DID analysis (with IV) while limiting the sample to cross-listed listings vs. VRBO-only listings. Results are similar to our baseline, suggesting that our findings are robust although we cannot distinguish the source of bookings for cross-listed listings.

To capture the influence of VRBO competition, Table 5 reports the DID results (with IV) for four subsamples: Airbnb loose listings vs. VRBO loose listings in areas with above-median competition index; Airbnb loose listings vs. VRBO loose listings in areas with below-median competition index; Airbnb strict listings vs. VRBO strict listings in areas with above-median competition index; and Airbnb strict listings vs. VRBO strict listings in areas with below-median competition index. Both the strict/loose status and competition index are as of April 2018, the month right before Airbnb adopted the 48-hour rule. These results suggest that the positive effects of the 48-hour rule on price and occupancy are greater in low competition areas, and this pattern holds for both loose and strict listings. One interpretation is that less VRBO competition allows Airbnb to internalize greater network effects between hosts and guests, which reinforces the positive effect of the 48-hour rule on price and quantity.

To summarize, we find that the 48-hour rule increased price and occupancy for Airbnb listings. However, this effect is weaker for Airbnb strict listings although those listings face a substantive guest cancellation rule change due to the 48-hour rule, and the effect is attenuated when Airbnb-VRBO competition is more fierce in the local area before the 48-hour rule. These findings are consistent with the argument that the 48-hour rule generates conflicting interests between Airbnb guests and strict hosts, which counteracts the classical positive network effects between guests and hosts. If this explanation is true, we should see some Airbnb hosts react negatively to the 48-hour rule, especially those that suffer more from the conflicting interests. The next subsection explores these supply side responses.

## 6.2 Supply-Side Response

A potential host that already owns or manages a property can decide whether to list the property as a short-term rental, where to list it, what features to offer (guest cancellation policy, instant booking, likelihood to cancel guest reservation, property amenities), what days are available on the calendar, and what price to charge. As discussed in Section 6.1, price and occupancy changed post the 48-hour rule, probably driven by both a change in guest demand and host efforts to accommodate the demand in price and availability. This subsection will explore hosts' non-price decisions.

The first panel of Figure 2 plots the number of listings on Airbnb and VRBO per zipcode-month from 2017 to 2019. The second panel plots the number of Airbnb-first listings that cross-list on VRBO and the number of VRBO-first listings that cross-list on Airbnb. It appears that the gap in the number of listings on Airbnb and VRBO narrowed quickly after the 48-hour rule, but the change in cross-listed listings is not as visible.

In the first two columns of Table 6, we assess the effect of the 48-hour rule on the number of Airbnb listings at the zipcode-month-platform level. In particular, we use a Poisson regression to estimate:

$$\begin{aligned} NumListings_{kzt} = \alpha_z + \alpha_t + \delta X_{zt} + \beta_1 Airbnb_k + \beta_2 Airbnb_k \times Post_t \\ + [\gamma_1 Airbnb_k \times HighComp_z + \gamma_2 HighComp_z \times Post_t \\ + \gamma_3 Airbnb_k \times Post_t \times HighComp_z] \\ + \varepsilon_{kt}, \end{aligned} \tag{6}$$

where $NumListings_{kzt}$ is the count of listings on platform $k$ from zipcode $z$ in month $t$, $\alpha_z$ is zipcode fixed effect, $\alpha_t$ is month fixed effect, and $X_{zt}$ captures time-varying tourism attributes in the zipcode. $HighComp_z$ equals 1 if zipcode $z$'s average competition index is above the median of all zipcodes in the city as of April 2018. Without the terms in the brackets, the key DID coefficient, $\beta_2$, captures the effect of the 48-hour rule on $Y$ for Airbnb listings. With the terms in the brackets, the triple DID coefficient $\gamma_3$ captures the extra effect of the rule on the zipcodes with above-city-median competition from VRBO.

In the first two columns of Table 6, the DID specification compares the count of Airbnb listings per zipcode-month (including cross listings) with the count of VRBO-only listings, while Column 1 reports the baseline results and Column 2 includes the triple interaction with above-city-median competition (as of April 2018). The rest of Table 6 repeats the same exercise, but Columns 3 and 4 compare the count of cross-listings (rather than all Airbnb listings) vs. VRBO-only listings, and Columns 5 and 6 limit listing count to new listings where a listing is labelled new to a particular platform if it first appeared on that platform in the study month. All columns use a Poisson regression with zipcode fixed effects and year-month fixed effects. Standard errors are clustered by zipcode.

Results indicate that, post the 48-hour rule, the number of Airbnb listings per zipcode month declines 2.55%, but the number of cross-listed listings increase 0.42%, relative to VRBO-only listings.[25] Columns 2 and 4 further indicate that the decline in the count of Airbnb listings is not sensitive to Airbnb-VRBO competition, but the increase in the number of cross-listed listings is greater with more platform competition (0.35% in low competition areas vs. 1.06% in high competition areas). Columns 5 and 6 indicate that the decline in Airbnb listings is largely driven by a decline in new listings. In particular, according to Column 5, new listings on Airbnb declined 6.49% after the 48-hour rule as compared to new VRBO-only listings.[26] And this effect is stronger in zipcodes with above-city-median competition with VRBO before the adoption of the 48-hour rule.

To better understand how the total count of cross-listed listings is driven by an individual listing's multi-homing decision, we run the DID analysis at the listing-month level utilizing

[25] Because the estimation is done in a Poisson model, the marginal effect (in percent) of a one-unit change in a variable is exp(coefficient)-1. Therefore, $exp(-0.0258) - 1 = -0.0255$, and $exp(0.0042) - 1 = 0.0042$.

[26] The marginal effect based on the Poisson coefficient is $exp(-0.0671) - 1 = -0.0649$.

Probit:

$$
\begin{aligned}
CrossList^*_{it} \ or \ Exit^*_{it} &= \alpha_t + \delta_1 X_{it} + \delta_2 X_{zt} \\
&+ \beta_1 AirbnbFirst_i + \beta_2 AirbnbFirst_i \times Post_t \\
&+ [\gamma_1 AirbnbFirst_i \times HighComp_i + \gamma_2 HighComp_i \times Post_t \\
&+ \gamma_3 AirbnbFirst_i \times Post_t \times HighComp_i] \\
&+ \varepsilon_{it}, \\
CrossList_{it} &= 1 \ if \ CrossList^*_{it} > 0, \\
Exit_{it} &= 1 \ if \ Exit^*_{it} > 0,
\end{aligned}
\tag{7}
$$

where $CrossList^*_{it}$ is the continuous index function for the dummy $CrossList_{it}$, which is equal to 1 if listing $i$ is cross-listed on both platforms in month $t$. $AirbnbFirst_i$ is a time-invariant dummy equal to 1 if listing $i$ was first observed as an Airbnb listing (rather than a VRBO listing)[27] We do not use the contemporaneous Airbnb listing status $Airbnb_{it}$ because it could change in response to the 48-hour rule and is therefore endogenous. The key DID coefficient, $\beta_2$, captures the effect of the 48-hour rule on the cross-listing decision of Airbnb-first listings, as compared to VRBO-first listings. Including the terms in the brackets, the triple DID coefficient $\gamma_3$ captures the extra effect of the 48-hour rule in high-competition areas. We control for listing attributes $X_{it}$ but not listing fixed effects because of the potential incidental parameter problems in the Probit specification, but all results are robust if we use a linear probability model with listing fixed effects.

The Probit results reported in Table 7 Columns 1 and 2 suggest that, post the 48-hour rule, Airbnb-first listings are on average 15.77% more likely to cross-list on VRBO than VRBO-first listings cross-list on Airbnb,[28] and this effect is stronger in the zipcodes with high competition from VRBO before the 48-hour rule. The next two columns of Table 7 extend the same Probit specification to study an individual listing's decision to exit specific platforms. We label listing $i$ as exiting platform $k$ in month $t$ if this listing was inactive on that platform for at least three months. The reported coefficients suggest that Airbnb-first listings are on average 1.28% less likely to exit Airbnb post the 48-hour rule, as compared to VRBO-first listings exiting VRBO, and this decline is greater in high competition zipcodes.

[27] This variable is defined using all the historical data we can observe (back to May 2015 for Airbnb listings and January 2017 for VRBO listings).

[28] The Probit coefficient reported in Table 7 implies a marginal effect of 15.77%.

Combining this with Table 6 results on the count of all, cross-listed listings and new listings, we conclude that the relative drop in the number of Airbnb listings (as compared to VRBO-only listings) are mostly driven by fewer entries rather than more exits after the 48-hour rule. The decline in the exit probability is also consistent with the earlier findings that the 48-hour rule expands the demand for Airbnb services and a simultaneous increase in both price and quantity make it more lucrative to stay. Interestingly, the same force does not make it more lucrative to enter Airbnb as a new listing, probably because the 48-hour rule mandates better services and thus more initial investment from the host.

A remaining question is what type of Airbnb listings tend to exit or cross-list post the rule. To answer this question, we compare strict and loose hosts within Airbnb listings (as of April 2018). More specifically, we run the following DID analysis using Probit conditional on the listing-month observations on Airbnb:

$$\begin{aligned} CrossListOnVRBO^*_{it} \text{ or } ExitAirbnb^*_{it} &= \alpha_t + \delta_1 X_{it} + \delta_2 X_{zt} \\ &+ \beta_1 Strict0418_i + \beta_2 Strict0418_i \times Post_t \\ &+ [\gamma_1 Strict0418_i \times HighComp_i + \gamma_2 HighComp_i \times Post_t \\ &+ \gamma_3 Strict0418_i \times Post_t \times HighComp_i] \\ &+ \varepsilon_{it}, \\ CrossListOnVRBO_{it} &= 1 \ if \ CrossListOnVRBO^*_{it} > 0, \\ ExitAirbnb_{it} &= 1 \ if \ ExitAirbnb^*_{it} > 0, \end{aligned} \tag{8}$$

where $Strict0418$ is a dummy equal to 1 if listing $i$ adopted a strict guest cancellation policy as of April 2018. Results presented in Column 5 of Table 7 suggest that, as compared to loose hosts, strict hosts are more likely to cross list on VRBO post the 48-hour rule if they face below-city-median competition from VRBO, but less likely to cross list if the competition environment is above-city-median. This seemingly counter-intuitive result is driven by the fact that, within Airbnb-first listings, strict hosts are more likely to locate in high-competition areas and the probability of strict hosts cross-listing on VRBO has already more than doubled that of loose hosts even before the 48-hour rule (Table 2). In other words, the increased tendency to cross list on VRBO, as we have observed in Table 6 and the first two columns of Table 7, is likely driven by strict listings in low-competition areas and loose listings in high-competition areas.

Turning to an individual listing's exit decision within Airbnb, Column 6 of Table 7 suggests that strict listings (as of April 2018) are less likely to exit Airbnb post the 48-hour rule than loose listings, especially in high-competition areas. This is intuitive because strict listings tend to be more desired properties in high competition areas but those listings that exit (the 'exiters') are usually linked to much worse properties in low competition areas (Appendix Table A3).[29]

Conditional on offering a listing for short-term rent, its host can alter listing features such as its guest cancellation policy and the ability of guests to instant book. To examine how these features change after the 48-hour rule, we apply the following DID specification (by Probit) to the full sample of listing-months:

$$\begin{aligned} ListFeature^*_{it} &= \alpha_t + \delta_1 X_{it} + \delta_2 X_{zt} \\ &+ \beta_1 AirbnbFirst_i + \beta_2 AirbnbFirst_i \times Post_t \\ &+ [\gamma_1 AirbnbFirst_i \times HighComp_i + \gamma_2 HighComp_i \times Post_t \\ &+ \gamma_3 AirbnbFirst_i \times Post_t \times HighComp_i] \\ &+ \varepsilon_{it}, \\ ListFeature_{it} &= 1 \; if \; ListFeature^*_{it} > 0, \end{aligned} \tag{9}$$

which effectively puts Airbnb-first listings in the treatment group and VRBO-first listings in the control group. As in Equation 7, we use the time-invariant variable $AirbnbFirst_i$ instead of the contemporaneous listing status $Airbnb_{it}$ because the latter could change in response to the 48-hour rule. Because these regressions focus on how hosts may change $ListFeature_{it}$ in response to the 48-hour rule, the right hand side controls on listing attributes ($X_{it}$) exclude the three listing features that hosts can directly change (instant booking, guest cancellation policy and host cancellation reviews).[30]

Column 1 of Table 8 shows that Airbnb-first listings are 5.62% less likely to adopt a strict cancellation policy post the 48-hour rule.[31] This change is not as evident in the raw

[29] Appendix Table A3 compares the pre-48-hour-rule statistics for listings that stay on Airbnb (stayers) and listings that are inactive for at least 3 months on Airbnb after the 48-hour rule (exiters). It is striking that the exiters had much fewer reservations per month than stayers (3.77 vs. 7.82), much lower price per night (131.5 vs. 176.4), much lower occupancy rate (18.7% vs. 36.3%), a greater likelihood of any host cancellation (12.24% vs. 4.35%), but are more likely to be a loose host in an area facing less VRBO competition.

[30] We also tried to use the lagged Superhost status rather than the contemporaneous status in $X_{it}$ because some host-chosen attributes may affect how platforms determine the Superhost status on a quarterly basis, results are robust.

[31] The Probit coefficient reported in Table 8 Column 1 (-0.1175) implies a marginal effect of -5.62%.

data (the first panel of Figure 3) before we control for other listing attributes and zipcode fixed effects. Column 2 of Table 8 includes the triple interaction with the dummy of whether the listing faces above-city-median competition. It finds that the tendency to refrain from a strict cancellation policy is stronger in high competition areas. This makes sense because the 48-hour rule forces strict hosts to honor guest cancellations, which makes a strict cancellation policy less valuable to hosts. The rule may have also made listings' cancellation policies more salient to guests, which may further highlight the potential costs guests may face under a strict cancellation policy.

The next two columns of Table 8 examine whether a listing offers instant booking differently post the 48-hour rule. Results suggest that Airbnb-first listings are 6.17% less likely to offer instant booking after the 48-hour rule, as compared to VRBO-first listings.[32] In comparison, the difference is not as evident in the raw data (the second panel of Figure 3) before we control for other listing attributes and zipcode fixed effects. Table 8 also suggests that the decline in instant booking on Airbnb is mostly driven by high-competition areas.

Zooming into the sample of Airbnb listings, Columns 1 and 2 of Table 9 look at what types of hosts are more likely to withdraw instant booking post the 48-hour rule. Unsurprisingly, hosts that offered strict cancellation before the rule was adopted are 7.37% more likely than loose hosts to disallow instant-booking post the rule if they operate in high competition areas, and 4.02% more likely in low competition areas. Hosts that cross-listed on VRBO before the rule was adopted are 9.77% more likely than Airbnb-only listings to disallow instant booking post the rule if they operate in high competition areas, and 6.09% more likely if they are low competition areas. These results are sensible, because the rule is most binding on strict hosts, cross-listing gives them more room to get around the rule, and they can be more selective without instant booking in accepting guests.

The next two columns of Table 9 study host cancellation. Recall that only Airbnb records host cancellation through automatic listing reviews, and thus we can only compare strict and loose hosts (as of April 2018) within Airbnb. Figure 4 plots the average number of host cancellation reviews per listing-month for strict and loose Airbnb hosts as of April 2018. While strict hosts have always had more cancellation reviews than loose hosts, the gap grows even larger post the 48-hour rule. Consistently, regression results in Table 9 suggest that strict hosts are on average more likely to cancel guest reservation post the 48-hour rule than loose hosts if they operate in an area with above-city-median competition from VRBO,

[32]The Probit coefficient reported in Table 8 Column 3 (-0.0977) implies a marginal effect of -6.17%.

and the effect is stronger if these strict hosts already cross-listed on VRBO before the rule adoption time.

Above all, supply-side evidence finds that the total number of listings per zipcode month has dropped on Airbnb relative to VRBO post the 48-hour rule. In particular, new listings are fewer on Airbnb after the 48-hour rule, and existing Airbnb hosts, though less likely to exit the platform, demonstrate a tendency to deviate via cross-listing, less instant-booking and more host-cancellation. This is despite the fact that price and occupancy per listing-month have increased on Airbnb after the 48-hour rule. The effect is particularly strong for strict hosts, as they are the most affected by the 48-hour rule, and for cross-listed listings, as they can get around the 48-hour rule on VRBO. This suggests that the 48-hour rule may have generated enough negative effects on these hosts and consequently motivated them to defy the increased attraction of Airbnb post the 48-hour rule.

## 6.3 Implications for Guest Welfare

The above reduced-form results paint a mixed picture of the impact of the 48-hour rule on guests: on the one hand, the rule mandates more flexibility in Airbnb bookings and an average Airbnb listing is more likely to offer a flexible or moderate cancellation policy, both of which should be beneficial to individual guests; on the other hand, some hosts react to the rule by entering fewer listings, expanding their cross-listing on VRBO, or lowering service quality in terms of being less likely to offer instant booking and engaging in more host cancellations. In addition, the average listing price increases post the 48-hour rule, which may further hurt guests. How do these mixed effects net out in terms of guest welfare?

To answer this question, we adopt a structural model to describe an individual guest's demand for short-term rental listings. In particular, we define the market as online short-term entire-home rentals in each zipcode-month, where Airbnb and VRBO are assumed to be the only two platforms that supply this market. Each guest chooses among all Airbnb entire-home listings available in the target zipcode-month. Since we do not have data on hotel reservations or other short-term stays (such as a friend's or relative's house or a bed and breakfast), our analysis can only address guest welfare *conditional on* those that choose to stay at an entire-home short-term rental on Airbnb or VRBO. Under this restriction, we define the market size (per zipcode-month) as the total number of Airbnb and VRBO listings times 30 days, and the outside good as the most popular VRBO-only listing in that same zipcode-month.[33]

Following Berry(1994), we assume that each guest chooses a listing to maximize their utility, where the utility associated with listing $i$ in zipcode $z$ month $t$ can be written as:

$$\begin{aligned} U_{i,t} &= EU_{it} + \epsilon_{it} \\ &= \alpha_i + \alpha_t + \beta \cdot log(P_{it}) + \delta_1 \cdot X_{it} + \delta_2 \cdot X_{zt} \\ &+ \gamma_1 \cdot AirbnbOnly_{it} + \gamma_2 \cdot AirbnbOnly_{it} \cdot Post_t \\ &+ \gamma_3 \cdot CrossListed_{it} + \gamma_4 \cdot CrossListed_{it} \cdot Post_t \\ &+ \epsilon_{i,t}. \end{aligned} \tag{10}$$

Assuming $\epsilon_{it}$ conforms to the logistic distribution, we can express the market share of listing $i$ at time $t$ as $s_{it} = \frac{exp(EU_{it})}{1+\sum_j exp(EU_{jt})}$. Thus:

$$ln(s_{it}) - ln(s_{0t}) = EU_{it} \tag{11}$$

This is equivalent to regressing the difference of log market share between listing $i$ and the outside good ($ln(s_{it}) - ln(s_{0t})$) on listing fixed effects ($\alpha_i$), year-month fixed effects ($\alpha_t$), log price, listing's time-varying non-price attributes ($X_{it}$), zipcode's time-varying attributes ($X_{zt}$), the platform on which a listing is listed (the dummies of $AirbnbOnly_{it}$ and $CrossListed_{it}$, with VRBO-only as the default), and the interaction between the source of the listing (the platform on which it is listed) and the post dummy. To the extent that the 48-hour rule increased the benefit of trade to all Airbnb guests (e.g., because Airbnb waived cancellation fees within 48 hours of booking and guests do not need to pay as close attention to guest cancellation policies within those 48 hours), the coefficients of these interactions ($\gamma_2$ and $\gamma_4$) should be positive to reflect these direct effects. As shown above in the reduced-form regressions, the 48-hour rule has also generated changes in listing price, non-price listing attributes, and the source of a listing. To account for these indirect effects, we include them on the right-hand side as observed. Later on, to compute the total effect of the 48-hour rule on guest utility, we will combine the reduced-form effects we have found on $P$ and $X$ with the coefficients identified in the structural model to incorporate these indirect effects.

As in all discrete-choice models for individual consumers, we are concerned that $log(P)$

[33] Listings that cross-list on Airbnb and VRBO are treated as Airbnb listings, and are thus counted as inside goods.

might be endogenous because guests may be aware of unobserved changes in the listing attributes (e.g., new furniture as shown in property photos) and hosts may price according to these changes. To address the concern, we instrument for entire-home listing prices by using the listing prices of private-room and shared-room listings in the same zipcode-month. The underlying assumption is that entire-home and private or shared-room listings appeal to different sets of guests, but share common cost shocks in the same zipcode-month.

As shown in the first column of Table 10, the instruments are strongly correlated with $log(P)$, with the first stage F-statistics equal to 29.33. Columns 2 and 3 report the OLS and IV estimation results of Equation 11. Results suggest that guests are sensitive to the listing price, and guests appreciate star ratings, a loose guest cancellation policy, instant booking, and a lack of host cancellation reviews on Airbnb. Post the 48-hour rule, guests tend to associate a positive utility change for both the listings that appear on Airbnb only and the listings that cross-list on Airbnb and VRBO.

We compute the effect of the 48-hour rule on each listing's utility as:

$$\Delta U = \underbrace{\gamma_2 \cdot AirbnbOnly_{it} + \gamma_4 \cdot CrossListed_{it}}_{\substack{\text{direct effects of} \\ \text{the 48-hour rule on U}}} + \underbrace{\beta \cdot \Delta log(P) + \delta_1 \cdot \Delta X_{it}}_{\substack{\text{indirect effects} \\ \text{of 48-hour rule} \\ \text{via host changes} \\ \text{in P and X}}}, \tag{12}$$

where $\Delta log(P)$ and $\Delta X_{it}$ are the average marginal effects derived from the reduced form DID estimates in earlier tables. The only exception is host cancellation review. Since such reviews are only available on Airbnb, we cannot identify how the 48-hour rule changes cancellation reviews on Airbnb relative to VRBO. Instead, we use the average before-after difference in the raw data (of Airbnb listings) as a proxy. To aggregate the effect of $\Delta U$ on guest welfare, we compute how the market share of each listing would change accordingly, and sum up the changes in guest-maximized utility as the overall change in consumer surplus.

Table 11 reports the estimated changes in consumer surplus for the ten cities separately. In particular, we run Equation 11 for each city, which allows city-specific tastes from guests. Intuitively, because guests like instant booking and a loose guest cancellation policy but dislike price and host cancellation, utility changes in these terms trade off with each other, leading to net gains in five cities that have relatively less competition from VRBO (DC, Boston, Chicago, and Austin, Seattle) but net loss in the other, more competitive cities (Los Angeles, Houston, Atlanta, New York, and New Orleans). This decreasing relationship between the change in consumer surplus and platform competition is driven by the fact that more Airbnb-VRBO competition motivates some Airbnb hosts to cross-list and reduce service quality after the 48-hour rule. The first two rows of Table 11 also compute guest utility gains from loose and strict listings on Airbnb (as of April 2018) separately. Unsurprisingly, guests enjoy net gains from loose listings, but net losses from strict listings because hosts of strict listings tend to engage in more negative reactions to the 48-hour rule in terms of reducing the ability instant book and engaging in more host cancellations.

## 6.4 Implications for Airbnb GBV

Turning to Airbnb as a platform, its rule-making is tied to its own commercial interests, which we approximate by gross booking value (GBV) given that Airbnb derives most of its revenue from commission fees that are proportional to booking value. In particular, for city $c$ in month $t$, we consider:

$$\begin{aligned} \text{Airbnb GBV}_{ct} = {} & \text{NumListings}_{ct} \\ & \times \text{AvgP}_{ct}(\text{AvgX}_{ct}) \\ & \times \text{AvgOccupancy}_{ct}(\text{AvgX}_{ct}), \end{aligned} \tag{13}$$

where $X$ stands for listing attributes and the parentheses imply that price and occupancy depend on $X$. For each city, we rerun the reduced-form estimation in Sections 6.1 and 6.2 to identify the average effect of the 48-hour rule on NumListings, AvgP, Avg Occupancy, Avg X. The only exception is host cancellation review, as such reviews are only available on Airbnb and we cannot identify how the 48-hour rule causes a change in these reviews on Airbnb vs. VRBO. Hence we use the average before-after differences in the raw data (of Airbnb listings) as a proxy.

Table 12 presents the estimated changes in Airbnb GBV for each city following the 48-hour rule.[34] In contrast to the mixed effects on guest welfare change (Table 11), we find that Airbnb GBV increased for each of the ten cities. However, consistent with Table 11, this gain declines with the degree of Airbnb-VRBO competition across the ten cities. This is intuitive, as more VRBO competition allows Airbnb hosts, especially those who are directly bound by the 48-hour rule, to escape the negative effect of the rule through reduced entry,

[34]More details of Table 12 are presented in Appendix Table A4.

more cross-listing, and lower service quality, all of which would hurt Airbnb's GBV.

Unfortunately, we do not observe the degree of guest cancellation before and after the 48 hour rule, so the above calculation of Airbnb GBV misses the changes in Airbnb service fees related to guest cancellation. Similarly, the above calculation concerning guest welfare misses the potential benefits that guests may enjoy from free cancellation thanks to the 48-hour rule.

Another caveat is that we cannot conduct a back-of-the-envelope calculation on host welfare because we do not observe the extent of guest cancellation or a host's cost of complying with the 48-hour rule, cross-listing, offering loose (rather than strict) guest cancellation policy, and screening guests without instant booking. All these costs could change post the 48-hour rule, and could be sufficiently substantial to offset the average revenue increases for an Airbnb listing.

# 7 Discussion and Conclusion

To summarize, this paper examines the role of Airbnb as the governor of its own ecosystem. Using the 48-hour rule as an example, we demonstrate that this pro-guest rule led to higher prices and occupancy for Airbnb listings, likely because the rule expanded guest demand for Airbnb. However, on the supply side, we observe a relative decline in the number of Airbnb listings, an increase in Airbnb-first listings being cross-listed on VRBO, and some decline of service quality on Airbnb in terms of instant booking and host cancellations. These negative effects are in part driven by hosts of strict listings — the type of listings that were most affected by the 48-hour rule — escaping the 48-hour rule in areas with relatively high competition between Airbnb and VRBO. Our back-of-the-envelope calculations suggest that the 48-hour rule increased Airbnb's GBV but guests do not always benefit from the rule given the subsequent price and quality changes.

In terms of platform competition, our findings have three important implications for the ongoing antitrust debate.

First, platform competition puts a natural constraint on platforms with positive network effects. Much of the ongoing concerns about two-sided platforms start with positive network effects between different sides of a platform. Policy reports such as Furman et al. (2019), Cremer et al. (2019), and the Stigler Committee (2019) have all cited network effects as one of the primary reasons for concerns regarding market tipping, winner-takes-all, and the inability for market competition to solve the problems arising from market concentration. However, we show that Airbnb's 48-hour rule—a pro-guest policy that in theory should trigger a new round of positive network effects and thus attracting both guests and hosts to expand Airbnb at the cost of VRBO—has also pushed some hosts away from Airbnb and towards VRBO.

More interestingly, these "push away" effects are stronger in the areas with more Airbnb-VRBO competition before the 48-hour rule, which explains why Airbnb enjoys less growth in price, occupancy, or GBV if the local area has more platform competition. In other words, it seems that platform differentiation, ease of multi-homing, and interoperability between Airbnb and VRBO have helped alleviate the risk of market tipping due to positive network effects. This is consistent with many theoretical papers reviewed by Jullien and Sand-Zantman (2021).

Based on the differential effects of the 48-hour rule, we argue that the rule generated a conflict of interest between guests and strict hosts on Airbnb, and such conflicting interests are a natural economic force to limit the power and danger of positive network effects, especially in the areas that already accommodate viable platform competition.

Second, platform competition is shaped not only by platform rule-making but also by how different users react differently to the rule. While the 48-hour rule triggered a direct conflict of interest between guests and strict hosts on Airbnb, it is more subtle that users on the same side (strict hosts and loose hosts) experience different impacts from the rule and adjust differently in response to the rule. As more Airbnb hosts cross-list on VRBO (than vice versa), more hosts drop instant booking on Airbnb (relative to VRBO), more strict hosts engage in host cancellation on Airbnb (relative to loose hosts), and more of these effects occur in high competition areas, the 48-hour rule may have intensified the competition between Airbnb and VRBO, although Airbnb adopted it for differentiation.

Third, antitrust consideration about two-sided platforms depends on what welfare standard we adopt. Our back-of-the-envelope calculations suggest that the 48-hour rule increased Airbnb GBV in all of the ten cities in our sample, but the increase is less in the cities with more Airbnb-VRBO competition. At the same time, guest welfare from all listings can be net negative, especially in cities with sufficient Airbnb-VRBO competition before the 48-hour rule. This discrepancy highlights a sharp contrast between the classical consumer welfare standard and a recently-touted goal of promoting market competition.

In particular, it has been argued that maximizing the welfare of final consumers might be too narrow a goal for antitrust. For instance, Shapiro (2021) proposes to replace the "consumer welfare standard" with a "promoting competition standard." Our findings suggest that these two approaches may imply quite different trade-offs between different economic players. If promoting competition means a greater degree of Airbnb-VRBO competition in our context, such competition tends to hamper a platform's incentives to adopt a pro-guest policy such as the 48-hour rule. Even in the markets where the platform is incentivized to adopt it, some hosts may be hurt by the rule while guests may have a net gain or a net loss post the rule. Whether such a rule should be encouraged or discouraged under the "promoting competition standard" may depend on exactly how one defines the welfare objective (guest welfare only, guest and host welfare, or guest, host and platform welfare).

To push it further, our findings point to a potential trade-off between efficiency and fairness. In the areas with high platform competition, Airbnb has less incentives to adopt the 48-hour rule, probably because it has a lesser ability to internalize the positive network effects between guests and hosts, and this could hurt guest welfare. Under the most stringent consumer welfare standard, this could imply less efficiency. However, in the same high competition areas, hosts find it easier to escape the 48-hour rule by cross-listing and downgrading quality. This means that platform competition may reduce the extent of asymmetric treatment facing hosts. If rule symmetry is correlated with fairness, platform competition may help in fairness (for hosts) but at the cost of efficiency (for guests). How to incorporate these intricate effects of platform competition in antitrust analysis warrants further research.

Finally, we note that our empirical setting is limited to two match-making platforms in short-term rentals. While Airbnb and VRBO are the two best-known short-term rental platforms in the US, they target some of the same guests as hotels, bed and breakfasts, and other home-sharing services. They also compete for properties on the supply side with long-term rentals and other property uses. Since our competition index is limited to Airbnb-VRBO competition, it does not capture the market definition that antitrust agencies may use in a similar context. Moreover, our study is specific to short-term rental services; thus, our findings may not be readily applicable to other types of platform economies. Whether other digital platforms involve similar intricacies regarding multi-sided balancing vis-à-vis platform competition is certainly worthy of further study.

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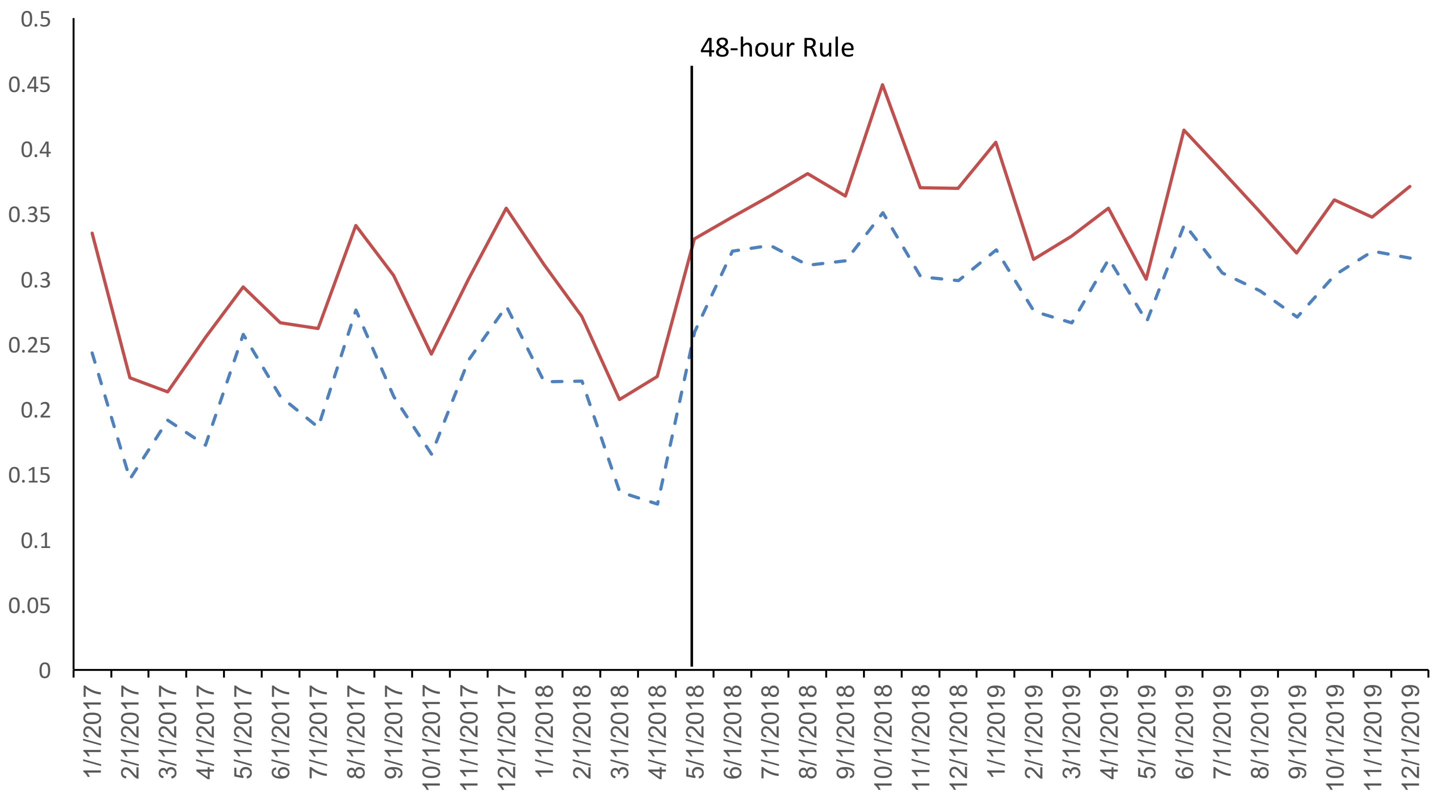
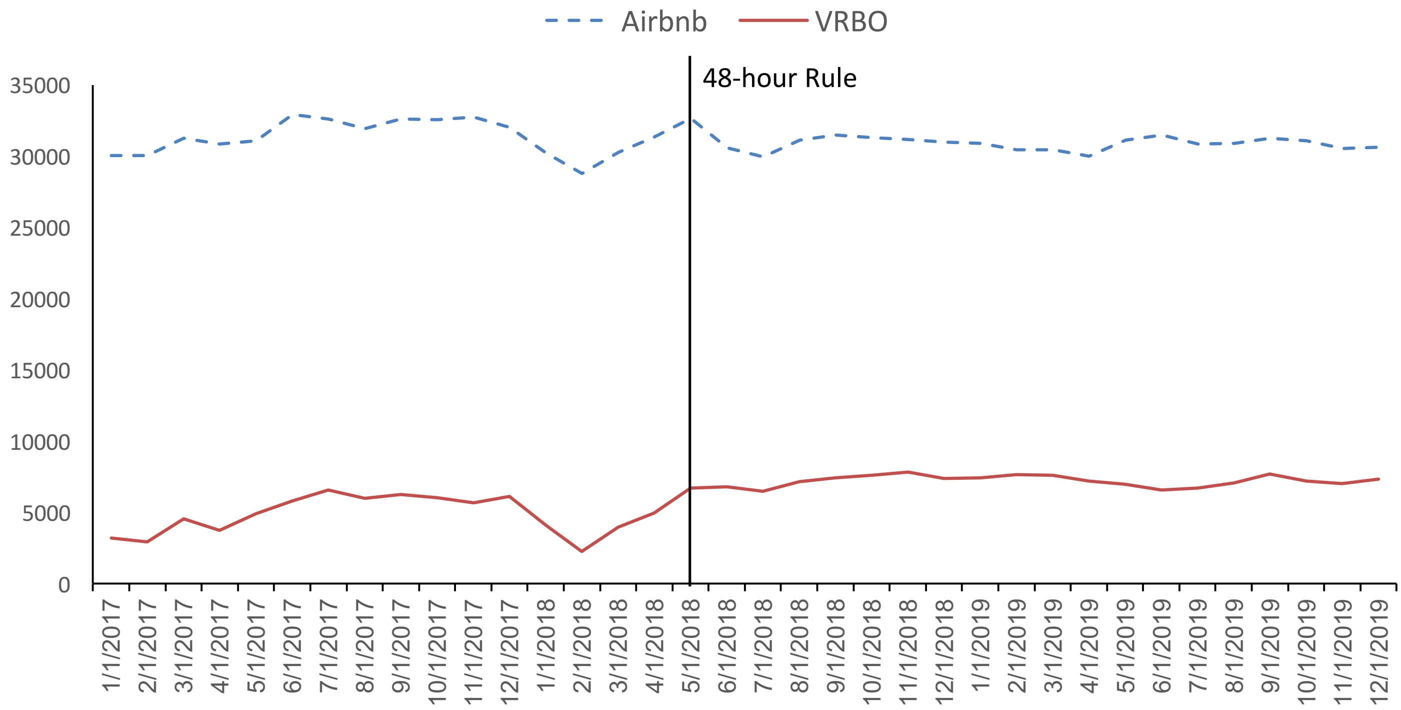
**(a) Average Listing Price**

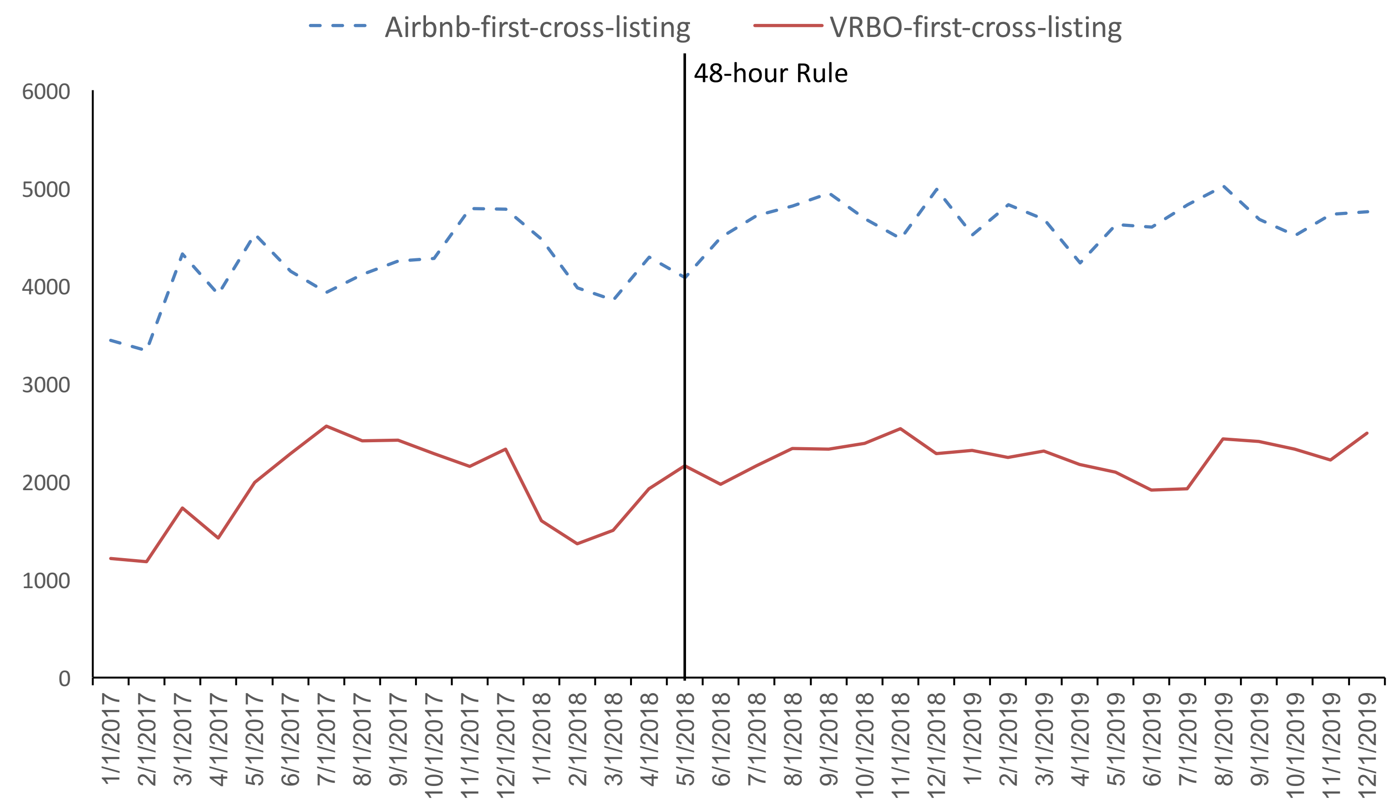



**(b) Average Occupancy Rate**

**Figure 1. Entire Home Listing Price and Occupancy Rate on Airbnb and VRBO**

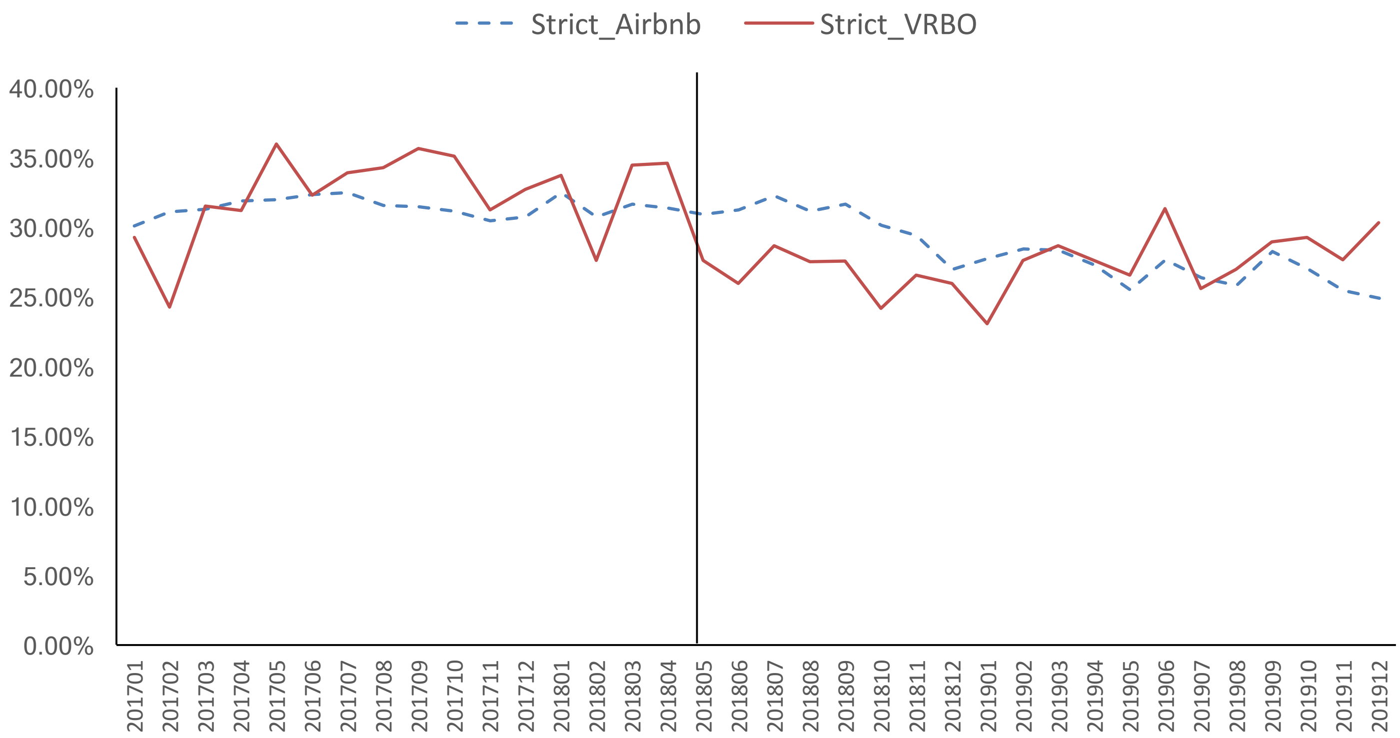



**(a) # of Listings**

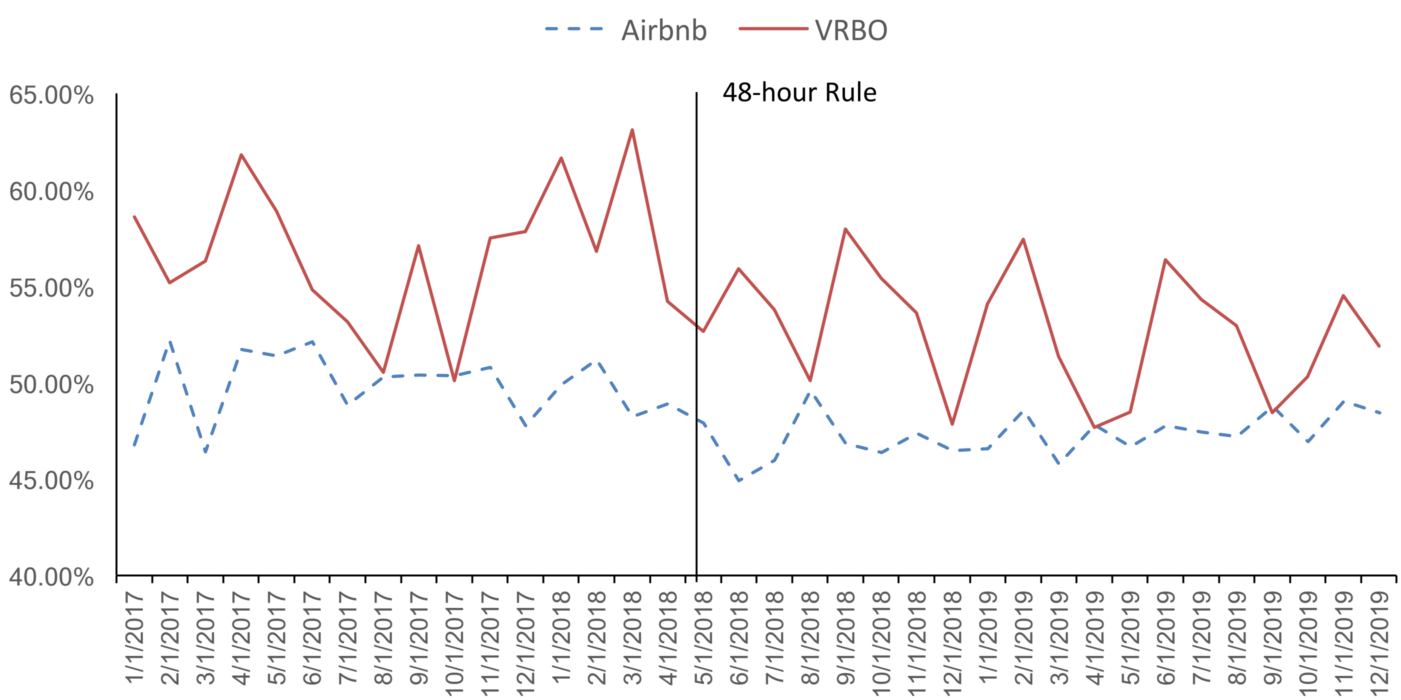



**(b) # of Cross-listings**

**Figure 2. # of Entire Home Listings and # of Cross-listings on Airbnb and VRBO**




**(a) % of Listings with Strict Guest Cancellation Policy on Airbnb and VRBO Over Time**




**(b) # of Listings with Instant Booking on Airbnb and VRBO Over Time**

**Figure 3. % of Entire Home Listings with Guest Cancellation Policy and Instant Booking**

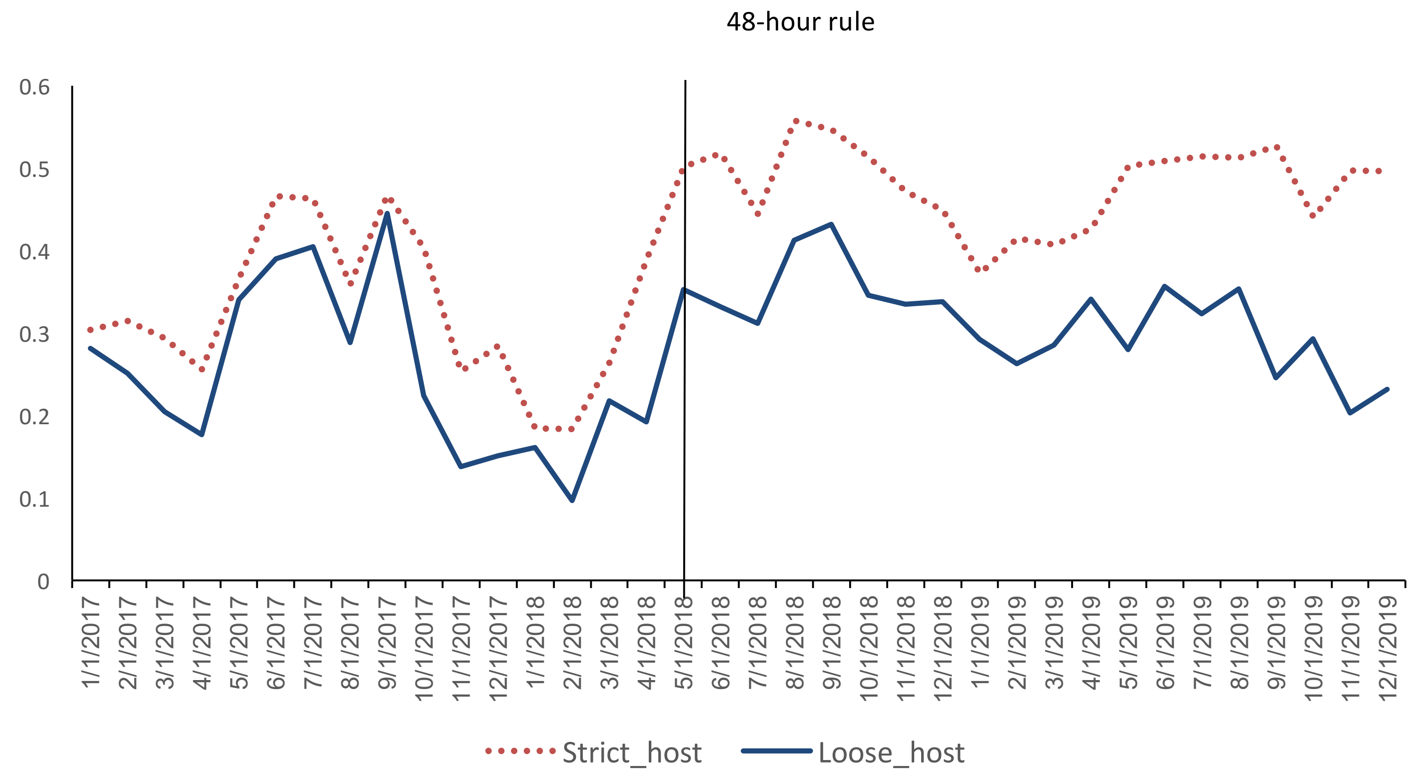



**Figure 4. Average # of Automated Host Cancellation Review per Entire Home Listing on Airbnb**

**Table 1: Summary statistics by listing-month**

| | Airbnb Only | | VRBO Only | | Cross-Listing | |
|---|---|---|---|---|---|---|
| | **Mean** | **N** | **Mean** | **N** | **Mean** | **N** |
| Price | 165.39 | 863,380 | 179.25 | 203,225 | 172.12 | 131,412 |
| # of reservations | 5.25 | 863,380 | 4.22 | 203,225 | 6.09 | 131,412 |
| Occupancy rate | 24.72% | 863,380 | 29.47% | 203,225 | 27.53% | 131,412 |
| # of host cancellations | 0.74 | 863,380 | - | | 0.93 | 131,412 |
| Having any host cancellation (dummy) | 10.22% | 863,380 | - | | 12.17% | 131,412 |
| Loose Cancellation | 71.30% | 863,380 | 67.33% | 203,225 | 69.72% | 131,412 |
| Strict Cancellation | 28.70% | 863,380 | 32.67% | 203,225 | 30.18% | 131,412 |
| Competition Index with VRBO | 0.124 | 863,380 | - | | 0.21 | 131,412 |
| Review Number | 13.45 | 863,380 | 10.07 | 203,225 | 13.72 | 131,412 |
| Review rating | 4.53 | 863,380 | 4.59 | 203,225 | 4.54 | 131,412 |
| Superhost proportion | 6.67% | 863,380 | 8.22% | 203,225 | 7.52% | 131,412 |
| Instant booking | 48.2% | 863,380 | 54.3% | 203,225 | 52.7% | 131,412 |
| No. Bedrooms | 1.37 | 863,380 | 1.92 | 203,225 | 1.96 | 131,412 |
| No. Bathrooms | 1.33 | 863,380 | 1.56 | 203,225 | 1.41 | 131,412 |
| No. of hotel rooms per zip code | 255.35 | 863,380 | 237.27 | 203,225 | 245.77 | 131,412 |
| No. of theme parks per zip code | 0.58 | 863,380 | 0.77 | 203,225 | 0.62 | 131,412 |
| No. of national parks per zip code | 0.31 | 863,380 | 0.56 | 203,225 | 0.45 | 131,412 |
| No. of restaurants per zip code | 32.41 | 863,380 | 33.65 | 203,225 | 32.93 | 131,412 |
| No. of tourism attractions per zip code | 5.78 | 863,380 | 7.93 | 203,225 | 6.33 | 131,412 |

*Note: Unit of observation is entire home listing-month, sample period is from January 2017 to December 2019. The first four columns include listings that are listed on Airbnb only or VRBO only in the study month, respectively. The last two columns include listings that are cross-listed on both Airbnb and VRBO in the study month. Of the listings that were first listed on Airbnb in our data, 11.77% have been cross-listed on VRBO; of the listings that were first listed on VRBO in our data, 36.53% have been cross-listed on Airbnb.*

**Table 2: Summary statistics by listing types and time**

| | Airbnb-first listings | | VRBO-first listings | |
|---|---|---|---|---|
| | Loose as of 4/2018 | Strict as of 4/2018 | Loose as of 4/2018 | Strict as of 4/2018 |
| Before the 48-hour rule (1/2017 - 4/2018) | | | | |
| Avg. Monthly Price | 157.74 | 172.44 | 173.79 | 182.11 |
| Avg. # of Monthly Reservation | 3.96 | 5.10 | 3.65 | 4.30 |
| Avg. Monthly Occupancy Rate | 17.27% | 26.62% | 20.54% | 34.63% |
| Avg. Monthly Cross-listing Rate | 6.98% | 15.49% | 37.65% | 40.55% |
| Avg. # of Monthly Cancellation Reviews | 0.23 | 0.32 | - | - |
| After the 48-hour rule (5/2018 - 12/2019) | | | | |
| Avg. Monthly Price | 161.82 | 174.62 | 175.12 | 183.27 |
| Avg. # of Monthly Reservation | 4.38 | 5.54 | 3.89 | 4.52 |
| Avg. Monthly Occupancy Rate | 21.02% | 29.91% | 22.38% | 36.79% |
| Avg. Monthly Cross-listing Rate | 9.35% | 18.21% | 38.99% | 41.21% |
| Avg. # of Monthly Cancellation Reviews | 0.31 | 0.49 | - | - |

*Note: Unit of observation is entire home listing-month. A listing is labeled Airbnb-first if it first appeared on Airbnb in our data, and VRBO-first if it first appeared on VRBO in our data.*

**Table 3: Effects of the 48-hour rule on price and occupancy (full sample)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable | Log(price) | Log(occupancy) | Log(price) | Log(occupancy) | Log(price) | Log(occupancy) |
| Sample | Airbnb vs VRBO-only (OLS) | | Airbnb vs VRBO-only (IV) | | Airbnb vs VRBO-only (IV) | |
| Lag # of cancellation review | -0.0602*** | -0.0438*** | -0.0588*** | -0.0426*** | -0.0582*** | -0.0417*** |
| | (0.0244) | (0.0103) | (0.0105) | (0.0147) | (0.0107) | (0.0152) |
| Airbnb_host | -0.0010 | -0.0025 | -0.0015 | -0.0018 | -0.0017 | -0.0068 |
| | (0.0020) | (0.0014) | (0.0182) | (0.0141) | (0.0492) | (0.0396) |
| Airbnb_host * Post 48-hour rule | 0.0283*** | 0.0202*** | 0.0269*** | 0.0211*** | | |
| | (0.0107) | (0.0062) | (0.0098) | (0.0077) | | |
| Airbnb_host * Post 48-hour rule period 1 | | | | | 0.0181** | 0.0201*** |
| | | | | | (0.0075) | (0.0071) |
| Airbnb_host * Post 48-hour rule period 2 | | | | | 0.0345*** | 0.0219*** |
| | | | | | (0.0045) | (0.0063) |
| Listing controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Tourism characteristics controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Listing FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,198,017 | 1,198,017 | 1,198,017 | 1,198,017 | 1,198,017 | 1,198,017 |
| R-square | 0.625 | 0.522 | 0.637 | 0.519 | 0.569 | 0.527 |
| F-test on pre-treatment (p-value) | 0.21 | 0.27 | 0.21 | 0.27 | 0.28 | 0.36 |

*Note: This table uses entire home listing-month observations on Airbnb and VRBO from 2017 to 2019. In all columns, Airbnb_host is equal to one if the listing is listed on Airbnb in the study month. Columns 1-2 report OLS coefficients. In Columns 3-6, we use a listing's Airbnb_host status as of April 2018 as an instrument for Airbnb_host. Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels. Post 48-hour rule period 1 refers to 5/2018-2/2019 and Post 48-hour rule period 2 refers to 3/2019-12/2019.*

**Table 4: Effects of the 48-hour rule on price and occupancy (by subsamples)**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | log(price) | log (occupancy) | log(price) | log (occupancy) |
| Sample | Airbnb (Loose 04/2018) vs VRBO-only (Loose 04/2018) IV | | Airbnb (Strict 04/2018) vs VRBO-only (Strict 04/2018) IV | |
| Lag # of cancellation review | -0.0539*** | -0.0378*** | -0.0658*** | -0.0448** |
| | (0.0081) | (0.0140) | (0.0240) | (0.0225) |
| Airbnb_host | 0.0525 | 0.0058 | 0.0295 | 0.0030 |
| | (0.0590) | (0.0147) | (0.0992) | (0.1344) |
| Airbnb_host * Post 48-hour rule | 0.0338*** | 0.0214*** | 0.0257*** | 0.0193*** |
| | (0.0086) | (0.0071) | (0.0114) | (0.0074) |
| Listing controls | Yes | Yes | Yes | Yes |
| Tourism characteristics controls | Yes | Yes | Yes | Yes |
| Year-month FE | Yes | Yes | Yes | Yes |
| Listing FE | Yes | Yes | Yes | Yes |
| Observations | 853,429 | 853,429 | 547,813 | 547,813 |
| R-square | 0.541 | 0.385 | 0.627 | 0.571 |
| F-test on pre-treatment (p-value) | 0.33 | 0.25 | 0.27 | 0.29 |

*Note: This table uses entire home listing-month observations on Airbnb and VRBO from 2017 to 2019. In Columns 1-2, the sample is limited to all Airbnb or VRBO listings that offered a loose cancellation policy as of April 2018. In Columns 3-4, the sample is limited to all Airbnb or VRBO listings that offered a strict cancellation policy as of April 2018. In all columns, Airbnb_host is equal to one if the listing is listed on Airbnb in the study month, and we use a listing's Airbnb_host status as of April 2018 as an instrument for Airbnb_host. Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels.*

**Table 5: Effects of the 48-hour rule on price and occupancy (by subsamples)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent variable | log(price) | log(occupancy) | log(price) | log(occupancy) | log(price) | log(occupancy) | log(price) | log(occupancy) |
| | Above-city-median competition as of 04/2018 | | | | Below-city-median competition as of 04/2018 | | | |
| Sample | Airbnb (Loose 04/2018) vs VRBO-only (Loose 04/2018) IV | | Airbnb (Strict 04/2018) vs VRBO-only (Strict 04/2018) IV | | Airbnb (Loose 04/2018) vs VRBO-only (Loose 04/2018) IV | | Airbnb (Strict 04/2018) vs VRBO-only (Strict 04/2018) IV | |
| Lag # of cancellation review | -0.0664*** | -0.0464*** | -0.0649*** | -0.0501*** | -0.0318*** | -0.0226*** | -0.0517*** | -0.0462*** |
| | (0.0165) | (0.0150) | (0.0168) | (0.0119) | (0.0066) | (0.0065) | (0.0167) | (0.0113) |
| Airbnb_host | -0.0230 | -0.0198 | -0.0234 | -0.0167 | -0.0408 | 0.0083 | 0.0223 | 0.0289 |
| | (0.0474) | (0.0222) | (0.0282) | (0.0242) | (0.0395) | (0.0102) | (0.0403) | (0.0450) |
| Airbnb_host * Post 48-hour rule | 0.0322*** | 0.0215*** | 0.0081*** | 0.0058** | 0.0535*** | 0.0427*** | 0.0277*** | 0.0259*** |
| | (0.0085) | (0.0019) | (0.0012) | (0.0031) | (0.0258) | (0.0160) | (0.0126) | (0.0068) |
| Tourism characteristics controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Listing controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Listing FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 495,386 | 495,386 | 279,672 | 279,672 | 233,206 | 233,206 | 189,753 | 189,753 |
| R-square | 0.756 | 0.433 | 0.541 | 0.388 | 0.892 | 0.907 | 0.426 | 0.428 |

*Note: This table uses entire home listing-month observations on Airbnb and VRBO from 2017 to 2019. In Columns 1,2,5,6, the sample is limited to all Airbnb or VRBO listings that offered a loose cancellation policy as of April 2018. the treatment group includes Airbnb listings that offered a loose cancellation policy as of April 2018, while the control group includes the same type of VRBO-only listings. In Columns 3,4,7,8, the sample is limited to all Airbnb or VRBO listings that offered a strict cancellation policy as of April 2018. The first four columns focus on listings that had above-city-median competition index as of April 2018. The last four columns focus on listings that had below-city-median competition index as of April 2018. In all columns, Airbnb_host is equal to one if the listing is listed on Airbnb in the study month, and we use a listing's Airbnb_host status as of April 2018 as an instrument for Airbnb_host. Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels.*

**Table 6: Effect of 48-hour rule on number of listings per platform-zip code-month (Poisson)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable | # of listings | # of listings | # of listings | # of listings | # of new listings | # of new listings |
| Sample | Airbnb vs VRBO-only | Airbnb vs. VRBO-only | Co-listing vs VRBO-only | Co-listing vs. VRBO-only | Airbnb vs VRBO-only | Airbnb vs. VRBO-only |
| Platform=Airbnb | 0.0211 | 0.0195 | 0.0315 | 0.0271 | 0.0019 | 0.0008 |
| | (0.0625) | (0.1527) | (0.112) | (0.0539) | (0.6214) | (0.3841) |
| Platform=Airbnb * Post 48-hour rule | -0.0258*** | -0.0253*** | 0.0042** | 0.0035*** | -0.0671*** | -0.0527*** |
| | (0.0075) | (0.00 67) | (0.0018) | (0.0013) | (0.0172) | (0.0199) |
| Platform=Airbnb * High_competition as of 4/2018 | | -0.0041 | | 0.0312 | | -0.025 |
| | | (0.0144) | | (0.245) | | (0.1534) |
| High_competition * Post 48-hour rule | | 0.0065 | | 0.0035* | | 0.0071 |
| | | (0.0328) | | (0.0019) | | (0.8111) |
| High_competition * Airbnb * Post 48-hour rule | | 0.0079 | | 0.0071*** | | -0.0152*** |
| | | (0.0312) | | (0.0020) | | (0.0047) |
| Tourism characteristics controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Zip code FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,750 | 1,750 | 1,750 | 1,750 | 1,750 | 1,750 |
| F-test on pre-treatment (p-value) | 0.36 | 0.36 | 0.21 | 0.21 | 0.51 | 0.27 |

*Note: Unit of observation is platform-zip code-month. In Columns 1,2,3,4, the dependent variable is # of entire home listings. In columns 5&6, the dependent variable is the number of new entire home listings that first appeared on the platform in the study month. We use Poisson regressions and report coefficient estimates. Standard errors are clustered by zip code. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

**Table 7: Effects of the 48-hour rule on cross-listing and exiting decisions (Probit)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable | Cross-list? | Cross-list? | Exit? | Exit? | Cross-list? | Exit? |
| Sample | Airbnb-first vs VRBO-first | Airbnb-first vs VRBO-first | Airbnb-first vs VRBO-first | Airbnb-first vs VRBO-first | Airbnb | Airbnb |
| Airbnb_first_host | -0.0178** | 0.0159* | -0.0098 | 0.0067 | | |
| | (0.0088) | (0.0091) | (0.0167) | (0.0264) | | |
| Airbnb_first_host * Post 48-hour rule | 0.0577*** | 0.0329*** | -0.1327*** | -0.0971*** | | |
| | (0.0038) | (0.0127) | (0.0326) | (0.0265) | | |
| Airbnb_first_host * High_competition as 0f 4/2018 | | 0.0112* | | -0.0261* | | |
| | | (0.0062) | | (0.0135) | | |
| High_competition * Post 48-hour rule | | 0.0111* | | -0.0096* | 0.1135*** | -0.0866*** |
| | | (0.0062) | | (0.0052) | (0.0227) | (0.0315) |
| High_competition *Airbnb_first * Post 48-hour rule | | 0.0665*** | | -0.1392*** | | |
| | | (0.0282) | | (0.0227) | | |
| Strict_host as of 04/2018 | | | | | 0.0207 | 0.0164 |
| | | | | | (0.1579) | (0.2871) |
| Strict_host * Post 48-hour rule | | | | | 0.0088* | -0.0371*** |
| | | | | | (0.0046) | (0.0103) |
| Strict_host * High_competition | | | | | 0.0133 | -0.0231** |
| | | | | | (0.0841) | (0.0102) |
| Strict_host * High_competition * Post 48-hour rule | | | | | -0.1729*** | -0.1169*** |
| | | | | | (0.0477) | (0.0428) |
| Tourism characteristics controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Listing controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Zip code FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,198,017 | 1,198,017 | 1,198,017 | 1,198,017 | 994,792 | 994,792 |
| F-test on pre-treatment (p-value) | 0.27 | 0.27 | 0.27 | 0.27 | 0.31 | 0.29 |

*Note: This table uses entire home listing-month observations from 2017 to 2019. In Columns 1,2, and 5, the dependent variable is whether the listing is also cross-listed on the other platform in the study month. In Columns 3, 4, and 6, the dependent variable is whether an Airbnb listing has been inactive for at least three months in the study month. Columns 1-4 use full sample including Airbnb-first and VRBO-first listings. Columns 1-4 use the full sample. Columns 5-6 use the sample of Airbnb listings only.For all columns, we use Probit regression and report coefficients. Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels.*

**Table 8: Effect of 48-hour rule on listing attributes (Probit)**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dep. Var | Strict Policy? | Strict Policy? | Instant Booking? | Instant Booking? |
| Sample | Airbnb-first vs VRBO-first | Airbnb-first vs VRBO-first | Airbnb-first vs VRBO-first | Airbnb-first vs VRBO-first |
| Airbnb_first | -0.0331 | -0.0175 | -0.0077 | -0.0061 |
| | (0.0527) | (0.717) | (0.1577) | (0.1902) |
| Airbnb_first * Post 48-hour rule | -0.1175*** | -0.0894*** | -0.0977*** | -0.0689*** |
| | (0.0367) | (0.0177) | (0.0321) | (0.0291) |
| Airbnb_first * High_competition as of 4/2018 | | 0.0507 | | -0.0222 |
| | | (0.413) | | (0.349) |
| High_competition * Post 48-hour rule | | -0.0475 | | -0.0622 |
| | | (0.1127) | | (0.1714) |
| High_competition *Airbnb * Post 48-hour rule | | -0.1108*** | | -0.1017*** |
| | | (0.0471) | | (0.0274) |
| Tourism characteristics controls | Yes | Yes | Yes | Yes |
| Listing controls | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes |
| Zipcode FE | Yes | Yes | Yes | Yes |
| Observations | 1,198,017 | 1,198,017 | 1,198,017 | 1,198,017 |
| F-test on pre-treatment (p-value) | 0.27 | 0.27 | 0.12 | 0.12 |

*Note: This table uses entire home listing-month observations on Airbnb and VRBO from 2017 to 2019. In Columns 1&2, the dependent variable is whether the listing offers a strict guest cancellation policy in the study month. In Columns 3&4, the dependent variable is whether the listing offers instant booking in the study month. For all columns, we use Probit regression and report coefficients. Standard errors are clustered by zip code. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

**Table 9: Effect of 48-hour rule on listing attributes within Airbnb (Probit)**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dep. Var | Instant booking? | Instant booking? | Host cancel? | Host cancel? |
| **Sample** | **Airbnb – High Competition** | **Airbnb – Low Competition** | **Airbnb – High Competition** | **Airbnb – Low Competition** |
| Strict_host 04/2018 * Post 48-hour rule | -0.0737** | -0.0217** | 0.0392*** | 0.0207 |
| | (0.0262) | (0.0092) | (0.0166) | (0.422) |
| Cross_listing 04/2018 * Post 48-hour rule | -0.0597*** | -0.0245** | 0.0207 | 0.0010 |
| | (0.0252) | (0.0117) | (0.0499) | (0.481) |
| Cross_listing 04/2018 * Strict host 04/2018 * Post 48-hour rule | -0.1108*** | -0.0516*** | 0.0648*** | 0.0132** |
| | (0.0299) | (0.0176) | (0.0271) | (0.0069) |
| Tourism characteristics controls | Yes | Yes | Yes | Yes |
| Listing controls | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes |
| Zipcode FE | Yes | Yes | Yes | Yes |
| Observations | 653,384 | 341,408 | 653,384 | 341,408 |

*Note: This table uses entire home listing-month observations on Airbnb from 2017 to 2019. In Columns 1-2, the dependent variable is whether the Airbnb listing offers instant booking in the study month. In Columns 3-4, the dependent variable is whether the Airbnb listing has received any automated cancellation review in the study month. Columns 1 &3 limit the sample to Airbnb listings operating in areas with above-city-median competition index as of April 2018. Columns 2 &4 limit the sample to Airbnb listings operating in areas with below-city-median competition index as of April 2018. For all columns, we use Probit regression and report coefficients. On the right-hand side, Cross_listing 04/18 equal to one if the listing was listed on both Airbnb and VRBO as of April 2018. Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% level.*

**Table 10. Effect of 48-hour rule on guest utility (structural model)**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dep.Var | log(price) | Utility (log($s_i$)-log($s_0$)) | Utility (log($s_i$)-log($s_0$)) |
| Specification | 1st stage of 2SLS | Without IV | With IV results for log(price) |
| | **Airbnb** | **Airbnb vs VRBO** | **Airbnb vs VRBO** |
| Log(price_private_room) | 3.271*** | | |
| | (1.0272) | | |
| Log(price_shared_room) | 5.688*** | | |
| | (1.2409) | | |
| Post 48-hour rule | | -0.0048 | -0.0025 |
| | | (0.6498) | (0.6217) |
| Airbnb_single_listing 04/18 | | 0.0041 | 0.0068 |
| | | (0.3141) | (0.2410) |
| Airbnb_cross_listing 04/18 | | 0.0058 | 0.0042 |
| | | (0.0351) | (0.0124) |
| Airbnb_single_listing * Post 48-hour rule | | 0.0092*** | 0.0103*** |
| | | (0.0037) | (0.0041) |
| Airbnb_cross_listing * Post 48-hour rule | | 0.0142*** | 0.0126*** |
| | | (0.0053) | (0.0035) |
| Log(price) | | -1.3571*** | -1.0442*** |
| | | (0.0317) | (0.0017) |
| Instant booking | | 0.0339*** | 0.0348*** |
| | | (0.0067) | (0.0055) |
| Loose guest cancellation policy | | 0.0177** | 0.0164** |
| | | (0.0079) | (0.0037) |
| Host cancellation review on Airbnb | | -0.0573*** | -0.0557*** |
| | | (0.0202) | (0.0175) |
| Listing controls | Yes | Yes | Yes |
| Tourism controls | Yes | Yes | Yes |
| Cancellation policy controls | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Listing FE | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes |
| Zipcode FE | Yes | Yes | Yes |
| Observations | 994,792 | 1,198,017 | 1,198,017 |
| R-square | 0.782 | 0.477 | 0.556 |
| F-test on 1st stage | 29.33 | - | - |

*Note: This table uses entire home listing-month observations on Airbnb and VRBO from 2017 to 2019. Column 1 reports the 1st stage regression of log(price) on two instruments: log(price) of private room and log(price) of shared room in the same zip code-month. Columns 2&3 regress log(# of occupied days/market size) of the focal listing – log (# of occupied days/market size) of the outside good) on log(price) and other listing attributes (relative to the outside good). For each zip code-month, market size is defined as total # of listings * 30 days, outside good is defined as the most popular VRBO only listing in that zip code-month. We set Airbnb_single_listing and Airbnb_cross_listing equal to one if the listing was listed on Airbnb only or on both Airbnb and VRBO as of April 2018. Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels.*

## Table 11 Guest Utility Change Post 48-hour Rule

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Group | Compe-tition Index as of 4/2018 | Gain/Loss ($) based on Airbnb_single_listing* 48-hour rule | Gain/Loss ($) based on Airbnb_cross_listing *48-hour rule | Gain/Loss ($) based on price change | Gain/Loss ($) based on changes in instant booking | Gain/Loss ($) based on changes in guest cancellation policy | Gain/Loss ($) based on changes in host cancellation | Net changes in guest utility ($) | Net changes in guest utility (%) | Net changes (%) using guest optimal choice of utility |
| Loose Host 4/18 | - | 49896.00 | 16145.44 | -21457.57 | -14163.18 | 18499.87 | -3673.86 | 45246.70 | 6.36% | 6.89% |
| Strict Host 4/18 | - | 34816.32 | 19527.00 | -19854.92 | -106543.23 | 30242.38 | -7565.60 | -49378.05 | -9.24% | -10.39% |
| D.C. | 0.08 | 2482.43 | 699.18 | -1049.22 | -1855.23 | 887.24 | -220.29 | 944.12 | 12.43% | 13.52% |
| Boston | 0.09 | 2988.65 | 1048.77 | -1573.83 | -2703.35 | 1408.41 | -330.44 | 838.21 | 9.83% | 10.24% |
| Chicago | 0.11 | 2988.65 | 1048.77 | -1573.83 | -2817.65 | 1449.55 | -330.44 | 765.04 | 7.78% | 8.03% |
| Austin | 0.12 | 3984.87 | 1398.36 | -2098.43 | -4249.82 | 1701.30 | -440.59 | 295.69 | 6.65% | 7.01% |
| Seattle | 0.12 | 6641.45 | 2796.72 | -4196.87 | -8269.53 | 3925.94 | -881.17 | 16.54 | 0.23% | 0.24% |
| Los Angeles | 0.14 | 8301.81 | 3495.90 | -5246.09 | -10548.68 | 4836.83 | -1101.47 | -261.71 | -0.61% | -0.65% |
| Houston | 0.15 | 10792.35 | 4544.67 | -6819.91 | -15755.66 | 6654.61 | -1431.91 | -2015.84 | -4.07% | -4.10% |
| Atlanta | 0.16 | 11622.53 | 4894.26 | -7344.52 | -17251.53 | 7198.19 | -1542.05 | -2423.11 | -5.26% | -5.41% |
| New York | 0.21 | 15773.43 | 6642.21 | -9967.56 | -23462.11 | 9271.41 | -2092.79 | -3835.40 | -8.35% | -8.72% |
| New Orleans | 0.25 | 19924.34 | 8390.16 | -12590.61 | -30165.35 | 11856.08 | -2643.52 | -5228.90 | -9.48% | -9.56% |

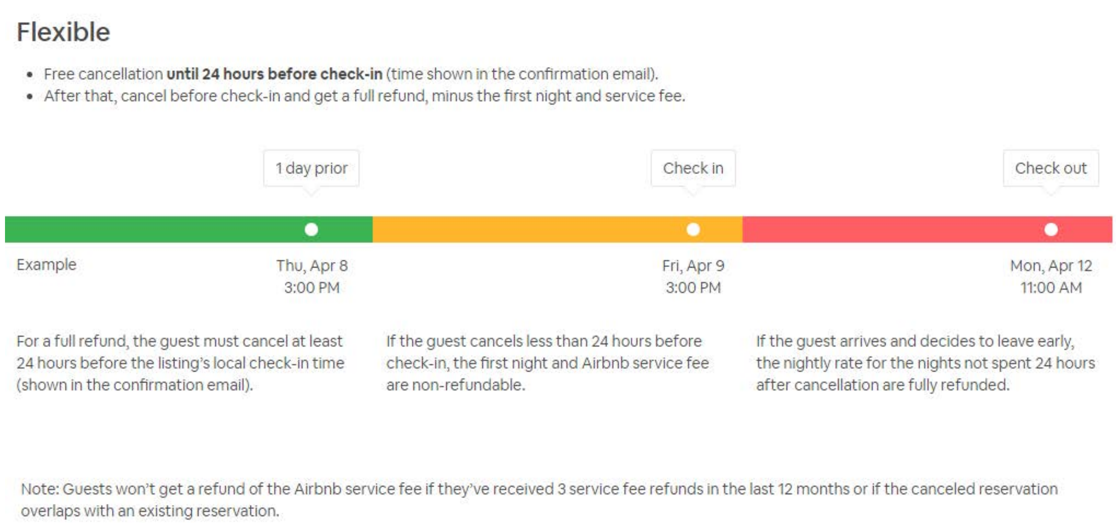
*Note: This table computes total guest utility changes across all entire home listings after the 48-hour rule, normalized in $ according to the price coefficient in the structural model of guest utility. Columns 2 & 3 use coefficients of Airbnb_single_listing*Post 48-hour rule and Airbnb_cross_listing*Post 48-hour rule in the structural model. Columns 4,5,6 use the estimated reduced-form effects of the 48-hour rule on price, instant booking, and guest cancellation policy (akin Tables 3 and 8) and the structural coefficients corresponding to these listings attributes in the utility regression (akin Table 10). Column 7 uses the before-after difference of host cancellation reviews on Airbnb from the raw data and the corresponding coefficient in in the utility regression. All above-mentioned regressions are run separately for each city, to account for city-specific changes post the 48-hour rule. Column 8 sums up Columns 2-7. Column 9 reports the same content of Column 8 in % instead of $. Column 10 accounts for guests choosing the highest utility from existing listings per zip code-month.*

**Table 12: Back-of-envelope calculation for Airbnb GMV after the 48-hour rule**

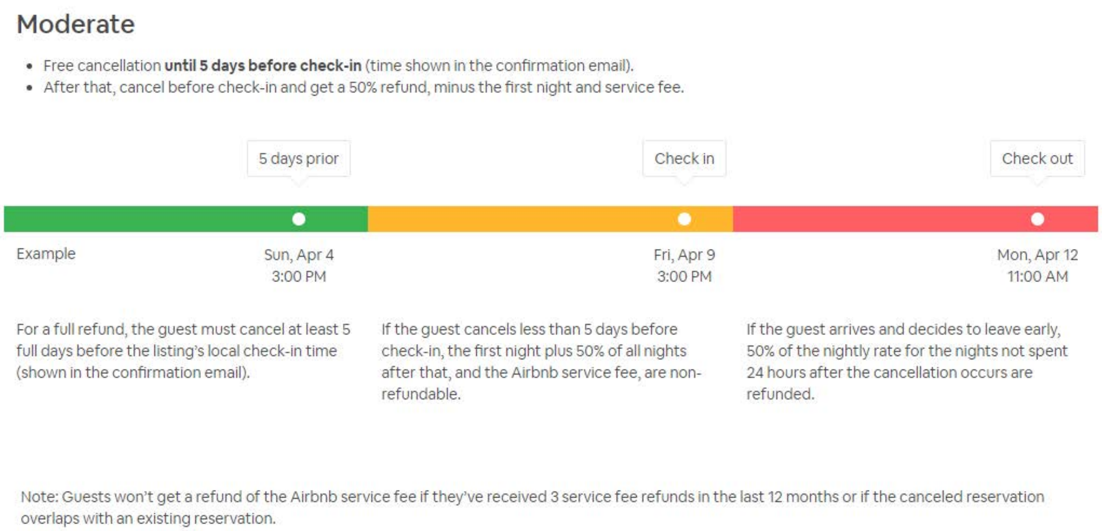
| City | Competition Index as of 4/2018 | Effect of 48-hour rule on Airbnb Hosts: Gain/Loss ($ MM) before considering listing attribute changes | Gain/Loss ($ MM) from changes in host cancellation, guest cancellation policy, and instant booking | Net Gain/Loss ($ MM) after 48-hour rule | Net Benefit/Loss (%) after 48-hour rule |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| D.C. | 0.08 | $18.34 | -$2.63 | $15.71 | 19.26% |
| Boston | 0.09 | $42.63 | -$4.60 | $38.03 | 18.85% |
| Chicago | 0.11 | $39.76 | -$1.78 | $37.98 | 18.04% |
| Austin | 0.12 | $26.71 | -$1.61 | $25.10 | 16.54% |
| Seattle | 0.12 | $13.08 | -$1.72 | $11.36 | 13.67% |
| Los Angeles | 0.14 | $27.12 | -$1.19 | $25.93 | 10.36% |
| Houston | 0.15 | $10.17 | -$3.35 | $6.82 | 10.23% |
| Atlanta | 0.16 | $11.32 | -$2.47 | $8.85 | 8.79% |
| New York | 0.21 | $29.03 | -$1.65 | $27.38 | 4.58% |
| New Orleans | 0.25 | $5.55 | -$1.33 | $4.21 | 2.30% |

*Note: This table computes total Airbnb GMV changes across all entire home listings after the 48-hour rule, based on the estimated reduced-form effects of the 48-hour rule on price and occupancy rate (akin Table 3) and on listing attributes (akin Table 8). Column 4 sums up Columns 2 & 3 in dollars, Column 5 reports the same content of Column 4 in % instead of $.*

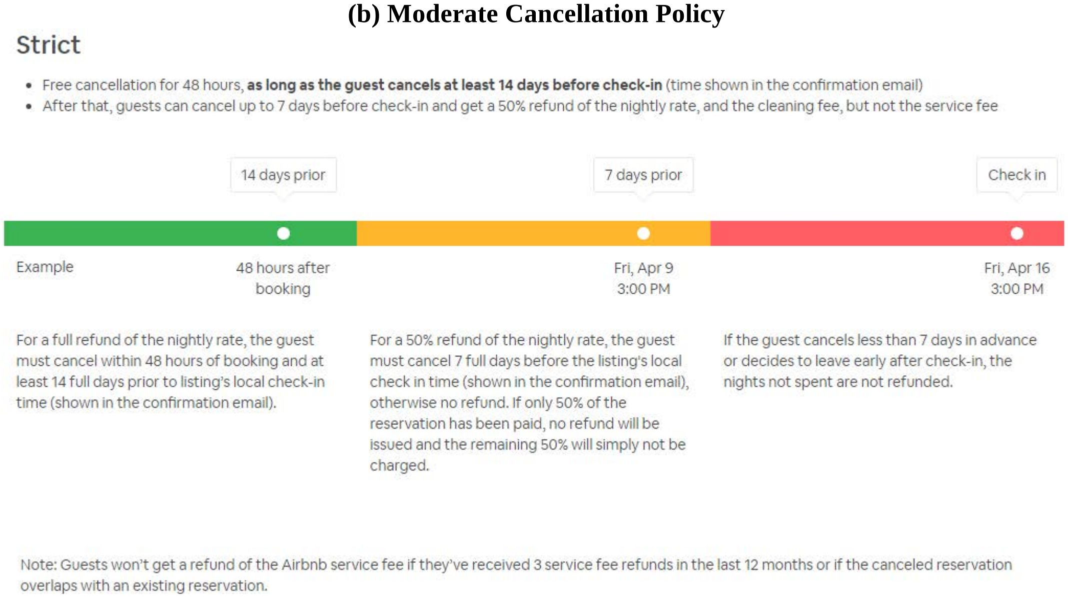
## Appendix Figures




**(a) Flexible Cancellation Policy**




**(b) Moderate Cancellation Policy**




**(c) Strict Cancellation Policy**

**Figure A1. Airbnb guest cancellation policy structure**

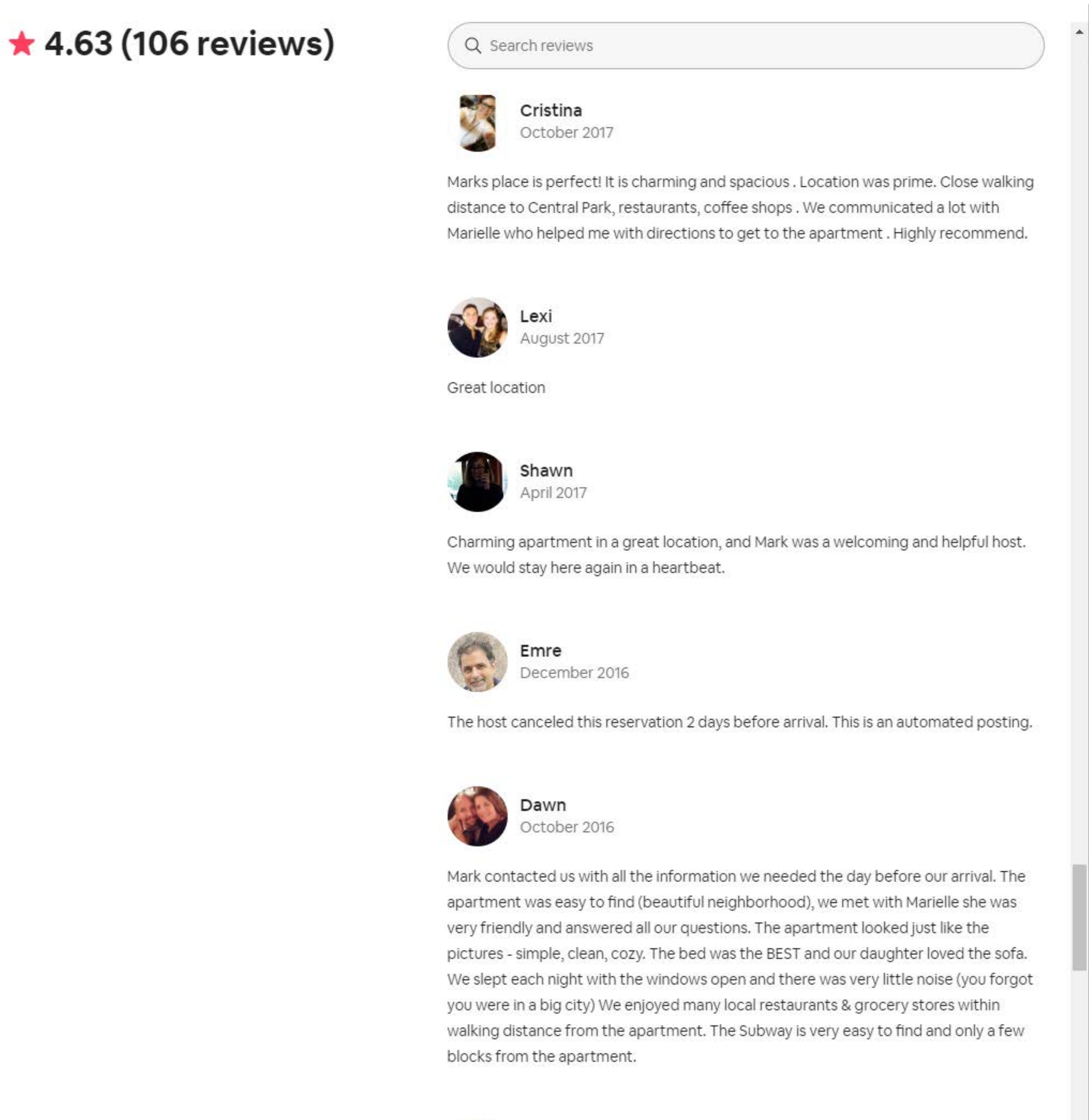



**Figure A2. Example of automated host cancellation review on Airbnb**

## Appendix Tables

**Table A1: Effects of the 48-hour rule on price and occupancy (single listings only, robustness check for Tables 3 and 4)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep.Var | log(price) | log (occupancy) | log(price) | log (occupancy) | log(price) | log (occupancy) |
| Sample | Airbnb-only vs VRBO-only IV | | Airbnb-only (Loose) vs VRBO-only (Loose) IV | | Airbnb-only (Strict) vs VRBO-only (Strict) IV | |
| Airbnb_host | -0.0018 | -0.0051 | 0.0313 | 0.0084 | -0.0028 | -0.0036 |
| | (0.0011) | (0.0044) | (0.0882) | (0.0131) | (0.0099) | (0.0087) |
| Airbnb_host * Post 48-hour rule | 0.0241*** | 0.0196*** | 0.0285*** | 0.0245*** | 0.0162*** | 0.0141*** |
| | (0.0116) | (0.0082) | (0.0086) | (0.0047) | (0.0045) | (0.0054) |
| Listing controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Cancellation policy controls | Yes | Yes | - | - | - | - |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Listing FE | Yes | Yes | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Zipcode FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,066,605 | 1,066,605 | 752,420 | 752,420 | 863,380 | 863,380 |
| R-square | 0.698 | 0.556 | 0.514 | 0.484 | 0.589 | 0.432 |

*Note: This table uses entire home listing-month observations from 2017 to 2019. In Columns 1-2, the sample is limited to Airbnb-only and VRBO-only listings. In Columns 3-4, the sample is further limited to all Airbnb-only or VRBO-only listings that offered a loose cancellation policy as of April 2018. In Columns 5-6, the sample is further limited to all Airbnb-only or VRBO-only listings that offered a strict cancellation policy as of April 2018. In all columns, Airbnb_host is equal to one if the listing is listed on Airbnb in the study month, and we use a listing's Airbnb_host status as of April 2018 as an instrument for Airbnb_host. Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels.*

**Table A2: Effects of 48-hour rule on price and occupancy (cross- and VRBO-only listings, robustness check for Tables 3 and 4)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep.Var | log(price) | log (occupancy) | log(price) | log (occupancy) | log(price) | log (occupancy) |
| Sample | Cross-listing vs VRBO-only IV | | Cross-listing (Loose) vs VRBO-only (Loose) IV | | Cross-listing (Strict) vs VRBO-only (Strict) IV | |
| Post 48-hour rule | -0.0010 | -0.0025 | 0.0462 | 0.0072 | -0.0046 | -0.0017 |
| | (0.0020) | (0.0014) | (0.0799) | (0.0112) | (0.0037) | (0.0021) |
| Airbnb_host * Post 48-hour rule | 0.0278*** | 0.0225*** | 0.0479*** | 0.0328*** | 0.0207*** | 0.0139*** |
| | (0.0109) | (0.0071) | (0.0137) | (0.0111) | (0.0077) | (0.0035) |
| Listing controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Cancellation policy controls | Yes | Yes | - | - | - | - |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Listing FE | Yes | Yes | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Zipcode FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 334,637 | 334,637 | 228,451 | 228,451 | 131,412 | 131,412 |
| R-square | 0.647 | 0.684 | 0.354 | 0.378 | 0.482 | 0.489 |

*Note: This table uses entire home listing-month observations from 2017 to 2019. In Columns 1-2, the sample is limited to cross-listings and VRBO-only listings. In Columns 3-4, the sample is further limited to all cross- and VRBO-only listings that offered a loose cancellation policy as of April 2018. In Columns 5-6, the sample is further limited to all cross- and VRBO-only listings that offered a strict cancellation policy as of April 2018. In all columns, Airbnb_host is equal to one if the listing is listed on Airbnb in the study month, and we use a listing's Airbnb_host status as of April 2018 as an instrument for Airbnb_host. Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels.*

**Table A3 Summary Statistics on Stayers and Exiters on Airbnb after 48-hour rule**

| | Stayers | Exits |
|---|---|---|
| # of reservations per month | 7.82 | 3.77 |
| Price | 176.4 | 131.5 |
| Occupancy rate | 36.3% | 18.7% |
| % of strict hosts | 33.9% | 13.6% |
| % with cancellation review | 4.36% | 12.24% |
| Avg. competition index | 0.38 | 0.13 |

*Note: This table compares the average statistics of stayers and exiters on Airbnb post the 48-hour rule. A listing is an exiter if it has been inactive 3+ months.*

**Table A4: Back-of-envelope calculation for Airbnb GMV after the 48-hour rule (details for Table 12)**

| City | Compe-tition Index | Total listings before 48-hour rule | # of listings change after 48-hour rule | Transaction Loss/Gain on cross-listings after 48-hour rule | Avg. Daily Rate ($) before 48-hour rule | Avg. Occupancy (in days) before 48-hour rule | Avg. Daily Rate ($) change after 48-hour rule | Avg. Occupancy (in days) change after 48-hour rule | Gain/Loss ($ MM) before considering listing attribute changes | Gain/Loss ($ MM) from changes in host cancellation, guest cancellation policy, and instant booking | Net Benefit/ Loss (%) after 48-hour rule |
|---|---|---|---|---|---|---|---|---|---|---|---|
| D.C. | 0.08 | 54,599 | 1,637 | -157 | 137.21 | 10.89 | 14.36 | 0.87 | 18.34 | -2.63 | 19.26% |
| Boston | 0.09 | 125,213 | 1,903 | -142 | 173.25 | 9.30 | 10.08 | 1.20 | 42.63 | -4.60 | 18.85% |
| Chicago | 0.11 | 134,677 | 1,421 | -74 | 157.89 | 9.90 | 9.76 | 1.08 | 39.76 | -1.78 | 18.04% |
| Austin | 0.12 | 120,845 | 1,339 | -247 | 139.55 | 9.00 | 6.37 | 1.03 | 26.71 | -1.61 | 16.54% |
| Seattle | 0.12 | 49,503 | 1,017 | -283 | 151.22 | 11.10 | 8.16 | 0.91 | 13.08 | -1.72 | 13.67% |
| Los Angeles | 0.14 | 140,501 | -1,021 | -1,173 | 188.53 | 9.45 | 9.59 | 0.68 | 27.12 | -1.19 | 10.36% |
| Houston | 0.15 | 59,695 | -1,345 | -272 | 143.25 | 7.80 | 8.33 | 0.93 | 10.17 | -3.35 | 10.23% |
| Atlanta | 0.16 | 83,718 | -475 | -338 | 138.25 | 8.70 | 4.39 | 0.77 | 11.32 | -2.47 | 8.79% |
| New York | 0.21 | 276,634 | -2,633 | -2,203 | 190.56 | 11.34 | 5.33 | 0.43 | 29.03 | -1.65 | 4.58% |
| New Orleans | 0.25 | 113,566 | -1,655 | -1,537 | 160.78 | 10.05 | 2.86 | 0.42 | 5.55 | -1.33 | 2.30% |