Platform as a Rule Maker: Evidence from Airbnb's Cancellation Policies

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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.

Keywords: Platform competition; Airbnb; VRBO; sharing economy

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1 Introduction

Many digital platforms function as a match-maker between two or more sides; for example eBay matches buyers and sellers, Uber matches riders and drivers, Airbnb matches guests and hosts, and Monster matches employers and workers. In the match-making process, a two-sided platform must set up rules to govern the behavior of market participants. However, unlike a government regulator that often acts as a third-party arbitrator between different stakeholders, a for-profit platform is directly involved in the business: it earns commissions, fees, and other revenues from one or more sides. This raises an immediate question: Does a multi-sided platform have incentives to treat different sides differently? If so, how would platform competition affect such incentives?

Many economists have studied this question in pricing, and concluded that asymmetric pricing is natural for two-sided platforms with positive network effects. For example, more guests on a short-term rental platform can attract more hosts to participate, and more hosts can attract more guests. These positive network effects may motivate platforms to subsidize the more price-sensitive side of their marketplaces and collect commissions and fees on the other side (Rochet and Tirole, 2003; Chevalier and Mayzlin, 2006; and Mayzlin et al., 2014). Sometimes, the subsidized side may even obtain the platform's service for free or receive rewards for joining or using the platform. However, this asymmetric treatment does not necessarily mean that side A of the platform benefits at the expense of side B, because more users on side A could make the platform more attractive to participants on side B. As a result, participants on side B could sometimes even prefer the platform to subsidize side A. More importantly, an asymmetric treatment of A and B does not necessarily imply a reduction in the total welfare of A, B, and the platform.

Meanwhile, however, much of the policy debate has focused on the potential of platforms to mistreat, abuse, or exploit one side of their marketplaces. For example, merchants were concerned about high transaction fees and anti-steering clauses of major credit card companies,[1] for the District Court decision in US vs. American Express, 2015. some app developers have complained about the high commission fees on Apple's iOS ecosystem,[2] there are legislative efforts to push ride-sharing platforms to treat drivers as employees rather than as contractors,[3] and some delivery workers for grocery, restaurant food, and merchandise shopping reportedly feel squeezed by platform algorithms.[4] Many of these concerns also attribute the alleged harm to stakeholders to a lack of competition at the platform level, and these assertions have further triggered antitrust investigations and legislative efforts to regulate certain practices of platforms worldwide.

The market for short-term rentals provides an excellent opportunity to study the interface of asymmetric treatment and platform competition. In particular, Airbnb and VRBO are the two major platforms that match the demand and supply of short-term home rentals in the US. In comparison with VRBO, Airbnb is more pro-guest with at least two unique rules.

First, upon a host's cancellation of a confirmed guest's rental reservation prior to the guest's arrival, Airbnb posts an automated system review on the host's listing. This cancellation review looks similar to any other review, but since it is system generated and only posted upon a confirmed cancellation by a host, it is credible and non-manipulable. VRBO has not adopted any similar rule for system-generated reviews in the cases of host cancellations.

Second, if a guest cancels their own reservation, the resultant process follows the listing's cancellation policy, which is selected by the listing's host, whereby the guest pays any corresponding penalties that are stipulated by the listing's cancellation policy. Beginning on May 1, 2018, Airbnb applied a global change requiring all listings on its platform 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. This guest-friendly grace period applies to all listings regardless of their hosts' chosen

[1] See, for instance, https://www.justice.gov/file/485746/download

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

[3] California Assembly Bill 5 and California Proposition 22, as well as the UK's Supreme Court; see, e.g., https://rb.gy/uv8k7l.

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

cancellation policies, and does not provide hosts with an ability to opt out. Again, VRBO does not have a similar rule across all listings.

To study these two pro-guest rules along with platform competition, we collect 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 2015 and December 2019.

We show that both pro-guest rules have the potential to benefit some Airbnb hosts but hurt other hosts. For example, for listings whose hosts cancelled guests' reservations, having any automated cancellation review leads to 6.37% fewer monthly reservations, 4.15% lower nightly rates, and 4.77% more vacancies. This is a significant cost for the cancelling host, and likely makes non-cancelling hosts more attractive on Airbnb. In contrast, the newly introduced 48-hour rule benefited nearly all Airbnb hosts by leading to more guest reservations on the platform, but it also increased costs for hosts with strict cancellation policies. Specifically, Airbnb listings with loose cancellation policies — which by definition should be unaffected by the 48-hour rule because they already allow free guest cancellation before the rule change — have seen their monthly reservation rates up 7.58%, nightly rates up 4.01%, and occupancy rates up 2.78% post the 48-hour rule, when compared to their VRBO listings with loose cancellation policies. In comparison, Airbnb listings with strict cancellation policies benefit 3.31% less in the number of monthly reservations, 2.27% less in nightly rates, and 1.95% less in occupancy rates, than their Airbnb listing counterparts with loose cancellation policies, although in net they still benefit from the 48-hour rule when compared with VRBO listings with loose cancellation policies.

To study the role of platform competition, we measure the local competition between Airbnb and VRBO[5] as the ratio of the number of VRBO listings to the number of Airbnb and VRBO listings within a 0.3-mile geographic radius of a focal listing, before the May-2018 introduction of the 48-hour rule. This measure creates an index of platform competition for

[5]Strictly speaking, both Airbnb and VRBO compete with hotels, bed and breakfasts, and other forms of short-term rentals in each geographic market. See more background in Section 3.

each Airbnb listing, allowing us to distinguish between listings that face different levels of competition with VRBO.

We find that platform competition has mixed effects on the pro-guest incentives of Airbnb. On the host side, the results suggest that a higher competition ratio amplifies the negative effect of an automated host cancellation review for listings with loose cancellation policies, but dampens it for listings with strict policies. Given the fact that strict listings tend to be associated with more popular properties and are more likely to be located in areas with more competition from VRBO, this suggests that Airbnb's incentive to drive for guest friendliness is not monotonic in platform competition.

On the guest side, we find that above-city-median competition with VRBO tempers the expansion effect of the 48-hour rule for Airbnb listings. In particular, for listings with above-city-median competition, Airbnb listings with loose guest cancellation policies, in comparison to VRBO listings with similar guest cancellation policies, exhibit increases of 6.33% in the number of monthly reservations, 3.19% in price, and 2.25% in occupancy rates after the 48-hour rule. These numbers are all higher if the listing's local competition is lower than the city median before the 48-hour rule (7.08%, 5.24% and 4.53%). A similar pattern holds for Airbnb listings with strict guest cancellation policies, with the above effects being 1.79%, 0.82%, 0.68% in areas of above-city-median competition, versus 3.88%, 2.77% and 2.63% in areas of below-city-median competition. It is interesting that listings with strict cancellation policies are more directly affected by the 48-hour rule than listings with loose policies, yet enjoy a smaller expansion in business as a result of the 48-hour rule.

Some antitrust scholars are concerned that dominant platforms are too harsh on one side (typically suppliers), because strong network effects may shield large platforms from viable competition, and those who may be squeezed by such platforms could have no alternative options.[6] Following this logic, some of the key questions are: (1) Can viable platform competition arise organically despite positive network effects between the two sides of each

[6]See, for instance, the 2019 Stigler report, https://www.chicagobooth.edu/research/stigler/news-and-media/committee-on-digital-platforms-final-report.

platform? (2) Does viable platform competition indeed temper a platform's incentives to squeeze its supply side? (3) How does a platform's pro-consumer rule affect different suppliers differentially vis-à-vis platform competition?

Our results speak to all of these questions. Although Airbnb is larger than VRBO today, VRBO was founded thirteen years before Airbnb (1995 vs. 2008). Both have exhibited dramatic growth over time, with VRBO targeting vacation entire-home rentals while Airbnb has sought a broader coverage of travelers and property types. The history of the two platforms suggests that platform competition does arise organically despite the natural network effects between guests and hosts on each platform. On the effects of platform competition, we show that more significant competition from VRBO gives an outside option to both hosts and guests, which sometimes tempers the benefits that Airbnb could reap from further turning the dial on the guest-friendliness of its rules, but sometimes strengthens the effectiveness of a pro-guest rule.

In particular, the 48-hour rule is overall beneficial to Airbnb in terms of attracting more traffic to the platform, but it imposes costs on some hosts and potentially squeezes their profits if the cost increase dominates the traffic increase. When there is viable competition at the platform level, hosts can multi-home. After the 48-hour rule, we find that the likelihood of cross-listing on both platforms increases, and the total number of listings on Airbnb decreases. The opposite moves in demand and supply imply that the network effects on Airbnb are not strong enough to generate "tipping" as some scholars have worried about for a general two-sided platform.

In addition, hosts of listings with strict cancellation policies — listings that were more likely to be cross-listed even before the 48-hour rule — are more likely to utilize host cancellations on Airbnb after the 48-hour rule, especially in more competitive areas. Recall that host cancellation reviews send a negative signal to the market and could hurt the host's future business on Airbnb. That some hosts still resort to this harmful act suggests that the 48-hour rule has been costly for them and they would rather get around it by cross-listing and cancelling on Airbnb if needed. Overall, the decrease in total listings, the increase in cross-listing, and the increase in host cancellations would all undermine the positive feedback between guests and hosts, thus reducing Airbnb's gain from the pro-guest rule.

In contrast, platform competition strengthens the punitive effect of the automated review of host cancellation for listings with loose cancellation policies, probably because *guests* can more readily switch to or multi-home on the competing platform and therefore are less tolerant of loose listings with a history of canceled guest reservations on Airbnb. These differential findings imply that platform competition does not always mitigate a platform's incentive to treat two of its sides asymmetrically, and thus any public policy in platform competition must consider its implications on all sides.

The remainder of the paper is organized as follows. Section 2 presents the literature review. Section 3 provides some background on Airbnb's cancellation policies. Section 4 describes the dataset and provides summary statistics. Section 5 reports our empirical findings. Section 6 discusses the implications of our findings for antitrust analysis and the platform's ecosystem, and Section 7 concludes.

2 Related Literature

2.1 Platform Policy and Competition

Earlier research on multi-sided platforms focused on pricing and how a platform may take advantage of positive network effects. Cailaud and Jullien (2003) show that platform pricing may follow a "divide and conquer" strategy, subsidizing participation on one side and profiting from the another. The degree of such asymmetry may depend 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). Platform competition may result in lower prices on two or more sides if those sides single-home. But when one side (e.g., buyers) single-homes and the other side (e.g., sellers) multi-homes, platforms may have incentives to charge more on the multi-homing side and further subsidize the single-homing side in order to attract their participation (Armstrong 2006). Put another way, competition can push platforms to subsidize the side that is more likely to single-home.

In practice, we observe that many platforms subsidize individual consumers by offering 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, the platforms usually earn revenue from the other sides (e.g. advertisers, sellers, and retail merchants). 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. Like many online platforms, these offline conventions charge low or zero admission fees to individual consumers but a substantial table fee to dealers. And such pricing is sensitive to platform competition: when the price to consumers is positive, the price is decreasing with competition, but pricing to dealers is insensitive to competition and in longer distances even increases with competition. In contrast, when the price to consumers is zero (and thus constrained), the price to dealers decreases more strongly with competition. These findings suggest that, at least in terms of pricing, platforms do change their asymmetric treatment between the sides in response to competition, though exactly how they respond depends on the ease of multi-homing on each side and the difficulty to adopt a negative price.

A growing literature recognizes similar incentives in the non-pricing decisions of platforms. In the 1980s and 1990s, many theories on non-pricing decisions focused on platform compatibility and interoperability, which dictate how easy it is for certain user groups to multi-home (see Farrell and Klemperer, 2007, for a review). More recent theories explore other non-pricing rules, such as the setup of consumer ratings, recommendation systems, search rankings, price transparency, information accuracy, certification systems, and minimum quality standards (see Belleflamme and Peitz, 2020, for a review). A common theme is examining whether platforms have an incentive to adopt a non-price rule that conflicts with consumer preferences. However, this comparison sets up a straw-man's argument, where the platform should give 100% weight to the consumer side, which is unrealistic given that most platforms are for-profit entities. If a society cares about the welfare of stakeholders on all sides, it is arguably more important to understand how for-profit platforms balance the interests of the multiple sides, as an internal governor of its own ecosystem.

On this front, a few studies offer stimulating insights. On quality standards, 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; the higher bar motivates some sellers to incur costs for quality improvements while other sellers give up on the badge and reduce effort. In a different setting, Jin et al. (2020) examine how the 2015 China Food Safety Law, which aims to help consumers, affects buyers and sellers on Taobao.com in China. They find that the new law improved the average quality of surviving sellers, though many small or non-reputable sellers exit, and market concentration increases. 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 in e-commerce. 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. 2018) or because too much transparency would intensify seller competition and reduce the platform's profit from the trade (Ellison and Ellison 2009; Johnen and

[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.

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).

A particularly interesting question is how platform competition affects a platform's role as an internal governor, especially with respect to non-price rules. In theory, the impact of competition could go both ways: for instance, Lizzeri (1999) shows that competition among certifiers results in more detailed quality information, but Bouvard and Levy (2018) find that platforms facing competition have weaker incentives to boost information accuracy. We are not aware of any systematic evidence in either direction, though mergers between two platforms are often followed by platform rule changes in commission fees, search algorithms, and other dimensions (Yao 2020; Farronato, Fong, and Fradkin 2020).

In our study, we observe a blanket change that affects all of Airibnb's guest-facing cancellation policies, but the same policy change has different impacts in markets facing different competition from VRBO. Our findings suggest that more viable competition from VRBO allows some hosts to escape from the harsher Airbnb policy towards hosts, which may further weaken the positive network feedback between guests and hosts. This reaction by hosts has the potential to discourage Airbnb from adopting friendlier policies towards guests in markets where it faces more competition, should Airbnb have a choice to set different cancellation policies in different markets. In contrast, competition with VRBO amplifies (dampens) the punitive effect of automated reviews of host cancellations for listings that offer loose (strict) cancellation policies, which arguably makes Airbnb more (less) guest-friendly in markets with mostly loose (strict) listings. These diverging effects of competition are consistent with the ambiguity suggested in the theoretical literature.

2.2 Reputation Systems and the Sharing Economy

Our paper contributes to the literature on review informativeness and reputation systems in online marketplaces (Senecal et al., 2004; Cox et al., 2009; Hu et al., 2009; Zhang and Sarvary, 2015; Dai et al., 2018). Works in this literature demonstrate that reviewers can have strategic incentives to manipulate reviews, which may result in under-reporting of negative reviews, particularly when users fear retaliation on platforms with reciprocal review systems (Bolton et al., 2013; Fradkin et al., 2017). Reviewers may also suffer from selection bias, where consumers are more likely to purchase and review products and services with which they are a priori satisfied (Li and Hitt, 2008; Masterov et al., 2015). Moreover, some reviewers may in fact be businesses leaving promotional or voluntary content (or even damaging the content of competitors) to artificially inflate their online reputations (Mayzlin et al., 2014; Benderson et al., 2018). Reviews that can be generated anonymously, even at a cost, may be susceptible to manipulation (Conitzer and Wagman, 2008 and 2014), and hosts on Airbnb can in fact boost the ratings of their listings by renting nights to friends or family, or to their own alternate accounts at lower prices.

The automated cancellation reviews we study do not suffer from these potential manipulations. Our study thus adds to this literature by focusing on what is objectively negative system reviews, which can only be triggered by seller actions to cancel guest reservations. This allows us to avoid issues concerning review authenticity. The benefit of doing so is significant, because even the sheer possibility of review manipulation may impact the beliefs and actions of both buyers and sellers, which may result in different equilibrium behaviors (Dellarocas 2006; Anderson and Simester 2014).

This paper also contributes to the growing literature on the sharing economy and Airbnb.[8] 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. Zervas et al. (2016) indicate that Airbnb listings have higher average ratings compared to the hotel industry.

[8] Recent works include Zervas et al. (2020), Edelman et al. (2017), Fradkin (2017), Fradkin et al. (2018), Kim et al. (2017), and Jia and Wagman (2020).

Wang and Nicolau (2017) suggest that host attributes are the most important price determinants of Airbnb listings. Our work complements the above by shedding some light on the dynamics behind a platform's choice between pro-guest and pro-host rules. In doing so, we also examine how guests incorporate information about host reliability into their bookings, and how pro-guest rules may impact hosts. Our findings suggest that perceived unreliability is associated with significant costs for sellers, and while pro-guest rules may harm some hosts, they can benefit hosts in net by attracting more traffic to the platform.

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 try to influence user behavior through a reputation system, but it cannot directly control the users. Without sufficient trust, hosts may not be willing to let strangers stay in their dwellings, and guests may not be willing to reserve an unseen dwelling that is not as standardized as a hotel. 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.

On Airbnb, short-term rental guests have to follow a listing's cancellation policy (flexible, moderate, or strict), 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 Figure 1, 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 (2015-2019) 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 2015 (Hill, 2015), according to Gibbs et al. (2018), host adoption of dynamic 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.[9] This option offer a 10% discount to guests and is only available 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 to their exclusion. Given this no-refund option is in some sense a partial dial back from the universal change of the 48-hour rule, the results reported in this paper (with data until December 2019) are likely more conservative than the true effects of the 48-hour rule.

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

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.[10] Figure 2 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.[11] Host 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 was cross-listed on both Airbnb and VRBO, the host can still rent it out on VRBO after cancelling the booking on Airbnb.

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

[10]The automated cancellation review format is: "The host canceled this reservation X days before arrival. This is an automated posting," where X ≥ 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.

[11]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.

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, nor offers a 48-hour grace period for guests who seek a full refund after booking a reservation.[12] 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 Data

We use all consumer-facing information and review content 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 2015 to December 2019. We also obtain such information for hosts who list their properties in these 10 cities on VRBO from Janaury 2017 to December 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 characteris-

[12] 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.

tics such as the host's unique identifier, listing zip code, approximate locale,[13] and property type (entire home, private room, or shared space). Throughout the paper, we focus on entire-home listings, which are both more numerous[14] and more comparable with the same type of listings on VRBO.[15]

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.

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.

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

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

[15] VRBO does not allow private room or shared space listings.

[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. We use regular monthly scrapes between January 2015 and December 2019 on Airbnb and between January 2017 and December 2019 on VRBO. In total, the listing-month sample includes 1,158,952 observations of 128,428 entire-home listings on Airbnb, and 203,225 observations of 33,872 listings on VRBO.

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 listing's 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.

The next step is computing the number of host cancellations for each Airbnb listing.[18] To do so, we take advantage of the fixed format of the automated reviews, e.g., "The host canceled this reservation X days before arrival. This is an automated posting." Searching

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

for such a format in listing reviews, we count the cumulative number of cancellation reviews for each Airbnb listing up to each specific month.

Table 1 summarizes the data for Airbnb and VRBO listings separately (2015-2019 for Airbnb and 2017-2019 for VRBO). On average, VRBO listings have a higher listing price than Airbnb listings,[19] but a lower number of reservations per month and a lower occupancy rate. The average review rating is high on both platforms, consistent with the literature. As for guest-facing cancellation policies, most listings on both platforms offer flexible or moderate cancellation (we refer to both as "loose") policies. Throughout the sample, 26.5% of Airbnb listings offer a strict cancellation policy, and 31.46% do so on VRBO. On the host side, the average number of host cancellation reviews is low per listing — about 11.47% of listings have at least one cancellation review in our sample, and 24% of such listings are located in New York City. On average, Airbnb listings comprise 87% of the total number of listings within a 0.3-mile radius (implying a competition index of 0.13), though some listings may be listed on both Airbnb and VRBO. For the period when we have both Airbnb and VRBO data (2017-2019), 13.21% of Airbnb listings are cross-listed on VRBO.

Focusing on Airbnb listings (2015-2019), Table 2 reports summary statistics on host cancellations, by the type of guest-facing cancellation policy offered by the Airbnb host, before and after Airbnb introduced the 48-hour rule. We consider three different groups of listings (0, 1, and 2+ cancellations). The table suggests that listings with strict cancellation policies are more likely to have two or more host cancellations than listings with loose cancellation policies. The distribution of host cancellations seems stable over time, but listings without host cancellations slightly increase after the May-2018 rule change.

For Airbnb listings (2015-2019), Table 3 tabulates price, reservations, and occupancy rate by the number of host cancellation reviews on Airbnb and the type of guest cancellation policy the host offers. On average, listings with a strict cancellation policy have more reservations, higher prices, and higher occupancy rates, which suggests that strict-cancellation listings may provide higher-quality accommodations that can attract more guests even under

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

strict cancellation policies. Together, Table 2 and Table 3 highlight that listing quality is multi-dimensional: the properties that adopt strict cancellation policies are more popular than other properties, but they also offer guests the least flexibility (in terms of guest cancellations) and the highest uncertainty (in terms of the likelihood of host cancellations) on average. This tradeoff is likely driven by the fact that most hosts on Airbnb manage few properties, and thus hosts of more popular properties face a tighter capacity constraint and a higher opportunity cost of guest flexibility.

Figure 3 presents the competition index and the number of listings for the cities covered in our dataset, mapping out this comparison using different shades for the level of VRBO competition by city, and different bubble sizes for the number of Airbnb listings in each city. New York City is the largest home-sharing market in our sample, with approximately 75,000 unique listing IDs over the sample period. Airbnb listings in New York City and New Orleans tend to have higher competition from VRBO listings, compared to other cities in our sample. Zooming into the top 30 zip codes in terms of the total number of listings (all in New York City), Figure 4 suggests that areas that have a higher number of Airbnb listings also face more competition from VRBO.

5 Empirical Analyses

5.1 Effects of the 48-Hour Rule

In this subsection, we assess the effects of Airbnb's introduction of the 48-hour rule on its listings. We use a difference-in-differences methodology (DID), which contrasts Airbnb and VRBO listings, before and after Airbnb introduced the 48-hour rule in May 2018. Our main hypothesis is that, after the new rule came into effect, Airbnb listings would benefit from a demand increase, as the new pro-guest rule should attract more reservations from new and existing guests. This is built on the assumption that Airbnb and VRBO listings follow similar pre-treatment trends before May 2018, which we confirm in statistical tests later on. A potential caveat of using VRBO 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.

Our baseline specification is:

$$y_{it} = \alpha_i + \alpha_t + \delta X_{st} + \beta Airbnb_i \times Post_4 8hr\_Rule_t + \varepsilon_{it}, \tag{1}$$

where i denotes an individual listing, t indexes month, $Airbnb_i$ is a dummy that equals 1 for Airbnb listings,[20] $Post\_48hr\_Rule_t$ is a dummy that equals 1 if t is on or after May 2018. Depending on the specification, the dependent variable Y_{it} is the number of reservations per month, log of the average listing price over the month, or log of the monthly occupancy rate. Year-month and listing fixed effects are denoted by α_t and α_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-book 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 in period $t-1$.

Because the number of monthly reservations is a count variable, we use a Poisson specification and report marginal effects. The price and occupancy regressions are OLS, reporting coefficient estimates. As shown in the last row of Table 4, all regressions pass the pre-treatment test; standard errors are clustered by zip code throughout.

Our baseline model (Column 1 of Table 4) suggests that Airbnb listings enjoy a 5.51% increase in the number of reservations (as compared to VRBO listings), after Airbnb allowed a 48-hour grace period on guest cancellations. This effect can be further decomposed into a 2.75% increase in the average monthly listing price and a 1.92% increase in occupancy rates.

[20] In another specification, $Airbnb_i$ is 1 for Airbnb listings with strict cancellation policies and 0 otherwise.

Within Airbnb listings, we explore heterogeneous effects according to a listing's guest-facing cancellation policy. For example, listings that offer loose cancellation policies before the policy change already offer more lenient guest cancellation policies than the 48-hour rule, and thus are largely unaffected, except that Airbnb guests can now get the platform fees refunded if they cancel within 48 hours (hosts are only charged platform fees on payments that are not refunded to guests). Hence, listings with loose cancellation policies should not face any direct cost increases from the new 48-hour rule, whereas their potential guests directly benefit from it. On the other hand, listings with strict cancellation policies may face higher costs as a result of the 48-hour rule, since their hosts no longer get to keep any percentage of the revenue if potential guests cancel within 48 hours of their bookings (for reservations at least 14 days away).

To assess such differences, we proceed with a similar empirical methodology but different treatment and control groups. In Columns 4 to 6 of Table 4, we define Airbnb listings with loose cancellation policies as the treatment group and VRBO listings of similar cancellation policies as the control. This comparison aims to tease out the effect from the increased demand as a result of the platform's new policy. Results show that Airbnb listings with loose cancellation policies benefit from the policy change, with a rise of 7.31% in the number of monthly reservations, 3.92% in listing price, and 2.74% in occupancy rate after May 2018.

To highlight the differential effect on other listings, we follow a similar specification but define the treatment group as the Airbnb listings with strict cancellation policies, and the control group as the Airbnb listings with loose cancellation policies. As shown in Columns 7 to 9 of Table 4, Airbnb listings with strict cancellation policies, relative to their Airbnb counterparts with loose policies, incur a 3.31% decrease in their monthly number of reservations, a 2.27% decrease in their average listing price, and a 1.95% decrease in their occupancy rate after the platform's policy change.

These relative effects are smaller than the demand increase enjoyed by the Airbnb listings with loose cancellation policies (7.31%, 3.92% and 2.74% in Columns 4-6), so the net effects are still positive for the listings with strict cancellation policies, if they are compared with

VRBO listings of loose cancellation policies. In other words, nearly all Airbnb listings benefit from a demand increase from the 48-hour rule, but the hosts that offer strict cancellation policies before the change benefit less. This could be because the 48-hour rule raises the costs of hosts with strict policies, or because these hosts were already close to their capacity constraints and thus had less room to improve in reservations and occupancy rate. However, their price increase post May 2018 is also of a smaller magnitude, which casts doubts on the second explanation. A third explanation is that the 48-hour rule motivates guests to pay closer attention to the guest-facing cancellation policy and associate a lower willingness to pay for listings with a strict policy. This is plausible for listings that maintain or adopt strict cancellation policies post the 48-hour rule. But since hosts can loosen their cancellation policies anytime, it does not explain why the effects of the 48-hour rule are smaller for hosts that had strict cancellation policies before the rule change. As shown later on, hosts that offered strict cancellation policies before the 48-hour rule are also more likely to use host cancellation after the 48-hour rule, which could directly reduce the number of reservations and occupancy on Airbnb.

5.2 Effects of System-Generated Cancellation Reviews

The vast majority of Airbnb listings in our sample have an average overall rating at or above 4-stars. Hence, system-generated host cancellation reviews may play an important role in potential guests' booking decisions. In particular, listings without a cancellation review may be perceived as offering a higher-quality product, which can result in additional reservations, higher occupancy rates, and higher prices.

Our baseline specification is:

$$y_{it} = \alpha_i + \alpha_t + \delta X_{st} + \beta HostCancel_{i,t-1} + \varepsilon_{it}, \tag{2}$$

where $HostCancel_{i,t-1}$, is the total number of cancellation reviews for listing i at time $t-1$. The dependent and control variables are the same as those in Equation 1. Figure 5 plots the average number of host cancellation reviews per listing over time. Aside from some seasonality over the holiday months, there is a notable difference in the trend immediately after Airbnb introduced the 48-hour rule in May 2018.

One may argue that some omitted demand factors may affect a listing's lagged cancellation review counts, its price, and other performance metrics. To search for instruments, we recognize that a listing's cancellation reviews are subject to external noise (e.g., extreme weather or the level of law enforcement dedicated to sniffing out illegal short-term rental operators in the city in a specific time), but guests may not have complete information about such noise. Taking advantage of this, we use the number of days with at least 1 inch of precipitation and the number of days with extreme temperatures (maximum ≥ 90 F or minimum ≤ 0 F) as instruments for the number of cancellation reviews.[21] The correlation between the precipitation instrument and the number of cancellation reviews is 0.842, and the correlation between the temperature instrument and the number of cancellations is 0.491. We further confirm the power of the instruments in a first-stage F-test (above 10) and their likely exogeneity in a Durbin-Wu-Hausman test.

In regressions for the number of reservations and occupancy rate, we include the average listing price as a control variable. To address the potential endogeneity of price, we use as instruments the average monthly price of another category of listings (private rooms or shared spaces), within a 10-mile radius of each entire-home listing. The different listing types tend to be correlated in terms of overall supply but may differ on the demand side due to the intention to attract different types of guests. The correlation between log(entire-home price) and log(private-room price) is 0.781, and the correlation between log(entire-home price) and log(shared-space price) is 0.571. The first-stage F-test for the joint significance of the coefficients of these instruments is 17.85.

Table 5 reports the results of two-stage least squares with these instruments. The first

[21] We use monthly weather data from NOAA (https://www.ncdc.noaa.gov/cdo-web/search) to obtain the instruments. We have latitude and longitude coordinates of each weather station, which we use to either assign a zip code to the station or to match a listing with its nearest station in cases where there are no weather stations in a zip code.

three columns are without listing fixed effects. They show that one more host cancellation review is associated with a 6.17% reduction in the number of reservations, a 7.71% decline in occupancy rate, but an insignificant change in listing price. When we include listing fixed effects, the negative effect of host cancellation reviews on price becomes significant (4.15% in Column 5). The negative effect on the number of reservations increases slightly to 6.88% and the negative effect on occupancy rates drops to 4.77% (both remain significant at 99% confidence).

For the control variables, it is notable that enabling Instant Book on a listing (i.e., guest bookings are immediately confirmed without requiring a host's manual approval) seems to benefit Airbnb listings, resulting in a 5.55% increase in the number of monthly reservations, a 1.46% increase in the listing's price, and a 4.59% rise in its occupancy rate. In comparison, both the total number of reviews and overall rating (in terms of stars) are correlated with reservations, price, and occupancy rate with statistical significance (mostly positive except for number of reviews on price). As expected, the Superhost status of a listing is related to more reservations, higher prices, and higher occupancy rates.

5.3 Platform Competition

Our findings thus far suggest that the two pro-guest rules of Airbnb have mixed effects on hosts. On the one hand, these rules make Airbnb more attractive to guests, and thus benefit hosts via increased demand. On the other hand, the rules may increase the costs of some Airbnb hosts, as some reservations may be cancelled by guests without compensating the host's opportunity costs, and the hosts may face economic penalties on future business if they engage in host cancellation. Hosts may also become more dependent on Airbnb, and face potentially more competition within Airbnb, if more guests end up joining Airbnb and staying on the platform due to its pro-guest rules. That is, as a result of these pro-guest rules, Airbnb could end up with more guests, more hosts, and more transactions. More generally, the potential increase of market concentration is a concern about platform competition.

Of course, an increase in market concentration at the platform level is not the only possibility of a future market evolution. It is also possible that, by raising the overall quality of hosts on Airbnb, competing platforms may be induced to focus on the lower end of the host quality spectrum, potentially exposing Airbnb to more platform competition.

Against this background, we focus on the extent of platform competition from VRBO in our sample period. VRBO, arguably the closest competitor to Airbnb in the US short-term rentals market (aside from hotels, bed and breakfasts, and other traditional suppliers), provides a similar service and faces similar tradeoffs in determining which pro-guest rules to adopt. In this competitive market, both hosts and guests can multi-home. Given Airbnb's apparent pro-guest strategy, VRBO may prefer the platform design of hiding host cancellations, as by doing so it may attract frustrated hosts from Airbnb and provide existing hosts with an incentive to stay on its platform. Guests, meanwhile, could view VRBO hosts as offering lower-quality service, on average, but lower quality may also mean lower costs; hence, VRBO can still attract consumers, especially those that are price sensitive but less quality sensitive. Consequently, the policies adopted by these competing platforms in equilibrium may feature differentiation in their pro-guest rules, which further implies differentiation in price, occupancy, and cancellation frequencies. By considering the extent of VRBO competition in our specifications, we aim to test how Airbnb's two pro-guest rules differentially affect Airbnb listings as a function of their competition from VRBO listings.

To show the raw data by platform competition, Figure 6 depicts the monthly trend of the number of Airbnb listings, Airbnb listing price, Airbnb listing occupancy rate, and the multi-homing proportion of listings from 2017 to 2019. In line with Figure 3, we group Atlanta, Houston, Los Angeles, New Orleans, and New York as high-competition cities, and group the other five as low-competition cities. This grouping is based on the fact that the average share of VRBO listings (in total listings at the zip code level) is higher in the first set of cities. This binary grouping is only for illustration in Figure 6. In the regression analysis, we will use a continuous competition index per listing (as defined in Section 4) to characterize high- and low-competition areas within each city.

As reported in Figure 6a, the number of Airbnb listings has no obvious change in low-competition cities after Airbnb introduced the 48-hour rule in May 2018, but it decreases slightly in the high-competition cities. Listing price and occupancy rates increase in both types of markets after May 2018, while the magnitude of the increase is greater in low-competition cities. Consistently, the proportion of listings that multi-home on both Airbnb and VRBO increase more after May 2018 in the high-competition cities than in the low-competition cities. All these patterns suggest that the 48-hour rule is more helpful to Airbnb in the cities with less platform competition.

This impression persists when we conduct the regression analysis. In particular, we separate the sample into high- and low-competition sub-samples, according to whether an Airbnb listing's local competition index as of April 2018 is above or below the city-median competition index at that time.[22] Within each subsample, we repeat the DID analysis of Equation 1 for all three listing outcomes.

Columns 1 to 6 of Table 7 focus on the high-competition sub-sample, which includes listings that had a local competition index above the city-median as of April 2018. In Columns 1-3, the treatment group is defined as Airbnb listings with loose cancellation policies in April 2018, while the control group is VRBO listings with similar (loose) cancellation policies as of April 2018. Columns 4-6 define the treatment group as Airbnb listings with strict cancellation policies in April 2018, compared to VRBO listings with similar (strict) cancellation policies. Results suggest that, after the 48-hour rule, Airbnb listings with loose (strict) cancellation policies benefit from a 6.33% (1.79%) increase in their number of monthly reservations, a 3.19% (0.82%) increase in price, and a 2.25% (0.68%) increase in occupancy rates.

Columns 7 to 12 follow the same structure, with a focus on the low-competition sub-sample, which includes listings that had a local competition index below the city-median as of April 2018. In all of these columns, the effect of the 48-hour rule is greater than that in the

[22]Using sample-median instead of city-median yields similar results. We prefer city-median because the competition index may differ systematically across cities for reasons other than Airbnb-VRBO competition (e.g. city wide regulation on short-term rentals).

high-competition sub-sample. Specifically, (7.08%, 5.24%, 4.53%) vs. (6.33%, 3.19%, 2.25%) for listings with loose cancellation policies, and (3.88%, 2.77%, 2.63%) vs. (1.79%, 0.82%, 0.68%) for listings with strict cancellation policies. Across the board, platform competition appears to dampen the benefits of business expansion for Airbnb listings because of the 48-hour rule.

Turning to the host side, we now report the effect of platform competition on the signalling value of automated reviews of host cancellations. Table 7 reports the estimation results of Equation 2 for four sub-samples: listings with loose cancellation policies ("loose listings") in high-competition areas, loose listings in low-competition areas, listings with strict cancellation policies ("strict listings") in high-competition areas, and strict listings in low-competition areas, all as of April 2018. A comparison of Columns 1/5/9 and Columns 2/6/10 indicates that, when the local competition index increases from below-city-median to above-city-median, the negative signal of one more host cancellation review becomes stronger for loose listings in all listing outcomes: the number of reservations drops more (-5.82% vs. -7.71%), the average price per night declines more (-4.33% vs. -7.29%), and a slightly larger drop in occupancy rates (-5.17% vs. -5.72%). This suggests that more competition with VRBO amplifies the negative signal of cancellation reviews for loose listings. One potential explanation is that Airbnb guests are more likely to multi-home in a competitive market, and as a result they are less tolerant of loose listings with a history of canceled guest reservations. Unfortunately, we do not observe guest multi-homing and therefore cannot test this hypothesis directly.

In contrast, if we compare Columns 3/7/11 and Columns 4/8/12, the results are opposite for listings with strict cancellation policies: having one more host cancellation review is still a negative signal, but its negative impact on listing performance is of a smaller magnitude if the listing is located in the high-competition area of a city than in its low-competition area. Across the board, the negative effects of host cancellation reviews are also smaller for strict listings than for loose listings in the same type of competition areas. Altogether, these results suggest that Airbnb guests are more forgiving as far as strict listings that have host cancellation reviews, especially in high-competition areas. This could happen because strict listings tend to be associated with more popular and harder-to-book properties. As a result, guests may be willing to sacrifice flexibility and uncertainty in an effort to secure these properties. This tradeoff does not exist for loose listings, which explains why host cancellation reviews are less tolerated for loose listings, especially when a property is located in a high-competition area within a city.

5.4 Supply-Side Dynamics

We have demonstrated thus far that listings within the same city may face different degrees of platform competition, and that such competition may play a role in how different pro-guest rules affect those listings and how their hosts react to those rules. In this subsection, we provide further analysis of the effects of the 48-hour rule on the supply side of Airbnb, including the effect on the number of Airbnb listings, hosts' decisions to multi-home, as well as their decisions to use host cancellation and alter their listings' guest-facing cancellation policies.

In Table 8, we first assess the effect of the 48-hour rule on the number of Airbnb listings and multi-homing listings. We do so by using the number of Airbnb listings (and multi-homing listings) at the zip-code-month level as the treatment group, while using the number of VRBO-only listings (i.e., not including listings that multi-home) as the control group. Columns 1 and 2 indicate that, post the 48-hour rule, the number of monthly Airbnb listings per zip code declines 2.79% in low-competition areas and 2.02% in high-competition areas. These two numbers are not statistically different from each other. Meanwhile, the number of multi-homing listings increases by 0.28% in low-competition areas and 1% in high-competition areas. The difference is highly significant. Consistently at the listing level, Column 3 suggests that Airbnb hosts are more likely to list their property on VRBO after the 48-hour rule in comparison to VRBO hosts listing their properties on Airbnb, and this increase is more conspicuous in high-competition areas than in low-competition areas.

Since the 48-hour rule imposes a minimum quality standard on guest cancellation policies, it is interesting to examine how hosts adjust their cancellation policies after the 48-hour rule. Figure 7 depicts trends of the number of listings with loose and strict cancellation policies, on Airbnb and VRBO separately. The vertical line marks the time that Airbnb introduced the 48-hour rule. Both Airbnb and VRBO listings track each other somewhat closely, and the number of listings with loose host cancellation policies exhibits an increase on both platforms after May 2018, whereas there appears to be a decrease in the number of listings with strict cancellation policies.

To further examine the causal effect of the 48-hour rule, we run a listing-level regression where the dependent variable is whether the listing adopts a strict cancellation policy as of month t, and the key independent variables are whether the listing is on Airbnb (vs. VRBO), whether month t is after the 48-hour rule, whether the listing is located in an area with above-city-median competition (as of April 2018), and their interactions. We control for listing attributes as well as city, zip-code and month fixed effects.

The results are reported in Column 4 of Table 8, and suggest that the fraction of Airbnb listings that offer strict cancellation policies dropped significantly after the 48-hour rule, with a larger decline in high competition areas than in low competition areas. This is understandable, as the 48-hour rule has forced all hosts to offer more flexibility in guest cancellations, which makes strict cancellation policies more homogenized with loose cancellation policies. Some hosts of strict listings may find it pointless to insist on a (dampened) strict cancellation policy on Airbnb.

In the same Table 8, Columns 5 and 6 focus on the Airbnb sample only. This allows us to characterize how loose and strict listings differ and how host cancellation reviews relate to cross-listing and exit decisions. The shortcoming is that we now lack a control group because we do not observe host cancellations on VRBO. In short, Column 5 suggests that cross-listing is more likely to occur if the host of the Airbnb listing offers a strict cancellation policy, has any cancellation reviews, or operates in high-competition areas. Column 6 shows that strict listings or listings in high-competition areas are less likely to exit Airbnb, while listings with any cancellation reviews are more likely to exit. This is consistent with the findings that strict listings tend to be associated with more popular properties, and host cancellation reviews are by and large a negative signal on Airbnb. In the raw data, 79% of the listings that exited Airbnb post the 48-hour rule had already offered flexible or moderate cancellation policies even before the 48-hour rule, but their average price and occupancy rate were much lower than an average listing on Airbnb.[23] This suggests that, although loose listings are not directly affected by the 48-hour rule, and the traffic expansion on Airbnb has on average benefited loose listings more than strict ones, the decline in the total number of Airbnb listings is mostly driven by loose listings associated with lower-quality properties. One explanation is that the 48-hour rule has intensified competition within Airbnb, as strict and loose listings become more homogenized in their cancellation policies, and some hosts of loose listings at the low end of property qualities find it difficult to survive such competition.

To further examine the difference between loose and strict listings, we run a regression on the Airbnb sample only, where the dependent variable is the dummy of whether an Airbnb listing is cross-listed on VRBO, and the key independent variables are whether the month is after the introduction of the 48-hour rule, and its interaction with whether the listing is located in a high-competition area of the respective city. As previously, we control for month and listing fixed effects, and cluster standard errors by zip code. This regression is conducted separately for flexible, moderate and strict listings (as of April 2018). Results are reported in Columns 1-3 of Table 9.

To our surprise, the rise in cross-listing is driven by the listings that had offered flexible or moderate cancellation policies before the 48-hour rule. At first glance, this seems counter-intuitive because only strict listings are directly affected by the 48-hour rule and the cost implications of the rule should push hosts of strict listings to "escape" to VRBO. This prediction does not pan out in the data, because hosts that offered strict cancellation policies

[23]The listings that exited Airbnb after the 48 hour rule had an average price of $131.45 before the 48-hour rule, as compared to $176.36 of stayers. They also differed in the average occupancy rate (18.72% for exiters vs. 36.28% for stayers) and the number of reservations per month (3.77 for exiters vs. 7.82 for stayers) before the 48-hour rule.

had already been much more likely to cross-list on VRBO even before the 48-hour rule (Table 3 Column 4). The rise of loose listings being cross-listed on VRBO is probably driven by an indirect effect: since the 48-hour rule has increased the (perceived) quality of strict listings, it intensifies competition within Airbnb, which could motivate hosts of some loose listings to seek extra revenue on an alternative platform.

The last two columns of Table 9 look at host cancellations on Airbnb. Within high-competition areas, Column 4 compares strict and loose listings before and after the 48-hour rule. In particular, we define the dependent variable as whether an Airbnb listing has any host cancellation in month t, while the key independent variables are whether the host offers a strict cancellation policy in month t, whether the host cross-lists on VRBO in t, whether t is post the 48-hour rule, and their interactions. As before, we include month fixed effects and listing fixed effects, and cluster standard errors by zip code. Results suggest that cross-listing hosts are more likely to cancel, especially if they offer a strict cancellation policy, and this tendency increases further after the 48-hour rule. In comparison, the same regression for listings in low-competition areas show no coefficient significant at the 95% confidence. This suggests that the 48-hour rule has motivated more host cancellations among hosts of cross-listed strict listings. This is understandable, because the 48-hour rule has introduced more uncertainty for hosts of strict listings on Airbnb, who could get around it by cross-listing their properties on both Airbnb and VRBO and cancelling an Airbnb reservation if needed. Although host cancellation is a negative signal and could hurt the host's future business on Airbnb, its negative impact on strict listings in high-competition areas is somewhat limited (Table 7), and the resultant profit loss on Airbnb is probably less than the the corresponding revenue gain from cross-listing on VRBO. Ironically, this reaction to the 48-hour rule — a rule that aims to increase guest flexibility when booking strict listings — ends up lowering the quality of service for some guests.

5.5 Back-of-the-Envelope Calculations of Airbnb's Gain from the 48-Hour Rule

A platform, as the governor of its own ecosystem, should not only address users of different sides as a match-making intermediary, but also consider the users as participants in the ecosystem. As a consequence, the governance frameworks created by the platform must take into account the interests of platform users. So far, our analysis has shown that positive network effects between guests and hosts indeed motivate Airbnb to adopt the 48-hour grace period as a pro-guest rule, and that such a rule has increased traffic for hosts while also increasing costs to some host types.

With respect to the competition between Airbnb and VRBO, different markets with different competitive landscapes may lead to different effects from Airbnb's introduction of the 48-hour rule. Using our results, we run several back-of-envelope calculations with respect to Airbnb's profit in each local market (i.e., by each city) after accounting for the competition level with VRBO.

Specifically, we first run the same analyses as in the previous subsections but taking each city as a separate sub-sample, assessing the effects of the 48-hour rule on the number of Airbnb listings, price, and occupancy rate within each of the 10 cities. We next collect the number of Airbnb listings in each city before and after the rule change. For Airbnb listings that also listed on VRBO, for simplicity, we assume these listings receive a similar number of reservations from the two platforms (i.e., in aggregate, equivalently, half of the total number of such listings have transactions with Airbnb guests, and the other half with VRBO guests). We further collect the average number of automated cancellation reviews in each city before and after the new Airbnb rule was introduced, and multiply it by the average effects of automated cancellation reviews on price and occupancy (in each city subsample) to assess the gain/loss after May 2018. The idea is to compare Airbnb's profit within the same city before and after the rule change, accounting for the effects on price and occupancy after May 2018.

Table 10 indicates that Airbnb listings in cities with higher competition from VRBO gain relatively less from Airbnb's new policy, when compared to those in lower-competition cities. The Airbnb policy change is arguably a form of quality enhancement from the perspective of guests, but competition appears to make Airbnb hosts less willing to engage in quality enhancement and more likely to multi-home. One potential explanation is that the policy change increased the costs of hosts with strict cancellation policies on Airbnb, and those hosts have a better ability to escape this pressure in more competitive markets. Their multi-homing or higher likelihood to use host cancellation can undermine the positive feedback between guests and hosts, making Airbnb's new policy less effective in more competitive markets.

To test such a hypothesis, we run an additional back-of-envelope calculation for listings that had strict cancellation policies before the 48-hour rule was introduced and remained on Airbnb afterwards (they could have any type of guest cancellation policy after the 48-hour rule). We have shown that the magnitudes of the positive effects on price, number of reservations and occupancy rate of such listings are not as large as for listings with loose cancellation policies; at the same time, they are still positive, implying that listings with strict cancellation policies do benefit from the platform's rule change. However, the rule change may also raise costs for those listings, which may force them to use more host cancellations to handle those costs. Although we do not know the real cost change for these hosts, we do know the negative consequences of host cancellations, which may be a proxy for these costs. In Table 11, we report back-of-the-envelope calculations of the net effects on listings with strict cancellation policies before May 2018. From the table, we observe that Airbnb listings with strict cancellation policies in higher competition cities are better off (gain more profit) compared to those in lower competition areas after the May-2018 rule change.

6 Discussion

In this section, we discuss the implications of our findings for antitrust analysis and the general economics of the platform's ecosystem.

As cited in Section 1, a significant amount of backlash against online platforms is triggered by supply-side complaints, which leads to the concern that some large platforms may have imposed costs on suppliers in their efforts to please consumers. When the questioned platform is large enough, it is argued that suppliers have nowhere to escape given the positive network effects on that platform, and thus platform competition should be a potential solution to the asymmetric and harsh treatment against some suppliers on that platform.

This logic seems to hinge on a few assumptions. For example, it assumes a strong network effect between two or more sides of a large platform, which tends to imply that an increase in demand should trigger an increase in supply on the same platform. This prediction is challenged by our empirical findings on the 48-hour rule: on the one hand, reservations, occupancy and average price have all increased on Airbnb relative to VRBO, which suggests that demand has expanded on Airbnb after the 48-hour rule; on the other hand, the number of listings declines on Airbnb, more hosts cross-list on VRBO, and host cancellations increase on Airbnb. The opposite moves in demand and supply suggest that the network effects may not be as strong as some policy makers have worried for a general two-sided platform.

Another assumption underlining the antitrust concern is that a supplier's ability to multi-home somewhere else will weaken the platform's incentive to squeeze some suppliers for more consumer friendliness. In this paper, we consider two pro-guest rules on Airbnb and find that their effectiveness is sometimes strengthened but sometimes weakened by platform competition. This suggests that platform competition may not always help to reduce the asymmetric treatment between the two sides.

An immediate question is *why* platform competition has different effects for different pro-guest rules. On the surface, the two rules are similar in guest-friendliness. They both target host quality: automated cancellation reviews help to discern high and low quality hosts on

Airbnb; and the 48-hour rule imposes a minimum quality standard, flexibility-wise, on all hosts. Both rules make Airbnb more attractive to guests (especially those that care more about quality), which in turn attracts hosts because of the positive network effects.

However, we note that platform competition allows *both* sides to switch or multi-home between platforms. For hosts that face a higher cost because of a pro-guest rule, they must trade off between (1) the benefits of accommodating more and higher-willingness-to-pay guests on Airbnb, and (2) an increase in operation costs if they decide to stay or single-home on Airbnb. This tradeoff not only depends on whether there is an alternative platform in the same market, but also on *how* the rule affects *guest* choice between the platforms and how guests trade off the multiple dimensions of listing quality.

Arguably, automated cancellation reviews affect all listings directly: by, in a sense, shaming those that cancel guest reservations, they boost the perceived quality of all non-cancelling listings.[24] In comparison, the 48-hour rule only enhances the quality of the listings that offer strict cancellation policies (26.5% of all Airbnb hosts) while keeping the quality of loose hosts (73.5%) unchanged. In other words, the wider coverage of cancellation reviews may represent a stronger treatment, which ends up attracting more quality-conscious guests to Airbnb, especially when Airbnb competes more intensively with VRBO in the market. This strengthening effect can be particularly strong for listings with loose cancellation policies, because they tend to be associated with less popular properties and have less of an "excuse" as far as capacity constraints in justifying host cancellation. The increased benefits of staying on Airbnb could motivate the 'long tail' of hosts to maintain or improve the quality of their listings on Airbnb rather than escape to VRBO. This may explain why the effectiveness of cancellation reviews as a signal of listing quality appears to increase in more competitive markets for listings with loose cancellation policies.

In comparison, the 48-hour rule is a limited treatment to Airbnb guests, because those guests sensitive to cancellation flexibility would have chosen flexible or moderate listings even

[24]The cancellation reviews could also depress the perceived quality of VRBO listings, if consumers believe that high-quality listings have incentives to join Airbnb and signal their quality there.

before the 48-hour rule. Given this limit, the rule ends up having a smaller effect in boosting demand in more competitive markets. As a result, for some Airbnb hosts, the benefits from attracting more guests on Airbnb could be limited as compared to the increased costs, which in turn motivates them to leave, cross-list on VRBO, or lower quality on Airbnb (e.g., by using more host cancellations) in more competitive markets. This makes the 48-hour rule less effective for Airbnb when they face more platform competition.

One may argue that the ambiguous role of platform competition in the asymmetric treatment of the different sides is irrelevant, because the final goal of antitrust policy is welfare rather than symmetry. To this end, it is important to ask whether a pro-guest rule by one platform is more welfare-enhancing if the market has more platform competition. Unfortunately, we do not have enough information to compute guest welfare, host welfare and platform profits precisely, so we only make some conjectures below.

On the guest side, cancellation reviews are akin to a disclosure policy on product quality, which in theory should foster guest sorting by their willingness to pay for quality, and motivate hosts to provide better quality. Although the sorting could lead to higher-quality products being more expensive, the common wisdom is that quality disclosure benefits consumers as a whole (see a review by Dranove and Jin, 2010). As shown in our findings, platform competition increases the signal value of cancellation reviews for loose listings. Since loose listings account for 73.5% of listings, this implies that platform competition should benefit most guests in terms of the information content of cancellation reviews.

In comparison, the 48-hour rule is akin to a minimum quality standard, which in theory could raise or lower guest welfare because it excludes guests from the choice of below-standard quality (Leland, 1979; Shapiro, 1986). However, since guests that prefer a below-standard quality could still go to VRBO for such quality, it is conceivable that the 48-hour rule is helpful in terms of overall guest welfare, especially when VRBO has a solid foothold in the market. That being said, some guests may find their welfare lift not as large as the 48-hour rule has intended, because they now face a higher risk of host cancellation by strict listings (although the 48-hour rule required such listings to provide more flexibility to guests).

On the host side, both rules have differential effects on different listings. The listings without host cancellations (89% of all Airbnb listings in our sample) are rewarded by the market when Airbnb posts a cancellation review on their competing listings, and this reward is greater for loose listings in a market with more platform competition. Similarly, listings that offer flexible and moderate cancellation policies (73.5%) are unaffected as far as costs by the 48-hour rule but benefit from the increased attractiveness of the Airbnb platform as a whole. It appears that these listings with loose policies — at least those that stay on Airbnb — are better off post the 48-hour rule, although they seem to benefit less from this windfall if the market has more platform competition. On the other hand, listings that cancel guest reservations (11%) are harshly punished for cancellation reviews. Moreover, the subset of listings with strict policies, which face higher costs due to the 48-hour rule (23.5%), are more likely to resort to host cancellation (a demand-reducing behavior) after the 48-hour rule, although they do enjoy some demand boost from the rule. In short, both pro-guest rules benefit the majority of listings on Airbnb, while hurting a minority of them.

To complete the picture, we note that Airbnb, as a platform, has likely benefited from both rules. Cancellation reviews make guests more willing to reserve non-cancelling listings at higher prices. Since 89% of listings on Airbnb in our sample are non-cancelling listings, the increased revenue gained by these listings could easily exceed the lost revenue of listings with cancellations. As for the 48-hour rule, Table 10 suggests that the net benefits to Airbnb are positive in all 10 cities, though they tend to be more positive in less competitive cities. Moreover, the 48-hour rule allows for a refund of Airbnb's own fee during the 48-hour grace period, which may attract more demand to the platform. The rule may also overcome a failure of collective actions, if the host of each strict listing fails to incorporate the potential gain that its unilateral adoption of a loose cancellation policy could bring to the whole platform.[25] In that case, the 48-hour rule could boost the profit of Airbnb as a platform and

[25] That is, every host had the choice of adopting a flexible, moderate or strict cancellation policies before the platform policy change. Adopting a loose (flexible or moderate) cancellation policy would have effectively granted the same 48-hour grace period to guests as far as the "refundability" of guest payments to hosts is concerned. Although hosts may recognize that loose cancellation policies can collectively raise the overall demand for Airbnb listings and potentially benefit all listings, each host was making their guest-facing

offer a way out for some strict hosts from this Prisoner's Dilemma.

Above all, our findings suggest that the two pro-guest rules are likely beneficial to most guests, to most Airbnb hosts, and to Airbnb as a platform. In the meantime, it could raise costs for a minority of listings on Airbnb, and hurt the profits of VRBO as a competeing platform. Unfortunately, platform competition does not necessarily reduce Airbnb's incentive to impose costs on hosts in the aim of guest-friendliness, nor is it clear how platform competition can help to simplify the guest tradeoff between different types of hosts.

7 Conclusion

To consider the role of a platform as the governor of its own ecosystem, we examined the effects of two pro-guest Airbnb rules, one for host cancellations and one for guest cancellations, on Airbnb listings in 10 US cities. We demonstrated that the two pro-guest rules have market consequences that, in net, may benefit Airbnb hosts, due to attracting more demand from guests. However, the effects of the policies are heterogeneous, and can drive some supply away from the platform and into a competing platform, as a function of the extent of competition in the vicinity of a listing.

Our findings further suggest that platform competition can have different and complex interactions with the effects of pro-guest rules, and may either dampen or reinforce them, as well as lead to heterogeneous effects on different hosts. In particular, the newly implemented 48-hour rule has made some hosts more likely to multi-home or altogether migrate to a competing platform. This could incentivize the competing platform to increase its efforts to attract specific host segments. To that effect, our results suggest that viable competition from another platform could temper a platform's ability to implement a pro-guest rule, and consequently impose limits on the benefits that the platform can gain from such a rule. However, cancellation reviews present an opposite example, where their signaling value on

cancellation policy choice in their own best interest, taking the other hosts' decisions as given. When a positive mass of hosts elect strict cancellation policies for their listings, the overall benefit of a single listing being switched from strict to flexible is negligible. In other words, the new 48-hour rule may have helped alleviate a situation along the lines of a Prisoner's Dilemma.

hosts that offer non-strict cancellation policies is strengthened by platform competition, which could further incentivize Airbnb to utilize them in more competitive markets.

It is important to 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, the guest and host cancellations we studied are specific to short-term rental services, which implies that our findings may not be readily applicable to other types of platform economies.

That being said, our study of the short-term rental context suggests that pro-guest rules do not necessarily trigger demand and supply to move in the same direction as one would expect in a platform with positive network effects, nor does platform competition always motivate the platform to become more pro-host and less pro-guest. The differential effects of pro-guest rules on different hosts also suggest complex welfare tradeoffs under such rules. How to incorporate these nuanced effects in the antitrust analysis of platform competition warrants further research.

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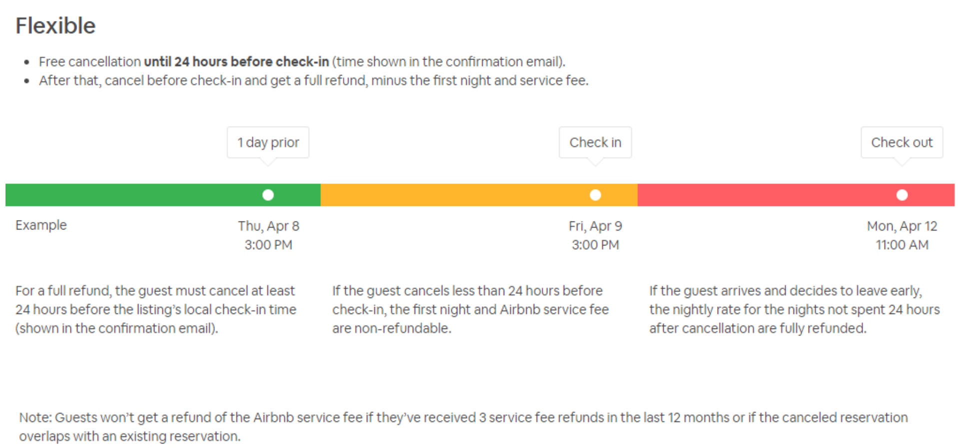
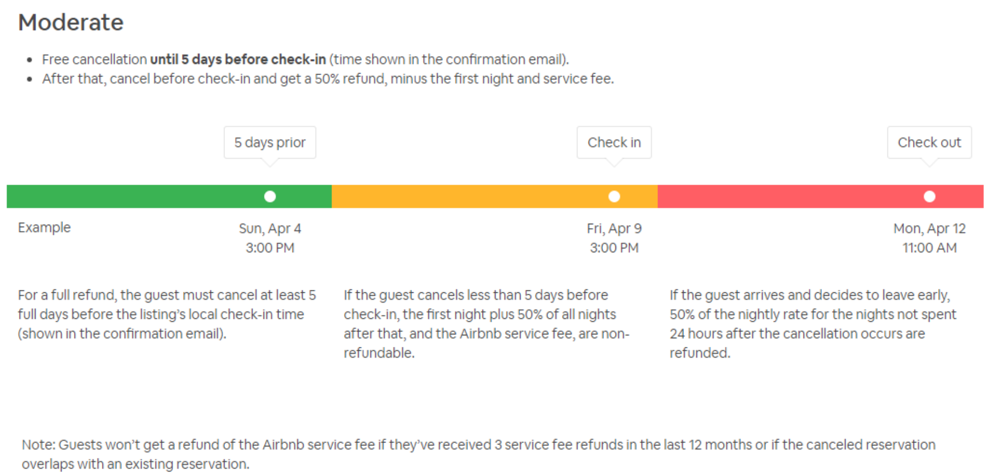
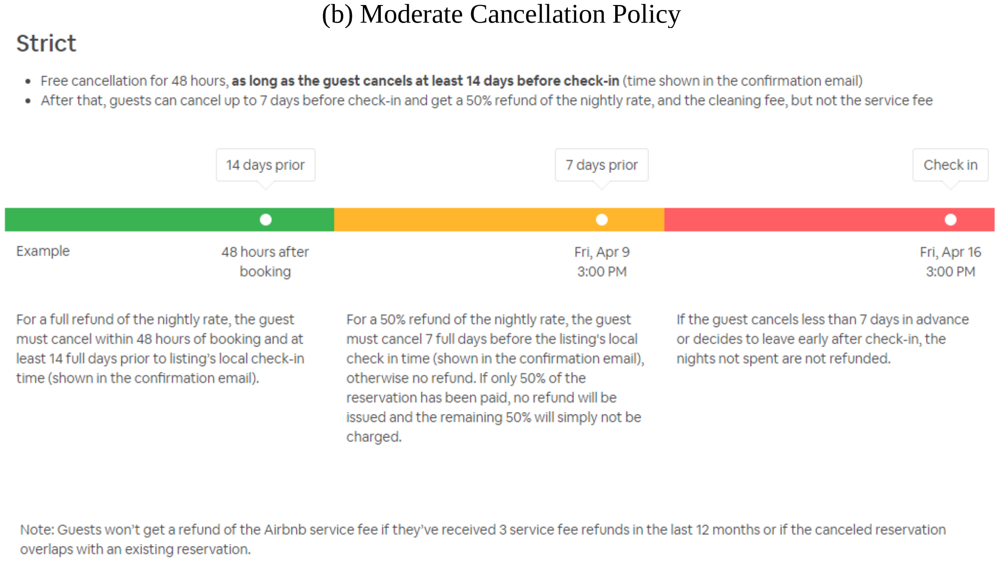


(a) Flexible Cancellation Policy



(b) Moderate Cancellation Policy



(c) Strict Cancellation Policy

Figure 1. Airbnb guest cancellation policy structure

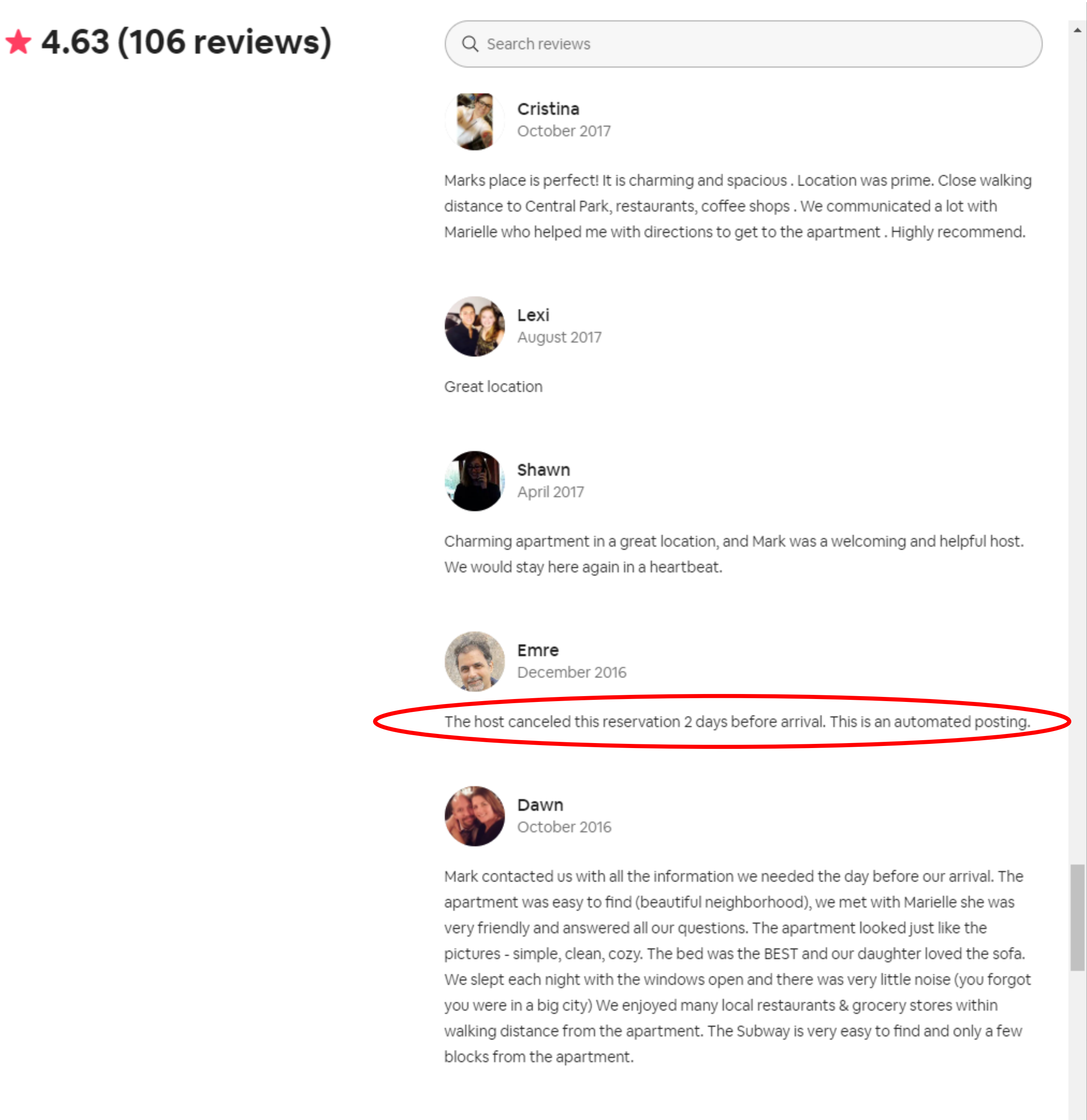


Figure 2. Example of automated cancellation review

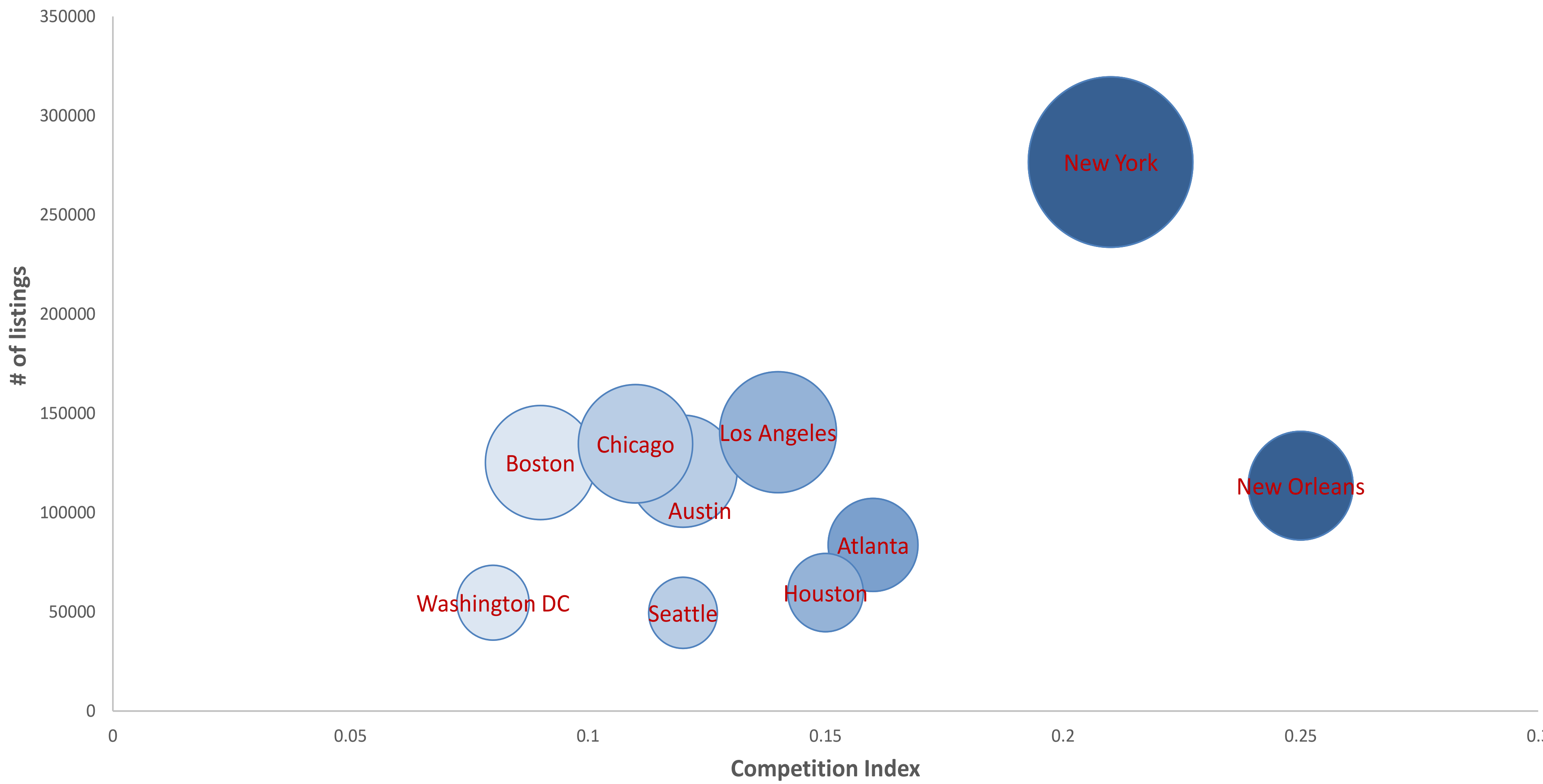


Figure 3. Map of cities covered in our data by competition level with VRBO and # of total listings

Note: The size of bubble stands for the # of listings. The larger the bubble, the more # of listings in that city. The shade level represents the competition index, the darker the bubble, the more competition from VRBO on Airbnb listings in that city.

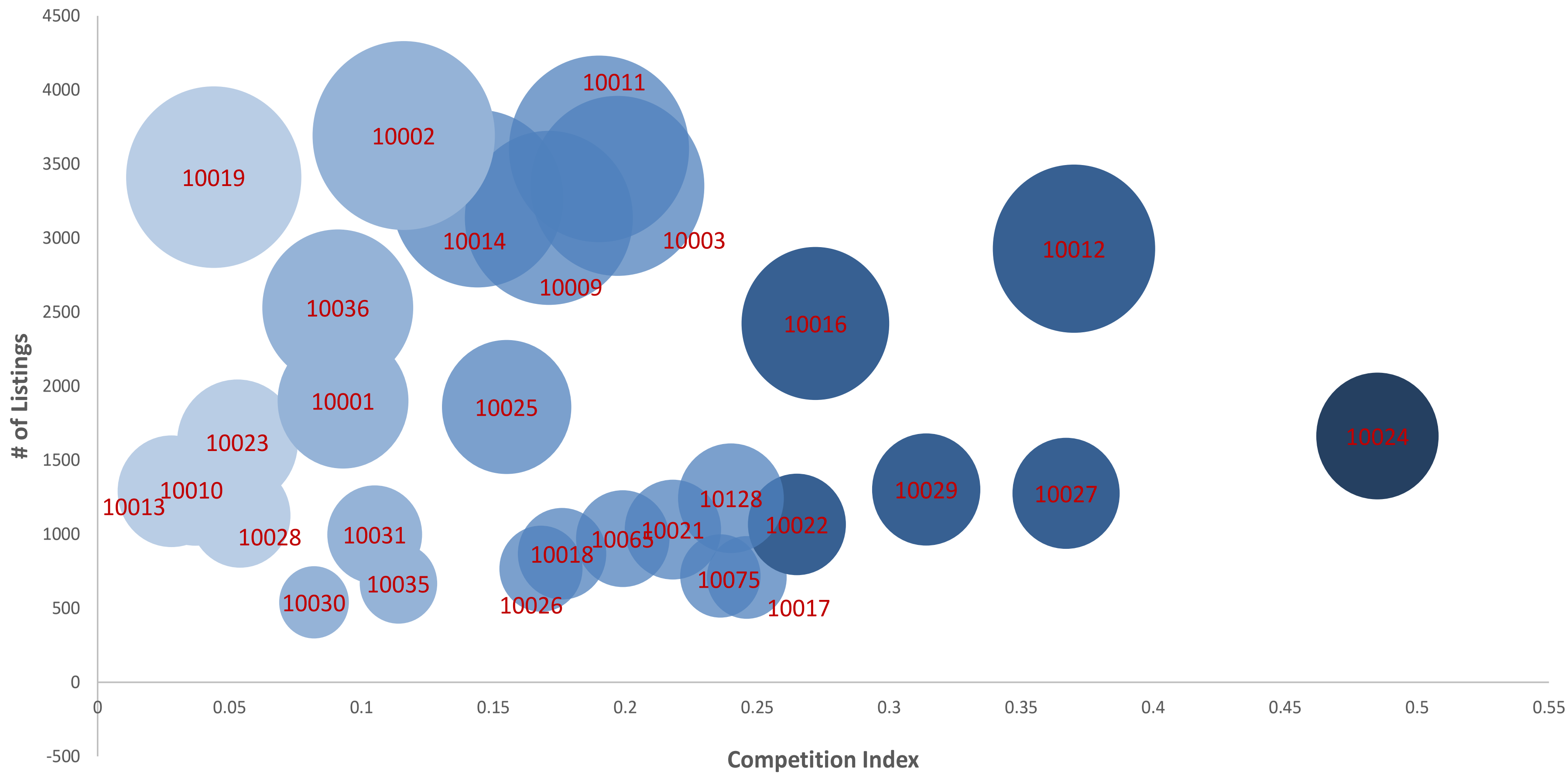


Figure 4. Map of top 30 zipcode by # of listings and competition level with VRBO

Note: The size of bubble stands for the # of listings. The larger the bubble, the more # of listings in that zipcode. The shade level represents the competition index, the darker the bubble, the more competition from VRBO on Airbnb listings in that zipcode.

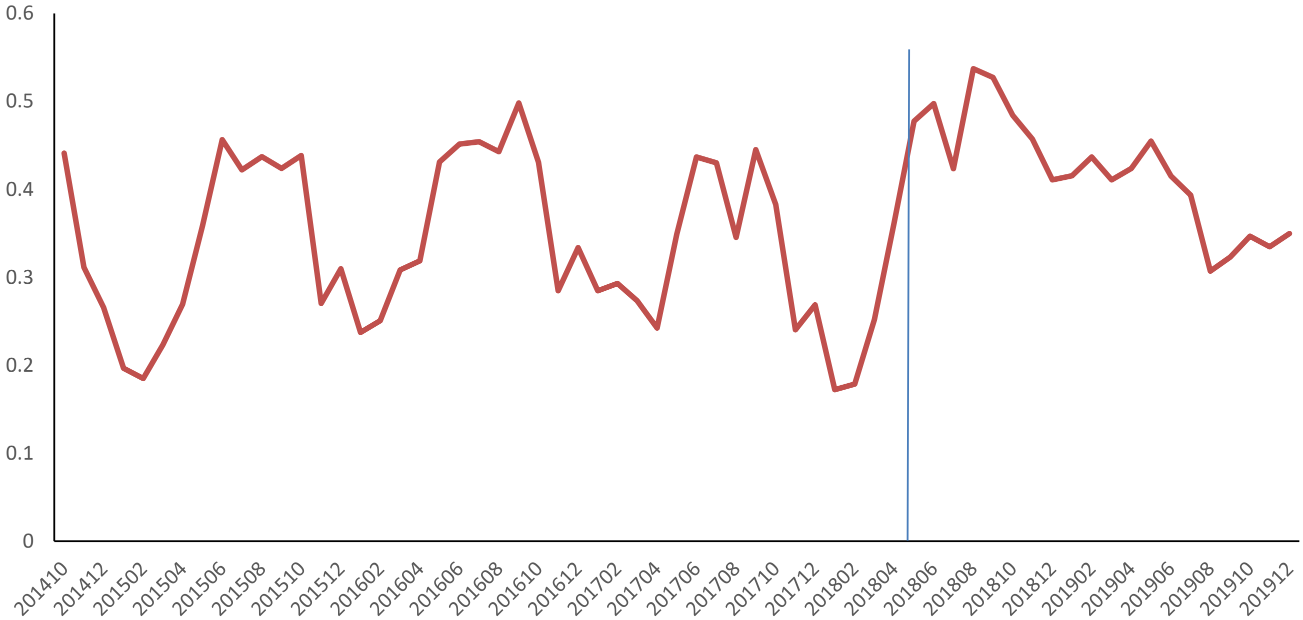
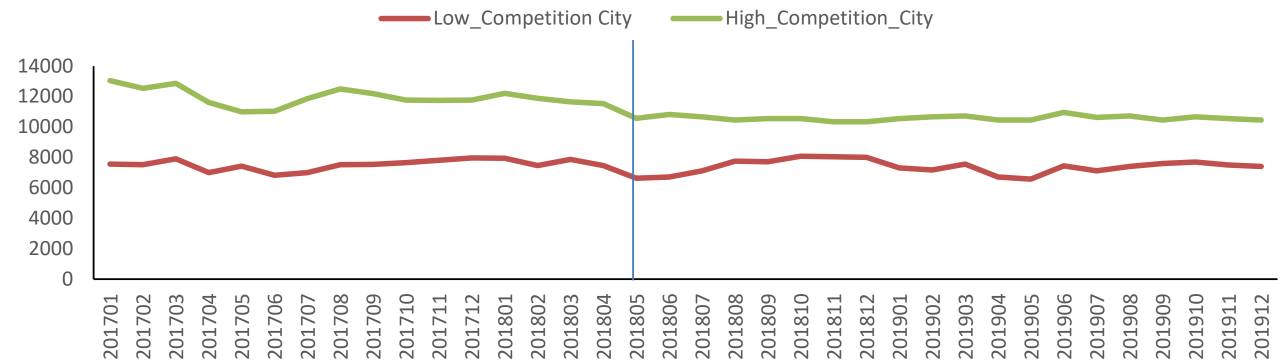
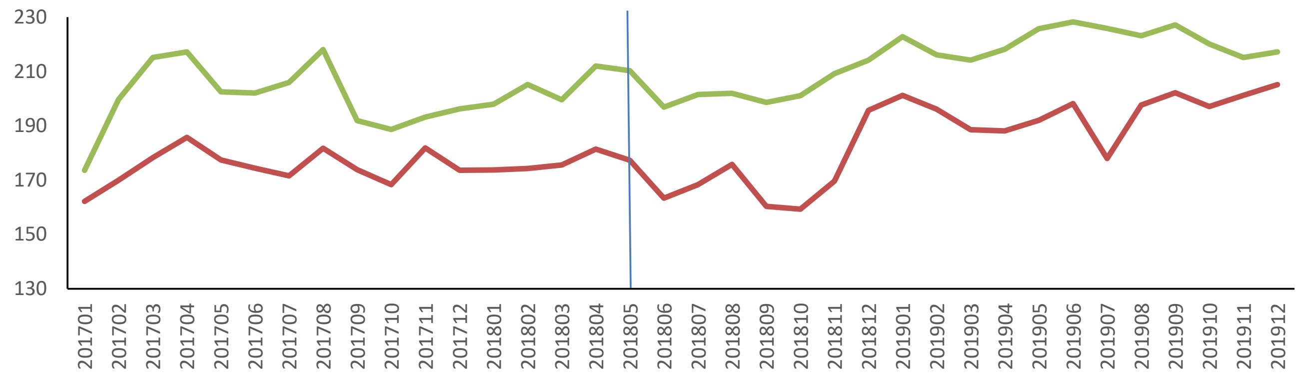


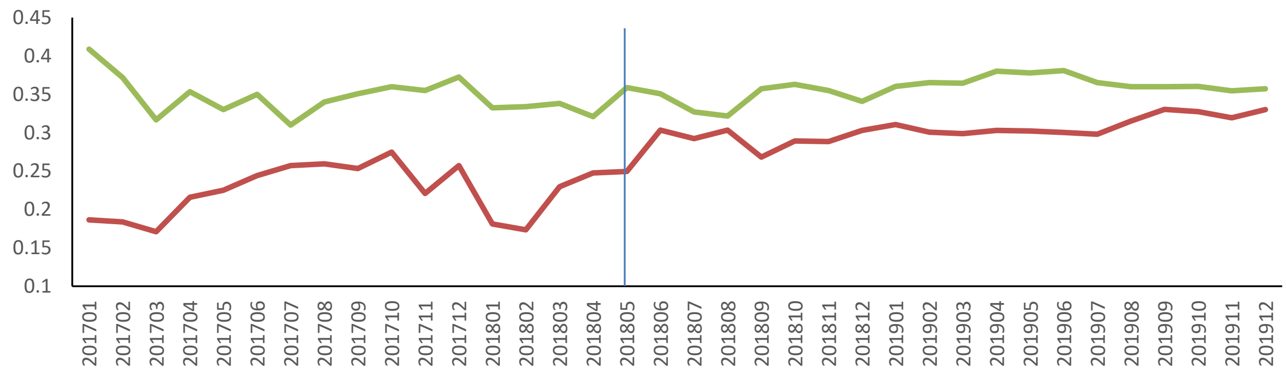
Figure 5. Average # of automated cancellation per listing over time



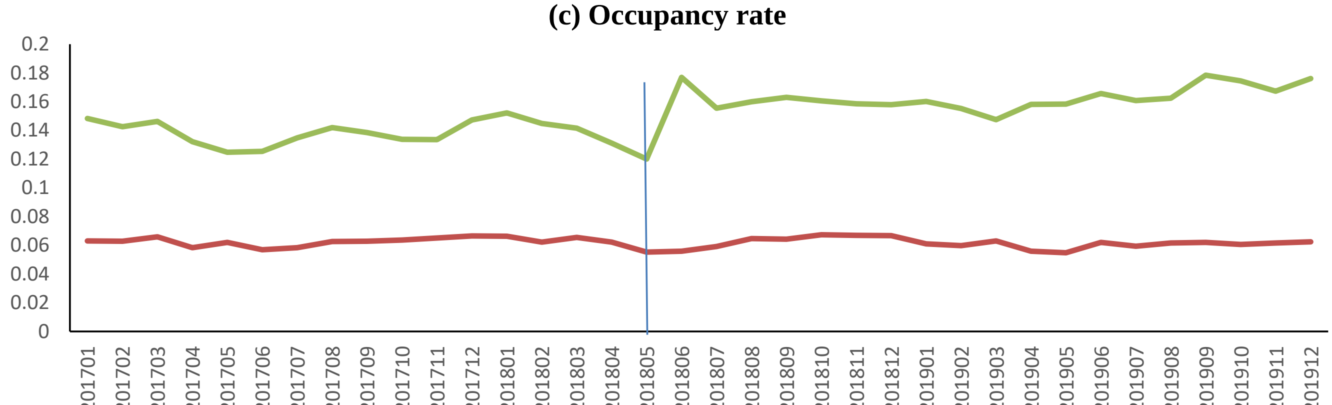
(a) # of listings over time



(b) Listing price



(c) Occupancy rate



(d) Cross-listing rate

Figure 6. Listing attributes in cities between high competitive level and low competitive level

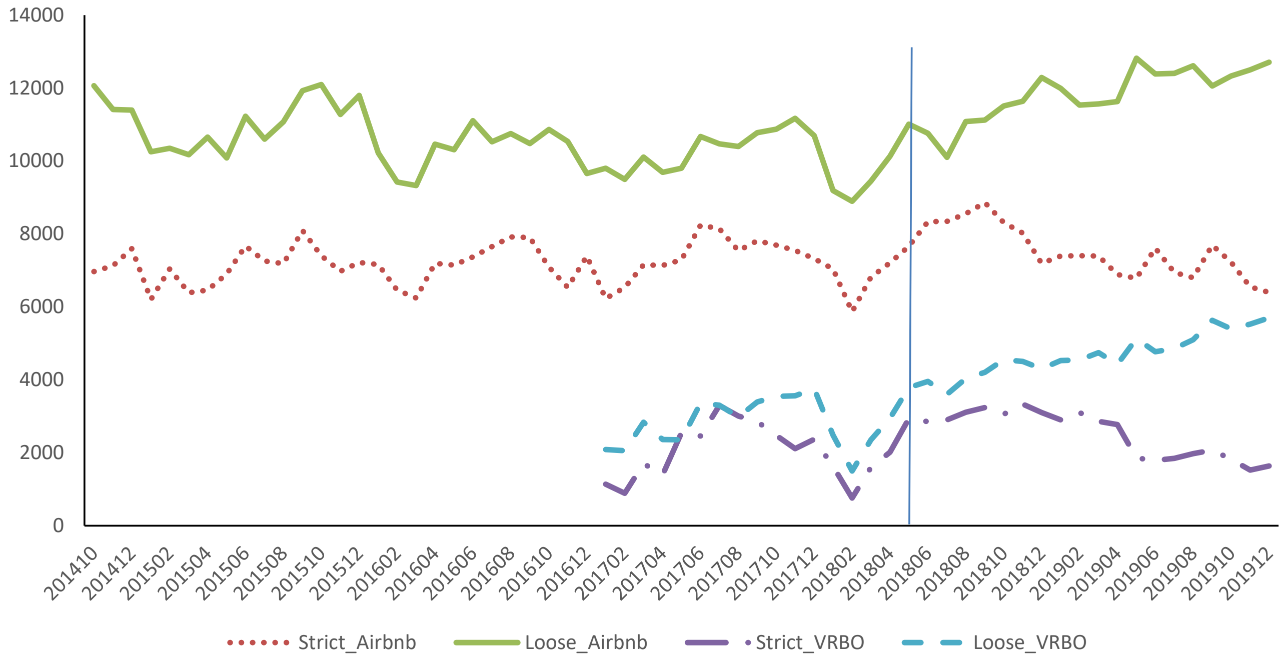


Figure 7. # of listings plot for different type of hosts in different platforms over time

Table 1: Summary statistics

	Airbnb			VRBO		
	Mean	Std.Dev	N	Mean	Std.Dev	N
Price	168.52	199.12	1,158,952	179.25	102.88	203,225
# of reservations	5.67	2.05	1,158,952	4.22	3.58	203,225
Occupancy rate	28.35%	0.347	1,158,952	23.02%	0.332	203,225
# of host cancellations	0.75	0.33	1,158,952	-	-	
Having any host cancellation (dummy)	11.47%	0.23	1,158,952	-	-	
Flexible Cancellation	39.00%	0.136	1,158,952	42.33%	0.072	203,225
Moderate Cancellation	34.50%	0.092	1,158,952	26.21%	0.105	203,225
Strict Cancellation	26.50%	0.078	1,158,952	31.46%	0.056	203,225
Competition Index with VRBO	0.124	0.21	1,158,952	-	-	
Cross-listing on VRBO (dummy)	13.21%	0.35	1,158,952	-	-	
Review Number	13.66	22.18	1,158,952	10.07	17.2	203,225
Review rating	4.53	0.32	1,158,952	4.59	0.28	203,225
Superhost proportion	7.18%	0.12	1,158,952	8.22%	0.11	203,225
No. Bedrooms	1.37	0.96	1,158,952	1.92	0.72	203,225
No. Bathrooms	1.33	0.41	1,158,952	1.56	0.28	203,225

Note: The unit of observation is at platform-listing-month level. Airbnb data covers 2015-2019, and VRBO data covers 2017-2019.

Table 2: Distribution of Airbnb listings by host cancellations (0,1,2+) and guest cancellation policies

	Before 48-hour rule (up to April 2018)	After 48-hour rule (on and after May 2018)
=1 if the listing has 0 host cancellation	87.41%	90.47%
with Flexible Cancellation Policy	38.62%	38.94%
with Moderate Cancellation Policy	35.05%	36.71%
with Strict Cancellation Policy	26.33%	24.35%
=1 if the listing has 1 host cancellation	5.37%	4.96%
with Flexible Cancellation Policy	50.26%	53.08%
with Moderate Cancellation Policy	27.77%	30.88%
with Strict Cancellation Policy	21.97%	16.04%
=1 if the listing has 2+ host cancellations	7.22%	4.58%
with Flexible Cancellation Policy	35.51%	41.44%
with Moderate Cancellation Policy	26.09%	34.42%
with Strict Cancellation Policy	38.40%	24.15%

Note: The sample consists of Airbnb listing-months from 2015 to 2019.

Table 3: Price, reservations, and occupancy of Airbnb listings by host cancellation and guest cancellation policies

	Avg. Monthly Price	Avg. # of Monthly Reservation	Avg. Monthly Occupancy Rate	Avg. Monthly Cross-listing Rate
Panel A: Whole sample of Airbnb listings				
with Flexible Cancellation Policy	187.84	3.81	31.58%	6.73%
with Moderate Cancellation Policy	188.98	4.41	33.53%	9.31%
with Strict Cancellation Policy	192.69	5.11	35.65%	16.62%
Panel B: Subsample by # of host cancellation				
a property has 0 host cancellation	186.52	3.59	29.66%	5.98%
with Flexible Cancellation Policy	185.95	3.10	27.41%	3.66%
with Moderate Cancellation Policy	187.12	3.62	30.82%	4.95%
with Strict Cancellation Policy	190.38	3.95	33.12%	9.33%
a property has 1 host cancellation	191.33	5.36	36.93%	10.73%
with Flexible Cancellation Policy	189.78	4.63	36.05%	6.77%
with Moderate Cancellation Policy	192.57	5.05	37.19%	8.52%
with Strict Cancellation Policy	195.66	6.21	39.27%	16.91%
a property has more than 1 host cancellations	188.33	4.92	33.25%	15.94%
with Flexible Cancellation Policy	187.79	3.72	31.27%	9.75%
with Moderate Cancellation Policy	187.26	4.55	32.59%	14.44%
with Strict Cancellation Policy	192.05	5.15	34.55%	23.62%

Note: The sample consists of Airbnb listing-months from 2015 to 2019.

Table 4: Effects of the 48-hour rule on reservations, price and occupancy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep.Var	# of reservations	log(price)	log (occupancy)	# of reservations	log(price)	log (occupancy)	# of reservations	log(price)	log (occupancy
Sample	**Airbnb vs VRBO**			**Airbnb (Loose) vs VRBO (Loose)**			**Airbnb (Strict) vs Airbnb (Loose)**		
Lag # of cancellation review	-0.0759***	-0.0602***	-0.0438***	-0.0713***	-0.0562***	-0.0371**	-0.0826***	-0.0627***	-0.0470**
	(0.0333)	(0.0244)	(0.0103)	(0.0192)	(0.0113)	(0.0166)	(0.0203)	(0.0219)	(0.0191)
Airbnb_host	-0.0073	-0.0010	-0.0025	0.0127	0.0554	0.0080			
	(0.0059)	(0.0020)	(0.0014)	(0.0147)	(0.0628)	(0.0175)			
Airbnb_host * Post 48-hour rule	0.0551***	0.0275***	0.0192***	0.0731***	0.0392***	0.0274***			
	(0.0214)	(0.0124)	(0.0049)	(0.0172)	(0.0102)	(0.0038)			
Strict Airbnb_host							-0.0029	-0.0046	-0.0017
							(0.0019)	(0.0037)	(0.0021)
Strict Airbnb_host * Post 48-hour rule							-0.0331***	-0.0227***	-0.0195***
							(0.0122)	(0.0102)	(0.0038)
Listing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cancellation policy controls	Yes	Yes	Yes	-	-	-	-	-	-
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	953,523	953,523	953,523	504,273	504,273	504,273	1,149,040	1,149,040	1,149,040
R-square		0.625	0.522		0.541	0.385		0.541	0.385
F-test on pre-treatment (p-value)	0.36	0.21	0.27	0.18	0.33	0.25	0.19	0.12	0.15

Note: This table uses listing-month observations on Airbnb and VRBO from 2017 to 2019 in first 6 columns but uses listing-month observations on Airbnb only from 2015 to 2019 in columns 7-9. In Columns 1-3, the treatment group includes all listings on Airbnb and the control group includes all listings on VRBO. In Columns 4-6, the treatment group includes all Airbnb listings that offered a loose cancellation policy as of April 2018, and the control group includes the same type of VRBO listings. In Columns 7-9, the treatment group includes all Airbnb listings that offered a strict cancellation policy as of April 2018 and the control group includes all Airbnb listings that offered a loose cancellation policy as of April 2018. We use Poisson regression and report marginal effects if the dependent variable is the number of reservations. We use OLS and report coefficients if the dependent variable is log(price) or log(occupancy). Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels.

Table 5: Effects of host cancellation reviews on reservations, price and occupancy (with instruments)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	# of reservations	log(price)	log (occupancy)	# of reservations	log(price)	log (occupancy)
Sample	All Airbnb Listings					
Lag # of cancellation review	-0.0617***	0.0125	-0.0771***	-0.0688***	-0.0415***	-0.0477***
	(0.0236)	(0.0177)	(0.0094)	(0.0150)	(0.0144)	(0.0141)
Log(price)	-0.0502***		-0.2363***	-0.0047**		-0.2335***
	(0.0157)		(0.0471)	(0.0021)		(0.0165)
Response rate	0.0011***	-0.0004**	0.0041***	-0.0025***	-0.0003*	-0.0054**
	(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0014)
# of reviews	0.0017***	-0.0006***	0.0022***	-0.0106***	-0.0017*	-0.0015
	(0.0000)	(0.0000)	(0.0001)	(0.0027)	(0.0008)	(0.0009)
Overall rating	0.0900***	0.1222***	0.1533***	-0.0327	-0.0033	0.0627
	(0.0143)	(0.0262)	(0.0153)	(0.0228)	(0.00342)	(0.0734)
# of photos	0.0018***	0.0033***	0.0015***	-0.0071***	-0.0066**	-0.0042
	(0.0002)	(0.0006)	(0.0005)	(0.0006)	(0.0028)	(0.0034)
bedrooms	-0.0233***	0.0910***	0.0547***			
	(0.0080)	(0.0128)	(0.0048)			
bathrooms	0.0054	0.7475***	0.0564***			
	(0.0065)	(0.0155)	(0.0092)			
Max # of guests	0.0248***	0.0727***	0.0001			
	(0.0021)	(0.0040)	(0.005)			
Superhost/premier partner	0.0264***	0.0858***	0.0401***			
	(0.0075)	(0.0080)	(0.0128)			
Minimum stay	-0.119***	0.00454	0.0109*			
	(0.0111)	(0.0032)	(0.0053)			
Instant book	0.0555***	0.0146***	0.0459***			
	(0.0044)	(0.0039)	(0.0078)			
Listing FE	No	No	No	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,149,040	1,149,040	1,149,040	1,149,040	1,149,040	1,149,040
R-square		0.521	0.232		0.901	0.426

Note: This table uses listing-month observations on Airbnb from 2015 to 2019. We use Poisson regression and report marginal effects if the dependent variable is the number of reservations. We use OLS and report coefficients if the dependent variable is log(price) or log(occupancy). In all columns, we use 2SLS to predict the lag number of cancellation reviews using rainfall and extreme temperature in the lag period as instruments. In the reservation and occupancy regressions, we use the price of other listing types (i.e., private room and shared space) within 10 miles of the study listing as an instrument to predict price in the first stage. Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels.

Table 6: Effects of the 48-hour rule on reservations, price and occupancy by high and low competition index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	# of reservations	log (price)	log (occu-pancy)	# of reservations	log (price)	log (occu-pancy)	# of reservations	log (price)	log (occu-pancy)	# of reservations	log (price)	log (occu-pancy)
	Airbnb (Loose) vs VRBO (Loose)			**Airbnb (Strict) vs VRBO (Strict)**			**Airbnb (Loose) vs VRBO (Loose)**			**Airbnb (Strict) vs VRBO (Strict)**		
Lag # of cancellation review	-0.0829***	-0.0782***	-0.0531**	-0.0805***	-0.0721***	-0.0502**	-0.0392***	-0.0343***	-0.0280***	-0.0617***	-0.0505**	-0.0469**
	(0.0263)	(0.0264)	(0.0206)	(0.0285)	(0.0167)	(0.0172)	(0.0082)	(0.0060)	(0.0091)	(0.0172)	(0.0211)	(0.0127)
Airbnb_host	-0.0057	-0.0255	-0.0108	-0.0109	-0.0194	-0.0221	-0.0185	-0.012	0.00397	-0.0189	0.0210	0.0534
	(0.0941)	(0.0202)	(0.0111)	(0.0301)	(0.0395)	(0.0285)	(0.0317)	(0.0103)	(0.0178)	(0.0179)	(0.0158)	(0.0343)
Airbnb_host*Post 48-hour rule	0.0633***	0.0319***	0.0225***	0.0179***	0.0082***	0.0068**	0.0708***	0.0524***	0.0453***	0.0388***	0.0277***	0.0263***
	(0.0252)	(0.0095)	(0.0039)	(0.0029)	(0.0027)	(0.0031)	(0.0195)	(0.0273)	(0.0204)	(0.0117)	(0.0114)	(0.0108)
Competition Level	High	High	High	High	High	High	Low	Low	Low	Low	Low	Low
Listing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	396,924	396,924	396,924	224,085	224,085	224,085	186,855	186,855	186,855	152,039	152,039	152,039
R-square		0.755	0.430		0.541	0.385		0.894	0.901		0.426	0.428

Note: This table uses listing-month observations on Airbnb and VRBO from 2017 to 2019. We use Poisson regression and report marginal effects if the dependent variable is the number of reservations. We use OLS and report coefficients if the dependent variable is log(price) or log(occupancy). In Columns 1,2,3,7,8,9, 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 listings on VRBO. In Columns 4,5,6,10,11,12, the treatment group includes Airbnb listings that offered a strict cancellation policy as of April 2018, while the control group includes the same type of listings on VRBO. The first six columns focus on listings that had above-city-median competition index as of April 2018. The last six columns focus on listings that had below-city-median competition index as of April 2018. Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels.

Table 7: Effects of the 48-hour rule on reservations, price and occupancy by high and low competition index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	# of reservations		# of reservations		log(price)		log(price)		log (occupancy)		log (occupancy)	
	Loose Listing		**Strict Listing**		**Loose Listing**		**Strict Listing**		**Loose Listing**		**Strict Listing**	
Lag # of cancellation review	-0.0771***	-0.0582***	-0.0508**	-0.0621***	-0.0729***	-0.0433***	-0.0347***	-0.0559***	-0.0572***	-0.0517***	-0.0421**	-0.0465**
	(0.0263)	(0.0264)	(0.0206)	(0.0247)	(0.0230)	(0.0125)	(0.0132)	(0.0176)	(0.0177)	(0.0162)	(0.0208)	(0.0227)
Competition Level	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Listing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	567,524	309,088	187,172	85,256	567,524	309,088	187,172	85,256	567,524	309,088	187,172	85,256
R-square		0.771	0.478		0.571	0.420		0.854	0.887		0.445	0.457

Note: This table uses listing-month observations on Airbnb from 2015 to 2019. We use Poisson regression and report marginal effects if the dependent variable is the number of reservations. We use OLS and report coefficients if the dependent variable is log(price) or log(occupancy). Columns 1,2,5.6,9,10 focus on Airbnb listings that offered a loose cancellation policy as of April 2018; Columns 3,4,7,8,11,12 focus on Airbnb listings that offered a strict cancellation policy as of April 2018. The odd number columns focus on listings that had above-city-median competition index as of April 2018. The even number columns focus on listings that had below-city-median competition index as of April 2018. In all columns, we use 2SLS to predict the lag number of cancellation reviews using rainfall and extreme temperature in the lag period as instruments. In the reservation and occupancy regressions, we use the price of other listing types (i.e. private room and shared space) within 10 miles of the study listing as an instrument to predict price in the first stage. Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels.

Table 8: Effects of the 48-hour rule on supply dynamics in Airbnb

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	# of listings	# of listings	Cross-listing?	Strict policy?	Cross-listing?	Exit?
Sample	**Airbnb vs VRBO**	**Cross-listing vs VRBO**	**Airbnb vs VRBO**	**Airbnb vs VRBO**	**Airbnb**	**Airbnb**
Airbnb_host	0.0208	0.0267	-0.0128*	-0.0258		
	(0.0632)	(0.311)	(0.0068)	(0.0712)		
Airbnb_host * Post 48-hour rule	-0.0279***	0.0028***	0.0481***	-0.0921***		
	(0.0048)	(0.0011)	(0.0027)	(0.0374)		
High_competition_area * Post 48-hour rule	0.0031	0.0037**	0.0129**	-0.0241		
	(0.0412)	(0.0018)	(0.0059)	(0.0412)		
High_competition_area *Airbnb * Post 48-hour rule	0.0072	0.0072***	0.0618***	-0.1328***		
	(0.0312)	(0.0020)	(0.0282)	(0.0528)		
Strict_host					0.2102***	-0.0782***
					(0.0481)	(0.0245)
Host_cancellation					0.0821***	0.0051**
					(0.0205)	(0.0024)
High_competition_area					0.0755***	-0.0509***
					(0.0192)	(0.0204)
Host_cancellation * High_competition_area						0.0072
						(0.0512)
Strict_host * Host_cancellation						-0.0744***
						(0.0310)
Strict_host * Host_cancellation * High_competition_area						-0.1021***
						(0.0392)
Zipcode controls	Yes	Yes	-	-	-	-
Listing controls	-	-	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,750	1,750	953,523	953,523	1,149,040	1,149,040
R-square			0.522		0.541	0.385

Note: Columns 1-2 use aggregated data of Airbnb and VRBO from 2017 to 2019. The dependent variable is the total number of listings (Column 1) or the number of cross-listings (Column 2) per zipcode-month on each platform. Columns 3-4 use listing-month observations on Airbnb and VRBO from 2017 to 2019 while columns 5-6 use listing-month observations on Airbnb from 2015 to 2019. The dependent variable is whether the listing is also cross-listed on the other platform at the study period (Columns 3 and 5), whether the host offers strict cancellation policy at the study period (Column 4), and whether the listing was inactive for at least 6 months after May 2018 (column 6). For Columns 1-4, the treatment and control groups are listed in the sample row with the first part indicating the treatment group. On the right-hand side, Strict_host represents a dummy equal to one if the listing offered a strict cancellation policy in April 2018; and High_competition_area represents a dummy equal to one if the listing had above-city-median competition index as of April 2018. We use Poisson regression and report marginal effectse if the dependent variable is the number of listings (Columns 1-2). We use Probit regression and report coefficients if the dependent variable is a dummy (Columns 3-6). Standard errors are clustered by zip code. ***, ** and * indicate significance at 1%, 5% and 10% levels.

Table 9: Effects of the 48-hour rule on the supply dynamics of Airbnb hosts

	(1)	(2)	(3)	(4)	(5)
Dep. Var	Cross-listing?	Cross-listing?	Cross-listing?	Host cancel?	Host cancel?
Sample	**Airbnb Flexible**	**Airbnb Moderate**	**Airbnb Strict**	**Airbnb (Strict vs Loose) – High Competition Area**	**Airbnb (Strict vs Loose) – Low Competition Area**
High_competition_area * Post 48-hour rule	0.0414**	0.0391***	-0.0108***		
	(0.0202)	(0.0141)	(0.0023)		
Cross_listing * Strict host				0.0521***	0.0108
				(0.0118)	(0.412)
Cross_listing * Pos 48-hour rule				0.0201	0.0014
				(0.0311)	(0.121)
Cross_listing * Strict host * Post 48-hour rule				0.0657***	0.0149*
				(0.0312)	(0.0082)
Listing controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes
Observations	451,991	399,838	307,122	633,284	515,756

Note: This table uses listing-month observations on Airbnb from 2015 to 2019. The dependent variable is whether the Airbnb listing is cross-listed on VRBO at the study period (Columns 1-3), and whether the Airbnb listing has received automated cancellation review at the study period (Columns 4-5). All regressions are Probit and report coefficients. On the right-hand side, Strict_host represents a dummy equal to one if the listing offered a strict cancellation policy in April 2018; High_competition_area represents a dummy equal to one if the listing had above-city-median competition index as of April 2018. and Cross_listing 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% levels.

Table 10: Back-of-envelope calculation for Airbnb GMV after the 48-hour rule

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 Host Cancellation	Gain/Loss ($ MM) from Host Cancellation	Net Benefit/Loss ($ MM) after 48-hour rule
D.C.	0.08	54,599	1,637	-157	137.21	10.89	14.36	0.866	18.34	(0.07)	18.27
Boston	0.09	125,213	1,903	-142	173.25	9.30	10.08	1.198	42.63	(0.06)	42.57
Chicago	0.11	134,677	1,421	-74	157.89	9.90	9.76	1.075	39.76	(0.07)	39.70
Austin	0.12	120,845	1,339	-247	139.55	9.00	6.37	1.031	26.71	(0.05)	26.65
Seattle	0.12	49,503	1,017	-283	151.22	11.10	8.16	0.911	13.08	(0.05)	13.03
Los Angeles	0.14	140,501	-1,021	-1,173	188.53	9.45	9.59	0.675	27.12	(0.05)	27.07
Houston	0.15	59,695	-1,345	-272	143.25	7.80	8.33	0.932	10.17	(0.06)	10.12
Atlanta	0.16	83,718	-475	-338	138.25	8.70	4.39	0.772	11.32	(0.04)	11.28
New York	0.21	276,634	-2,633	-2,203	190.56	11.34	5.33	0.433	29.03	(0.09)	28.94
New Orleans	0.25	113,566	-1,655	-1,537	160.78	10.05	2.86	0.417	5.55	(0.06)	5.48

Table 11: Back-of-envelope calculation on the effects of the 48-hour rule on strict hosts relative to loose hosts on Airbnb

City	Compe-tition Index	Total Listing with strict cancellation policy before 48-hour rule	Total Listings with strict cancellation policy 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 Host Cancellation	Gain/Loss ($ MM) from Host Cancellation	Net Benefit/Loss ($ MM) after 48-hour rule
D.C.	0.08	19,335	16,558	139.23	13.04	13.61	0.7	(0.33)	(0.20)	(0.53)
Boston	0.09	33,665	29,365	180.77	12.12	7.74	1.07	(0.74)	(0.18)	(0.93)
Chicago	0.11	37,246	34,277	163.91	10.28	5.48	1.02	2.85	(0.19)	2.66
Austin	0.12	30,519	28,065	146.56	12.36	4.9	0.88	0.99	(0.15)	0.85
Seattle	0.12	6,681	6,335	154.91	12.51	5.21	0.87	0.62	(0.13)	0.49
Los Angeles	0.14	25,381	23,025	191.52	8.82	8.16	0.45	(0.25)	(0.04)	(0.30)
Houston	0.15	15,537	14,682	143.30	6.28	7.41	0.73	1.53	(0.06)	1.47
Atlanta	0.16	25,363	24,995	142.86	7.56	2.63	0.49	1.88	(0.04)	1.84
New York	0.21	67,450	66,751	191.33	9.92	3.74	0.17	3.36	(0.09)	3.27
New Orleans	0.25	43,765	43,261	165.01	9.25	1.44	0.09	0.46	(0.07)	0.39

Note: Strict (loose) hosts refer to the Airbnb hosts that offered strict (loose) cancellation policy before the 48-hour rule, regardless of their cancellation policy post the rule