NBER WORKING PAPER SERIES

SAFETY REVIEWS ON AIRBNB: AN INFORMATION TALE

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Working Paper 31855
http://www.nber.org/papers/w31855

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2023, Revised January 2024

We are grateful to AirDNA for providing the data and to our home universities for financial support. Marshall Van Alstyne, Matthias Hunold, Xiang Hui, Meng Liu, Peter Coles, Francine Lafontaine, Ying Fan, Juan Pablo Atal, Juan Camilo Castillo, Sophie Calder-Wang, Yufeng Huang, Zhe Yuan, Jisu Cao, and participants at the Luohan Academy Webinar, Washington University at St. Louis, Boston University, University of Michigan, University of Pennsylvania, the 2022 MaCCI annual conference, the 2022 IIOC annual conference, the 2022 INFORMS Marketing Science and virtual conference, and the 2023 Strategy and Economics of Digital Markets conference have provided constructive comments. Tejas Nazare, Nour Ben Ltaifa, and Hunter Petrik provided excellent research assistance. The content and analyses in this paper reflect the authors' own work and do not relate to any institution or organization with whom the authors are affiliated. None of us has a financial relationship with Airbnb or competing short term rental platforms. All rights reserved. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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JEL No. D83,L15,R3

ABSTRACT

Consumer reviews, especially those expressing concerns of product quality, are crucial for the credibility of online platforms. However, reviews that criticize a product or service may also dissuade buyers from using the platform, creating an incentive to blur the visibility of critical reviews. Using Airbnb and official crime data in five major US cities, we find that both reviews and self experiences concerning the safety of a listing's vicinity decrease guest bookings on the platform. Counterfactual simulations suggest that a complete removal of vicinity safety reviews (VSR) would hurt guests but increase revenues from reservations on Airbnb, with positive sorting towards listings formerly with VSR. Conversely, incorporating VSR in a listing's overall ratings or highlighting VSR could generate opposite effects. Either way, the interests of consumers are not always aligned with the interests of a revenue-centric platform. Because VSR are more closely correlated with official crime statistics in low-income and minority neighborhoods, our findings suggest that suppressing or highlighting VSR would have different effects on different neighborhoods.

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1 Introduction

Information design is crucial for online platforms. Take consumer feedback as an example: not only does it allow future buyers to discern high- and low-quality sellers, it also encourages good sellers to maintain high quality and motivates poor-performing sellers to improve quality. Arguably, reputation mechanism is even more effective online than offline, because online platforms can gather consumer feedback in a standardized format, make it available globally, and aggregate it in a way that is salient and easy to digest and search, if they so choose (see reviews by Einav et al., 2016; Tadelis, 2016; Luca, 2017).[1]

Critical consumer feedback (i.e., reviews criticizing a product or service) is particularly important for online reputation systems, whether it is a simple choice of positive/neutral/negative, a star rating, or detailed reviews with free-flowing text, photos, or even videos. It is likely that an e-commerce website that continuously lists all products or services as rated five stars or with 100% positive feedback would quickly lose credibility. Indeed, the literature has shown that consumers respond significantly to critical feedback, although consumers tend to under-report critical feedback. Many platforms try to encourage consumer feedback—including critical feedback—by offering status, coupons, and merchandise discounts. Some platforms also encourage sellers to respond to consumer reviews.

However, platforms face mixed incentives regarding critical consumer feedback. On the one hand, future buyers may compare listings on the focal platform and prefer those with no or less critical feedback. Such within-platform sorting may benefit the platform, as high-quality sellers often charge a higher price or enjoy a higher probability of selling. On the other hand, buyers always have an outside good in mind; observing many listings with critical feedback on a platform may dissuade buyers from using the platform at all. The danger of losing a potential buyer could motivate a platform to blur the visibility of critical consumer feedback, by keeping it private to the platform, deleting it after a short time of posting, or making it difficult to find despite public posting.

More specifically, critical consumer feedback may generate three information externalities on a digital platform: first, buyer A's critical feedback on product listing X may deter herself and other buyers from buying X in the future. This "within-listing-across-buyer" effect is typical in a reputation system and is well-studied. Second, critical feedback regarding X may lead other buyers to infer that listings similar to X may have similar quality concerns even if they have not themselves received such feedback. This is a "cross-listing-cross-buyer" effect. Third, a poor experience with listing X may motivate buyer A to give critical feedback to X and reassess other buyers' critical feedback towards other listings or even the whole feedback system. This "cross-listing-within-buyer" effect is often omitted because Bayesian updating assumes that learning from others' experience is the same as learning from self experience if the information has the same accuracy. However, in practice, self-experience can be much more salient to an

[1]Recent examples include YouTube, which has adopted a policy of hiding dislike counts on shared videos (see, e.g., `https://rb.gy/xhhqnd`), and Instagram, which has given users the option of hiding likes (see, e.g., `https://rb.gy/tacuj5`).

individual. Few researchers have quantified the second and third externalities explicitly; one exception is Nosko and Tadelis (2015), who show that buyers that have bought from a more reputable seller on eBay are more likely to return to the platform to transact with *any* sellers, above and beyond the likelihood to transact with the same seller that created that good experience.

In this paper, we use user reviews about vicinity safety of short-term rentals to demonstrate the importance of these information externalities. Safety around a listing's vicinity is an important dimension of quality given the listing's physical location. The host of a listing cannot do much to change its vicinity safety but prior guests may comment on it in their reviews. Such reviews may inform other guests of the vicinity safety risk for nearby listings, which is a built-in cross-listing externality. Consumer reviews regarding vicinity safety are often of a critical tone because guests that have *chosen* to stay at a dwelling owned or managed by an anonymous host usually assume the neighborhood is reasonably safe. At the same time, almost no hosts would volunteer to discuss neighborhood safety in their listing descriptions, because any mention (even the phrase of "perfectly safe") may call guest attention to safety concerns.

Using all Airbnb listings and their reviews in five major US cities (Atlanta, Chicago, Los Angeles, New Orleans, and New York City) from 2015/5 to 2019/12, we use a Lexicon approach to identify safety reviews posted by Airbnb guests. We find that 0.51% of the 4.8 million guest reviews express concerns of safety, among which 48.08% are about safety issues near but outside the focal property (referred to as vicinity safety reviews, or VSR) rather than safety issues inside the property (referred to as listing safety reviews, or LSR). Further sentiment analysis suggests that VSR and LSR identified by our algorithm are significantly more negative in sentiments than an average review. Although VSR and LSR only account for a tiny fraction of guest reviews, 4.43% of listing-months ever have any VSR since May 2015, and 8.49% of listing-months ever have any VSR or LSR. These facts imply that safety concerns are noticed by guests, regardless of whether they relate to the actual dwelling or its nearby surroundings. At the same time, the low occurrence of VSR and LSR makes learning through self-experience a lengthy process. Thus, guests with safety concerns mostly rely on the platform's online review system and/or external information.

Since guest feedback may reflect guests' subjective opinion of their stay experience, we obtain (local) government-reported crime statistics for the five sample cities, by zip code and month. The data suggest that, as VSR accumulate slowly on Airbnb, the rank correlation between the normalized total count of VSR in a zip code up to a month t and the normalized official crime statistics of that zip code-month is increasing over time. For low-income or minority zip codes, the rank correlation can be as high as 0.75 by the end of our sample period (2019/12). This suggests that the VSR, though noisy and subjective, do reflect real safety risks in the related zip codes to some degree.

As expected, when we follow the same listings before and after they receive any VSR or LSR, there is a significant drop in the listing's monthly occupancy rate as well as its average paid price per night. The effect is stronger for LSR (-2.58% in occupancy and -1.52% in price) than VSR (-1.82% in occupancy and -1.48% in price), but all are statistically significant with 99% confidence. These findings suggest that prospective guests are concerned about both listing and vicinity safety, and have different sensitivities to changes in these two types of safety reviews. In addition to this classical "within-listing-cross-buyer" effect in listing reputation, we also find a significant negative effect from VSR of nearby listings, where nearby listings are defined as those within 0.3 mile radius of the focal listing according to Airbnb's proxy longitude and latitude of each listing. This "cross-listing-cross-buyer" effect corresponds to the second information externality as mentioned above.

To document the third externality, we zoom into the guests that wrote VSR on Airbnb (referred to as VS guests). Compared to the guests that have used Airbnb with similar frequencies and booked similar listings (in terms of crime and VSR) but never write any VSR in our dataset, VS guests are 60.07% less likely to book future stays on Airbnb after posting the VSR. And when they do book on Airbnb, they tend to book in areas with fewer official crimes, fewer overall VSR, and a lower percentage of listings with any VSR. The learning is weaker if the focal listing that triggered the VS guest's VSR had previously received any VSR from other guests, but even in this case, the VS guests are still 51.62% less likely to book future stays on Airbnb after posting their own VSR. This suggests that self experience is much more salient than reading other guests' VSR; thus, the online review system is not fully effective as far as conveying all the information embedded in VSR.

Platform wide, we argue that these information externalities —especially VSR spillovers to nearby listings (the second externality) and VS guests' strong reactions to their own vicinity safety experiences (the third externality)—may undermine a platform's incentives to post and highlight VSR as critical feedback. Interestingly, in a recent policy change effective December 11, 2019, Airbnb announced that, going forward, guest reviews about listings that include "content that refers to circumstances entirely outside of another's control" may be removed by the platform.[2] This policy change, if strictly enforced, could imply that VSR are discouraged and may be subject to deletion by the platform while LSR are still permitted. To be clear, we find no evidence suggesting that Airbnb has omitted or deleted VSR in any systematic way after the 2019/12 policy. But the announcement itself suggests that Airbnb has broad discretion regarding the collection, posting, or removal of consumer reviews, especially those that include contents that the platform believes to be irrelevant or useless. Our analysis of VSR aims to shed light on the potential economic incentives behind a platform's review policy.

To do so, we must incorporate listing competition because within- and cross-platform sortings have different implications for the platform. To account for listing competition, we obtain a dataset of competing entire-home VRBO listings and use a discrete choice model to estimate consumer utility from Airbnb entire-home listings, while treating VRBO listings in the same zip code-month as the outside good. We then use the structural estimates to quantify consumer surplus under the status quo of our sample (i.e., VSR are largely permitted) versus three counterfactual information regimes: eliminating all VSR ("no

[2] See, e.g., `https://rb.gy/0pu5ck` and `https://rb.gy/9y6bum` .

disclosure"), adjusting the rating of each listing to account for the number of VSR of the listing itself and nearby listings ("VSR-adjusted ratings"), or alerting all guests to the existing VSR and making them as informed as those that have written VSR themselves ("high alert").

Compared to the status quo, we find that no disclosure of VSR would decrease consumer surplus in the market by 0.032% and increase revenues from reservations on Airbnb by 0.041%, with positive sorting towards listings formerly with VSR. Conversely, VSR-adjusted ratings would increase the market consumer surplus by 0.004% but decrease Airbnb's GBV by 0.142%. High alert would increase the market consumer surplus by 3.065% to 4.144% and change Airbnb's GBV by +0.301% (+$10.1 millions) to -1.304% (-$44 millions), depending on whether we allow listing price to change by 1% in response and whether we assume the high alert on vicinity safety also applies to the VSR for nearby listings. In short, the interests of consumers and Airbnb are not always aligned, because guest sorting from Airbnb to off-Airbnb alternatives would hurt Airbnb's GBV with certainty but the within-Airbnb sorting between listings with and without VSR may increase or decrease Airbnb's GBV depending on how sensitive guests are to pricing and perceived vicinity safety of listings.

Although the overall welfare effects are moderate (because VSR is rare in the data), they mask large distributional effects: more VSR transparency benefits the listings without VSR at the cost of the listings with VSR. Because listings with VSR are more likely to locate in low-income or minority neighborhoods, consumer sorting upon VSR transparency would generate sizable GBV shifts across hosts in different neighborhoods. These effects highlight a tradeoff as far as generating higher revenues and attracting hosts in low-income and minority areas on the one hand, which can enhance the economic impact of the platform in underserved neighborhoods, and providing additional value to guests on the other.

As detailed below, we contribute to the empirical literature of online feedback and seller reputation, and the rising literature of information design in online platforms. As an information intermediary, online platforms have more incentives than a traditional seller to alleviate information asymmetries between buyers and sellers. But they are still inherently different from a social planner, because they may put more weight on their own business interests than on the welfare of buyers and sellers on the platform, and they may not fully internalize the impact of their policies on competing platforms. Our empirical findings highlight these differences. We also document how the impact of a platform's review policy may vary for neighborhoods of different incomes or with different minority representation, as being inclusive could be important for the platform or the social planner. These findings can help facilitate ongoing discussions as to what role and responsibility digital platforms should have as far as collecting and disseminating quality-related information online.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 provides background regarding Airbnb's review system. Section 4 describes the dataset, defines VSR and LSR, and provides summary statistics. Section 5 reports reduced-form evidence for the three information externalities of safety reviews. Section 6 incorporates all of these externalities into a structural demand model and predicts how listings' GBV and consumer surplus would change under three counterfactual scenarios. Section 7 discusses the implications of our findings and future research directions.

2 Related Literature

Safety review is a type of buyer-to-seller feedback; thus, our study is directly related to the literature on online feedback and seller reputation.

The efficacy of online reputation depends on how consumers respond to buyer feedback posted on the platform. Researchers have shown that consumers are more likely to purchase from sellers with better buyer feedback and, conditional on purchase, are willing to pay more to reputable sellers (see reviews by Bajari and Hortacsu, 2004; Tadelis, 2016; Einav et al., 2016). Consistently, we find that having any safety reviews associated with a listing tends to negatively impact the occupancy and price of the listing because safety reviews dampen the listing's reputation on Airbnb. The magnitude of this effect on the occupancy rate is comparable to a 70.18% reduction in the listing's average guest ratings, confirming the finding in Chakravarty et al. (2010) that consumers are more responsive to critical feedback than to positive feedback.

Beyond the classical within-listing-across-buyer effect, we are one of the few that attempt to quantify the spillover effects of critical feedback. By definition, vicinity safety reviews may generate spillovers among listings in nearby geographies, should guests infer the overall safety of the vicinity from multiple nearby listings. We find that for a focal listing, a higher percentage of other nearby listings with VSR is negatively associated with the focal listing's occupancy rate, as well as its price. This cross-listing-cross-buyer spillover has different implications for hosts and guests: hosts without VSR may suffer from the negative externality of nearby listings with VSR; but from a prospective guest's perspective, this is a positive information externality that could help them make more informed choices ex ante. Hence, the information design optimal to the hosts or the platform can be different from that optimal to guests, a key point we examine in the counterfactual analysis.

While the cross-listing-cross-buyer spillover is specific to the nature of vicinity safety, we argue the cross-listing-within-buyer spillover of critical feedback is more generalizable to other online platforms. As shown by Nosko and Tadelis (2015), buyers that have had a good experience from a reputable seller on eBay are more likely to return to eBay for sales with *any* sellers. Similarly, we show that having a negative vicinity safety experience tends to motivate a guest to avoid booking *any* listings on Airbnb in our sample cities and, if she books again at all, to avoid both the listings and the areas that have any VSR. Compared to Nosko and Tadelis (2015), we show that the cross-listing-within-buyer spillover is not only limited to the extensive margin (whether to return to the platform for future transactions); but it also motivates the experienced buyer to adjust how she interprets the presence of VSR in other listings. Using a structural approach, we take a deep dive into the implications of these spillover effects for the welfare of guests, the revenue of hosts and the platform, and the distributional changes across different types of neighborhoods.

Most of the aforementioned literature of seller reputation is conditional on buyer feedback that online platforms aggregate and present to consumers. However, buyer feedback is under-provided partly because reviewers are not compensated for submitting reviews. For example, 64% of eBay transactions are rated by buyers in the sample studied by Hui et al. (2021), and 73.5% of New York City UberX trips are rated by passengers (Liu et al., 2021). In comparison, 44.6% of Airbnb trips in our sample have received feedback from guests, which is in line with the guest review rate reported by Fradkin et al. (2021) based on earlier Airbnb data in 2014.

Since accurate feedback is a public good subject to under-provision, many platforms attempt to encourage buyer feedback by offering status, coupons, and merchandise discounts (Li and Xiao, 2014; Cabral and Li, 2015; Li et al., 2020; Fradkin et al., 2015; Fradkin and Holtz, 2023). Some even encourage sellers to respond to consumer reviews. Proserpio and Zervas (2017) find that hotels responding to user online reviews enjoy 0.12-star increase in ratings and a 12% increase in review volume. When hotels start responding, they tend to receive fewer but longer negative reviews because unsatisfied consumers become less likely to leave short indefensible reviews when hotels are likely to scrutinize them. Similarly, Chevalier et al. (2018) find that managerial responses stimulate consumers' reviewing activity, especially the negative reviews that are seen as more impactful. This effect is reinforced by the fact that managers respond more frequently and in more detail to negative reviews. These findings suggest that allowing managerial response can be viewed as a platform policy that effectively highlights and addresses critical feedback. In contrast, the 2019 Airbnb policy that motivates this study, if fully implemented, could discourage buyers from providing critical feedback on certain quality dimensions such as vicinity safety, and thus exacerbate the public good problem of critical feedback.

The imperfect review rate is particularly problematic as far as critical feedback is concerned. Studies have shown that buyers tend to under-report bad experiences, with potential explanations that include fear of retaliation (Dellarocas and Wood, 2008), preference to leave the platform after a bad experience (Nosko and Tadelis, 2015), pressure to provide above-average ratings (Barach et al., 2020), and social connections to the rated sellers (Fradkin et al., 2015). For arguably rare, bad experiences such as safety, the probability of observing pertinent feedback from prior buyers could be further reduced, simply because the chance of experiencing a safety issue is small in absolute terms, even if a neighborhood has safety risks. A platform policy that discourages VSR could reinforce an existing bias against critical feedback.

Another consequence of the bias against critical feedback is that safety reviews on any Airbnb listing accumulate slowly over time. This could affect the overall informativeness of safety reviews. As shown below, between 2015 and 2019, we observe a growing rank correlation between a zip code's normalized cumulative VSR count and the zip code's normalized official crime statistics in low income and minority areas. This suggests that cumulative VSR do contain useful information regarding a zip code's actual safety status, with informativeness that may increase over time. The rare occurrence of VSR further highlights the importance of cross-listing-cross-buyer and cross-listing-within-buyer spillovers, because they magnify the impact of the rare experiences and thus make the gradual accumulation of VSR more informative. In comparison, a few studies argue that online feedback systems may become less informative over time because of the aforementioned feedback bias reasons (Barach et al., 2020; Klein et al., 2009; Hui et al., 2021). Most of these studies infer feedback informativeness from the content of feedback or policy variations within the feedback system. Our approach is different, as we compare online feedback with a completely independent data source.

More broadly, our study contributes to the growing literature of information design in online platforms. Because feedback is under-provided and there is a selection against critical feedback, researchers have studied the design of feedback systems in terms of who is allowed to provide feedback (Klein et al., 2016; Mayzlin et al., 2014; Zervas et al., 2021), how to improve the authenticity of feedback (Wagman and Conitzer, 2008; Conitzer et al., 2010; Conitzer and Wagman, 2014), when the feedback is revealed to the public (Bolton et al., 2013; Fradkin et al., 2021), what kind of feedback is shown to the public, and how to aggregate historical feedback (Staats et al., 2017; Dai et al., 2018).

Interestingly, some platforms highlight critical consumer feedback, so that future consumers are aware of potential risks associated with the target seller or target product. An economic reason to do so is that many consumers on online platforms tend to be more responsive to critical feedback than to positive feedback (Chakravarty et al., 2010). Highlighting such feedback may hurt the sellers with critical feedback but divert buyers towards other sellers on the same platform with zero or not as much critical feedback. If this sorting effect generates more revenue for the platform or reinforces the platform's reputation as far as honesty and transparency, the platform would have an incentive to highlight critical feedback.

In our setting, we offer a counterexample where a platform's review policy has the potential to discourage buyers from providing a specific type of critical feedback. The discouragement can occur when a platform hides, obfuscates, or deletes critical feedback. To be clear, there are legitimate reasons to do so in some situations: for example, a platform may find certain feedback fake, abusive, or misleading ex post; omitting such feedback could make the information system more authentic and informative for both buyers and sellers (Luca and Zervas, 2016; Chevalier and Mayzlin, 2006).

At the same time, theories have shown that platforms may be strategically motivated to omit certain information, including critical feedback. For instance, Kovbasyuk and Spagnolo (2018) explain why sometimes platforms seek to erase some historical bad records of sellers, in order to increase matching rates. Romanyuk and Smolin (2019) show that platforms such as Uber may seek to hide some buyer information (say, destination) prior to completing a buyer-seller match, because doing so would avoid sellers waiting for a specific type of next buyer which would reduce the overall matching rate on the platform. These two papers differ in the direction of information withholding: the former withholds seller-relevant information from future buyers, while the latter withholds buyer-relevant information from future sellers. Both suggest that the party from whom the information is kept hidden may be worse off and the platform has an incentive to trade off their welfare loss against the welfare gain of the other side of the platform and the platform's overall matching rate.

As shown in our counterfactual analysis, the platform may have economic incentives to downplay vicinity safety reviews, because the more guests are alerted about vicinity safety, the lower the matching rate for the whole platform. In theory, such incentives could be dominated by a sorting effect, if posting or highlighting VSR could direct buyers towards safer listings on the same platform and motivate the safer listings to increase their prices sufficiently high to compensate for the platform's loss from a lower matching rate. Our counterfactual analysis suggests that this is not the case.

Finally, we are not the first to study safety issues regarding online short-term rental platforms. Suess et al. (2020) find that non-hosting residents with a higher emotional solidarity with Airbnb visitors are more supportive of Airbnb hosts, and residents hold different views about safety ("stranger danger") and Airbnb depending on whether they have children in the household. Local planners pay attention to the impact of online short-term rentals on neighborhood noise, congestion, safety, and local housing markets (Gurran and Phibbs, 2017; Nieuwland and Van Melik, 2020; Kim et al., 2017). Zhang et al. (2021) shows that regulations that negatively affect Uber/Lyft services may also negatively affect the demand for Airbnb. Han and Wang (2019) document a positive association between commercial house-sharing and the rise of crime rate in a city, while non-commercial house-sharing does not have this association. A number of studies find that an increase in Airbnb listings — but not reviews — relates to more neighborhood crimes in later years (Xu et al., 2019; Maldonado-Guzmán, 2020; Roth, 2021; Han et al., 2020; Filieri et al., 2021). More specifically, Airbnb clusters are found to correlate positively with property crimes such as robbery and motor vehicle theft, but negatively with violent crimes such as murder and rape. Also, Airbnb listings of the type in which guests may share a room with other unrelated guests are found to be more related to crimes (Xu et al., 2019; Maldonado-Guzmán, 2020) and to skirting local regulations (Jia and Wagman, 2020).

Our study complements this growing literature, by highlighting safety reviews, distinguishing vicinity and listing safety reviews, and documenting consumer responses to safety reviews or experiencing safety issues. Although we cannot identify the effect of Airbnb on local crime rates, our work helps quantify guest preferences regarding safety, and clarify how the interests of guests, different hosts and the platform diverge with respect to the disclosure of VSR. As shown in our counterfactuals, disclosing and highlighting VSR could encourage guests to shy away from potentially unsafe listings and disproportionately affect hosts in certain areas.

3 Background of Airbnb's Review System

Over the past decade, short-term vacation rental markets have quickly expanded worldwide. Airbnb, the leading home-sharing marketplace, now offers 6.6 million active listings from over 4 million hosts in more than 220 countries and regions.[3] As with any lodging accommodation, the specific location of a listing can affect the experience of its guests. For instance, if a property is located in a relatively unsafe area, crimes such as carjacking or burglary may be more likely. In Los Angeles, the number of victims to crimes such as theft or burglary at short-term rental lodgings reportedly increased by 555% in 2017-2019.[4] As is common in the lodging industry, guests, who may be traveling outside their home towns and are therefore less familiar with local neighborhoods, are responsible for their own safety in the areas in which they choose to stay. In particular, as with hotels, guests receive little to no protection from rental platforms as far as crimes they may experience in a listing's vicinity.[5]

However, prior to making a reservation, potential guests may refer to a number of sources to gauge the safety of a listing's area — these sources include local news, crime maps, websites that summarize neighborhoods[6], and perhaps most readily linked to each listing, the listing's reviews from prior guests.[7] Airbnb enables guests and hosts to blindly review each other after a guest's stay.[8] In an effort to appease hosts, and perhaps to encourage more listings across a larger number and variety of neighborhoods, a recent Airbnb policy effective December 11, 2019 announced that, going forward, guest reviews about a listing that include "content that refers to circumstances entirely outside of another's control" may be irrelevant and subject to removal.[9] This policy change implies that reviews about the safety of a listing's vicinity ("vicinity safety reviews" or VSR) may be deemed irrelevant and subject to removal, since such a safety aspect is outside the control of the host. As detailed below, we compare the frequency of VSR (as observed on Airbnb) from mid 2015 to the end of 2020 but find no evidence indicating that Airbnb has enforced this policy post 2019/12 as far as vicinity safety is concerned. However, anecdotes suggest that some reviews that touched on neighborhood safety have been removed.[10] The policy does not apply

[3]See Airbnb's official statistics as of December 31, 2022 available at `https://news.airbnb.com/about-us/#:~:text=Airbnb%20was%20born%20in%202007,every%20country%20across%20the%20globe.`

[4]See, e.g., `https://rb.gy/1eohbw` .

[5]See, e.g., `https://rb.gy/nwetrv` and `https://rb.gy/wrqvy4` .

[6]See, e.g., `https://www.neighborhoodscout.com/`.

[7]Reviews have been well established as having a potential effect on buyer decisions and sellers' reputations, particularly in the tourism industry (Schuckert et al., 2015). The literature also suggests that critical information in reviews in particular can have an effect on guest decisions and be useful to platforms in distinguishing seller and product quality (Jia et al., 2021).

[8]If one side does not review the other, the other's review becomes visible after 14 days.

[9]See, for example, `https://rb.gy/0pu5ck` and `https://rb.gy/9y6bum` .

[10]For example, on Jan. 27, 2020, a tweet from "PatrickR0820" wrote "I used @Airbnb when we went to Atlanta for the Panthers game. In my review I left numerous things that could be fixed as well as 'the area that it is located in, is pretty sketchy.' My review and 4 other similar recent reviews were deleted because it wasn't relevant." Another tweet by "AveryBrii" on May 18, 2021 stated: "@Airbnb is such a joke!!! we literally had a car stolen at the place we stayed at, didn't get refunded (which wahtever) & then i try to leave a review to inform others that it clearly was not a safe area (cops told us this & other info that i tried to include) & they didn't post." A journalist also describes his experience on Bloomberg Opinion: "Airbnb Took Down My Negative Review. Why?" (May 26, 2021 by Timothy L. O'Brien), accessed at `https://rb.gy/dxfkxw` , on November 26, 2021.

to "listing safety reviews" (LSR), because these reviews are about the safety within the listed property, which presumably can be more readily controlled and improved by the listing's host.

It is difficult to pin down exactly why Airbnb adopted this new review policy in 2019/12. If Airbnb believes that the main role of online reviews is to motivate hosts to provide high-quality services to guests, review content regarding something outside the host's control may not help in that regard. Anecdotes suggest that hosts have complained about the harm they suffer from "irrelevant" reviews about the vicinity of their listings,[11] and this policy change could be a way to address these complaints. Another reason might be the concern of review accuracy: arguably, vicinity safety is a subjective feeling subject to the reviewer's prior and interpretation, and it is often difficult to prove correct or wrong. However, similar accuracy concerns could apply to other review content, though the degree of objectiveness may vary. A third reason may have something to do with the aspiration of being inclusive. Airbnb has advocated for inclusive design, which is defined as "consciously designing products, services, and environments that don't create barriers to belonging."[12] The same aspiration may have motivated Airbnb to adopt an anti-discrimination policy, establish a permanent anti-discrimination team, and encourage designs and services friendly to users with disabilities. To the extent that vicinity safety reviews are more present in low-income or minority neighborhoods, the new review policy could be another effort to make the platform more friendly to hosts in economically disadvantaged neighborhoods. The key question we address in this paper is how the new policy, if fully implemented as far as VSR is concerned, would redistribute the economic benefits and costs among hosts, guests, and the platform.

To be clear, Airbnb has adopted other methods to address neighborhood safety directly. For example, Airbnb introduced a neighborhood support hotline in 2019/12[13], around the same time as Airbnb adopted the new review policy. This hotline is primarily intended to be a means for neighbors of Airbnb listings to contact the platform in certain situations (e.g., in the event of a party taking place at a listed property). In addition, since our main analysis sample ends in 2019/12 and we do not know how many guests that left VSR in our sample would have used the hotline should the hotline exist at the time of the review, we cannot predict how the hotline could counter some of the effects shown in our analysis. That being said, hotline usage is ex post and is not visible to future guests, hence its impact on guests can be fundamentally different from the impact of reviews visible under each listing on Airbnb.

Airbnb's review system also allows guests to leave a 1-5 star rating by specific categories (cleanliness, accuracy, check-in, communication, location, and value), in addition to leaving an overall rating and detailed review. According to Airbnb's response to a host's question, location rating is meant to "help future guests get a sense of the area and tends to reflect proximity to nearby destinations."[14] Hence, location

[11] Nina Medvedeva, "Airbnb's Location Ratings as Anti-Black Spatial Disinvestment in Washington D.C." Platypus: The CASTAC Blog (March 16, 2021) accessed at `https://rb.gy/ottzf9` .

[12] See, e.g., `https://rb.gy/eq7ltv` .

[13] See, e.g., `https://rb.gy/sykoim` .

[14] See, e.g., `https://rb.gy/qs13gh` .

rating could capture many location-specific aspects such as local transit, nearby stores, neighborhood walkability and noise, and may not be directly related to vicinity safety.

4 Data

Data of short-term rental listings. The main dataset we use has information on the set of short-term rental listings that had been advertised on Airbnb from 2015/5 to 2019/12, and on VRBO from 2017/6 to 2019/12, in five US cities (Atlanta, Chicago, Los Angeles, New Orleans, and New York). The data was acquired from AirDNA, a company that specializes in collecting Airbnb and VRBO data. For Airbnb listings, this dataset includes the textual contents of all Airbnb listing reviews in those cities. We have no access to reviews on VRBO. The original data from AirDNA extends to 2020/12 but demand for short-term rentals has changed dramatically because of the COVID-19 pandemic, so our main analysis uses data up to 2019/12 but we use data till 2020 to infer Airbnb's (lack of) enforcement of its 2019/12 policy beyond 2019.

Each listing is identified by a unique property ID and comes with time-invariant characteristics such as the listing zip code, listing's property type (entire home, private room, shared room, or hotel room) as well as the host's unique identifier. Listings also have time-variant characteristics, including average daily rate,[15] the number of reservations, days that are reserved by guests, occupancy rate,[16] number of reviews, overall rating scores,[17] the listing's Superhost status,[18] the listing's guest-facing cancellation policy,[19] the average number of words in the listing's reviews, the number of listings in the same zip code, and whether the listing is cross-listed on VRBO.[20]

Our unit of observation is listing-month. We focus on "active listings" (listings whose calendars are not indicated as 'blocked' in the dataset for an entire month), and exclude observations with an average daily rate (ADR akin price per night) over \$1000, as some hosts may set their rates prohibitively high in lieu of blocking their calendars. We use regular monthly scrapes between 2015/5 and 2019/12 on Airbnb (2017/6 to 2019/12 for VRBO). In total, the sample comprises 2,866,238 listing-months observations on Airbnb, and 201,718 listing-months observations on VRBO.

Definition of safety reviews on Airbnb. We define two different types of safety reviews —

[15] Average daily rate (ADR) is calculated by dividing the total revenue, including both nightly rates and cleaning fees, earned by the host from reservations over a given month by the total number of nights in that month's reservations.

[16] Occupancy rate is calculated by dividing the number of booked nights by the sum of the available nights and booked nights.

[17] Overall rating scores are normalized to 0-10 range. Our dataset also includes location star ratings. Adding it as an extra control variable does not change our main results, so we do not report it in this paper. Results are available upon request.

[18] Superhost refers to a status badge related to metrics concerning a listing's performance. Hosts who meet the following criteria, evaluated quarterly, receive a Superhost designation: (i) Completed at least 10 reservations in the past 12 months; (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 12 months.

[19] Cancellation policy could be strict, moderate, flexible. For simplicity, we use a dummy variable to indicate whether a listing's cancellation policy is strict or not.

[20] Only listings with entire home that could be both listed on Airbnb and VRBO.

listing safety reviews (LSR) and vicinity safety reviews (VSR). LSR are those reviews that describe issues pertaining to safety within a listing (e.g., "the listing is unsafe because there are fire hazards", "the listing is unsafe because of the slippery tub", or "we saw mice in the kitchen three times during our stay"). VSR contain information pertaining to the safety of the nearby vicinity or neighborhood of the listing (e.g., "the neighborhood is not safe", "shady neighborhood", or "unsafe area"). While there is considerable research regarding the use of machine learning for automated content analysis, these methods typically require a large number of hand-labeled examples for training. We instead use a lexicon approach due to its simplicity and transparency. Lexicons are also found to have high levels of precision as compared to machine learning approaches (Zhang et al., 2014; Hutto and Gilbert, 2014), and have been used extensively in the literature (Monroe et al., 2008; Dhaoui et al., 2017).

To identify a suitable set of keywords, we use an iterative approach, starting with terms such as "unsafe," "dangerous," and "scary" and all of their synonyms, to obtain an initial keyword set; next, we manually inspect reviews containing such keywords so as to identify additional keywords. We then select keywords based on the accuracy of safety reviews.

More specifically, we conduct two iterations of manual labeling. In the first iteration, three research assistants (comprising both male and female and different races) labeled 1.4K reviews that were generated from the Lexicon approach algorithm with the initial keyword set for both LSR and VSR. While labeling, for each review the reviewers identified (i) whether the review pertains to neighborhood and/or listing safety, (ii) whether the review has a negative sentiment with respect to neighborhood and/or listing safety, and (iii) three specific keywords that supported the reviewer's decision in (i) and (ii). With these human-labeled keywords, we obtain an updated list of vicinity and listing safety keywords such that the percentage of critical reviews regarding vicinity safety (listing safety) in the 1.3K sample with such a human-selected keyword is greater than 0% (10%).

In the second iteration of labeling, two research assistants (male and female) of different races labeled 3.1K reviews that were generated from the Lexicon approach algorithm with the updated keyword set for both LSR and VSR, such that 5 reviews associated with each keyword were randomly selected. In this iteration, reviewers labeled whether each review pertains to negative sentiment about vicinity and/or listing safety. The final set of keywords is the one where each vicinity safety (listing safety) keyword has a percentage of negative-sentiment vicinity safety (listing safety) reviews greater than or equal to 60% from both reviewers' second-iteration labeling results. After two iterations, we expanded the list to 41 vicinity safety keywords and 50 listing safety keywords, as delineated in Appendix Table A1.[21]

The keyword lists developed above are not the only inputs we use to define vicinity or listing safety reviews. As far as VSR, to improve precision and to ensure that the text is indeed describing issues

[21] Most of the keywords appear relatively infrequently, and removing any one of them alone has little effect on the results. For example, one may argue that "government housing" suggests a low-income area rather than vicinity safety issues. Including it in our vicinity safety keyword list would only identify three more vicinity safety reviews and removing the keyword has no qualitative impact on the results.

pertaining to the safety of a listing's vicinity and not other aspects of a listing, we identified a list of 24 location keywords that tend to indicate a statement about the surrounding area (e.g., "neighborhood", "area", "outside") in Appendix Table A1. We then categorized the matching reviews into those in which the vicinity safety keyword occurred within 20 words of a location keyword as vicinity safety reviews, and those in which the listing safety keyword occurred outside of the 20-word context as listing safety reviews.[22] Next, we selected 13 'negative' keywords, and filtered out double-negative reviews where the keyword occurs within 5 words of a safety keyword.

Overall, our approach resulted in 11.8k matched VSR and 12.8k matched LSR across the 5 sample cities. In total, they account for 0.25% and 0.27% of all the observed Airbnb reviews respectively. From 2015/5 to 2019/12, only 4.43% of listings ever had any VSR, and only 8.49% of listing ever had any safety reviews (VSR or LSR).

As shown in Appendix Figures A1 and A2, the top matching vicinity safety keywords are "unsafe" (4,519), "homeless" (3,398), "yelling" (854), and "uneasy" (733), and the top matching listing safety keywords are "worst" (1,803), "mold" (1,350), "stained" (1,172), and "filthy" (1,135). As an additional validation check, we sampled several thousand matches at random, and manually labeled them as relevant or not, finding 78.21% and 75.64% accuracy for vicinity safety keywords and listing safety keywords, respectively.[23] The mislabeled data often used figurative language ("scary how perfect this neighborhood is") or used safety words in other contexts (e.g., "watched a scary movie on Netflix"). While any such method will be imperfect, we did not find any evidence suggesting that the error rates were systematically biased for some neighborhoods over others. However, we did restrict our keywords to English, so the method will be less effective in areas with many non-English reviews.

To check whether the safety reviews defined above are indeed critical feedback as we intend to identify, we employ a pre-trained NLP model from Hugging Face to determine the sentiment score of all reviews [24]. According to the analysis, the overall average sentiment score across all available reviews is 0.79. Specifically, VSR show a relatively neutral average sentiment score of 0.06, while sentences containing VSR safety keywords tend to have a negative average sentiment score of -0.31. In contrast, the non-VSR reviews have an average sentiment score matching the overall average of 0.79. On the other hand, LSR demonstrate a comparatively lower average sentiment score of -0.41, and sentences with safety keywords within the LSR category have the most negative average sentiment score of -0.76. In comparison, the

[22]While the 20-word window is arbitrary, a sensitivity analysis suggests no qualitative difference when using a slightly longer or shorter window. Moreover, the average review had roughly 50 words, so this seemed to restrict to the 1-2 sentences around the keyword match.

[23]This indicates a 21.79% false-positive error rate for vicinity safety reviews (24.36% for listing safety reviews). Since our lexicon approach aims to minimize the false-positive rate while allowing false negatives, the safety reviews identified by this approach tends to make the estimated impact of safety reviews more conservative than the true effect.

[24]The utilized model is a fine-tuned checkpoint of DistilBERT-base-uncased, accessible at `https://huggingface.co/distilbert-base-uncased-finetuned-sst-2-english`. It demonstrates a noteworthy accuracy of 91.3% on the development set. The sentiment scoring system ranges from -1 to 1, where a score of -1 indicates an extremely negative sentiment, and a score of 1 indicates an extremely positive sentiment.

non-LSR reviews have an average sentiment score again aligning with the overall average of 0.79. These patterns suggest that our Lexicon approach has successfully captured the negative sentiment when guests comment on listing or vicinity safety issues during their stay.

Official crime and demographic statistics. A second dataset we collect covers official crime records from databases tracking crimes in Chicago[25], New Orleans[26], New York City[27], Atlanta[28], and Los Angeles.[29] These databases cover different types of crimes, including property-related crimes and violent crimes. In terms of the geographical granularity of crimes, we consider crime events at the zip code level. We also obtain median income and other demographic information at the zip code level from 2014, one year before our Airbnb sample period begins, from the United States Census Bureau[30]. We make the assumption that the income and demographic information did not change significantly over our sample period. Throughout the paper, we refer to a zip code as high-income (H) or low-income (L) according to whether its average income is above or below the median of the city it locates in. Similarly, we refer to a zip code as minority (M) or white (W) according to whether its percentage of minorities in population is below or above the city median.

Variable Definition. Above all, Appendix Table A2 defines the key variables used in this paper, including listing attributes (such as price, occupancy rate, safety reviews, and ratings) and neighborhood attributes (such as income, population, and crime statistics by zip code).

Summary of VSR and LSR on Airbnb. Table 1 summarizes the data at the listing-month level, where vicinity safety (VS) Airbnb listings are defined as observations that have a positive number of vicinity safety reviews (VSR) before the reporting month, while "normal" Airbnb listings do not have any VSR before the reporting month. As the table indicates, about 4% of the total observations are VS listings. On average, VS listings have higher occupancy rates, a higher number of reservations, a higher fraction of Superhosts, and a higher number of reviews than normal listings. In contrast, the nightly rates and overall rating of VS listings are lower on average than normal listings. The mean number of cumulative VSR (aggregated up to the reporting month) is 0.06 across all Airbnb listings, and the mean number of cumulative listing safety reviews (LSR) is 0.06. Appendix Figures A3 and A4 demonstrate the distribution of VS keywords for four groups of zip codes (high-income, low-income, white, and minority). Comparing high-income with low-income (and white with minority) groups, it appears that the low-income (minority) group dominates the volume of VSR.

Did Airbnb enforce its new review policy after 2019/12? To infer whether Airbnb has enforced its 2019/12 policy as far as vicinity and listing safety is concerned, Figure 1 displays the percentage of VSR and LSR on Airbnb, as identified by our Lexicon method, from 2015/7 to 2020/12. While both VSR

[25] Official crime data in Chicago: `https://rb.gy/atjsss` .
[26] Official crime data in New Orleans: `https://rb.gy/4vue82` .
[27] Official crime data in New York City: `https://rb.gy/iwrwp2` .
[28] Official crime data in Atlanta: `https://rb.gy/96txbl` .
[29] Official crime data in Los Angeles: `https://rb.gy/tebnla` .
[30] See, e.g., `https://www.census.gov/data.html`.

VARIABLES	All listings (N=2,866,238)		VS listings (N=126,868)		Normal listings (N=2,739,370)	
	mean	p50	mean	p50	mean	p50
occupancyrate	0.56	0.64	0.68	0.78	0.56	0.64
occupancyrate_dummy	0.85	1.00	0.95	1.00	0.85	1.00
adr	164.69	125.51	134.15	106.31	166.10	126.67
No._of_reservations	3.77	3.00	5.76	5.00	3.68	3.00
No._of_reservationdays	14.16	14.00	18.56	21.00	13.95	14.00
lag_VSR_cumu_dummy	0.04	0.00	1.00	1.00	0.00	0.00
lag_LSR_cumu_dummy	0.05	0.00	0.20	0.00	0.04	0.00
lag_VSR_cumu	0.06	0.00	1.34	1.00	0.00	0.00
lag_LSR_cumu	0.06	0.00	0.26	0.00	0.05	0.00
lag_VS_listing_radius_pct	0.07	0.04	0.10	0.07	0.07	0.03
safety_score (1-10, constructed by us)	4.96	5.09	2.83	2.33	5.06	5.23
ratingoverall (1-10)	9.18	9.60	9.09	9.20	9.18	9.60
review_utd	33.71	15.00	93.02	70.00	30.96	14.00
No._of_listing_zip	540.67	449.00	554.66	481.00	540.02	447.00
cross_listing	0.02	0.00	0.03	0.00	0.02	0.00
superhost	0.23	0.00	0.26	0.00	0.23	0.00
strict_cp	0.50	0.00	0.58	1.00	0.49	0.00
ave_wordcount_cumu_review	53.83	50.43	57.49	53.91	53.66	50.20
median_income_zip	57,187	50,943	42,645	34,432	57,861	51,427
population_zip	48,158	45,747	42,514	36,654	48,419	46,025
white_pct_zip	0.53	0.59	0.41	0.38	0.53	0.60
h_zip	0.52	1.00	0.29	0.00	0.53	1.00
w_zip	0.60	1.00	0.44	0.00	0.61	1.00
crime_cumu	19,435	9,650	31,230	14,205	18,889	9,475

Table 1: Summary Statistics of Airbnb Listings (2015/7-2019/12, unit of observation=listing-month)

and LSR have increased drastically after 2020/3, neither shows any discontinuous jumps from 2019/12 to 2020/2 as compared to the month-to-month fluctuation before 2019/12. The increase post 2020/3 is likely driven by guests' high attention to safety issues due to the pandemic rather than Airbnb's change of review policy in 2019/12, because that policy, if significantly enforced, should have led to a *differential reduction* of VSR relative to LSR.

To double check, we have also examined the number of VSR/LSR removed in each quarter, by comparing the reviews available on Airbnb from time to time. We find that almost all of the removed VSR/LSR were from inactive listings. In short, we conclude that no evidence suggests Airbnb has enforced its 2019/12 policy for VSR up to the end of 2020.

How do VSR correlate with official crime statistics? We also test the rank correlation between the official crime records and VSR. Specifically, we use the percentile rank of normalized crime records in each zip code-month within each city — calculated as the number of reported crime cases in a month, divided by the size of the population in that zip code. For each month, we rank the normalized crime data within each city, and determine the percentile crime rank of the zip code for that month. For VSR, we use the percentile rank of the number of cumulative VSR in the zip code up to the reporting

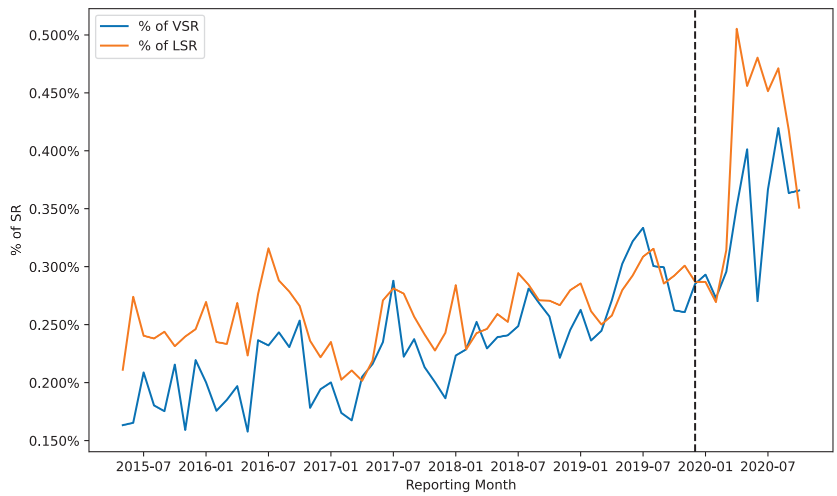

Figure 1: Percentage of Vicinity Safety Reviews (VSR) and Listing Safety Reviews (LSR) on Airbnb Over Time

month.[31] We then test the percentile rank correlation index between the crime records and VSR in each month, resulting in the time-series correlation trends depicted in Figure 2, which illustrates the correlation trends for the four different groups of zip codes (high-income, low-income, white, and minority). Figure 2 indicates that the correlation in low-income and minority groups exhibits an increasing trend, suggesting that the percentile rank of VSR in a zip code is more likely to reflect the actual crime reports in the zip code over time in these areas.

5 Reduced-form Effects of Safety Reviews

This section presents reduced-form evidence from listing-level and guest-level analyses. Listing-level analysis documents the within-listing-cross-buyer effects of safety reviews as well as the cross-listing-cross-buyer effects of VSR. Guest-level analysis captures the cross-listing-within-buyer effects of VSR.

5.1 Listing-Level Analysis

Baseline results. We begin by assessing the effects of VSR and LSR by listing-month. Our hypothesis is that if potential guests view VSR and LSR as a proxy for safety around or within a listing, such reviews would reduce the guests' willingness to book the listing. Our base specification is given by:

$$y_{j,t} = \alpha_j + \alpha_{k,t} + \delta X_{j,t} + \beta_1 Crime_{j,t-1} + \beta_2 LSR_{j,t-1} + \beta_3 VSR_{j,t-1} + \beta_4 VSRADIUS_{j,t-1} + \epsilon_{j,t}, \quad (1)$$

[31] Due to data limitations, we assume that both records begin with clean slate (0 records) as of the beginning of our dataset.

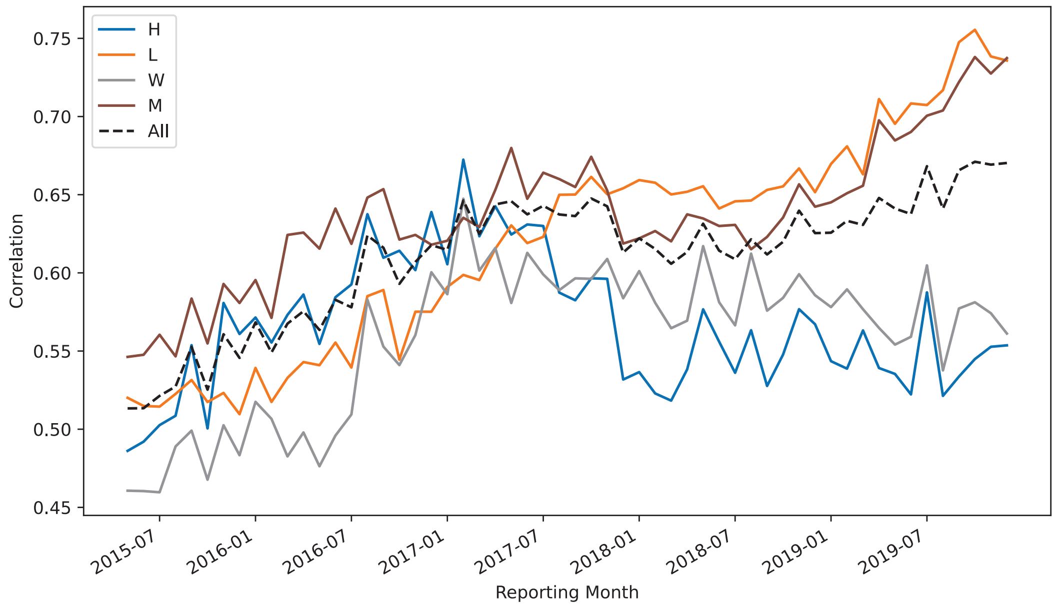

Figure 2: Correlation between the rank of normalized crime flow and the normalized total VSR

where j denotes a listing j-month t observation, $Crime_{j,t-1}$ is a log transformed variable that indicates the normalized number of cumulative official crime reports since the start of the sample period for the zip code where listing j is located, $LSR_{j,t-1}$ and $VSR_{j,t-1}$ are two dummy variables that equal 1 if the listing has at least one LSR and VSR, respectively, before month t, $VSRADIUS_{j,t-1}$ is the percentage of listings that have at least one VSR within a 0.3-mile radius of listing j prior to month t, $X_{j,t}$ are listing-level controls (logged except for dummy variables), including the number of reviews, overall ratings, cancellation policy, number of listing in the same zip code, cross-listing status (i.e., whether the listing is also listed on VRBO), and whether the listing is hosted by a Superhost. The dependent variable $y_{j,t}$ is either the log of listing j's average daily rate (ADR) in month t, or the log of listing j's monthly occupancy rate (calculated as log of 1 plus the occupancy rate).[32] Listing and City–year-month fixed effects are denoted by α_j and $\alpha_{k,t}$, respectively, where the city of listing i is denoted by k. Standard errors are clustered by Airbnb property ID. The primary assumption is that, within a listing, the presence and timing of safety reviews are correlated with the true safety condition around or inside the listing and do not reflect selective reporting, fake reviews, or other strategic reasons once we control for other time-varying listing attributes.

Our main specifications in Table 2 indicate that both VSR and LSR significantly decrease a listing's price (ADR) and occupancy. Specifically, for an average Airbnb listing in our sample, having any VSR is associated with a 1.82% reduction in the listing's monthly occupancy rate and a 1.48% reduction in its

[32]Some listing-month observations have an occupancy rate of 0 and consequently are missing an average reserved daily rate in the dataset for those months, though the dataset does offer a separate "listing price" (i.e., a base rate) for those listings. To extrapolate the ADR of these listings in the months in which they are missing, we calculate the mean ratio of their ADR to their listing price in the months in which they are available, and multiply this average by the listing price in the missing months (if available, or by using the listing price from the nearest month in which it is available).

average price per reserved night; having an LSR is associated with a 2.58% drop in occupancy and 1.52% in price. LSR thus have a larger effect on price and occupancy than VSR, possibly because some prospective guests have a specific geographic area (e.g., neighborhood) in mind, regardless of safety issues concerning that area, whereas LSR describe safety issues that pertain to the listing itself. The percentage of listings with VSR within a 0.3-mile radius is associated with lower prices and lower occupancy, suggesting that guests may also infer vicinity safety from the VSR of nearby listings.

	(1)	(2)
SAMPLE	whole	whole
MODEL	OLS	OLS
VARIABLES	log_occupancy_rate	log_adr
lag_VSR_cumu_dummy	-0.0182***	-0.0148***
	(0.00140)	(0.00219)
lag_LSR_cumu_dummy	-0.0258***	-0.0152***
	(0.00135)	(0.00210)
lag_VS_listing_radius_pct	-0.00859***	-0.00872**
	(0.00253)	(0.00390)
lag_log_crime_cumu_norm	0.0693***	-0.0508***
	(0.00826)	(0.0130)
lag_log_review_utd	0.00420***	0.0117***
	(0.000415)	(0.000678)
log_No._of_listing_zip	-0.0212***	0.0146***
	(0.00185)	(0.00289)
log_rating_overall	0.0257***	-0.00240
	(0.00128)	(0.00200)
superhost	0.0175***	0.00817***
	(0.000586)	(0.000845)
cross_listing	0.0311***	-0.00564
	(0.00278)	(0.00384)
strict_cp	0.000601	0.0123***
	(0.000803)	(0.00126)
	(0.0119)	(0.0185)
Observations	2,866,238	2,866,238
R-squared	0.559	0.928

Note: *** $p < 0.01$, ** $p < 0.05$, All regressions control Time*City FE and Property ID FE, with standard errors clustered by Property ID. The variable crime_cumu is normalized by the population.

Table 2: Main Results of Reduced-form Listing-level Analysis of Airbnb Listings

In contrast, normalized official crime records is associated with lower prices but higher occupancy. A potential explanation is that hosts are aware of safety issues in the areas of their listings, and proactively lower their rates when their listings are located in relatively unsafe areas. These lower prices attract more guest bookings, perhaps either because guests tend not to seek information about crimes in the neighborhood or because they prioritize price. In particular, for the average Airbnb listing in our sample, given a 1% increase in the normalized official crime records, the daily rate is 0.05% lower whereas the occupancy rate is 0.07% higher.

Robustness. Our first robustness check tries to separate the extensive and intensive margins. Column 1 of Table 3 considers as the dependent variable a dummy that equals 1 when a listing's occupancy rate is positive and 0 otherwise. It reports a positive coefficient on $Crime_{j,t-1}$, suggesting that the variable $Crime_{j,t-1}$ not only describes the relative crime status of a zip code, but may also capture the relative guest traffic to the area, where areas with relatively high guest traffic (e.g., downtown areas) tend to have a higher number of reported (normalized) crimes.

Comparing the coefficients on VSR and LSR for the whole-sample specifications (Table 2) to the conditional sample with positive occupancy rates (Columns 2 and 6 of Table 3), we find that the coefficients are similar but have somewhat higher magnitudes for the whole sample. One exception is that the coefficient on $Crime_{j,t-1}$ becomes negative after we condition the sample on listings with any positive occupancy rate, suggesting that the positive coefficient on this variable in the whole sample is driven by the extensive margin only, whereas the intensive margin is consistent with the prior that bookings tend to decline for listings located in a zip code with higher crime statistics over time.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SAMPLE	whole	occ>0	review_utd<=13	review_utd>13	whole	whole	whole
MODEL	OLS	OLS	OLS	OLS	OLS	OLS	OLS
VARIABLES	occupancy rate dummy	log occupancy rate	log occupancy rate	log occupancy rate	log occupancy rate	log occupancy rate	log occupancy rate
lag_VSR_cumu_dummy	-0.0132***	-0.0129***	-0.0212***	-0.0100***	-0.0180***	-0.0155***	-0.0152***
	(0.00155)	(0.00119)	(0.00541)	(0.00146)	(0.00140)	(0.00140)	(0.00139)
lag_LSR_cumu_dummy	-0.0131***	-0.0213***	-0.0362***	-0.0173***	-0.0251***	-0.0228***	-0.0224***
	(0.00153)	(0.00114)	(0.00458)	(0.00142)	(0.00135)	(0.00136)	(0.00136)
lag_VS_listing_radius_pct	-0.0100**	-0.00575**	-0.00760**	-0.00334	-0.00864***	-0.00848***	-0.00847***
	(0.00416)	(0.00238)	(0.00378)	(0.00342)	(0.00253)	(0.00263)	(0.00263)
lag_log_crime_cumu_norm	0.180***	-0.0167**	0.219***	0.0118	0.0693***	0.0652***	0.0653***
	(0.0123)	(0.00734)	(0.0150)	(0.0106)	(0.00826)	(0.00874)	(0.00874)
lag_log_ave_wordcount_cumu_review					-0.00890***		
					(0.000744)		
lag_r_sentiL_cumu_ave						0.0251***	
						(0.00215)	
lag_r_sentiN_cumu_ave							0.0228***
							(0.00120)
R-squared	0.420	0.499	0.565	0.522	0.559	0.560	0.560
VARIABLES		log adr	log adr	log adr	log adr	log adr	log adr
lag_VSR_cumu_dummy		-0.0126***	-0.00411	-0.0110***	-0.0150***	-0.0145***	-0.0146***
		(0.00201)	(0.00726)	(0.00231)	(0.00219)	(0.00219)	(0.00219)
lag_LSR_cumu_dummy		-0.0112***	-0.00152	-0.0124***	-0.0158***	-0.0150***	-0.0152***
		(0.00189)	(0.00705)	(0.00218)	(0.00210)	(0.00210)	(0.00210)
lag_VS_listing_radius_pct		-0.00848**	0.00263	-0.0140***	-0.00868**	-0.00993**	-0.00992**
		(0.00337)	(0.00620)	(0.00478)	(0.00390)	(0.00387)	(0.00387)
lag_log_crime_cumu_norm		-0.000974	-0.0600**	-0.0242	-0.0508***	-0.0490***	-0.0490***
		(0.0120)	(0.0240)	(0.0168)	(0.0130)	(0.0135)	(0.0135)
lag_log_ave_wordcount_cumu_review					0.00645***		
					(0.00106)		
lag_r_sentiL_cumu_ave						0.00572*	
						(0.00293)	
lag_r_sentiN_cumu_ave							-0.00124
							(0.00163)
R-squared		0.943	0.931	0.937	0.928	0.931	0.931
Observations	2,866,238	2,441,566	1,370,655	1,495,583	2,866,238	2,655,504	2,655,504

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions control Time*City FE and Property ID FE, with standard errors clustered by Property ID.

Table 3: Robustness Checks for Reduced-form Listing Level Analysis of Airbnb Listings

We conduct a number of additional checks. First, we split the sample by whether a listing has an above- or below-median number of reviews in a given month (median is 12), as a proxy for whether the listing is in its early or later "stage" of taking guest reservations, since only staying guests can post a review.[33] Another motivation for this partition is that prospective guests are more likely to notice safety reviews (both VSR and LSR) when listings have a lower number of reviews. Indeed, Columns 3 and 4 of Table 3 report that in the subsample of listings with 13 or fewer reviews, the negative effects of having any VSR and LSR on occupancy rate (2.12% for VSR and 3.62% for LSR) are higher than the corresponding negative effects for listings with more than 13 reviews (1.00% for VSR and 1.73% for LSR). However, Columns 7 and 8 indicate that as far as listings' daily rates are concerned, this comparison is reversed, possibly because hosts of newer listings may still be in the process of identifying their pricing for those listings. Second, we add additional controls for the average word count of a listing's reviews. [34] As Columns 5 and 9 of Table 3 indicate, the results do not qualitatively change from our main specifications when incorporating the additional control.

Heterogeneous effects. We next explore a number of heterogeneous effects. Table A3 provides summary statistics based on the type or area of a listing. In particular, the table reports different normalized zip code crime levels for listings in these categories. We proceed with a similar empirical methodology as in (Equation 1), but with different subsamples.

We begin by analyzing four groups of zip codes separately (high-income, low-income, white, and minority). Table 4 shows that VSR have negative effects on occupancy rates across all four subsamples. The negative effects of having any VSR on occupancy rates have higher magnitudes in high-income and white zip codes (1.76% and 1.89%) than in low-income and minority zip codes (1.72% and 1.75%). A similar comparison holds for LSR. One potential explanation is that guests may have different prior beliefs and different sensitivities to safety issues, and perhaps more so if their search targets a specific area that they believe is relatively safe. Hosts in different areas may also react differently to VSR and LSR, based on how they gauge guest perception and guest preferences.

We next consider subsamples comprising different listing types (entire home, private room, shared room, and hotel room). Additional heterogeneous effects may arise here because, for instance, for guests who seek partial spaces (private room, shared space) within a dwelling, safety issues may be more salient. The results in Appendix Table A4 indeed show that the magnitude of the negative effects from having any VSR and LSR on occupancy are larger for private rooms and shared spaces (2.10% and 3.01% for VSR and 3.08% and 2.89% for LSR, respectively) in comparison with entire-home listings (1.61% for VSR and 2.36% for LSR).

[33]To be clear, the same listing may be in both subsamples over time, but belong to only one of the subsamples in any given month.

[34]Host responses to safety reviews are not observed in our data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SAMPLE	H	L	W	M	H	L	W	M
MODEL	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
VARIABLES	log occupancy rate	log occupancy rate	log occupancy rate	log occupancy rate	log adr	log adr	log adr	log adr
lag_VSR_cumu_dummy	-0.0176***	-0.0172***	-0.0189***	-0.0175***	-0.0163***	-0.0138***	-0.0153***	-0.0136***
	(0.00257)	(0.00168)	(0.00215)	(0.00185)	(0.00389)	(0.00267)	(0.00330)	(0.00295)
lag_LSR_cumu_dummy	-0.0263***	-0.0247***	-0.0251***	-0.0265***	-0.0181***	-0.0123***	-0.0177***	-0.0114***
	(0.00196)	(0.00187)	(0.00178)	(0.00207)	(0.00284)	(0.00307)	(0.00269)	(0.00335)
lag_VS_listing_radius_pct	-0.0117***	-0.00449	-0.00780**	-0.00942***	-0.00261	-0.0126**	-0.00308	-0.0122**
	(0.00370)	(0.00346)	(0.00385)	(0.00335)	(0.00564)	(0.00535)	(0.00589)	(0.00516)
lag_log_crime_cumu_norm	0.0512***	0.171***	0.0427***	0.170***	-0.0496***	-0.0561***	-0.0478***	-0.0625**
	(0.0111)	(0.0137)	(0.00950)	(0.0168)	(0.0179)	(0.0213)	(0.0150)	(0.0265)
Observations	1,484,474	1,381,764	1,716,774	1,149,464	1,484,474	1,381,764	1,716,774	1,149,464
R-squared	0.552	0.569	0.551	0.573	0.921	0.924	0.919	0.925

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions control Time*City FE and Property ID FE, with standard errors clustered by Property ID.

Table 4: Reduced-form Listing-level Analysis of Airbnb Listings By Four Area Types

5.2 Guest-Level Analysis

We conduct guest-level analyses to test whether guests who leave any VSR (henceforth, VS guests) act differently before and after they post their first VSR in comparison to otherwise similar guests who did not leave any VSR. This aims to capture the cross-listing-within-buyer effect of VSR. To that end, we assume that the first VSR that a VS guest posts for one of the listings in our sample (i.e., covering Airbnb listings in the five cities we consider, with reviews beginning in May 2015) is the first VSR that this guest posted. To reiterate, any such guests who have ever posted VSR in our sample are considered VS guests; otherwise, they are treated as "normal" users. To ensure that the VS users have had some experience on Airbnb prior to leaving their first VSR, we focus on the subset of VS users that left at least two reviews in the five sample cities before leaving their first VSR.

In order to match VS users with normal users, we use a K-nearest neighbor (KNN) method to select the two most similar control (normal) users for each treatment (VS) user. The user characteristics used in the KNN method (as of the time of the treatment user's first VSR) are the user's number of prior reviews, the average normalized crime reports in the cities in which the user stayed (based on their prior reviews), the average number of VSR for listings for which the user left reviews, the average percentage of overall VS listings in the same zip codes as well as in the 0.3-mile radius area as listings for which the user had previously left reviews, and the average number of words for the reviews that the user posted before. The matching is done for each month (i.e., based on new treatment users in each month). The same "treatment month" is applied (hypothetically) to control users that are matched with a treatment (VS) user, based on the latter's timing of their first VSR.

To assess if the treatment and control users have the same tendency to post VSR, we also calculate the propensity score for each user in our matched sample. In particular, we regress the dummy of a user

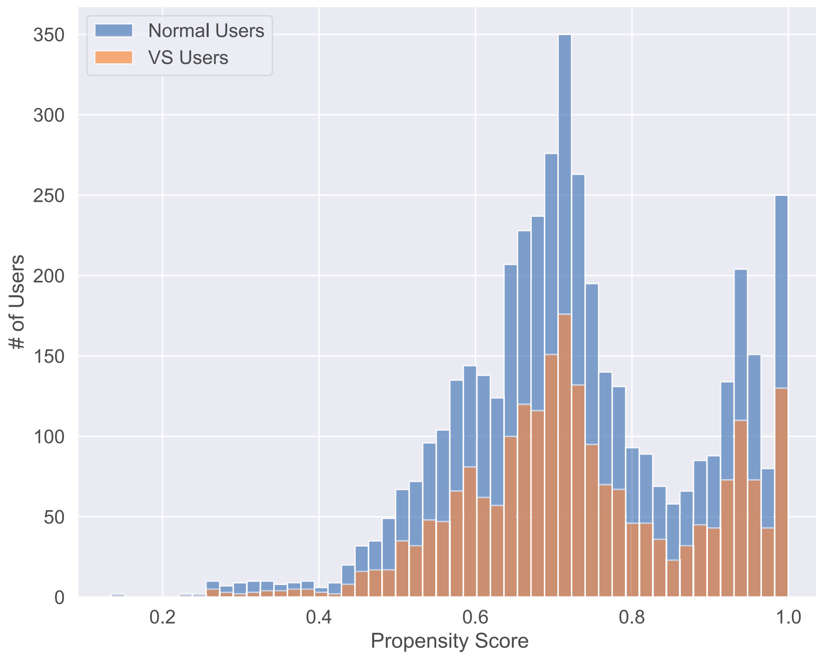

Figure 3: Distribution of Propensity Scores for VS users (treated) and Normal users (control)

being a VS user on the number of reservations she had made on Airbnb before the treatment time, the average zip code-wide crime rate of these reservations at the time of reservation, the average number of VSR in these reservations, the percent of listings with any VSR in the zip code as well as in the 0.3-mile radius area of these reservations, and the average number of words for the reviews that the user posted before. For a treated user, the treatment time is when she wrote her first VSR in our sample. For a control user, the treatment time is when the treatment user she is paired with wrote her first VSR in our sample. Table 5 reports that the treatment and control users are similar as far as the characteristics considered in the KNN method; the two user groups also have similar propensity scores, as shown in Figure 3.

	Panel A: VS users				Panel B: Normal users			
VARIABLES	mean	p50	sd	N	mean	p50	sd	N
reservation_pre	2.76	2.00	1.51	2,252	2.72	2.00	1.43	4,504
log_ave_crime_cumu_norm_pre	0.93	0.28	1.95	2,252	0.81	0.27	1.44	4,504
ave_vsr_cumu_pre	0.63	0.50	0.44	2,252	0.64	0.50	0.43	4,504
ave_vs_listing_zip_pct_pre	0.06	0.05	0.04	2,252	0.06	0.05	0.04	4,504
ave_vs_listing_radius_pct_pre	0.09	0.07	0.07	2,252	0.08	0.07	0.06	4,504
log_ave_wordcount_cumu_review_pre	4.37	4.39	0.64	2,252	4.36	4.39	0.63	4,504
propensity_score	0.74	0.72	0.15	2,252	0.73	0.71	0.15	4,504

Table 5: Summary Statistics by VS and Normal Users in the DID Sample

We first test whether VS users behave differently in terms of subsequent reservations on Airbnb after their first VSR (as exhibited by their subsequent listing reviews). We use a difference-in-differences methodology (DID) as follows:

$$y_{it} = \alpha_t + \alpha_p + \beta \cdot VS\_user_i + \gamma \cdot VS\_user_i \times post_t + \epsilon_{i,t}, \tag{2}$$

where the subscript p denotes the treatment-control pair identified in the sample construction.

We construct several measures for the dependent variable y_{it}: the first is the number of reviews that user i wrote in month t. We use it as a proxy of user i's Airbnb reservations in t, which can be zero and thus captures both the extensive and intensive margins. Because it is a count variable, we use a Poisson regression instead of ordinary least squares. The other measures of y_{it} include the normalized cumulative count of officially reported crimes in the zip codes of user i reserved listings in month t, the number of VSR in i reserved listings, the percentage of VS listings in the zip codes as well as in the 0.3-radius area of the i reserved listings, and whether the reserved listings have any VSR. These variables capture the types of listings that i books on Airbnb conditional on her booking at all (the intensive margin). The dummy VS_user_i equals 1 for VS users and 0 otherwise, and the dummy $post_t$ equals 1 if t is after the time of the first VSR of VS user i. The key variable is the interaction between VS_user_i and $post_t$ while $post_t$ alone is absorbed in year-month fixed effects α_t. Treatment-control pairs fixed effects are denoted by α_p. Standard errors are robust and clustered by treatment-control pairs.

In Panel A of Table 6, Column 1 reports results from a Poisson model based on an unbalanced monthly panel data, indicating that VS users tend to book fewer reservations (as evidenced by subsequent reviews) after posting their first VSR. In particular, the average monthly number of subsequent reviews is expected to be 60.07% lower for VS users in comparison with normal users.[35] Columns 2-6 assess whether VS users are more sensitive to safety information when booking subsequent Airbnb listings after posting their first VSR. Results suggest that the subsequent listings chosen by VS users tend to locate in zip codes that have fewer normalized crime reports, are less likely to have VSR, and are less likely to locate in zip codes that have a higher overall percentage of VSR or a higher percentage of other listings with VSR. This suggests that VS users, relative to normal users, are more sensitive to safety information after posting their first VSR.

One may argue that the extent of learning through self-experience would depend on a guest's prior about vicinity safety. Unfortunately, we have no data on each guest's home town and therefore cannot approximate their prior with the type of vicinity they normally live in. Nevertheless, some VS users may have seen some VSR left by a listing's previous guests, and that listing eventually triggered their own VSR, and therefore would not respond as vigorously to their own vicinity safety experience as other VS users. To test this, we create a dummy (First-Is-First) indicating whether a VS user's own VSR was the

[35] This is not the coefficient of the treatment dummy (-0.918) because we use a Poisson model for this regression, i.e., the applicable percentage is $1 - e^{-.918}$.

	(1)	(2)	(3)	(4)	(5)	(6)
SAMPLE	monthly reservation	reserved property	reserved property	reserved property	reserved property	reserved property
MODEL	Poission	Poission	Logit	OLS	OLS	OLS
VARIABLES	reservation monthly	VSR_cumu	VSR_cumu dummy	crime_cumu norm	VS_listing pct zip	VS_listing pct radius
Panel A: Full sample						
VS_user × post	-0.918***	-0.697***	-0.490***	-0.927***	-0.0250***	-0.0247***
	(0.0601)	(0.135)	(0.113)	(0.112)	(0.00267)	(0.00505)
Observations	254,056	22,265	22,237	22,415	22,415	22,415
Panel B: Subsample	VS use's 1st VSR is the 1st VSR of the listing					
VS_user × post	-0.961***	-0.793***	-0.696***	-0.961***	-0.0280***	-0.0275***
	(0.0667)	(0.146)	(0.129)	(0.127)	(0.00271)	(0.00551)
Observations	202,262	17,743	17,726	17,893	17,893	17,893
Panel C: Subsample	VS use's 1st VSR is not the 1st VSR of the listing					
VS_user × post	-0.726***	-0.372	0.256	-0.710***	-0.00872	-0.00854
	(0.139)	(0.298)	(0.239)	(0.228)	(0.00838)	(0.0129)
Observations	51,794	4,522	4,511	4,522	4,522	4,522

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions control treatment-control pair ID FE with standard errors clustered by pair ID.

Table 6: Reduced-form Guest-level Analysis: DID for VS users (treated) and Normal Users (control)

first VSR on the focal listing. About 79.6% of VS users have First-Is-First = 1. We then rerun the DID analysis for the subsamples of First-Is-First = 1 and First-Is-First = 0, respectively. Each subsample includes the VS users with the specific value of First-Is-First and their matched normal users. Regression results are reported in Panels B and C of Table 6. If the above prediction is correct, the VS users with First-Is-First = 1 should demonstrate greater changes post their own VSR experience, as compared to those with First-Is-First = 0.

Indeed, the coefficients reported in Panel B of Table 6 (for First-Is-First = 1) are of a larger magnitude than those in Panel C (for First-Is-First = 0). The estimates in Panel C are noisier and sometimes insignificant, in part because only 20.4% of VS users may have seen previous VSR on the focal listing before posting their own VSR. That being said, even these VS users demonstrate a strong decline of Airbnb bookings post their own VS experience (-51.62% Column 1) as compared to -61.75% for VS users with First-Is-First = 1 and -60.07% for all VS users, suggesting that the VSR left on the focal listings before our VS users' own VSR experience have a limited influence on their prior of vicinity safety before booking the focal listing and one's own vicinity safety experience is a still a salient shock ex post. This points to a significant cross-listing-within-buyer effect of VSR.

We further examine whether VS users subsequently act differently as a function of the area (high-income, low-income, minority or white) in which they posted their first VSR. To do so, we group VS users according to the zip code of the listing for which they posted their first VSR, and proceed to conduct the DID analysis separately for each of the four subsamples.

	(1)	(2)	(3)	(4)
SAMPLE	1st_vsr_h_zip	1st_vsr_l_zip	1st_vsr_w_zip	1st_vsr_m_zip
MODEL	Logit	Logit	Logit	Logit
VARIABLES	h_zip	h_zip	w_zip	w_zip
Panel A: Full sample				
VS_user × post	-0.351**	0.316***	-0.628***	0.682***
	(0.160)	(0.0990)	(0.135)	(0.105)
Observations	6,205	14,830	8,880	12,815
Panel B: Subsample	VS use's 1st VSR is the 1st VSR of the listing			
VS_user × post	-0.287*	0.370***	-0.646***	0.729***
	(0.169)	(0.111)	(0.149)	(0.117)
Observations	5,539	11,377	7,181	10,113
Panel C: Subsample	VS use's 1st VSR is not the 1st VSR of the listing			
VS_user × post	-0.887*	0.143	-0.545*	0.494**
	(0.496)	(0.218)	(0.327)	(0.247)
Observations	666	3,453	1,699	2,702

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions control treatment-control pair ID FE with standard errors clustered by pair ID. Use the booking sample for users whose 1sr VSR is posted on a property listing in a H, L, W, or M area, for regressions of (1), (2), (3), or (4), respectively.

Table 7: Reduced-form Guest-level Analysis: DID for VS users by the zip code of their VSR bookings

From the interaction term in Panel A of Table 7, it is apparent that VS users exhibit a positive effect on subsequent reservations in opposite type of zip codes (Columns 2 and 4) and a negative effect in the same type of zip codes (Columns 1 and 3). One explanation is that VS users expect a certain level of safety in the area of their booking, and when they encounter a negative shock, they prefer to avoid that type of area in subsequent stays.

One may argue that the tendency to avoid the same type of areas is driven by mean reversion rather than active learning. To address this, we repeat the exercise for the subsamples with First-Is-First=1 and First-Is-First=0 separately. Results are reported in Panels B and C of Table 7. Three of the four columns (Columns 2-4) are consistent with the argument that learning through self-experience is stronger when the VS user did not see any other VSR on the focal listing before her own VSR. The only exception is when the self VSR is in a high-income zip code (Column 1). In that case, both VS users of First-Is-First equal to 1 or 0 decrease their likelihood of booking future Airbnb stays in high-income zip codes (which is consistent with learning) but the coefficient on the DID interaction term is of a larger magnitude for those with First-Is-First = 0, though the difference is not statistically significant. Compared with other columns, this column has less statistical power because VSR are rarer in high-income zip codes. Overall, we conclude that the tendency to avoid the type of zip code that triggered VS users' own VSR is partly driven by learning from one's own VSR experience.

To push it further, we reorganize our DID sample into another eight subsamples depending on whether a VS user has previously had Airbnb stays in the same type of area that triggered her own VSR experience.

For example, if her own VSR experience was in a low-income (L) area, she may or may not have had Airbnb stays in low-income areas before. This gives us the subsamples of HL, LL, LH, and HH, where the second letter indicates the income type of the area that triggered the VS user's own VSR, and the first letter represents the income type area of her prior experience. Similarly, we can create the subsamples of WM, MM, MW, and WW depending on whether the area is primarily white or minority. All matched normal users belong to the same subsample as the VS users with whom they are paired.

Results are reported in Appendix Tables A5 and A6. In the raw data, we know VSR are more likely to occur in low-income and minority areas, but listings in these areas also account for over 60% of all Airbnb bookings; thus, the sample sizes of LH and LL are larger than those of HL and HH and the sample sizes of MW and MM are larger than those of WM and WW. If we focus on Column 1 of Table A5, the VS users in LH are the most 'surprised' (in terms of reducing future reservations on Airbnb) among the four L/H groups and the VS users in MW are the most surprised among the four M/W groups. This is intuitive because the VS users with at least one L or M stay before their own VSR experience in H or W may have high vicinity safety expectations in H or W and are consequently most disappointed when vicinity safety issues arise in those areas. In contrast, the VS users in HL or WM are not as surprised (Column 1), likely because they had a lower prior for vicinity safety in the L or M areas. Nevertheless, conditional on booking on Airbnb, they tend to book listings with fewer VSR following their own VSR. These patterns confirm the cross-listing-within-buyer effect of self-experience with vicinity safety.

6 Structural Estimation and Counterfactual Analysis

So far, reduced-form evidence supports all three information externalities of VSR: having any VSR on a listing may reduce the listing's price and occupancy, likely because VSR discourage future buyers from booking on that listing (a within-listing-across-buyer effect); VSR on nearby listings reduce bookings and price on the focal listing even if listing itself does not have any VSR (a cross-listing-cross-buyer effect), and a guest that wrote VSR tends to avoid other listings/vicinities with any VSR in future booking or avoid booking on Airbnb at all (a cross-listing-within-buyer effect).

However, it is difficult to use these reduced-form estimates to understand the implications of the externalities for hosts and platforms, because they do not address listing competition. In particular, listings with and without VSR may compete against each other on Airbnb, and all Airbnb listings compete with the prospect guest's outside options (including listings on competing short-term-rental platforms, hotels, bed and breakfasts, a friend's couch in the destination city, or no travel at all). To address this shortcoming, we resort to a structural model that describes how guests choose among competing short-term-rental listings.

6.1 Demand Model and Estimation

We define the market as online short-term entire-home rentals in each zip code-month, where Airbnb and VRBO — the two largest short-term-rental platforms in the US — are assumed to be the only two platforms that supply this market. Each guest chooses among all Airbnb entire-home listings available in the target zip code-month, with the pool of VRBO-only listings in the same zip code-month as the outside good.[36] We focus on entire-home listings because only entire-home listings are available on VRBO. Since our VRBO data period is from 2017/6 to 2019/12, our analysis in this subsection considers Airbnb entire-home listings from 2017/6 to 2019/12 only.

Following Berry (1994), we assume that each prospective guest chooses an Airbnb entire-home listing or the outside good (VRBO) so as to maximize her utility from the listing, where the utility associated with listing j in zip code z of city k and month t can be written as:

$$\begin{aligned} U_{j,t} &= EU_{j,t} + \epsilon_{j,t} \\ &= \alpha_j + \alpha_{k,t} + \delta \cdot X_{j,t} + \beta_0 \cdot log(ADR_{j,t}) + \beta_1 \cdot Crime_{z,t-1} \\ &+ \beta_2 \cdot LSR_{j,t-1} + \beta_3 \cdot VSR_{j,t-1} + \beta_4 \cdot VSRADIUS_{j,t-1} + \epsilon_{j,t}. \end{aligned} \tag{3}$$

If $\epsilon_{j,t}$ conforms to the logistic distribution, we can express the market share of listing j at time t as $s_{j,t} = \frac{exp(EU_{j,t})}{1+\sum_m exp(EU_{m,t})}$. Thus:

$$ln(s_{j,t}) - ln(s_{0,t}) = EU_{j,t} \tag{4}$$

This is equivalent to regressing the difference of log market share between listing j and the outside good ($ln(s_{j,t}) - ln(s_{0,t})$) on the attributes of listing j in month t.[37] The right-hand side of Equation 4 is similar to Equation 1 except for two changes: first, we exclude the number of Airbnb listings in the zip code-month because the discrete choice model already accounts for the size of the choice set; second, we include the log of the listing's ADR (price). To the extent that $log(ADR)$ might be endogenous, we instrument it by the average attributes of entire-home listings within a 0.3-mile radius of the focal listing in the same zip code-month, following Berry et al. (1995) . The underlying assumption is that these so-called "BLP" instruments are correlated with price because of horizontal competition (whereby competitors' attributes affect margins) but are excluded because they do not affect the focal listing's utility directly. As shown in the bottom of Table 8, the instruments are strongly correlated with $log(ADR)$, leading to a first stage F-statistics as high as 288.5.

The OLS and IV estimation results of the utility function are reported in the two columns of Table 8. They suggest that guest reservations are sensitive to price, and guests dislike listings with any VSR

[36]Listings that co-list on Airbnb and VRBO are treated as Airbnb listings, thus inside goods.

[37]Following Berry (1994), we attempted an alternative specification of nested logit, where all Airbnb listings in the market belong to one nest and the outside good VRBO belongs to another nest. This estimation (with and without instruments) produces a nesting parameter outside the theoretical range of $(0, 1)$, which leads us to conclude that the nested logit specification is no better than the simple logit in our setting.

	(1)	(2)
SAMPLE	Entire home	Entire home
MODEL	OLS	IV
VARIABLES	utility	utility
log_adr	-1.100***	
	(0.00903)	
log_adr_iv		-6.735***
		(1.609)
lag_VSR_cumu_dummy	-0.0914***	-0.147***
	(0.0121)	(0.0199)
lag_LSR_cumu_dummy	-0.101***	-0.204***
	(0.0107)	(0.0315)
lag_VS_ehlisting_radius_pct	-0.129**	-0.240***
	(0.0549)	(0.0634)
lag_log_crime_cumu_norm	0.249***	0.102
	(0.0932)	(0.105)
lag_log_review_utd	0.0220***	0.132***
	(0.00347)	(0.0317)
log_rating_overall	0.304***	0.373***
	(0.0279)	(0.0339)
superhost	0.0651***	0.159***
	(0.00424)	(0.0272)
cross_listing	0.0570***	0.0211
	(0.0144)	(0.0180)
strict_cp	-0.0405***	-0.0151*
	(0.00534)	(0.00905)
Observations	1,014,301	1,014,301
R-squared	0.800	0.789
First stage F statistics		288.5

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions control Time*City FE and Property ID FE, with standard errors clustered by Property ID. The 1st stage of regression uses the average attribute of entire home listings within a 0.3-mile radius area on Airbnb. The attributes include *review_utd*, *rating_overall*, *superhost*, *cross_listing*, and *strict_cp*. The 1st stage OLS regression controls Time*City FE and Property ID FE, with standard errors clustered by Property ID.

Table 8: Utility estimation

or LSR, everything else being equal. Based on the IV estimates, the guest's disutility from a listing with any VSR (as compared to no VSR) is equivalent to 2.2% of average daily rate ($164.7), namely $3.62.[38] And this disutility is comparable to the guest's disutility from observing any VSR in 61.25% of all listings within a 0.3 mile radius of the focal listing.[39] Consistent with our reduced-form results, these structural estimates confirm the existence of the "within-listing-cross-buyer" and "cross-listing-cross-buyer" effects of VSR.

Note that the coefficients of $VSR_{j,t-1}$ and $VSRADIUS_{j,t-1}$ capture how an *average* prospective guest in our sample *perceives* the vicinity safety around listing i at the time of choice. Because VSR only account for 0.25% of all guest reviews, the vast majority of the guests may have not experienced any vicinity safety issues on Airbnb (or have experienced but never reported it in a user review) before

[38] We derive it by $-0.147/(-6.735) \cdot \$164.7 = \$3.62$.

[39] We derive it by $-0.147/(-0.240) = 61.25\%$.

t. Indeed, if we rerun Equation 4 excluding the VS users identified in our reduced-form analysis, the estimated coefficients barely change. This means that estimates from Equation 4 can only yield reliable estimates for the within-listing-cross-buyer and cross-listing-cross-buyer effects, but not the cross-listing-within-buyer effect driven by VS users learning from their own VSR experience.

Such learning has already been captured in our reduced-form guest-level analysis; thus, a key question is how to incorporate the DID estimate into the structural framework. This is important not only because this extra "cross-listing-within-buyer" effect is in addition to the other two effects we can identify directly from the vast majority of Airbnb guests but also because self experience sheds light on the guest's *realized* utility when she stays in a listing with vicinity safety issues. Although such realized utility, as reported in guest reviews, has only occurred to a tiny fraction of Airbnb stays, a fully informed guest should expect the realized utility when she chooses where to stay. As documented by Jin and Sorensen (2006); Allcott (2011); Train (2015); Reimers and Waldfogel (2021), the difference between realized and perceived utility is essential for evaluating how consumer surplus changes under different information regimes.

In particular, Figure 4 illustrates the role of perceived and realized utility in consumer surplus. Consider two demand curves: the inner one represents demand for Airbnb listings under high alert of VSR while the outer one represents demand under less information about VSR. When prospective guests perceive the listings to be safer than they actually are, the market clears at a higher price and more bookings than in high alert (i.e. $P_{\text{less info}} > P_{\text{full info}}$ and $Q_{\text{less info}} > Q_{\text{full info}}$). Those who book under less information consist of two types of guests: some have a high willingness to pay and would have booked on Airbnb even if they know the high alert ex ante, their realized consumer surplus is area A; the others have a relative low willingness to pay and would not book on Airbnb should they know the listings are actually less safe than they appear, their realized consumer surplus turns out negative (area B). Hence the total realized consumer surplus is A-B under less information. In comparison, under high alert, the realized consumer surplus is A+C where C represents the extra consumer surplus that fully-informed guests could obtain via a lower equilibrium price.

There is another way to arrive at the same conclusion. Let us denote the white trapezoid between the two demand curves as area D. Under less information, the perceived consumer surplus is A+D while the realized consumer surplus is A-B; under full information, both the perceived and realized consumer surplus are A+C. Thus, the difference between the realized consumer surplus in full and less information, (A+C)-(A-B)=C+B, can also be written as the difference between their perceived consumer surplus plus an adjustment that reflects the shift of the demand curve for all consumers that would purchase under less information, namely (A+C)-(A+D)+(D+B)=C+B. We will use this alternative expression to compute consumer surplus changes in the counterfactual analysis.

As shown below, our counterfactual analysis assumes the listing choices made by VS users *after* they wrote VSR on Airbnb reflects their updated interpretation of VSR on all potential listings. Since this updated interpretation incorporates their true experience in the stay that triggered their VSR, we assume

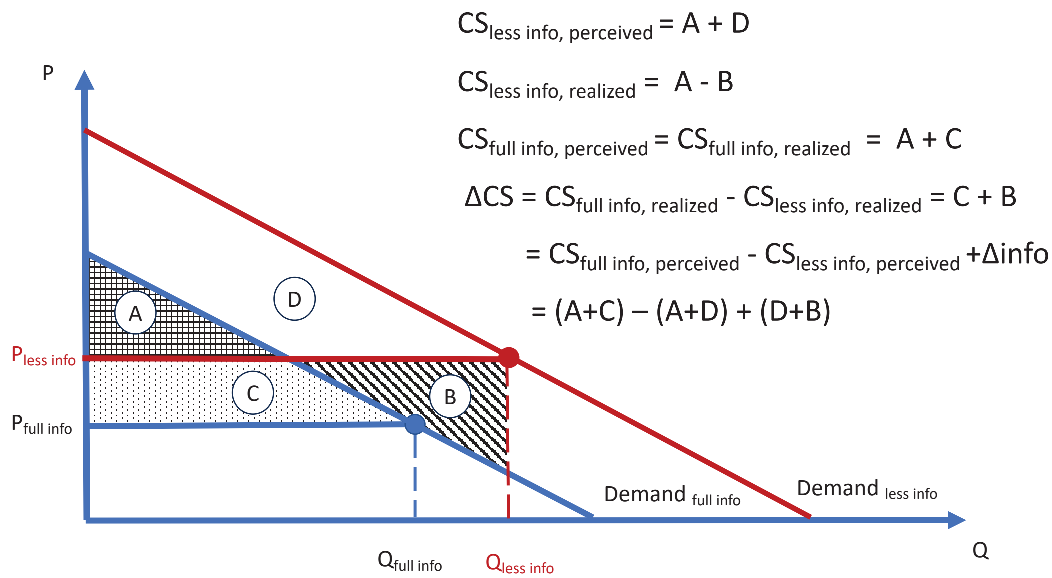

Figure 4: Consumer Surplus Under high alert of VSR (Realized) Or Less Information of VSR (Perceived)

it captures the realized utility from VSR. This means that VS users would have a new β_3 in the utility function upon their own VSR experience. Changes in their β_3 would capture the difference between perceived and realized utility driven by VSR.

We calibrate a new β_3 that would explain why the number of Airbnb bookings of VS users has dropped 60.07% post their own VS experience, according to our guest-level DID analysis (Table 6 Column 1). Following the procedure described in Appendix B, our calibration suggests that the VS users must have changed their β_3 by -2.17, which is more than 14 times of the estimated β_3 of the whole sample (-0.147). This suggests that the cross-listing-within-buyer effect of VSR – based on a guest's own VSR experience – is strong and would have an impact on booking decisions should all normal users interpret the VSR the same way as these VS users.

6.2 Counterfactual Analysis

We consider three counterfactual information regimes as compared to the status quo. The first counterfactual regime is "no disclosure", where all the VSR are removed in our data. Conceptually, this is equivalent to an extreme interpretation and implementation of Airbnb's 2019/12 policy on VSR. The other extreme regime is "high alert", where we assume all users react to VSR as much as VS users react to their own reported VSR.

Between the two extremes, we explore a third scenario that incorporates VSR so that each listing's overall rating is adjusted to account for the number of VSR of the listing itself as well as listings in a 0.3-

mile radius area ("VSR-adjusted ratings"). In particular, we compute a safety score for each observation by using the reversed percentile of the number of VSR of the listing itself and listings in a 0.3-mile radius area for each city-month, normalizing it on a range from 0 to 10 with a uniform distribution, and then adjusting the new overall rating as a weighted average of the overall rating and the safety score, where the overall rating has a weight of 6/7, to account for the 6 ratings originally included by Airbnb of communication, accuracy, cleanliness, check-in, location, and value. Admittedly, the uniform distribution assumption is ad hoc. Because the existing distribution of a listing's overall rating is skewed towards the high end, this adjustment pulls down the ratings of the listings with VSR for themselves or nearby. We choose to do so in order to highlight how the platform and platform users gain or lose when VSR-adjusted ratings not only highlight the relative difference between VS and normal listings on Airbnb but also undermine the overall vicinity safety perception of Airbnb listings relative to the outside good.

We now elaborate how we calculate consumer welfare under each scenario. For the status quo, we use the IV results in Column 2 of Table 8 to calculate $EU_{j,t}$ for each Airbnb listing-month, and then normalize it into US dollars. By definition, this is the guest's perceived utility. Following Small and Rosen (1981) and McFadden (2001), in a simple logit model as ours, a consumer's expected utility from her utility-maximizing choice depends on the inclusive value of the choice set (namely $ln(1+\sum_k exp(EU_{j,t}))$. As depicted in Figure 4, a consumer's perceived utility may guide her choice of listing ex ante, but her realized utility may deviate from her perceived utility. To measure the realized utility, we use the calibrated change of β_3 to update β_3 in the utility function (while taking everything else unchanged) and recompute the utility.

For the counterfactual of no-disclosure, we set all VSR as zero in the (perceived) utility function, recompute $EU_{i,t}$ for each Airbnb entire-home listing, and simulate its market share. This assumes everything else remains the same when the platform removes all VSR, which could be violated if listings adjust prices after the regime shift. Since the vast majority of our data precede Airbnb's new review policy and Airbnb seems far from fully implementing the policy, we cannot observe such price adjustments directly. The reduced-form regressions in Table 2 associate the presence of VSR in VS listings with a 1.48% difference in price. Hence in an alternative calculation, we assume the no-disclosure regime may enable a 1% price increase in VS listings while the price of normal listings remains unchanged. This gives us a comparison between no disclosure with price changes versus no disclosure without price changes.

The high alert counterfactual is equivalent to assuming the guests have full information and therefore their perceived utility is the same as the realized utility calculated above. As in the no disclosure regime, we first simulate the high alert regime without price changes and then introduce an ad-hoc price change (-1% for VS listings) to illustrate how price changes may alleviate the impact of making all users highly alert to VSR.

Under the counterfactual of VSR-adjusted ratings, we adjust each listing's overall rating to account for the number of VSR of the listing itself as well as listings in a 0.3-mile radius area. This calculation assumes the platform has one additional safety rating dimension in addition to the existing 6 rating dimensions (cleanliness, accuracy, check-in, communication, location, and value). Since we do not know how much prices would adjust with such a rating change, we assume an ad-hoc price change (-1% for VS listings) and simulate market shares with and without price changes under this counterfactual.

After we compute the perceived and realized utility under each scenario, we can quantify changes in consumer surplus from the status quo to any counterfactual. Defining each zip code-month (z, t) as a unique market, our analysis includes 9,440 markets in total. We further define market size Mz, t as the total reserved days for all listings in the market (z, t). Following Reimers and Waldfogel (2021) and Figure 4, the consumer surplus changes in a single market from the status quo to the high alert scenario can be computed as:

$$\begin{aligned}\Delta CS_{z,t} = \frac{M_{z,t}}{\beta_0}\cdot \Bigg[& ln(1+\sum_j exp(U_{jt,highalert})) - ln(1+\sum_j exp(U_{jt,perceived})) \\ & +\sum_j((U_{jt,perceived} - U_{jt,highalert})\cdot s_j)\Bigg].\end{aligned} \tag{5}$$

Similar calculations are performed for scenarios of VSR-Adjusted Ratings and No Disclosure.

Table 9 reports the consumer surplus results under different counterfactuals.[40] The first two rows refer to no disclosure with and without price changes; the next two rows refer to VSR-adjusted ratings with and without price changes; the last four rows refer to high alert with and without price changes and with and without a "radius effect," where the radius effect allows for the same updated distaste for VSR to apply to the VSR in nearby listings as well. To quantify the radius effect, we assume that the estimated coefficient of $VSRADIUS$ (β_4) would increase in the same proportion as the calibrated coefficient of VSR (β_3), should guests extrapolate the high alert of vicinity safety concerns to nearby VSR in the same way as a listing's own VSR. This extreme scenario is designed to illustrate the potential consequences in case prospective guests become sensitive to *any* VSR under high alert.

Table 9 indicates that, under high alert without price changes and without a radius effect, overall consumer surplus under high alert (without a radius effect) increases by roughly 3.218%, which is slightly less if we incorporate the hypothetical 1% price drop of VS listings (3.065%) and slightly higher if we allow a radius effect in high alert (4.144% and 3.988%), because high alert helps guests reduce their stays in relatively unsafe listings.

Consumer surplus under no disclosure declines as compared to the status quo (by 0.032% without price change and 0.013% with price changes) because consumers cannot use VSR to sort between listings. Consumer surplus under VSR-adjusted-rating increases slightly as compared to the status quo (by 0.004%

[40] The consumer surplus reported in Table 9 is for an average user in an average reservation day across all 9,940 zip code-months.

Δ Consumer Surplus (versus Status quo)	All Listings $	All Listings %
No Disclosure w/o P change	-2.2 K	-0.032%
No Disclosure w/ P change	-0.9 K	-0.013%
VSR-Adjusted Ratings w/o P change	0.3 K	0.004%
VSR-Adjusted Ratings w/ P change	0.6 K	0.008%
High Alert w/o P change & w/o radius effect	218.2 K	3.218%
High Alert w/ P change & w/o radius effect	207.8 K	3.065%
High Alert w/o P change & w/ radius effect	281.0 K	4.144%
High Alert w/ P change & w/ radius effect	270.4 K	3.988%

Table 9: Counterfactual Analysis: Simulated Changes in Consumer Surplus in the market

without price change and 0.008% with price changes), because the VSR-adjusted ratings shed light on VSR, though this change is milder than in the high alert counterfactual.

These estimated changes in consumer surplus are conservative, in part because our definition identifies only 0.25% of all Airbnb reviews as VSR, and only 4.43% of listings ever had any VSR in our 2015-2019 sample. Because of this, no disclosure only moves 0.74% of market share from VRBO and normal Airbnb listings to VS listings (before we take into account any price change), and the VSR-adjusted ratings only move 0.32% of market share away from VS listings. In comparison, the dramatic high alert counterfactual would move 5.05% of market share away from VS listings, leaving less than 1% of users choosing VS listings (with or without price change).

Table 10 reports GBV changes based on simulated market shares in each scenario. No disclosure generates 0.127% more GBV for entire home listings on Airbnb in our sample (assuming the price for VS listings increases by 1%). Conversely, VSR-adjusted ratings could decrease Airbnb's GBV by 0.224% (assuming the price for VS listing decreases by 1%). In both counterfacturals, the interests of Airbnb and consumers are misaligned: consumers would prefer more transparency through VSR-adjusted ratings but a GBV-centric Airbnb would prefer no disclosure.

Interestingly, the high alert regime could change Airbnb's entire-home GBV positively or negatively, ranging from +0.301% ($10.1 million) to -1.304% ($-44 million), depending on whether we allow the price of VS listings to drop by 1% in response and whether we assume the high alert also applies to the VSR for nearby listings through the radius effect. These overall effects are driven by an enormous redistribution of GBV from a 82.91-84.38% drop in VS listings to a 3.58-5.38% gain in normal listings and a 5.3-18.18% gain in VRBO listings. The overall impact on Airbnb GBV could be positive or negative because the within-platform sorting from VS to normal listings tends to have positive GBV effects for Airbnb but the cross-platform sorting from Airbnb to VRBO listings has negative effects for Airbnb. The radius effects under high alert strengthens the latter, and thus further hurts Airbnb's GBV. Similarly, VSR-adjusted ratings pull down the overall ratings of most Airbnb listings by construction. As a result, the cross-platform sorting generates a negative effect that exceeds the potential positive effect of within-platform sorting.

To explore the distributional effects of our counterfactual regimes, Table 11 breaks down the counterfactual GBV changes in Airbnb listings by the four types of zip codes. Since VS listings are more likely to locate in low-income and minority zip codes, no disclosure benefits Airbnb listings in these zip codes, at the cost of high-income and white zip codes.[41] In the counterfactual of VSR-adjusted ratings, Airbnb listings lose GBV in all four types of zip codes because the way we construct safety scores in the VSR-adjusted ratings brings down the overall ratings of most Airbnb listings, which motivates guests to switch away from Airbnb. This effect is even stronger for high-income and white zip codes than for low-income and minority zip codes, likely because price tends to be higher in high-income and white zip codes.

ΔGBV (versus Status quo)	Airbnb VS Listings %	Airbnb Normal Listings %	Airbnb Listings %	VRBO Listings %	All Listings %
No Disclosure w/o P change	12.360%	-0.696%	0.041%	-1.471%	-0.203%
No Disclosure w/ P change	7.745%	-0.329%	0.127%	-1.152%	-0.080%
VSR-Adjusted Ratings w/o P change	-0.682%	-0.110%	-0.142%	1.208%	0.076%
VSR-Adjusted Ratings w/ P change	3.669%	-0.457%	-0.224%	0.891%	-0.044%
High Alert w/o P change w/o radius effect	-84.382%	5.380%	0.312%	5.298%	1.116%
High Alert w/ P change w/o radius effect	-83.569%	5.320%	0.301%	5.222%	1.095%
High Alert w/o P change w/ radius effect	-83.721%	3.635%	-1.298%	18.183%	1.846%
High Alert w/ P change w/ radius effect	-82.913%	3.580%	-1.304%	18.062%	1.821%
Market Share					
Status quo	5.984%	83.069%	89.053%	10.947%	100%
No Disclosure w/o P change	6.723%	82.491%	89.214%	10.786%	100%
No Disclosure w/ P change	6.383%	82.796%	89.179%	10.821%	100%
VSR-Adjusted Ratings w/o P change	5.943%	82.978%	88.921%	11.079%	100%
VSR-Adjusted Ratings w/ P change	6.266%	82.690%	88.955%	11.045%	100%
High Alert w/o P change & w/o radius effect	0.935%	87.539%	88.473%	11.527%	100%
High Alert w/ P change & w/o radius effect	0.993%	87.488%	88.481%	11.519%	100%
High Alert w/o P change & w/ radius effect	0.974%	86.088%	87.063%	12.937%	100%
High Alert w/ P change & w/ radius effect	1.033%	86.043%	87.076%	12.924%	100%

Table 10: Counterfactual Analysis: Simulated Market Shares and Changes in GMV

In contrast, high alert generates strong sorting away from low-income and minority zip codes towards high-income and white zip codes. When the radius effect is allowed, the GBV of Airbnb listings in white zip codes also declines because some of the listings in these zip codes, even if they do not have VSR themselves, are susceptible to VSR in nearby listings.

Another effort to highlight the distributional effects of the counterfactual regimes is zooming into the 10 zip code-month markets that have the worst VSR in our data. In particular, for each city in the five sampled cities, we list all zip code-months that have at least 10 Airbnb listings, sort them by counts of VSR, and take the top two. Our final sample of 10 worst VSR markets consists of two months of zip

[41] If we allow 1% price change, white zip codes also enjoy a moderate increase of GBV because some VS listings are located in white zip codes.

ΔGBV (versus Status quo)	Airbnb Listings H	L	W	M
No Disclosure w/o P change	-0.240%	0.472%	-0.105%	0.381%
No Disclosure w/ P change	-0.047%	0.393%	0.037%	0.337%
VSR-Adjusted Ratings w/o P change	-0.130%	-0.161%	-0.136%	-0.157%
VSR-Adjusted Ratings w/ P change	-0.313%	-0.088%	-0.270%	-0.117%
High Alert w/o P change w/o radius effect	2.239%	-2.653%	1.315%	-2.029%
High Alert w/ P change w/o radius effect	2.209%	-2.636%	1.294%	-2.017%
High Alert w/o P change w/ radius effect	0.577%	-4.184%	-0.322%	-3.576%
High Alert w/ P change w/ radius effect	0.553%	-4.161%	-0.338%	-3.559%

Table 11: Counterfactual Analysis: Changes in GBV By Four Area Types

Δ Consumer Surplus (versus Status quo)	All Listings (Sampled) $	All Listings (Sampled) %
No Disclosure w/o P change	-13	-0.141%
No Disclosure w/ P change	-6	-0.062%
VSR-Adjusted Ratings w/o P change	1	0.008%
VSR-Adjusted Ratings w/ P change	2	0.021%
High Alert w/o P change & w/o radius effect	1173	12.836%
High Alert w/ P change & w/o radius effect	1116	12.210%
High Alert w/o P change & w/ radius effect	1832	20.047%
High Alert w/ P change & w/ radius effect	1772	19.390%

Table 12: Counterfactual Analysis: Simulated Consumer Surplus changes
(10 sample zip code months only)

codes 60624 (Chicago), 10454 (New York City), 90011 (Los Angeles), 70116 (New Orleans), and 30303 (Atlanta). All of them are located in low-income areas, with 80% of them in minority areas.

As shown in Table 13, no disclosure would increase the market share of VS listings in these markets from 37.81% to 41.41% (without price change), at the expense of normal and VRBO listings, resulting in a 0.141% decline in consumer surplus. Interestingly, the total Airbnb GBV also declines in these local markets despite an increase in the overall market share of Airbnb listings, because it encourages sorting from more expensive normal listings to less expensive VS listings. For the same reason, in the high alert counterfactual, the sorting goes the other way from VS listings to normal and VRBO listings, resulting in a 12.210%-20.047% gain of consumer surplus and a 8.72-20.21% gain of Airbnb GBV in these markets. Both extremes suggest that for the markets with the worst VSR, the financial interests of Airbnb could be aligned with consumers towards more transparency of VSR in the review system.

In comparison, as shown in Tables 12 and 13, the counterfactual of VSR-adjusted ratings demonstrates a misalignment between consumers and Airbnb. It generates slightly more consumer surplus (0.008-0.021%) but lowers Airbnb's total GBV from these local markets (-0.198% to -1.348%). The misalignment occurs because the VSR-adjusted ratings, as we construct them, pull down the average ratings of most Airbnb listings; as a result, the GBV loss from cross-platform sorting (from Airbnb to VRBO) dominates the potential GBV increase from the within-platform sorting between VS and normal listings. This

ΔGBV (versus Status quo)	Airbnb VS Listing (sample zip-month) %	Airbnb Normal Listing (sample zip-month) %	Airbnb Listing (sample zip-month) %	VRBO Listing (sample zip-month) %	All Listing (sample zip-month) %
No Disclosure w/o P change	9.523%	-5.488%	-1.989%	-8.223%	-3.207%
No Disclosure w/ P change	6.837%	-3.142%	-0.816%	-6.512%	-1.929%
VSR-Adjusted Ratings w/o P change	-0.405%	-0.135%	-0.198%	3.327%	0.491%
VSR-Adjusted Ratings w/ P change	2.268%	-2.447%	-1.348%	1.544%	-0.783%
High Alert w/o P change w/o radius effect	-79.532%	50.523%	20.212%	30.800%	22.281%
High Alert w/ P change w/o radius effect	-78.495%	49.716%	19.834%	30.402%	21.899%
High Alert w/o P change w/ radius effect	-81.209%	36.372%	8.967%	154.272%	37.359%
High Alert w/ P change w/ radius effect	-80.315%	35.777%	8.720%	153.045%	36.920%
Market Share					
Status quo	37.808%	55.336%	93.144%	6.856%	100%
No Disclosure w/o P change	41.409%	52.299%	93.708%	6.292%	100%
No Disclosure w/ P change	39.993%	53.598%	93.591%	6.409%	100%
VSR-Adjusted Ratings w/o P change	37.655%	55.261%	92.916%	7.084%	100%
VSR-Adjusted Ratings w/ P change	39.056%	53.982%	93.038%	6.962%	100%
High Alert w/o P change & w/o radius effect	7.739%	83.294%	91.032%	8.968%	100%
High Alert w/ P change & w/o radius effect	8.213%	82.847%	91.060%	8.940%	100%
High Alert w/o P change & w/ radius effect	7.105%	75.463%	82.567%	17.433%	100%
High Alert w/ P change & w/ radius effect	7.518%	75.134%	82.651%	17.349%	100%

Table 13: Counterfactual Analysis: Simulated Market Shares and GMV Changes (10 sample zip code months only)

misalignment is similar to what we have seen across all markets in the data (Tables 9 and 10).

7 Conclusion

Taking vicinity safety reviews as an example of critical feedback on Airbnb, we show that VSR not only have the classical effect of guiding future buyers towards listings without VSR, but they also generate spillovers for nearby listings and motivate guests that have written VSR to learn and update their understanding of VSR on other listings. As a result, they are less likely to book future stays on Airbnb, and when they do book, they tend to book listings without VSR and in areas with fewer official crime reports and fewer VSR.

Using a structural approach to account for listing competition on and off Airbnb, we show that expanding the disclosure of VSR may disproportionately affect hosts in low income and minority areas, and that a GBV-centric platform may prefer to limit the disclosure of VSR altogether, even though the aggregate surplus of guests appears to increase when the VSR are instead emphasized to alert prospective guests.

Combined, our findings highlight the economic incentives behind a platform's information policy regarding critical feedback. On the one hand, the platform's general booking value (GBV) may stand to decrease under the high alert of VSR if the alerted guests become sensitive to all VSR; and listings in low-income and minority zip codes may stand to lose a disproportionate share of revenues than their counterparts in high-income and white zip codes. On the other hand, consumer surplus under the high alert regime is higher than under the status quo and the no-disclosure regimes. The platform thus faces a tradeoff as far as generating higher revenues and attracting hosts in low-income and minority areas on the one hand, and providing additional value to its buyers on the other.

To the extent that being inclusive is one motivation behind Airbnb's new review policy, our findings suggest that the policy, if fully implemented, may have some unintended consequences on consumers and listings without VSR. How to balance the economic interests of all users is a challenge to platforms and policy makers that strive to maximize social welfare. One potential solution is that the platform may import external information about vicinity safety and present it as an alternative to VSR for each listing. Unfortunately, crime statistics (when available) may not fully capture all of the safety concerns a guest may have in mind at the time of booking. Another alternative is to incorporate VSR into the overall ratings of a listing (as in our "adjusted rating" counterfactual); our counterfactual analysis suggests that this moderate regime may have a small negative effect on Airbnb GBV while slightly boosting consumer surplus. The magnitudes of these predictions depend on how we normalize VSR and weigh them in the overall ratings. How to adjust ratings in line with the platform or the social planner's objective certainly merits future research.

There are a number of limitations to our analyses. First, guest reviews in our data do not include potential responses from hosts. Second, in the guest-level analysis, we only observe a guest's reservation provided that they have made any Airbnb reservations in the five major US cities we consider and posted a review on Airbnb. If VS users are more vocal and thus more likely to post subsequent reviews after their first VSR, then our findings underestimate the negative effects on their subsequent booking activity; if, however, VS users are less likely to post subsequent reviews, then our findings overestimate the effects. Third, we do not have listing reviews for VRBO listings nor do we have hotel booking data to explicitly consider hotels as an outside option in our utility estimation.[42] Fourth, our main analysis ends in 2019/12, the same month when Airbnb announced its new review policy. Because we do not know exactly how Airbnb implements its new policy,our counterfactual simulations are hypothetical.

These limitations suggest additional directions for future work. In particular, VRBO does not have a policy of discouraging reviews about the vicinity of listings, as Airbnb introduced in 2019/12. This may facilitate an interesting comparison between VRBO and Airbnb listings in the same locales, given a sample period that encompasses Airbnb's introduction of its new review policy. In addition, one welfare aspect that is difficult to quantify but may be relevant for Airbnb is the long-run entry and exit of users. As shown in our counterfactual analysis, a policy that encourages and highlights VSR could disproportionately hurt Airbnb hosts in relatively unsafe neighborhoods. In the long run, this could lead

[42] Hotels, in particular, may offer enhanced safety measures to their guests through security arrangements and by having door and security staff.

to a smaller choice set for guests, drive away some types of hosts and guests, and affect the economic parity across different neighborhoods.

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Online Appendix A: Supplemental Figures and Tables

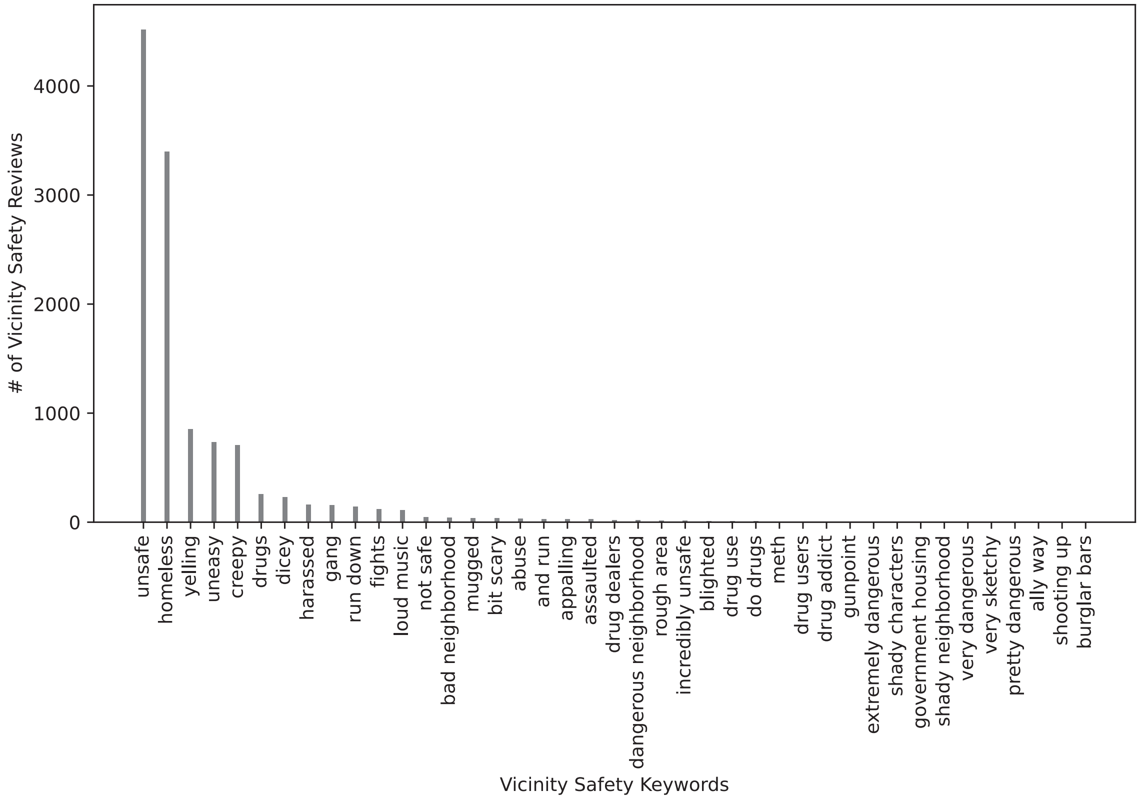

Figure A1: Distribution for keywords of vicinity safety review

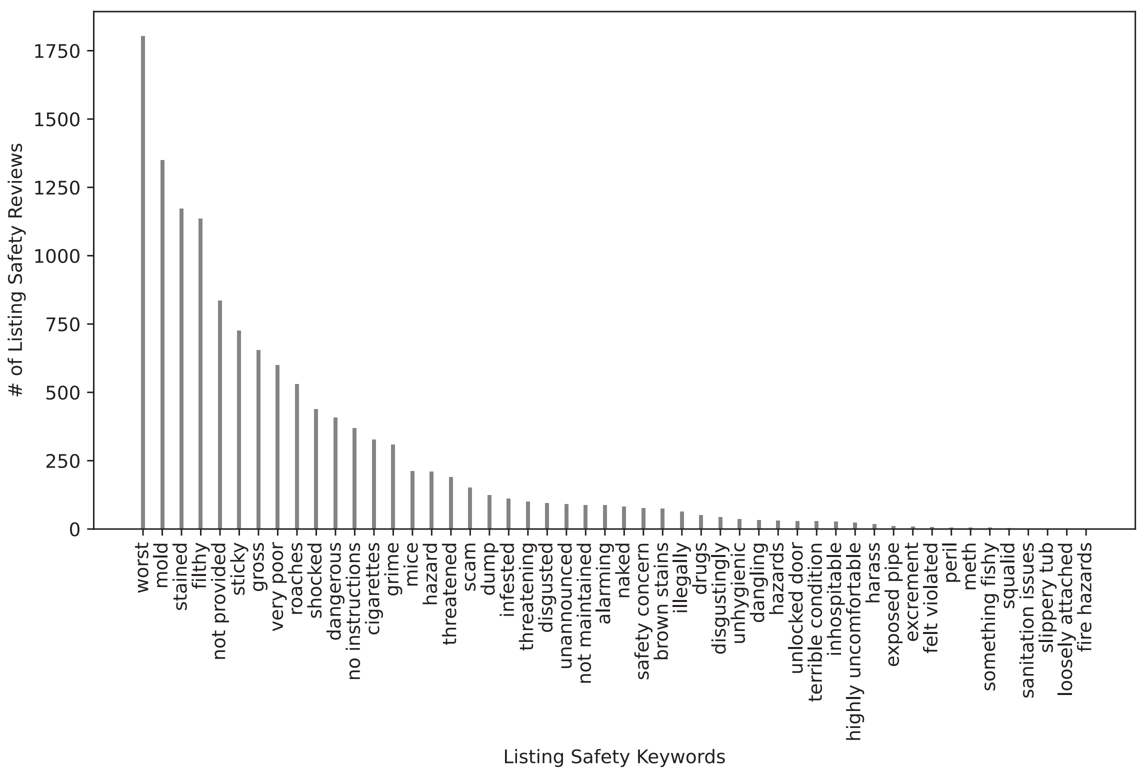

Figure A2: Distribution for keywords of listing safety review

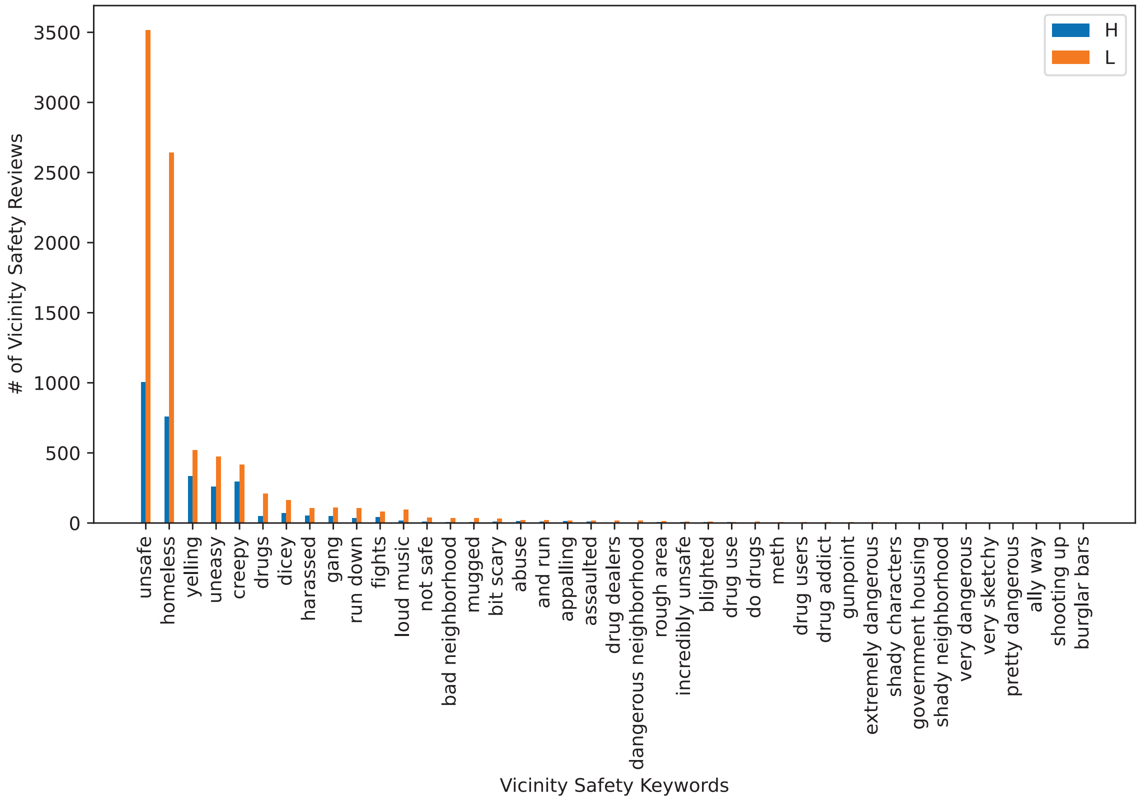

Figure A3: Distribution for keywords of vicinity safety review in H & L zip codes

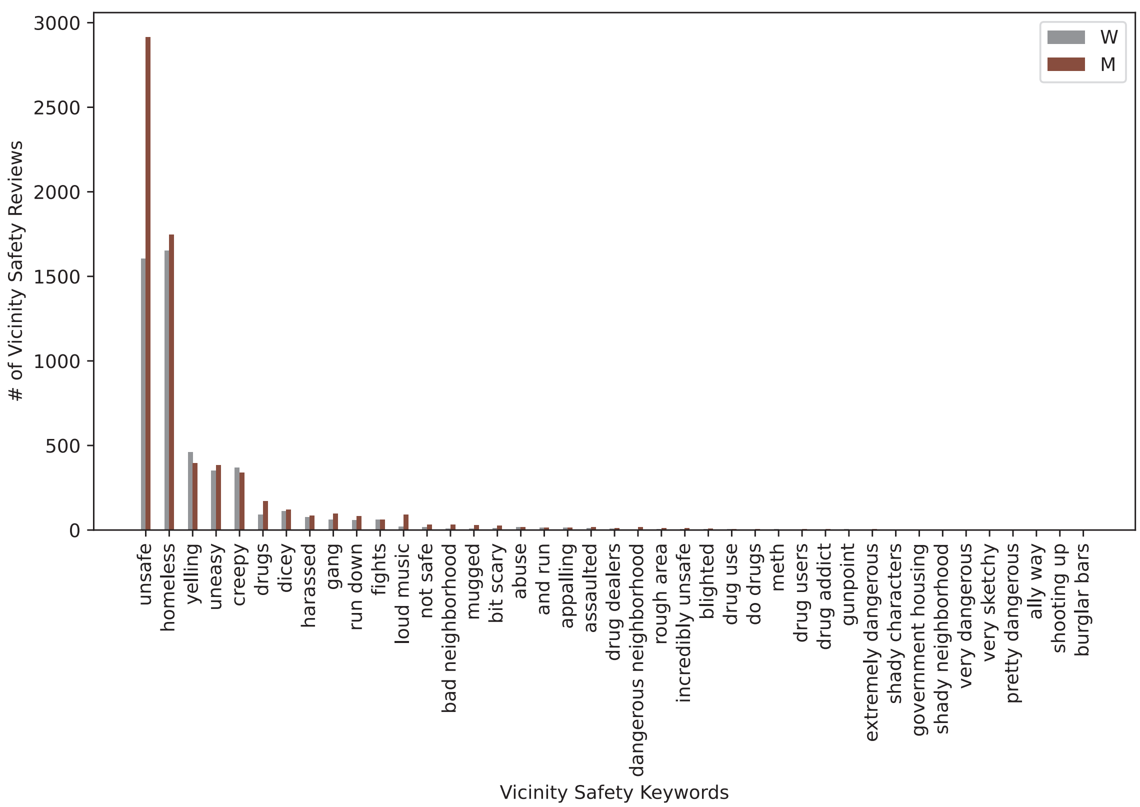

Figure A4: Distribution for keywords of vicinity safety review in W & M zip codes

Vicinity safety keywords:	‘abuse’, ‘ally way’, ‘and run’, ‘appalling’, ‘assaulted’, ‘bad neighborhood’, ‘bit scary’, ‘blighted’, ‘burglar bars’, ‘creepy’, ‘dangerous neighborhood’, ‘not safe’, ‘dicey’, ‘do drugs’, ‘drug addict’, ‘drug dealers’, ‘drug use’, ‘drug users’, ‘drugs’, ‘extremely dangerous’, ‘fights’, ‘gang’, ‘government housing’, ‘gunpoint’, ‘harassed’, ‘homeless’, ‘incredibly unsafe’, ‘loud music’, ‘meth’, ‘mugged’, ‘pretty dangerous’, ‘rough area’, ‘run down’, ‘shady characters’, ‘shady neighborhood’, ‘shooting up’, ‘tenement area’, ‘uneasy’, ‘unsafe’, ‘very sketchy’, ‘yelling’
Listing safety keywords:	‘alarming’, ‘threatening’, ‘brown stains’, ‘cigarettes’, ‘dangerous’, ‘dangling’, ‘peril’, ‘disgusted’, ‘disgustingly’, ‘drugs’, ‘dump’, ‘excrement’, ‘exposed pipe’, ‘felt violated’, ‘filthy’, ‘fire hazards’, ‘something fishy’, ‘very poor’, ‘mold’, ‘grime’, ‘not maintained’, ‘gross’, ‘harass’ ‘hazard’, ‘hazards’, ‘highly uncomfortable’, ‘safety concern’, ‘illegally’, ‘infested’, ‘inhospitable’, ‘loosely attached’, ‘meth’, ‘mice’, ‘naked’, ‘no instructions’, ‘not provided’, ‘scam’, ‘unhygienic’, ‘roaches’, ‘sanitation issues’, ‘shocked’, ‘slippery tub’, ‘squalid’, ‘stained’, ‘sticky’, ‘terrible condition’, ‘threatened’, ‘unannounced’, ‘unlocked door’, ‘worst’,
Vicinity location keywords:	‘neighborhood’, ‘area’, ‘feel’, ‘felt’, ‘night’, ‘location’, ‘walking’, ‘people’, ‘seemed’, ‘outside’, ‘looked’, ‘looks’, ‘late’, ‘surrounding’, ‘located’, ‘neighbourhood’, ‘walked’, ‘areas’, ‘feeling’, ‘streets’, ‘street’, ‘outside’, ‘parking’, ‘neighbors’
Negative keywords:	‘hardly’, ‘never’, ‘scarcely’, ‘seldom’, ‘barely’, ‘no’, ‘not’, ‘without’, ‘nothing’, ‘nobody’, ‘neither’, ‘nor’, ‘none’

Table A1: Vicinity and listing safety review keywords

VARIABLES	Explanation
occupancy_rate	Occupancy Rate = Count of Reservation Days / (Count of Reservation Days + Count of Available Days).
occupancy_rate_dummy	occupancy_rate_dummy = 1 of occupancy rate is greater than 0, otherwise equals to 0.
adr	Price per night in USD. ADR = Total Revenue / Booked Nights. Includes cleaning fees.
No._of_reservations	# of reservations in a property listing in a month.
No._of_reservationdays	# of days reserved in a property listing in a month.
lag_VSR_cumu_dummy	Lag of the VSR_dummy, which indicates whether a listing ever have any VSR before a reporting month.
lag_LSR_cumu_dummy	Lag of the LSR_dummy, which indicates whether a listing ever have any LSR before a reporting month.
lag_VSR_cumu	Lag of the VSR_cumu, which indicates the number of cumulative sum of VSRs before a reporting month.
lag_LSR_cumu	Lag of the VSR_cumu, which indicates the number of cumulative sum of VSRs before a reporting month.
lag_VS_listing_radius_pct	Lag of the percentage of listings that ever have any VSR in a 0.3 mile radius area before a reporting month.
safety_score	Calculated by using the reversed percentile of the number of VSR of the listing itself and listings in a 0.3-mile radius area for each city-month,normalizing it on a range from 0 to 10 with a uniform distribution.
ratingoverall	The overall rating score shown to the users. Normalized on a range from 0 to 10 with a uniform distribution.
ratingcommunication	The commucation rating score shown to the users. Normalized on a range from 0 to 10 with a uniform distribution.
ratingaccuracy	The accuracy rating score shown to the users. Normalized on a range from 0 to 10 with a uniform distribution.
ratingcleanliness	The cleanliness rating score shown to the users. Normalized on a range from 0 to 10 with a uniform distribution.
ratingcheckin	The check-in rating score shown to the users. Normalized on a range from 0 to 10 with a uniform distribution.
ratinglocation	The location rating score shown to the users. Normalized on a range from 0 to 10 with a uniform distribution.
ratingvalue	The value rating score shown to the users. Normalized on a range from 0 to 10 with a uniform distribution.
review_utd	# of reviews in a property listing until a reporting month.
No._of_listing_zip	# of listings in a zip code.
cross_listing	Dummy variable indicates whether the property listing is also listed on VRBO in a reporting month.
superhost	Dummy variable indicates whether the property listing is hosted by a superhost in a reporting month.
strict_cp	Dummy variable indicates whether the property listing has a strict cancellation positlity in a reporting month.
ave_wordcount_cumu_review	Average word counts for cumulative reviews in a reporting month.
median_income_zip	Median income for households in a zip code (using 2014 census data).
population_zip	# of population in a zip code (using 2014 census data).
white_pct_zip	Percentage of white population in a zip code (using 2014 census data).
h_zip	Dummy variable shows if the median income of a zip code exceeds the city's median income level.
w_zip	Dummy variable signifies if the white population percentage in a zip code surpasses the city's median white population percentage.
crime_cumu	# of cumulative crime until a reporting month in a zip code.
crime_cumu_norm	Normalized # of cumulative crime until a reporting month in a zip code by the population in the same zip code.
r_sentiL_cumu_ave	The average sentiment score is calculated for cumulative reviews up to a reporting month, using the Lexicon approach.
r_sentiN_cumu_ave	The average sentiment score is calculated for cumulative reviews up to a reporting month, using the NLP approach.

Table A2: Variable Definition

	Panel A: H			Panel B: L			Panel C: W			Panel D: M		
VARIABLES	mean	p50	N	mean	p50	N	mean	p50	N	mean	p50	N
occupancy_rate	0.56	0.64	1,484,474	0.57	0.65	1,381,764	0.56	0.64	1,716,774	0.57	0.65	1,149,464
occupancy_rate_dummy	0.84	1.00	1,484,474	0.86	1.00	1,381,764	0.85	1.00	1,716,774	0.85	1.00	1,149,464
adr	190.38	149.00	1,484,474	137.08	103.62	1,381,764	188.33	147.48	1,716,774	129.37	98.07	1,149,464
No._of_reservations	3.65	3.00	1,484,474	3.91	3.00	1,381,764	3.71	3.00	1,716,774	3.87	3.00	1,149,464
No._of_reservationdays	13.86	14.00	1,484,474	14.48	15.00	1,381,764	13.99	14.00	1,716,774	14.41	15.00	1,149,464
lag_VSR_cumu_dummy	0.02	0.00	1,484,474	0.07	0.00	1,381,764	0.03	0.00	1,716,774	0.06	0.00	1,149,464
lag_LSR_cumu_dummy	0.05	0.00	1,484,474	0.05	0.00	1,381,764	0.05	0.00	1,716,774	0.05	0.00	1,149,464
lag_VSR_cumu	0.03	0.00	1,484,474	0.09	0.00	1,381,764	0.04	0.00	1,716,774	0.08	0.00	1,149,464
lag_LSR_cumu	0.05	0.00	1,484,474	0.06	0.00	1,381,764	0.06	0.00	1,716,774	0.06	0.00	1,149,464
lag_VS_listing_radius_pct	0.05	0.02	1,484,474	0.09	0.05	1,381,764	0.05	0.03	1,716,774	0.09	0.05	1,149,464
safety_score	5.62	6.15	1,484,474	4.26	3.67	1,381,764	5.31	5.76	1,716,774	4.45	3.87	1,149,464
ratingoverall	9.23	9.60	1,484,474	9.13	9.50	1,381,764	9.23	9.60	1,716,774	9.11	9.50	1,149,464
ratingcommunication	9.57	10.00	1,484,474	9.52	10.00	1,381,764	9.57	10.00	1,716,774	9.52	10.00	1,149,464
ratingaccuracy	9.41	10.00	1,484,474	9.35	10.00	1,381,764	9.41	10.00	1,716,774	9.34	10.00	1,149,464
ratingcleanliness	9.21	10.00	1,484,474	9.11	10.00	1,381,764	9.21	10.00	1,716,774	9.09	10.00	1,149,464
ratingcheckin	9.55	10.00	1,484,474	9.51	10.00	1,381,764	9.55	10.00	1,716,774	9.50	10.00	1,149,464
ratinglocation	9.53	10.00	1,484,474	9.08	9.00	1,381,764	9.52	10.00	1,716,774	9.01	9.00	1,149,464
ratingvalue	9.22	10.00	1,484,474	9.17	10.00	1,381,764	9.22	10.00	1,716,774	9.16	10.00	1,149,464
review_utd	33.07	14.00	1,484,474	34.40	15.00	1,381,764	33.65	15.00	1,716,774	33.80	15.00	1,149,464
No._of_listing_zip	502.69	463.00	1,484,474	581.47	428.00	1,381,764	609.92	512.00	1,716,774	437.24	372.00	1,149,464
cross_listing	0.02	0.00	1,484,474	0.02	0.00	1,381,764	0.03	0.00	1,716,774	0.02	0.00	1,149,464
superhost	0.25	0.00	1,484,474	0.22	0.00	1,381,764	0.24	0.00	1,716,774	0.22	0.00	1,149,464
strict_cp	0.50	0.00	1,484,474	0.49	0.00	1,381,764	0.51	1.00	1,716,774	0.48	0.00	1,149,464
ave_wordcount_cumu_review	53.93	50.67	1,484,474	53.72	50.15	1,381,764	54.40	51.18	1,716,774	52.98	49.25	1,149,464
median_income_zip	75,865	71,278	1,484,474	37,121	35,112	1,381,764	69,745	68,346	1,716,774	38,432	37,116	1,149,464
population_zip	43,535	41,453	1,484,474	53,124	51,791	1,381,764	44,706	38,752	1,716,774	53,313	54,440	1,149,464
white_pct_zip	0.68	0.72	1,484,474	0.37	0.32	1,381,764	0.69	0.72	1,716,774	0.28	0.30	1,149,464
h_zip	1.00	1.00	1,484,474	0.00	0.00	1,381,764	0.78	1.00	1,716,774	0.13	0.00	1,149,464
w_zip	0.90	1.00	1,484,474	0.27	0.00	1,381,764	1.00	1.00	1,716,774	0.00	0.00	1,149,464
crime_cumu	14,737	7,735	1,484,474	24,483	12,205	1,381,764	20,925	8,347	1,716,774	17,211	11,637	1,149,464

Table A3: Summary Statistics of Airbnb Listings by Four Area Types

	Panel E: Entire Home			Panel F: Private Room			Panel G: Shared Room			Panel H: Hotel Room		
VARIABLES	mean	p50	N	mean	p50	N	mean	p50	N	mean	p50	N
occupancy_rate	0.58	0.67	1,745,432	0.55	0.63	1,016,553	0.44	0.41	94,722	0.46	0.43	9,531
occupancy_rate_dummy	0.87	1.00	1,745,432	0.83	1.00	1,016,553	0.77	1.00	94,722	0.87	1.00	9,531
adr	212.81	170.46	1,745,432	91.67	76.25	1,016,553	58.23	39.36	94,722	197.16	153.87	9,531
No._of_reservations	3.86	3.00	1,745,432	3.65	3.00	1,016,553	3.31	2.00	94,722	5.79	5.00	9,531
No._of_reservationdays	14.45	15.00	1,745,432	13.93	14.00	1,016,553	11.44	9.00	94,722	12.53	11.00	9,531
lag_VSR_cumu_dummy	0.05	0.00	1,745,432	0.04	0.00	1,016,553	0.04	0.00	94,722	0.06	0.00	9,531
lag_LSR_cumu_dummy	0.06	0.00	1,745,432	0.04	0.00	1,016,553	0.03	0.00	94,722	0.03	0.00	9,531
lag_VSR_cumu	0.06	0.00	1,745,432	0.06	0.00	1,016,553	0.06	0.00	94,722	0.11	0.00	9,531
lag_LSR_cumu	0.07	0.00	1,745,432	0.05	0.00	1,016,553	0.03	0.00	94,722	0.04	0.00	9,531
lag_VS_listing_radius_pct	0.06	0.03	1,745,432	0.07	0.04	1,016,553	0.08	0.05	94,722	0.06	0.04	9,531
safety_score	4.90	5.05	1,745,432	5.10	5.23	1,016,553	4.83	4.87	94,722	4.52	4.38	9,531
ratingoverall	9.26	9.60	1,745,432	9.09	9.50	1,016,553	8.74	9.30	94,722	9.03	9.40	9,531
ratingcommunication	9.61	10.00	1,745,432	9.48	10.00	1,016,553	9.18	10.00	94,722	9.38	10.00	9,531
ratingaccuracy	9.47	10.00	1,745,432	9.29	10.00	1,016,553	8.91	10.00	94,722	9.26	10.00	9,531
ratingcleanliness	9.27	10.00	1,745,432	9.02	10.00	1,016,553	8.64	9.00	94,722	9.24	10.00	9,531
ratingcheckin	9.59	10.00	1,745,432	9.47	10.00	1,016,553	9.16	10.00	94,722	9.47	10.00	9,531
ratinglocation	9.43	10.00	1,745,432	9.15	10.00	1,016,553	8.87	9.00	94,722	9.46	10.00	9,531
ratingvalue	9.25	10.00	1,745,432	9.14	10.00	1,016,553	8.86	9.00	94,722	9.01	9.00	9,531
review_utd	34.28	16.00	1,745,432	34.20	14.00	1,016,553	19.24	8.00	94,722	21.77	7.00	9,531
No._of_listing_zip	562.51	481.00	1,745,432	513.44	401.00	1,016,553	433.98	339.00	94,722	504.51	449.00	9,531
cross_listing	0.04	0.00	1,745,432	0.00	0.00	1,016,553	0.00	0.00	94,722	0.00	0.00	9,531
superhost	0.25	0.00	1,745,432	0.22	0.00	1,016,553	0.11	0.00	94,722	0.13	0.00	9,531
strict_cp	0.53	1.00	1,745,432	0.43	0.00	1,016,553	0.52	1.00	94,722	0.41	0.00	9,531
ave_wordcount_cumu_review	55.03	51.60	1,745,432	52.94	49.48	1,016,553	42.84	38.70	94,722	37.27	33.14	9,531
median_income_zip	59,726	54,023	1,745,432	53,568	47,050	1,016,553	48,929	40,873	94,722	60,291	56,337	9,531
population_zip	44,465	38,752	1,745,432	54,260	54,440	1,016,553	52,003	48,852	94,722	35,315	30,648	9,531
white_pct_zip	0.56	0.61	1,745,432	0.48	0.46	1,016,553	0.45	0.44	94,722	0.55	0.60	9,531
h_zip	0.59	1.00	1,745,432	0.41	0.00	1,016,553	0.37	0.00	94,722	0.59	1.00	9,531
w_zip	0.68	1.00	1,745,432	0.48	0.00	1,016,553	0.43	0.00	94,722	0.74	1.00	9,531
crime_cumu	22,154	9,569	1,745,432	15,269	9,806	1,016,553	13,058	9,260	94,722	29,232	13,756	9,531

Table A3: Summary Statistics of Airbnb Listings By Four Listing Types

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SAMPLE	EH	PR	SR	HR	EH	PR	SR	HR
MODEL	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
VARIABLES	log occupancy rate	log occupancy rate	log occupancy rate	log occupancy rate	log adr	log adr	log adr	log adr
lag_VSR_cumu_dummy	-0.0161***	-0.0210***	-0.0301***	-0.0372**	-0.0131***	-0.0171***	-0.0235*	-0.0164
	(0.00171)	(0.00249)	(0.00915)	(0.0181)	(0.00275)	(0.00376)	(0.0130)	(0.0408)
lag_LSR_cumu_dummy	-0.0236***	-0.0308***	-0.0289***	-0.0621**	-0.0201***	-0.00809**	-0.0102	0.0269
	(0.00158)	(0.00265)	(0.0108)	(0.0285)	(0.00248)	(0.00406)	(0.0168)	(0.0410)
lag_VS_listing_radius_pct	-0.0107***	-0.00419	-0.0282**	0.0154	-0.00485	-0.0115**	-0.0154	0.0310
	(0.00338)	(0.00396)	(0.0130)	(0.143)	(0.00540)	(0.00571)	(0.0277)	(0.205)
lag_log_crime_cumu_norm	0.0439***	0.120***	0.169***	-0.411**	-0.0694***	-0.00732	-0.302**	0.969***
	(0.00996)	(0.0153)	(0.0617)	(0.167)	(0.0156)	(0.0233)	(0.136)	(0.320)
Observations	1,745,432	1,016,553	94,722	9,531	1,745,432	1,016,553	94,722	9,531
R-squared	0.540	0.581	0.593	0.621	0.887	0.858	0.894	0.918

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions control Time*City FE and Property ID FE, with standard errors clustered by Property ID.

Table A4: Reduced-form Listing-level Analysis of Airbnb Listings By Four Listing Types

	(1)	(2)	(3)	(4)	(5)	(6)
MODEL	Poission	Poission	Logit	OLS	OLS	OLS
VARIABLES	reservation monthly	VSR_cumu	VSR_cumu dummy	crime_cumu norm	VS_listing pct zip	VS_listing pct radius
Sample	Monthly Reservation	Reserved Property	Reserved Property	Reserved Property	Reserved Property	Reserved Property
Subsample	1st VSR booking in H, at least 1 booking before 1st VSR in L					
VS_user × post	-1.215***	-0.796***	-0.598***	-0.945***	-0.0292***	-0.0378***
	(0.0990)	(0.247)	(0.227)	(0.200)	(0.00394)	(0.00604)
Observations	69,417	6,101	6,101	6,155	6,155	6,155
Subsample	1st VSR booking in L, at least 1 booking before 1st VSR in L					
VS_user × post	-0.806***	-0.618***	-0.421***	-0.926***	-0.0224***	-0.0175***
	(0.0740)	(0.162)	(0.135)	(0.134)	(0.00340)	(0.00675)
Observations	175,770	15,556	15,533	15,648	15,648	15,648
Subsample	1st VSR booking in L, all booking before 1st VSR in H					
VS_user × post	-0.730**	-1.445**	-1.105	-0.190	-0.00572	-0.0326
	(0.342)	(0.642)	(0.711)	(1.055)	(0.0216)	(0.0239)
Observations	6,612	462	462	462	462	462
Subsample	1st VSR booking in H, all booking before 1st VSR in H					
VS_user × post	-0.730	-1.474	-0.720	-1.949**	-0.0567***	-0.0717***
	(0.445)	(1.312)	(0.941)	(0.759)	(0.0164)	(0.0185)
Observations	2,135	146	141	146	146	146

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions control treatment-control pair ID FE with standard errors clustered by pair ID. The subsamples are defined by whether the VS users' 1st VSR post is in the L area and whether VS users have bookings in the L area before their 1st VSR post.

Table A5: Reduced-form Guest-level Analysis: DID for the VS Users whose 1st VSR booking and bookings before 1st VSR are in areas of H or L.

	(1)	(2)	(3)	(4)	(5)	(6)
MODEL	Poission	Poission	Logit	OLS	OLS	OLS
VARIABLES	reservation monthly	VSR_cumu	VSR_cumu dummy	crime_cumu norm	VS_listing pct zip	VS_listing pct radius
Sample	Monthly Reservation	Reserved Property	Reserved Property	Reserved Property	Reserved Property	Reserved Property
Subsample	1st VSR booking in W, at least 1 booking before 1st VSR in M					
VS_user × post	-1.012***	-0.877***	-0.727***	-1.502***	-0.0261***	-0.0337***
	(0.0911)	(0.211)	(0.191)	(0.185)	(0.00398)	(0.00596)
Observations	104,313	8,959	8,959	9,031	9,031	9,031
Subsample	1st VSR booking in M, at least 1 booking before 1st VSR in M					
VS_user × post	-0.869***	-0.546***	-0.306**	-0.550***	-0.0247***	-0.0176**
	(0.0814)	(0.175)	(0.146)	(0.135)	(0.00360)	(0.00759)
Observations	140,874	12,698	12,675	12,772	12,772	12,772
Subsample	1st VSR booking in M, all booking before 1st VSR in W					
VS_user × post	-0.595*	-1.774**	-1.298*	-0.664	-0.00956	-0.0406**
	(0.331)	(0.757)	(0.740)	(1.153)	(0.0212)	(0.0193)
Observations	5,656	383	383	383	383	383
Subsample	1st VSR booking in W, all booking before 1st VSR in W					
VS_user × post	-0.994**	-0.848	-0.454	-1.039**	-0.0353	-0.0433
	(0.433)	(1.110)	(0.829)	(0.430)	(0.0240)	(0.0373)
Observations	3,091	225	220	225	225	225

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions control treatment-control pair ID FE with standard errors clustered by pair ID. The subsamples are defined by whether the VS users' 1st VSR post is in the M area and whether VS users have bookings in the M area before their 1st VSR post.

Table A6: Reduced-form Guest-level Analysis: DID for the VS Users whose 1st VSR booking and bookings before 1st VSR are in areas of W or M.

Online Appendix B: Calibrate the cross-listing-with-buyer effect of VSR for the structural model

This appendix explains how we use the reduced-form DID results of VS users to calibrate the coefficient of having any VSR in the structural demand model.

According to Table 6 Column 1, the DID coefficient on treated $\times$ post is -0.918 in a Poisson regression of the number of Airbnb reservations, which is a 60.07% decrease for VS users relative to normal users. Given the average number of reservations per month for a single VS user in our sample is 0.1092 and review rate is 44.56%, a VS user's Airbnb reservations are $(0.1092 \times 60.07\%/0.4456 = 0.147$ fewer than a normal user after she has reported a VS issue in her first VSR. This can be expressed by:

$$\begin{aligned} &[\#Airbnbbooking_{VS\ user,aft} - \#Airbnbbooking_{VS\ user,bef}] \\ &-[\#Airbnbbooking_{NM\ user,aft} - \#Airbnbbooking_{NM\ user,bef}] = -0.147 \end{aligned} \tag{6}$$

Recall that we define an average guest's utility from listing j as:

$$\begin{aligned} U_{j,t} &= EU_{j,t} + \epsilon_{j,t} \\ &= \alpha_j + \alpha_{k,t} + \delta \cdot X_{j,t} + \beta_0 \cdot log(ADR_{j,t}) + \beta_1 \cdot Crime_{z,t-1} \\ &+ \beta_2 \cdot LSR_{j,t-1} + \beta_3 \cdot VSR_{j,t-1} + \beta_4 \cdot VSRADIUS_{j,t-1} + \epsilon_{j,t}. \end{aligned}$$

If we assume self experience of vicinity safety issues only changes β_3, we can write:

$$\beta_3 = \beta_{3,NM} + \Delta\beta_3 \cdot [i = \text{VS User}]$$

where $\beta_{3,NM}$ indicates normal users' sensitivity to observing any VSR in a listing, $[i = \text{VS User}]$ is a dummy equal to one for VS users, and thus $\beta_{3,NM} + \Delta\beta_3$ indicates VS users' updated sensitivity to VSR.

Assuming VS and normal users have the same tendency to book short-term rentals, the DID results can be rewritten as user i's market share for all Airbnb choices $\sum_{j\in Airbnb} s_{ij}$:

$$\left(\frac{\partial \sum_{j\in Airbnb} s_{ij}}{\partial VSR}\right)_{i=VS\ user} - \left(\frac{\partial \sum_{j\in Airbnb} s_{ij}}{\partial VSR}\right)_{i=NM\ user} = -0.147 \tag{7}$$

The market share of all Airbnb reservations is:

$$\sum_{j\in Airbnb} s_{ij} = 1 - s_{i,VRBO} = 1 - \frac{1}{1 + \sum_{j\in Airbnb} exp(U_{ij})} \tag{8}$$

Then:

$$\left(\frac{\partial \sum_{j\in Airbnb} s_{ij}}{\partial VSR}\right)_{i=NM\ user} = \beta_{3,NM} \cdot s_{NM\ user,VRBO} \cdot \sum_{j\in Airbnb\ \&\ VSR} s_{NM\ user,j} \tag{9}$$

$$\left(\frac{\partial \sum_{j\in Airbnb} s_{ij}}{\partial VSR}\right)_{i=VS\ user} = (\beta_{3,NM} + \Delta\beta_3) \cdot s_{VS\ user,VRBO} \cdot \sum_{j\in Airbnb\ \&\ VSR} s_{VS\ user,j} \tag{10}$$

Denote a user's total probability of choosing any Airbnb listings with any VSR as:

$$s_{NM\ user,Airbnb\ \&\ VSR} = \sum_{j\in Airbnb\ \&\ VSR} s_{NM\ user,j} \tag{11}$$

$$s_{VS\ user,Airbnb\ \&\ VSR} = \sum_{j \in Airbnb\ \&\ VSR} s_{VS\ user,j} \tag{12}$$

The DID results can be written as:

$$\begin{aligned}&(\beta_{3,NM} + \Delta\beta_3) \cdot s_{VS\ user,VRBO} \cdot s_{VS\ user,Airbnb\ \&\ VSR} \\ &-\beta_{3,NM} \cdot s_{NM\ user,VRBO} \cdot s_{NM\ user,Airbnb\ \&\ VSR} = -0.147\end{aligned} \tag{13}$$

Note that we observe normal users' market shares in the data because almost all users are normal users, but we do not observe VS users' market shares because we cannot track VS users in all Airbnb and $VRBO$ bookings. However, the utility framework spells out how these two types of users should differ. More specifically, the model implies:

$$\frac{s_{NM\ user,VRBO}}{s_{VS\ user,VRBO}} = s_{NM\ user,VRBO} + s_{NM\ user,Airbnb\ \&\ VSR=0} + exp(\Delta\beta_3) \cdot s_{NM\ user,Airbnb\ \&\ VSR} \cdot \tag{14}$$

This implies:

$$s_{VS\ user,VRBO} = \frac{s_{NM\ user,VRBO}}{s_{NM\ user,VRBO} + s_{NM\ user,Airbnb\ \&\ VSR=0} + exp(\Delta\beta_3) \cdot s_{NM\ user,Airbnb\ \&\ VSR}} \tag{15}$$

Similarly:

$$\begin{aligned}\frac{s_{NM\ user,Airbnb\ \&\ VSR}}{s_{VS\ user,Airbnb\ \&\ VSR}} = \ & exp(\Delta\beta_3) \cdot (s_{NM\ user,VRBO} + s_{NM\ user,Airbnb\ \&\ VSR=0} + exp(\Delta\beta_3) \\ & \cdot s_{NM\ user,Airbnb\ \&\ VSR})\end{aligned} \tag{16}$$

This implies:

$$\begin{aligned}s_{VS\ user,Airbnb\ \&\ VSR} = \ & \frac{1}{exp(\Delta\beta_3)} \\ & \cdot \frac{s_{NM\ user,Airbnb\ \&\ VSR}}{s_{NM\ user,VRBO} + s_{NM\ user,Airbnb\ \&\ VSR=0} + exp(\Delta\beta_3) \cdot s_{NM\ user,Airbnb\ \&\ VSR}}\end{aligned} \tag{17}$$

Plug these into the DID results:

$$\begin{aligned}&(\beta_{3,NM} + \Delta\beta_3) \cdot s_{VS\ user,VRBO} \cdot s_{VS\ user,Airbnb\ \&\ VSR} \\ &-\beta_{3,NM} \cdot s_{VS\ user,VRBO} \cdot s_{VS\ user,Airbnb\ \&\ VSR} = -0.147\end{aligned} \tag{18}$$

Because almost all users are normal users, the data gives us $s_{NM\ user,VRBO}$ (market share of $VRBO$), $s_{NM\ user,Airbnb\ \&\ VSR=0}$ (total market share of all normal Airbnb listings), as well as $s_{NM\ user,Airbnb\ \&\ VSR}$ (total market share of all Airbnb VS listings). We also know $\beta_{3,NM}$ from the utility regression. Thus, the only unknown in the above equation is $\Delta\beta_3$. We can readily solve for it and obtain $\Delta\beta_3 = -2.17$.