Competition and Reputation in a Congested Marketplace: Theory and Evidence from Airbnb*

Michelangelo Rossi†

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Abstract

I study how competition affects the role of reputation in encouraging sellers to exert effort. First, I model the reputation-building process in a frictional marketplace. Here, the relative number of buyers and sellers affects how the two sides of the market share the surplus from a match. With more competitors, sellers exert less effort since their share of transactions' surplus is lower. Then, I test this prediction by exploiting the introduction of a rental regulation on Airbnb. More competition significantly depresses ratings about effort. To address rating inflation and selection of guests, I provide an estimation of hosts' effort exploiting the relationship between different categories of ratings reported by the same guests. The negative impact of a 10 percent increase in the number of competitors is equivalent to the variation from the 80th to the 20th percentile of the estimated effort distribution.

Keywords: Reputation, Competition, Platform Design.

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†Télécom Paris, Institut Polytechnique de Paris, France. E-mail: michelangelo.rossi@telecom-paris.fr.

1 Introduction

Digital platforms rely on review systems to provide sellers with incentives to exert effort. Sellers exert effort to produce high-quality products, improve their reputation, and enjoy higher profits. However, the process of reputation building does not take place in a vacuum. Sellers compete with each other; the intensity of competition affects both profits and reputation building. This paper studies how changes in the number of competitors affect the role of reputation in providing incentives for sellers to exert effort. Higher competition may help to discipline sellers. Yet, having more competitors erodes reputational premia which may discourage sellers from exerting costly effort.

Understanding which of the two effects dominates empirically is a relevant question for the design of online marketplaces. Buyers benefit from having a larger pool of sellers to match and trade with. However, the efficiency of a large digital marketplace may be reduced if the number of competitors on their side affects sellers' incentives to exert effort and the quality of transactions for buyers.

In this paper, I study the impact of variations in the number of competitors on sellers' effort decisions using data from Airbnb. Previous works have shown that the entry of Airbnb hosts in a city expands the number of available rooms with a positive effect on consumers' welfare (Zervas, Proserpio and Byers, 2017; and Farronato and Fradkin, 2018). Still, having more competitors also impacts hosts' incentives to exert effort. I show that when the number of competitors increases, Airbnb hosts rent their dwellings for fewer nights, and they exert less effort.

Competition has proven to be beneficial for sellers' productivity in several settings. However, most of the recent empirical studies focused on relatively concentrated industries (Syverson, 2004), with fewer actors involved (Matsa, 2011), or protected by high tariffs (Schmitz Jr, 2005). Conversely, in a congested digital marketplace, entry costs are relatively small and the number of competitors is very high: as a result, the market power of each seller is low. However, the effect of a change in the number of competitors may depend on the overall market concentration. Aghion, Bloom, Blundell, Griffith and Howitt (2005) present empirical evidence in favor of an inverted-u shaped relationship between competition and innovation. Their study suggests that an increase in the number of competitors decreases sellers' investment after passing a certain threshold. Adding further evidence to these contributions, the empirical findings of my paper suggest that competitive forces can discipline markets' quality provision in concentrated industries, but their effects is damaging in very competitive environments such as digital platforms.

To shed light on the empirical analysis, I develop a model in which hosts exert effort to build their reputation in a congested marketplace. Hosts and guests match with frictions due to the hosts' capacity constraints: hosts have limited number of apartments for rent. Thus, the relative number of guests and hosts on the two sides of the market (the market tightness) impacts the value of reputation that results from hosts' effort. In highly competitive settings, guests can extract all transactions' surplus, and hosts' profits tend to zero, irrespective of their reputations. With more guests for each host, a larger share of the surplus goes to hosts. Yet, the expected surplus from a transaction depends on hosts' reputation: those with a positive reputation have more to gain from a reduction in competition since the surplus size and their share are larger. Accordingly, the premium for exerting effort decreases with more competitors, and hosts exert less effort when the number of competitors increases.

To test the model's prediction, I analyze the relationship between the effort exerted by Airbnb hosts and the number of their competitors. I measure hosts' effort by studying ratings' categories such as *communication* and *check-in* that are specifically related to hosts' actions. To measure the number of competitors, I create host-specific consideration sets by counting the number of listings surrounding each host within a radius of 0.5, 1, and 2 kilometers. Doing so, I assume that Airbnb hosts compete more strongly with listings closely located to them, relative to those further away.[1]

The identification strategy exploits a unique quasi-experiment to isolate the effect of changes in the number of competitors from other confounders. In particular, I take advantage of a regulatory enforcement on short-term rentals that occurred in San Francisco in 2017.

In 2015, the San Francisco City Council imposed several restrictions and a formal registration for short-term rentals on digital platforms.[2] Yet, the regulation was effectively enforced only two years later, when Airbnb signed a settlement agreement with the City Council in May 2017. The platform has been actively engaged in the listings' registration process since September 2017. The percentage of Airbnb listings offering short-term lodging registered at the City Council Office increased from less than 15 percent in September 2017 to 100 percent in February 2018: hosts started to register, and those who could not, exited the platform. As a result, the number of short-term listings halved, dropping from 8,000 units in September 2017 to 4,000 in February 2018.

I exploit this regulatory enforcement as an exogenous shift in the number of listings surrounding each host. I focus on hosts renting short-term who are present on the platform before and after the settlement. By such selection, I abstract from hosts' decision to enter or exit due to the regulation's enforcement. All hosts renting short-term in San Francisco are affected by the settlement agreement. On the other hand, the exposure to this "shock" differs: the variation in the number of competitors is heterogeneous across hosts. I take advantage of this heterogeneity in the treatment. To measure each host's exposure, I use the percentage of listings surrounding each host that were not yet registered in September 2017. More listings are likely to exit after the settlement for higher values of this percentage since few already complied with the regulation. I employ this measure as a predictor for the variation in the number of listings surrounding each host after the regulation's enforcement. Thus, I identify the effect of variations in the number of competitors by using the differential changes

[1]This is in line with Zervas et al. (2017), who show that the impact of Airbnb entry on hotels' revenues is sensitive to the distance between hotels and Airbnb listings.

[2]Rentals are considered "short-term" if the properties are rented for less than 30 consecutive nights at a time.

in the exposure across listings over time. The core identifying assumption shares the intuition of a difference-in-differences estimator. Yet, the identification is based on an instrumental variable regression where the instrument is given by the interaction between the measure of exposure and time.

The results show a statistically significant negative impact of the number of competitors on ratings about hosts' effort. However, ratings' distributions are extremely concentrated, and the economic significance of this effect is hard to measure by looking at ratings. I exploit the relationship between ratings' categories reported by the same guests to account for the concentration of Airbnb ratings towards the highest grade. Two categories relate to hosts' efforts (*communication* and *check-in*), whereas one other does not (*location*). With a control function approach, I estimate the host's effort exerted in a rated transaction removing the unobserved guests' components (such as generosity or attitude) present in the ratings. Once I use the estimated hosts' effort measure, the effect of competition on hosts' effort becomes economically significant: the negative impact of a 10 percent increase in the number of competitors is equivalent to the variation from the 80th to the 20th percentile of the effort distribution. I extend this result by studying variations in the number of nights rented by hosts and I find that, with more competition, hosts rent fewer nights.

This paper contributes to the research on platform design, directed search, and reputation. It shows a novel relationship between transactions' quantity and quality in a context with frictions where sellers care about their reputation. Having more hosts to be matched with is beneficial for guests as in the classical two-sided market literature (Caillaud and Jullien, 2003, Rochet and Tirole, 2003, and Rochet and Tirole, 2006). Yet, platform's entry fees affect not only users' participation but also quality decisions. The change in tightness influences hosts' incentives to exert effort, negatively affecting the quality of transactions. The frictional matching between hosts and guests provides a micro-foundation for the cross-network externalities between the platform's sides. Modeling guests and hosts' matching using directed search captures several features of congested markets. Horton (2019), and Fradkin (2019) document congestion externalities in matching platforms. Cullen and Farronato (2020) empirically show how buyers and sellers react to fluctuations on the other side, proposing a directed search conceptual framework. I complement this literature by embedding reputation concerns in a directed search setting, and I show how the market tightness affects hosts' effort.

Several models in the directed search literature present settings with asymmetry of information in terms of private information (Faig and Jerez, 2005, Guerrieri, 2008), screening (Guerrieri, Shimer and Wright, 2010), signaling (Delacroix and Shi, 2013), and moral hazard (Guerrieri and Kondor, 2012). The work by Vellodi (2020) proposes a reputation model with learning and search where sellers are unaware of their quality. He studies how the process of reputation building affects competition creating entry barriers for those sellers with no reviews. With my paper, I turn this research question around, showing that competition forces affect reputation concerns. I propose a reputation model with hidden information and hidden action in line with Kreps, Milgrom, Roberts and Wilson (1982), Kreps and Wilson (1982), and Milgrom and Roberts (1982), where strategic sellers exert effort to imitate the "Stackelberg" types that always produce high quality. I consider an infinitely repeated environment with overlapping sellers' generations similar to Cremer (1986), Tadelis (1999), Tirole (1996), and Bar-Isaac (2007). These models do not investigate the relationship between competition and the incentives to exert effort.[3] I am aware of only two papers that explicitly analyze how variations in the extent of competition affect sellers' incentives. Kranton (2003) studies the decisions to provide high or low quality goods by a finite number of firms competing in a repeated game. After a firm produces low quality, its future profits are null, independently of the competition. Accordingly, an increase in the number of competitors only reduces the benefits of having a good reputation resulting in lower incentives to exert effort. Bar-Isaac (2005) allows firms' profits to depend on the number of competitors after a firm produces low quality. As a result, the effects of competition on effort are ambiguous. With a higher degree of competition, profits with bad reputation are lower (competition disciplines agents). At the same time, profits with good reputation are also lower (competition erodes reputational premia). The matching frictions between guests and hosts solve this ambiguity: with fewer competitors, sellers extract a higher share of the surplus. Yet, hosts' reputation positively affects the expected surplus, and hosts have higher reputation incentives to increase their share size.

A negative relationship between the competition and managerial incentives has already been discussed in theoretical papers with limited empirical support. Schmidt (1997) shows that manager's incentives are higher in a duopoly vis-à-vis a monopoly. However, when the number of competitors increases even further, incentives are lower since more competition reduces the gain from exerting effort. In line with this result, the model in this paper focuses on three salient characteristics of online platforms: a large marketplace with no market power on the sellers' side, reputation incentives driving investment, and the presence of frictional matching between two sides of the market.

Finally, this paper contributes to the empirical literature on online reputation and consumers' voice. To the best of my knowledge, no empirical studies investigate the relationship between competition and the reputation incentives to exert effort. Gutt, Herrmann and Rahman (2019) show that changes in the number of competitors affect rating distributions. Studying an online platform for restaurants, they document that more competition leads to a decrease in the average ratings. Elfenbein, Fisman and McManus (2015) study the effect of quality certification on the probability of making a sale on eBay. They show that certification's positive effect is higher in more competitive settings and when certification is scarce. This result is in line with a negative relationship between the number of competitors and sellers' effort. With more competition, fewer sellers exert effort. Thus, good reputation is more scarce, and its signaling power is higher. Finally, Gans, Goldfarb and Lederman (2021) investigate consumers online voice studying tweets about airlines via Twitter. In a context with potential loyal clients, they observe that firms are more likely to respond to voice in concentrated mar-

[3] For a comprehensive review of the theoretical literature about reputation, see Bar-Isaac and Tadelis (2008).

kets where customers are costlier to lose for airlines. The online setting I use to address my question (Airbnb) presents methodological advantages relative to previous works. Thanks to the multiple components of the Airbnb review system, I can use ratings about *communication* and *check-in* as a proxy for hosts' effort. Moreover, by using information about each Airbnb host's geographical location, I exploit the heterogeneous impact of the regulation for causal identification.

The paper is organized as follows. Section 2 describes the model and the testable predictions. In Section 3, I provide some background context about Airbnb and the institutional setting of short-term regulation in San Francisco. Next, I present the dataset, and I discuss my identification design in Section 4. Section 5 provides the main empirical findings. In Section 6, I illustrate a novel technique to estimate hosts' effort, and I show further results. I proceed with the robustness checks in Section 7. Section 8 concludes. All proofs, additional figures, and tables are in Appendix.

2 The Model

In this Section, I present the theoretical framework underlying my analysis. The model illustrates the incentives by sellers (in this case, Airbnb hosts) to build a reputation in a context with frictional matching. To do so, I build an overlapping-generations (OLG) model where 1) hosts stay on the platform for two periods; 2) the matching process between hosts and guests is frictional, and 3) reputation is the only source of hosts' heterogeneity.

In each period hosts and guests match with some probability. In case of a match, hosts decide to exert effort and build a reputation for the next stage. Two generations of hosts trade on the platform at the same time. Hosts with an established (good or bad) reputation compete with new entrants. On Airbnb, hosts differ in multiple dimensions apart from their reputation, and guests are likely to value other specifics such as the listings' location. By contrast, here hosts differ only over their reviews about past effort choices. Thus, this model describes a situation in which the interested guests have already narrowed down their search on those listings with certain characteristics, such as the same neighborhood. At this point, the listings in their consideration sets are homogeneous – they are *close* substitutes – and the only relevant differences regard hosts' reputation. This feature of the model is particularly related to the empirical design I propose in Section 4 where I exploit variations in the number of competitors located within 0.5, 1, and 2 kilometers of each host. Finally, a measure of hosts and guests populates the market, and hosts have no market power. Thus, this model provides a limit result that applies to settings (such as digital platforms) where changes in the number of competitors do not influence sellers' power to influence equilibrium prices.

The Section proceeds as follows. First, I describe the model environment. Then, I define the equilibrium and I characterize the equilibrium hosts' strategies. I prove that an equilibrium exists and it is unique, and I conclude with the main predictions of the model. All proofs are in Appendix A.

2.1 Environment

Hosts and guests populate the two sides of the market. Each guest is willing to rent a house, whereas each host owns a house and can rent it to a single guest. All agents are risk neutral.

In each period a unit mass of identical guests is present in the market and an infinite population of ex-ante symmetric hosts can potentially enter the market. Hosts who enter stay for two periods and then exit the market. I denote with subscript 1, variables regarding hosts who just entered the market (*junior* hosts); and with subscript 2, variables regarding hosts who entered in the previous period (*senior* hosts). In both periods, in case of a match with a guest, hosts decide whether to exert effort: $e = \{0,1\}$. Hosts' cost of effort, c, is random and it is realized if a host is matched with a guest. This realization is permanent across periods. The cost can take two values: $c = \{0,k\}$ with $k > 0$. Hosts draw $c = 0$ with probability π. The realized cost is hosts' private information, but the probability π is common knowledge. I assume that hosts always exert effort if they draw $c = 0$.[4]

To enter the market, hosts pay entry costs, f. At the beginning of each period, a review r is formed for each host and it is public information. Junior hosts have blank reviews: $r_1 = r_1^{\emptyset}$. In case of a match in the previous period, a senior host's review is $r_2 = r_2^+$ if the host exerted effort, and $r_2 = r_2^-$ if the host did not.[5] If the senior host did not match, the review shows that the host had no guests: $r_2 = r_2^{\emptyset}$. Then, each host posts price $p \in \mathbb{R}_+$. The couple of price and review (p,r) forms the host's offer. A measure $g(p,r)$ of guests directs the search to offer (p,r) and matches randomly. In the event of a match, each host draws the cost if not matched before, and chooses effort.

The matching process between hosts and guests is frictional. Market frictions are captured by a matching function M. With a measure h of hosts posting an offer and a measure g of guests directing to this offer, a measure $M(h,g) \leq \min(h,g)$ of matches is formed. Assuming constant returns to scale in the matching technology, the probability of a match is a function of the ratio between guests and hosts, denoted as the tightness: $\theta = \frac{g}{h}$. Hosts' probability of a match with tightness θ is $\alpha(\theta) \equiv \frac{M(h,g)}{h}$; whereas guests' probability is $\frac{\alpha(\theta)}{\theta} \equiv \frac{M(h,g)}{g}$. As it is standard, I assume that, for all $\theta \in [0,\infty)$: $\alpha(\theta) \in [0,1]$ and $\frac{\alpha(\theta)}{\theta} \in [0,1]$; $\alpha(\theta)$ is continuous, strictly increasing, twice differentiable, and strictly concave; $\alpha(\theta) - \theta\alpha'(\theta) > 0$; $\alpha(\infty) = \alpha'(0) = 1$ and $\alpha(0) = \lim_{\theta\to\infty} \theta\alpha'(\theta) = 0$.[6]

Hosts' profit from a transaction is $p - ce$. Guests' gross utility from a transaction, u, depends on host's effort and price: $u = ae + b - p$, with $a,b \geq 0$. To guarantee the efficiency of exerting effort, $a - k > 0$. Before the cost of effort is realized, hosts' expected profit is $\Pi = (p - k(1-\pi)e)\alpha(\theta)$. The

[4]This is equivalent to assume two types of hosts: strategic, choosing effort each period; and non-strategic ("Stackelberg" types), who always exert effort.

[5]Here hosts always receive a review and it perfectly represents the effort exerted. Imperfect monitoring cases where hosts may not exert effort and obtain a positive review do not change the model's predictions.

[6]The conditions are satisfied by urn-ball matching functions $\alpha(\theta) = \theta(1 - e^{-1/\theta})$ (as in Burdett, Shi and Wright, 2001), or Dagum (1975) functions such as the telephone matching $\alpha(\theta) = (\theta^{-\rho} + 1)^{-1/\rho}$ with $\rho > 0$ (as in Burdett, Coles, Kiyotaki and Wright, 1995).

expected utility for guests depends on their beliefs regarding host's effort μ: $U = (a\mu + b - p)\frac{\alpha(\theta)}{\theta}$.

2.2 Equilibria with Informative Reviews

In this setting, hosts post offers and guests direct their search toward the most attractive offers. Accordingly, guests' expected utility U is an equilibrium object, taken as given by agents.[7] When a positive mass of guests search toward an offer (p,r), their expected utility has to equal the equilibrium level U^E; whereas, for all offers that do not attract any guests, guests' expected utility is lower than U^E. This is true for all offers (posted or not in equilibrium), and it is a restriction on guests' beliefs regarding the tightness levels for all possible offers.[8] The equilibrium concept is symmetric perfect Bayesian equilibrium with hosts' pure strategies in prices. Observing hosts' offers, guests direct their search and form beliefs $\mu(p,r) \in [0,1]$ about hosts' effort decision in the current period. I restrict my analysis over a class of equilibria in which reviews are the only informative signals about hosts' effort such that $\mu(p,r) = \mu(r)$. I denote these equilibria as *equilibria with informative reviews*.[9]

Definition 1. *An equilibrium with informative reviews is a set of hosts' offers and probability to exert effort for juniors and seniors, $\mathscr{O}_1^E$, $\mathscr{O}_2^E$ together with a tightness function $\theta^E : \mathbb{R}_+ \times \{r_1^\emptyset, r_2^+, r_2^-, r_2^\emptyset\} \mapsto \mathbb{R}_+ \cup \infty$, a belief function $\mu^E : \{r_1^\emptyset, r_2^+, r_2^-, r_2^\emptyset\} \mapsto [0,1]$, and a utility level, $U^E \in \mathbb{R}_+$:*

1. *Hosts choose p and e to maximize profits;*

2. *The free entry condition for junior hosts is satisfied. For all offers and effort probabilities, $(p_1^\emptyset, r_1^\emptyset, \omega_1^\emptyset)$, $(p_2^+, r_2^+, \omega_2^+)$, $(p_2^-, r_2^-, \omega_2^-)$, and $(p_2^\emptyset, r_2^\emptyset, \omega_2^\emptyset)$,*

$$\begin{aligned}
&(p_1^\emptyset - k(1-\pi)\omega_1^\emptyset)\alpha(\theta^E(p_1^\emptyset, r_1^\emptyset)) + \beta(1-\alpha(\theta^E(p_1^\emptyset, r_1^\emptyset)))(p_2^\emptyset - k(1-\pi)\omega_2^\emptyset)\alpha(\theta^E(p_2^\emptyset, r_2^\emptyset)) \\
&\qquad + (1-\pi)(1-\omega_1^\emptyset)\beta\alpha(\theta^E(p_1^\emptyset, r_1^\emptyset))(p_2^- - k\omega_2^-)\alpha(\theta^E(p_2^-, r_2^-)) \\
&\qquad + (\pi + (1-\pi)\omega_1^\emptyset)\beta\alpha(\theta^E(p_1^\emptyset, r_1^\emptyset))(p_2^+ - k\frac{(1-\pi)\omega_1^\emptyset}{(1-\pi)\omega_1^\emptyset + \pi}\omega_2^+)\alpha(\theta^E(p_2^+, r_2^+)) - f \leq 0,
\end{aligned} \tag{2.1}$$

holding with equality if $(p_1^\emptyset, r_1^\emptyset, \omega_1^\emptyset) \in \mathscr{O}_1^E$, $\{(p_2^+, r_2^+, \omega_2^+), (p_2^-, r_2^-, \omega_2^-), (p_2^\emptyset, r_2^\emptyset, \omega_2^\emptyset)\} \in \mathscr{O}_2^E$;

[7] This is known as the "market utility" approach based on Peters (1991) and Peters et al. (2000), and commonly used in the directed search literature (Montgomery, 1991; Shimer, 1996; and Moen, 1997).

[8] Similar restrictions are present in directed search models with perfect (Acemoglu and Shimer, 1999; and Shi, 2009), and imperfect (Menzio, 2007; and Guerrieri et al., 2010, and Delacroix and Shi, 2013) information.

[9] In Appendix A, I discuss the assumption of the uninformative role of prices on guests' beliefs about hosts' effort. I show that limiting the signal to reviews is equivalent (in terms of equilibrium allocation) to restricting guests' beliefs (on and off the equilibrium) to sustain the hosts' favorite allocation with the highest level of effort by juniors.

3. *Guests direct the search to the best offers. For all offers (p,r),*

$$U^E \geq (a\mu^E(r)+b-p)\frac{\alpha(\theta^E(p,r))}{\theta^E(p,r)},$$

and $\theta^E(p,r) \geq 0$ with complementary slackness, where U^E is given by:

$$U^E = \max_{(p,r)\in\mathcal{O}_1^E\cup\mathcal{O}_2^E}(a\mu^E(r)+b-p)\frac{\alpha(\theta^E(p,r))}{\theta^E(p,r)},$$

or $U^E = 0$ if $\mathcal{O}_1^E$ and $\mathcal{O}_2^E$ are empty;

4. *Guests update beliefs about hosts' effort using Bayes formula when possible:*

$$\mu^E(r_1^\emptyset) = \pi + (1-\pi)\omega_1^\emptyset; \quad \mu^E(r_2^\emptyset) = \pi;$$
$$\mu^E(r_2^+) = \frac{\pi}{\pi+(1-\pi)\omega_1^\emptyset}; \quad \mu^E(r_2^-) = 0;$$

5. *The measure of guests directing their search to each possible offer adds up to one:*

$$g(p_1^\emptyset,r_1^\emptyset)+g(p_2^+,r_2^+)+g(p_2^-,r_2^-)+g(p_2^\emptyset,r_2^\emptyset) = 1.$$

In case of a match, senior hosts with costly effort exert effort with probability zero: $\omega_2^+ = \omega_2^- = \omega_2^\emptyset = 0$. They cannot commit to exert effort since guests direct their search before the effort decision. Accordingly, senior's expected profits with reviews r_2, $\Pi_2(p_2,r_2) = p_2\alpha(\theta_2(p_2,r_2))$, do not depend on host's cost of effort. At the beginning of their second period, seniors post prices to maximize $\Pi_2(p_2,r_2)$ after observing their reviews r_2, and taking guests' expected utility U^E as given. Thus, hosts with the same reviews post the same prices $p_2(r_2)$. After being matched, juniors with $c = k$ choose to exert effort with probability $\omega_1^\emptyset \in [0,1]$: they compare the cost of exerting effort today, k, with the difference in the future discounted returns with r_2^+ and r_2^-: $\beta[\Pi_2(p_2^+,r_2^+) - \Pi_2(p_2^-,r_2^-)]$. $\omega_1^\emptyset \in [0,1]$ is unique. The uniqueness of $\omega_1^\emptyset$ directly follows from the properties (monotonicity and concavity) of the senior profits $\Pi_2(p_2,r_2)$ relative to the guests' beliefs $\mu_2(r_2)$. Before being matched, junior post prices to maximize their expected profits, taking U^E as given. However, they will be on the platform next period and they take into account the value of having a match today in updating their reviews tomorrow. In particular, posting $(p_1^\emptyset,r_1^\emptyset)$, the probability to match and to update the review is $\alpha(\theta_1(p_1^\emptyset,r_1^\emptyset))$. In this case, with probability $(1-\pi)(1-\omega_1^\emptyset)$, they do not exert effort and seniors' profits are $\Pi_2(p_2^-,r_2^-)$; whereas, with probability $(1-\pi)\omega_1^\emptyset$, they exert effort and seniors' profits are $\Pi_2(p_2^+,r_2^+)$. Conversely, with probability $1-\alpha(\theta_1(p_1^\emptyset,r_1^\emptyset))$, there is no match and the seniors' profits are $\Pi_2(p_2^{\emptyset}, r_2^{\emptyset})$. Accordingly, juniors expected profit is:

$$\begin{aligned}\Pi_1 = &(p_1^{\emptyset} - k(1-\pi)\omega_1^{\emptyset})\alpha(\theta_1(p_1^{\emptyset}, r_1^{\emptyset})) + \beta(1-\alpha(\theta_1(p_1^{\emptyset}, r_1^{\emptyset})))\Pi_2(p_2^{\emptyset}, r_2^{\emptyset}) \\ &+ \beta(1-\pi)(1-\omega_1^{\emptyset})\alpha(\theta_1(p_1^{\emptyset}, r_1^{\emptyset}))\Pi_2(p_2^{-}, r_2^{-}) + \beta(\pi + (1-\pi)\omega_1^{\emptyset})\alpha(\theta_1(p_1^{\emptyset}, r_1^{\emptyset}))\Pi_2(p_2^{+}, r_2^{+}).\end{aligned} \tag{2.2}$$

Theorem 1. *An equilibrium with informative reviews exists and it is unique.*

Proof: See Appendix A. The existence and the uniqueness of the equilibrium relies on the continuity of the juniors' profit Π_1 and its monotonicity relative to the equilibrium utility level U^E. Because Π_1 is a decreasing function of U^E, there is only one U^E such that the free entry in Equation 2.1 is satisfied. For this value of U^E, the equilibrium prices, tightness levels, and effort choices are unique.

2.3 Entry Costs, Profits, and the Incentives to Exert Effort

The difference between senior profits with r_2^+ and r_2^- provides juniors with incentives to exert effort. Yet, profits also depends on the mass of entrants and its effects on the tightness levels associated with each offer. Higher entry costs reduce juniors' entry, increase hosts' profits, Π_1, and lower guests' expected utility U^E. However, the reduction in juniors' entry does not affect uniformly hosts' profits. Hosts with r_2^+ benefit more from having fewer competitors. This is clear when $b < U^E < a\mu(r_2^+) + b$ with high and low entry costs. In this case, guests never direct their search to seniors with r_2^- and $\Pi_2(p_2^-, r_2^-)$ is zero. Conversely, $\Pi_2(p_2^+, r_2^+)$ is higher with higher entry costs and fewer competitors. Standard assumptions about the matching process ensure that, for every level of entry costs, the probability to match is less elastic to changes in prices for higher $\mu(r_2)$. Therefore, with fewer competitors, senior hosts with r_2^+ can extract a higher proportion from the match surplus with a lower reduction in their chances of a match. As a result, the benefits of exerting effort increases and juniors with $c = k$ react accordingly.

Proposition 1. *Consider two equilibria with informative reviews in which entry costs are f_H and f_L with $f_H > f_L$. Then, relative to the equilibrium with f_L, with f_H: seniors' profits are strictly higher, and the probability to exert effort for juniors is weakly higher.*

Proof: See Appendix A. In the remaining part of the paper, I show empirical evidence supporting Proposition 1. In line with the model, I study guests' reviews reporting Airbnb hosts' effort decisions. I identify a negative and significant causal impact of the number of competitors on hosts' effort due to an increase in entry costs. To do that, I exploit the registration enforcement for short-term rentals implemented by the City Council of San Francisco at the end of 2017. The identification design closely follows the theoretical mechanism in Proposition 1: a rise in entry costs leads to an increase in market tightness, with more guests per host on the platform. The tightness change in the model is due to a reduction in hosts' entry, whereas the registration enforcement pushes away Airbnb hosts already on the platform. Still, the theoretical mechanism does not depend on a reduced entry (or a forced exit) of Airbnb hosts, but on a more general change in the number of competitors.

3 Empirical Setting and Dataset

In this Section, I introduce the empirical part of my work. First, I present the Airbnb setting and the regulation for short-term rentals in San Francisco. Then, I focus on the settlement agreement signed by the City Council and Airbnb in May 2017. Finally, I describe the dataset.

3.1 Airbnb

Airbnb is one of the leading digital platforms in the hospitality industry. I denote the Airbnb members who arrange and offer accommodations as guests and hosts, respectively. Upon registration, guests and hosts appear on the Airbnb platform with a personal webpage. Guests can search for hosts that match the location and the period of their stay. Then, they can select hosts, visit their webpages, and choose to book a listing. If a host accepts a guest's request, the listings is officially booked. After the guest's stay, host and guest have 14 days to review each other. Guests feedback consists of four elements: a written comment, private comments to the host, a one-to-five star rating about the overall experience, and six specific ratings regarding the following categories: *accuracy* of the listing description; *check-in* process at the beginning of the stay; *cleanliness* of the listing; *communicativeness* of the host; listing *location*; *value-for-money* of the stay. Ratings are not displayed singularly with the comments: only the rounded average of the score and subscores are published on the listing and the host webpages.[10]

3.2 The Short-Term Rentals Regulation in San Francisco

I restrict my analysis to San Francisco. I report a brief chronology of the City Council's regulations starting from the San Francisco Short-Term Rentals Regulation enacted in February 2015.

With an ordinance signed in October 2014 and effective from February 2015, the San Francisco City Council legalized short-term rentals in the city. Before this ordinance, San Francisco banned short rentals in residential buildings. This regulation introduces several limitations on who can offer lodging service on Airbnb: to be legally present on the platform, hosts have to face additional costs,

[10]The rounded averages contain all ratings received in previous transactions. All transactions receive the same weight. These pieces of information can be retrieved from some Airbnb Community Center webpages. See https://community.withairbnb.com/t5/Hosting.

respect extra requirements, and register at the Office of Short-Term Rentals (OSTR). In Appendix B, I provide a more detailed description of the regulation and associated restrictions for hosts. In the first two years after the introduction of the regulation, the enforcement of part of the law had proven to be difficult. In particular, registration rates at the OSTR were very low and digital platforms did not disclose to the authorities any personal information regarding their hosts. This situation triggered a long litigation between the City Council and Airbnb that ended with a settlement agreement signed in May 2017. According to the resolution, from September 2017, new hosts willing to offer short-term rentals have to "input their city Office of Short-Term Rentals registration number (or application pending status) to post a listing".[11] Moreover, a "pass-through registration" system is implemented by the platforms for hosts who are already renting short-term to send applications directly to the OSTR for consideration. Finally, from January 2018, all hosts renting short-term are required to be registered. If a listing is not registered at this date, the platforms cancel future stays and deactivate the listing until a registration number is provided.

3.3 The Inside Airbnb Dataset

The dataset comes from *Inside Airbnb*, a website tracking Airbnb listings present in specific locations over time. In my analysis, the dataset is formed by snapshots of Airbnb listings present in San Francisco at forty-seven different dates from September 2015 to September 2019. Data scraping is performed at the beginning of each month with three months missing and some multiple snapshots per month at the beginning of 2018.[12] I combine all the snapshots to form an unbalanced panel dataset composed of 29,696 listings and 360,440 listing observations over time. In each snapshot, listings are observed if they appear on the Airbnb website at the snapshot date. Accordingly, for each Airbnb listing in the dataset, entry, exit, and inactivity periods are identified.[13] When a listing is observed, several listing characteristics are displayed. Some are time-invariant such as the listing's location (longitude, latitude, and neighborhood) and dwelling's characteristics. Some others update at each snapshot, such as the number of guests' reviews and average star ratings, the price charged for one night, the number of nights in which the listing is available after the snapshot, and whether the listing displays the OSTR registration number.

Descriptive statistics are reported in Table 1. Panel A presents the characteristics of all listings

[11] The quote comes from the official announcement of the San Francisco City Attorney, available at https://www.sfcityattorney.org.

[12] The list of all snapshots follows: September 2015, November 2015, December 2015, February 2016, April 2016, May 2016, June 2016, July 2016, August 2016, September 2016, October 2016, November 2016, December 2016, January 2017, February 2017, March 2017, April 2017, May 2017, June 2017, July 2017, August 2017, September 2017, October 2017, November 2017 (two snapshots), December 2017 (two snapshots), January 2018 (two snapshots), February 2018, March 2018, April 2018, May 2018, July 2018, August 2018, September 2018, October 2018, December 2018, January 2019, February 2019, March 019, April 2019, May 2019, June 2019, July 2019, August 2019, September 2019.

[13] Airbnb hosts can remove their listings from Airbnb for a period of time and then re-enter with the same listing profile.

observed in the panel data. All the reported variables correspond to the last snapshot in which listings are observed. On average, listings are present on Airbnb for more than one year. The total number of reviews has a skewed distribution with more than half of listings having less than 5 reviews before exiting the platform. There is high variability in the price per night and the number of nights in which the listing is available (not booked) after the snapshot, implying that performances on Airbnb widely vary across listings. In contrast, the variation of the average rating is much lower. The percentages of short-term listings with a registration number confirm that 1) short-term rentals constitute the majority of transactions on Airbnb (more than 75 percent); 2) before the settlement agreement, the regulation imposed by the San Francisco City Council was largely ignored.

Panel B shows listings information about the number of reviews posted between two consecutive snapshots and the ratings' averages associated with these reviews. The number of reviews per snapshot is derived from the difference between the total number of reviews displayed in a snapshot and in the next one ($n_{i,t+1} - n_{i,t}$). Similarly, the average ratings per snapshot are computed using the average rating and the total number of reviews. I denote with $n_{i,t}$ and $\bar{R}^k_{i,t}$ the total number of reviews for listing i at snapshot t and the average rating for listing i at snapshot t for the category k, respectively. Then, the average rating per snapshot, $r^k_{i,t}$, for listing i at snapshot t and category k where $k \in \{$*overall, accuracy, check-in, cleanliness, communication, location, value*$\}$ can be computed as follows:[14]

$$r^k_{i,t} = \frac{\bar{R}^k_{i,t+1} n_{i,t+1} - \bar{R}^k_{i,t} n_{i,t}}{n_{i,t+1} - n_{i,t}}.$$

The number of reviews per snapshot varies by listing and snapshot. The average number of review per snapshot equals 1.4 with standard deviation 2.1. Much more limited variations are present for the average ratings per snapshot. The averages are higher than 9 for all the ratings with standard deviations always lower than 1.1. The average rating regarding the overall experience is 93.3 with standard deviation 9.2, that corresponds to an average of almost 5 stars with limited variation.[15]

In Appendix B.2, I provide descriptive statistics about the population of Airbnb listings before and after the agreement in May 2017. I discuss how listings that stayed on the platform after the settlement agreement are positively selected (in terms of ratings and number of reviews) compared to those exiting before the full registration enforcement in January 2018.

[14]Since $\bar{R}^k_{i,t}$ are rounded averages, the procedure is affected by measurement errors. To reduce these errors, I drop the observations corresponding with values of $r^k_{i,t}$ lower than 2 or greater than 10. For each rating, these values account for less than 2 percent of the sample. Moreover, I drop observations about snapshots with a number of reviews per snapshot greater than 26. I treat these snapshots as outliers due to the scraping method. They account for 0.08 percent of the sample.

[15]On Airbnb, guests can choose in a range of stars between 1 and 5. Still, the scraped variable regarding the average rating for the overall experience varies from 0 to 100. All other scraped ratings varies from 2 to 10.

Table 1: Summary Statistics

	Mean	SD	N	Min	Max
Panel A					
Days in Airbnb	387.72	413.83	29,696	0	1,471
Total number of reviews	22.41	50.96	29,696	0	747
Percent of the listing population:					
Less than 5 reviews	57%	-	16,927	-	-
Between 5 and 10 reviews	9%	-	2,673	-	-
Between 10 and 20 reviews	10%	-	2,968	-	-
Between 20 and 50 reviews	11%	-	3,266	-	-
Between 50 and 100 reviews	6%	-	1,782	-	-
More than 100 reviews	6%	-	1,781	-	-
Price per night	207.36	190.37	29,440	0	1,500
Availability next 30 days	9.22	11.12	29,696	0	30
Availability next 60 days	21.56	22.74	29,696	0	60
Availability next 90 days	35.74	34.61	29,696	0	90
Minimum nights required	9.25	19.30	29,696	1	365
Short-term rentals	79%	-	23,459	-	-
Registration displayed	29%	-	8,612	-	-
Panel B					
$\bar{R}_{i,t}^{overall}$	93.92	9.25	20,700.00	20	100
$n_{i,t}$	1.37	2.04	25,004	0	22
$r_{i,t}^{overall}$	93.29	8.93	14,799	20	100
$r_{i,t}^{accuracy}$	9.54	0.88	14,790	2	10
$r_{i,t}^{check-in}$	9.69	0.78	14,780	2	10
$r_{i,t}^{clean}$	9.33	1.08	14,794	2	10
$r_{i,t}^{comm}$	9.69	0.78	14,790	2	10
$r_{i,t}^{location}$	9.44	0.89	14,779	2	10
$r_{i,t}^{value}$	9.15	0.99	14,779	2	10

Note: Panel A refers to every single listing present in the panel data combining the snapshots from September 2015 to September 2019. All the statistics refer to the last snapshot in which the listing is observed. The variable "Days in Airbnb" corresponds to the difference between the last and the first snapshot in which the listing is observed. The "Percent of the listing population" groups listings by the number of reviews displayed in their last snapshot. The variable "Price per night" presents the nominal prices charged by guests measured in US dollars. I drop few outliers reporting prices higher than $1500. They account for 0.65 percent of the sample. Panel B refers to the variables constructed from the original dataset about the number of reviews written between two consecutive snapshots and the averages of the ratings associated with these reviews. Missing data about the variables "Average rating" are due to the high presence of listings with no reviews.

4 Identification Strategy

In this Section I discuss the identification strategy of the causal relationship between listing competition on Airbnb and the hosts' effort in line with Proposition 1 in Section 2. The model shows that variations in entry costs change market tightness (the proportion of hosts over guests) affecting hosts' incentives to exert effort: with fewer competitors (due to higher entry costs), hosts exert effort with higher probability to have better reputation in the future. The identification design closely follows this channel: the variation in the number of competitors is due to the change in entry conditions established by the settlement agreement.

The estimating regression to capture the causal impact of competition on hosts' effort is:

$$r_{i,t}^{effort} = \alpha_i + \rho_t + \beta \ln(L_{i,t}^d) + \varepsilon_{i,t}, \tag{4.1}$$

where α_i and ρ_t are the full set of dummy variables for each listing i and snapshot t. $r_{i,t}^{effort}$ is a measure of hosts' effort. I use two rating categories as proxies for hosts' effort: *check-in* and *communication*.[16] I denote the average rating per snapshot for listing i, snapshot t and category *check-in* and *communication* with $r_{i,t}^{check}$ and $r_{i,t}^{comm}$, respectively. I use $r_{i,t}^{effort}$ to refer to both averages.

$L_{i,t}^d$ represents the degree of competition faced by listing i at snapshot t. It is defined as the sum of all listings offering short-term lodging at snapshot t within d kilometers of listing i. I do not include listings offering long-term lodging since the regulation only applied to short-term rentals and they do not directly compete with short-term listings.[17] I use three values for d: 0.5, 1, and 2 kilometers. Using longer radii reduces the variability of the number of competitors over time and across listings because of the city center's size.[18] Not all listings within d kilometers may be close competitors of listing i. Yet, I do not differentiate among listings with different features: doing so, I estimate a lower bound of the competition's effects on hosts' effort.

With ordinary least squares (OLS), the correlation between $L_{i,t}^d$ and $\varepsilon_{i,t}$ produces inconsistent estimates of β. The main potential threat of endogeneity is the presence of omitted variables on the demand side. A high number of competitors is a signal of the attractiveness of the area and high demand. Thus, regressing $r_{i,t}^{effort}$ over $\ln(L_{i,t}^d)$ may partially capture the impact of changes in demand over hosts' effort and, according to the mechanism of the model, positively bias the estimates of β.

To tackle the endogeneity issues related to unobserved variations in demand, I implement an

[16] In Appendix E.1, I present and discuss the impact of competition for other ratings. Moreover, in Section 6.1, I provide an estimation of the effort exerted by hosts exploiting the correlation between ratings with a control function approach.

[17] Appendix Figure C.1 shows the distribution of the minimum number of nights hosts require guests to stay. More than 80 percent of short-term listings allows guests to stay for less than 4 nights. Differently, listings offering long-term lodging *cannot* set this number lower than 30 and they do not appear in guests' searches for shorter stays.

[18] In Appendix E.2 I replicate the analysis studying variations in the number of listings within 2 and 3 kilometers with no significant effects on hosts' effort.

IV strategy exploiting the settlement agreement between the San Francisco City Council and Airbnb. Accordingly, I restrict my analysis to listings offering short-term lodging that enter the platform before September 2017 and do not exit before January 2018.

I propose a measure γ_i^d for the *predicted* change in the sum of listings within d kilometers of listing i due to the registration enforcement. The measure γ_i^d is the percentage of short-term listings within d kilometers of listing i that do *not* display a registration number on their webpages few days before the settlement agreement became effective.[19] It is defined as follows:

$$\gamma_i^d = \frac{NRL_{i,Sept2017}^d}{L_{i,Sept2017}^d},$$

where $NRL_{i,Sept2017}^d$ and $L_{i,Sept2017}^d$ are the sum of listings present at the beginning of September 2017 and within d kilometers of listing i offering short-term lodging without registration numbers and the total sum of listings offering short-term lodging, respectively.[20] A value of γ_i^d close to 0 implies that the competition for listing i is not expected to change much since a high number of listings already displays a license. Conversely, high values of γ_i^d imply that the expected reduction in competition for listing i due to the settlement is likely to be more relevant.[21]

The instrumental variable is formed by the product between γ_i^d (the cross-sectional variation) and the time dummy $post_{Nov2017}$ taking value 1 for each snapshot after November 2017.[22] The power and the validity of this instrument depends on the strong correlation between γ_i^d and $L_{i,t}^d$, the exclusion restriction, and the monotonicity assumption about the effect of γ_i^d on $L_{i,t}^d$ and $r_{i,t}^{effort}$.

The *first stage* of the IV design documents a positive and significant relationship between the actual movement of the number of competitors and how the registration enforcement expected to change the degree of competition. The estimating equation of the *first stage* is the following:

$$\ln(L_{i,t}^d) = \alpha_i + \rho_t + \beta_1 post_{Nov2017} + \beta_2 \gamma_i^d \times post_{Nov2017} + \varepsilon_{i,t}, \tag{4.2}$$

where the endogenous variable $\ln(L_{i,t}^d)$ is regressed over the expected change in competition due to the settlement agreement. Results with listings and snapshot fixed effects are in Table 2 reporting

[19]The snapshot in September 2017 was scrapped on September 2, 2017, whereas the new registration process started September 6, 2017. See http://www.sfexaminer.com/airbnb-launches-new-registration-system/.

[20]If listing i is not active on the platform on September 2017, I compute the measure γ_i^d using the first month in which listing i is active before September 2017. In Appendix E.4, I show corroborating results computing the proportion of non-registered listings in May 2017.

[21]Appendix Figure C.2 shows the distribution of $\gamma_i^{0.5}$ for the short-term listings considered in this analysis: the values of $\gamma_i^{0.5}$ span from 0 to 1 with almost no listings with a $\gamma_i^{0.5} < 0.6$. In particular, more than 80 percent of listings have more than 90 percent non-registered competitors ($\gamma_i^{0.5} > 0.9$).

[22]From Appendix Figure B.2, November 2017 is the first snapshot with a significant drop in the number of short-term listings. In Appendix E.4, I report similar results using September 2017 as a starting date for the effects of the settlement.

standard errors clustered at listing level.[23]

The expected movement in the number of competitors, γ_i^d, is a good predictor for the actual change in competition after November 2017: the higher is the value of γ_i^d, the greater is the expected negative effect of the settlement agreement over the hosts' population around listing i (in line with the monotonicity assumption). For each distance, all coefficients β_2 are negative and significant with a F-statistics much above the standard threshold to detect the presence of weak instruments. The magnitude of the effects depends on the radius. In particular, the coefficients are greater in absolute value for larger radii: this effect is mainly mechanical since the number of competitors increases with the radius, whereas the range for the proportion of non-registered listings is always between 0 and 1. The coefficient β_1 captures the long-term positive trend in the number of listings on platform during the period of analysis (from 2015 to 2019).[24] The difference between the estimates of β_1 and β_2 is always negative and significant: it confirms the disrupting effects of the settlement agreement over the number of competitors that outweighs the positive long-term trend.

To show further evidence of the predictive power of γ_i^d relative to the number of competitors over time, I illustrate the evolution of $L_{i,t}^d$ for different values of γ_i^d with an event-study approach. I consider the following lead-lag model in which the degree of competition $L_{i,t}^d$ is regressed over the product between γ_i^d and a full set of dummy variables for each snapshot:

$$\ln(L_{i,t}^d) = \alpha_i + \rho_t + \sum_{\tau=Sept2015}^{July2019} \beta_\tau \gamma_i^d \times 1(t=\tau) + \varepsilon_{i,t}. \tag{4.3}$$

I present the results of the OLS estimates of Equation 4.3 in Figure 1. Here I plot the estimated β_τ over the snapshot dates from September 2016 (one year before the registration enforcement started to be implemented) to January 2019 (one year after the end of the enforcement implementation) using the number of competitors within 0.5 kilometer.

Before November 2017, the coefficients are close to zero and they do not exhibit a clear trend. This evidence shows that the evolution of Airbnb listings before the settlement agreement is not correlated with $\gamma_i^{0.5}$. Conversely, the number of listings after November 2017 is negatively correlated with $\gamma_i^{0.5}$: the number of short-term listings sharply decreases after the settlement agreement and competitors are more likely to exit if the value of $\gamma_i^{0.5}$ is higher.

With regard to the exclusion restriction, there is no evidence that the San Francisco Short-Term Rental Regulation was motivated by policymakers' concerns over the quality of the services on hospitality platforms.[25] However, other than reducing the number of listings present on the platform,

[23]In Appendix E.5 I present results with clustered standard errors at San Francisco district level and allowing for geographical correlation among competitors in line with Conley (1999).

[24]In Appendix E.3 I present corroborating results restricting on the analysis on snapshots from September 2016 to January 2019.

[25]The City Attorney, Dennis J. Herrera, never mentions the quality of the Airbnb service in his announcement of the

the regulation enforcement of the settlement agreement may have affected hosts' effort through the selection of hosts who stay after the enforcement of the registration. To account for hosts' selection, I restrict my analysis to those listings that enter before September 2017 and do not exit before January 2018, when the registration enforcement is completed. Moreover, in Appendix E.6, I replicate the analysis controlling for an extensive set of observables regarding the competitors' characteristics and composition. For this sample, the identification strategy excludes the presence of unobserved factors (such as the number of guests or tourists) that affect hosts' effort and that are correlated with the predicted variations in the number of listings for different areas of San Francisco. Figure 1 shows that the estimated β_τ associated with the months before September 2017 are close to zero and no trend is detected. I provide a similar analysis about the correlation between the instrumental variable and unobservables affecting hosts' effort with a second event-study. Ratings regarding effort $r_{i,t}^{effort}$ are regressed over the product between γ_i^d and a full set of dummy variables:

$$r_{i,t}^{effort} = \alpha_i + \rho_t + \sum_{\tau=Sept2015}^{July2019} \beta_\tau \gamma_i^d \times 1(t=\tau) + \varepsilon_{i,t}. \tag{4.4}$$

I present the results of the OLS estimates of Equation 4.4 with two event study graphs. In Figures 2 and 3, I plot the estimated β_τ over the snapshot dates considering the ratings about *check-in* and *communication*, respectively. In both Figures, the coefficients related to the months before May 2017 do not exhibit a statistically significant trend. In contrast, a positive trend is observable after the registration enforcement starts to be implemented. These pieces of evidence are in line with the exclusion restriction assumption: unobservables affecting ratings regarding hosts' effort do not correlate with the instrumental variable before the registration enforcement.[26]

The positive trend after September 2017 supports the prediction of the model: when hosts face less competition (for higher values of γ_i^d), their incentives to exert effort increase. In particular, hosts should exert effort even before the proper enforcement of the regulation in the expectation of higher costs; and a perceivable upward time trend can be observed between May 2017 and September 2017.[27] Finally, the positive trend after September 2017 is not affected by the massive entry in August 2018 of listings offering long-term lodging as shown in Appendix Figure B.5. This is in line with the assumption that long-term listings do not directly compete with short-term listings.

settlement agreement, available at https://www.sfcityattorney.org.

[26]In Section 7.2, I present the event study graphs of all endogenous and response variables focusing on the period before the settlement. All evidence suggests that γ_i^d is not correlated with unobservables affecting the evolution of the number of competitors, and the ratings regarding effort before the regulation enforcement.

[27]In order to account for hosts' potential anticipation of the regulation in Appendix E.4, I corroborate the analysis using September 2017 as a starting date of the effects of the settlement, and computing the measure γ_i^d in May 2017.

Table 2: Impact of the Settlement Agreement on Competition (First Stage)

	$\ln(L_{i,t}^{0.5})$ (1)	$\ln(L_{i,t}^{1})$ (2)	$\ln(L_{i,t}^{2})$ (3)
$post_{Nov2017}$	1.036***	1.911***	2.518***
	[0.0774]	[0.0782]	[0.0467]
$\gamma_i^{0.5} \times post_{Nov2017}$	-1.551***		
	[0.0931]		
$\gamma_i^{1} \times post_{Nov2017}$		-2.590***	
		[0.0943]	
$\gamma_i^{2} \times post_{Nov2017}$			-3.283***
			[0.0537]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	4.222	5.484	6.732
F-test	472.9	1070.6	2929.5
Adjusted R^2	0.672	0.812	0.907
N	80,402	80,413	80,435

Note: Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses.

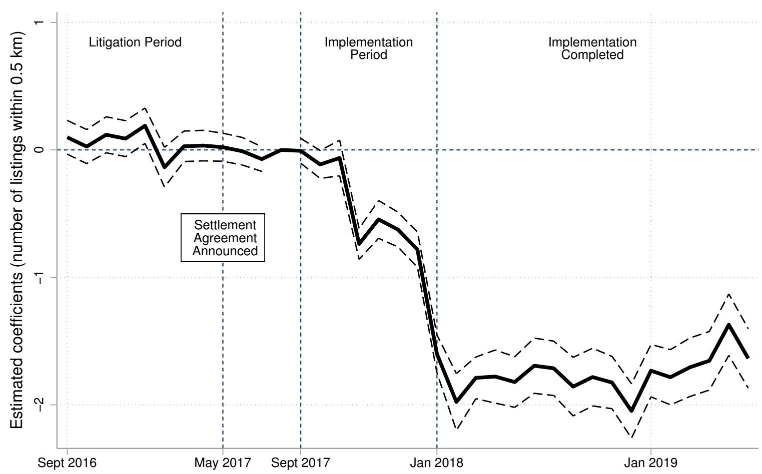

Figure 1: Estimated Coefficients from Equation 4.3: Number of Listings within 0.5 km

Note: In line with Equation 4.3, $\ln(L_{i,t}^{0.5})$ is regressed on listing and snapshot fixed effects, and on the products between $\gamma_i^{0.5}$ and snapshot dummies. Standard errors (10%) are clustered by listing. The graph plots the estimated coefficients on these products. The value of the coefficient corresponding to August 2017 ($\hat{\beta}_{Aug2017}$) is normalized to zero. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered.

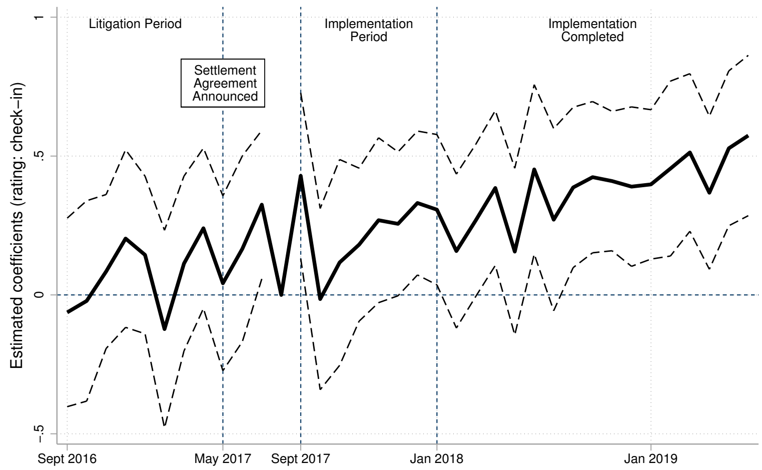

Figure 2: Estimated Coefficients from Equation 4.4: Ratings Regarding Check-in

Note: In line with Equation 4.4, $r_{i,t}^{check-in}$ is regressed on listing and snapshot fixed effects, and on the products between $\gamma_i^{0.5}$ and snapshot dummies. Standard errors (10%) are clustered by listing. The graph plots the estimated coefficients on these products. The value of the coefficient corresponding to August 2017 ($\hat{\beta}_{Aug2017}$) is normalized to zero. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered.

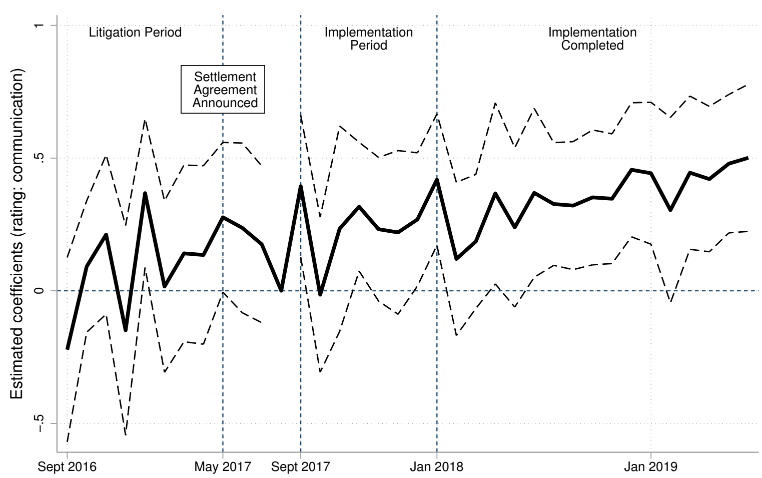

Figure 3: Estimated Coefficients from Equation 4.4: Ratings Regarding Communication

Note: In line with Equation 4.4, $r_{i,t}^{comm}$ is regressed on listing and snapshot fixed effects, and on the products between $\gamma_i^{0.5}$ and snapshot dummies. Standard errors (10%) are clustered by listing. The graph plots the estimated coefficients on these products. The value of the coefficient corresponding to August 2017 ($\hat{\beta}_{Aug2017}$) is normalized to zero. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered.

5 Main Results

I now present the main empirical results. To facilitate the comparison across different regressions, I always restrict my analysis to Airbnb listings that offer short-term lodging; enter the platform before September 2017; exit after January 2018; without missing data regarding $r_{i,t}^{check-in}$ and $r_{i,t}^{comm}$. I allow the variance of residuals to differ across listings by clustering standard errors at listing level.[28]

I start by estimating the OLS panel regressions that relate hosts' effort to competition, as represented in Equation 4.1. Appendix Table D.1 presents the results. For each rating, three regressions are performed: the independent variables vary depending on the distance used to delimit the competition faced by listings. The results suggest a not significant relationship between effort and competition measured as the sum of competitors within 0.5, 1 and 2 kilometers to each listing. As described in Section 4, the OLS panel regressions are likely to be affected by the presence of omitted determinants of demand: the higher is the number of Airbnb hosts in a specific area, the greater is the area attractiveness for guests. Because of this, causality cannot be inferred from the OLS panel model. Accordingly, I take advantage of the variation in the degree of competition due to the settlement agreement to estimate the effect of competition over hosts' effort.

Table 2 shows the statistical and economic significance of γ_i^d in predicting the number of competitors faced by each listing after November 2017 (the *first stage*). In particular, when γ_i^d increases by 0.1, the number of competitors within 0.5 kilometers decreases by more than 15 percent, those within 1 kilometer by more than 24 percent, and those within 2 kilometers by almost 33 percent.

Before presenting the results regarding the IV estimates, I show the effect of the expected change in competition due to the regulation (the instrument) on the hosts' ratings about effort. The estimating equation presents the same functional form as Equation 4.2:

$$r_{i,t}^{effort} = \alpha_i + \rho_t + \beta_1 post_{Nov2017} + \beta_2 \gamma_i^d \times post_{Nov2017} + \varepsilon_{i,t}. \tag{5.1}$$

This equation constitutes the *reduced form* of the IV estimates. Alternatively, it can be interpreted as a difference-in-difference design with a continuous control (the variable γ_i^d) that defines the extent to which the listing is affected by the regulation.

Table 3 presents the results. For every specification and rating, a positive and significant relationship between the instrument $\gamma_i^d \times post_{Nov2017}$ and hosts' effort is observed. Accordingly, higher values of γ_i^d, predicting a greater drop in the number of competitors, are associated with higher hosts' effort after November 2017. Thus, a lower number of competitors can be beneficial for hosts' ratings about effort. When $\gamma_i^{0.5}$ changes from 0 to 1, $r_{i,t}^{check-in}$ and $r_{i,t}^{comm}$ decrease by almost 3 percent. Drops by more than 4 percent are associated with longer distances γ_i^1 and γ_i^2.

[28] In Appendix E.5 I present results with clustered standard errors at the San Francisco district level and allowing for geographical correlation among competitors in line with Conley (1999).

The distributions of $r_{i,t}^{effort}$ (presented in Appendix Table B.1) are extremely concentrated and the magnitude of these changes accounts for almost half of ratings' standard deviations. The coefficients' estimates for the variable $post_{Nov2017}$ are negative and weakly significant. They do not undo the positiveness of the instruments' estimates and are in line with the reputation/career concerns that animate the theoretical model. After November 2017, hosts approach their *senior* stage on the platform with lower incentives to exert effort.

Finally, I turn to the IV estimates. $\ln(L_{i,t}^{d})$ is the only endogenous variable in Equation 4.1, and only one instrumental variable is derived to predict the impact of the regulation, $\gamma_i^d \times post_{Nov2017}$. Then, the two-stage least squares parameters correspond to the ratio between the coefficients of the *reduced form* and the *first stage* regressions. The estimates are in Table 4. The results show a significant and negative effect of the number of competitors over hosts' effort in line with the parameters of the *reduced form*. The negative and significant impact of the IV removes the upward bias of the OLS estimates where the confounding factors due to demand side lead to inconclusive results. The negative impact of competition over hosts' effort is in line with the prediction of Proposition 1. In a less competitive setting, reputation concerns become more relevant and hosts exert effort with higher probability. In particular, a 10 percent decrease in the number of competitors leads to an increase of more than 0.01 star for the ratings $r_{i,t}^{check-in}$ and $r_{i,t}^{comm}$. The distributions of $r_{i,t}^{effort}$ are very concentrated and a one-star change accounts for almost two standard deviations.[29]

The magnitude of the parameters monotonically decreases with distance: the lowest parameters for both ratings are associated with a distance of 2 kilometers. These results corroborate the assumption regarding the geographical extent of competition on the platform: listings located in the same area are likely to exert a greater competitive pressure relative to those further away.

6 Extensions

6.1 Rating Inflation, Biases and Effort Estimation

In Table 1 I show that Airbnb ratings are very concentrated towards the highest grade. This is in line with the analysis by Zervas, Proserpio and Byers (2020): they argue that the rating inflation on the platform can be partially attributed to the Airbnb bilateral review system and the related strategic considerations of hosts and guests. The presence of reviews' bias on Airbnb due to reciprocity and social interactions between parts has also been documented by Fradkin, Grewal and Holtz (2019) and Proserpio, Xu and Zervas (2018). This reputation inflation (Filippas, Horton and Golden, 2018) negatively impacts the ratings' informativeness for guests. It also complicates the magnitude's interpretation of the competition effect on ratings shown in Section 5.

[29] In Section 6.1, I provide an estimation of hosts' effort that facilitates the interpretation of the competition's effect.

Table 3: Impact of the Settlement Agreement on Hosts' Effort (Reduced Form)

	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$post_{Nov2017}$	-0.0707	-0.181**	-0.256**	-0.0615	-0.159*	-0.177*
	[0.0639]	[0.0918]	[0.108]	[0.0610]	[0.0858]	[0.0998]
$\gamma_i^{0.5} \times post_{Nov2017}$	0.281***			0.244***		
	[0.0722]			[0.0691]		
$\gamma_i^{1} \times post_{Nov2017}$		0.408***			0.357***	
		[0.105]			[0.0978]	
$\gamma_i^{2} \times post_{Nov2017}$			0.493***			0.375***
			[0.124]			[0.115]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.89	9.89	9.89	9.87	9.87	9.87
Adjusted R^2	0.0088	0.0088	0.0088	0.0091	0.0090	0.0090
N	80,402	80,413	80,435	80,402	80,413	80,435

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses.

Table 4: IV Estimates of the Impact of Competition on Hosts' Effort

	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.181***			-0.157***		
	[0.0481]			[0.0460]		
$\ln(L_{i,t}^{1})$		-0.158***			-0.138***	
		[0.0408]			[0.0382]	
$\ln(L_{i,t}^{2})$			-0.150***			-0.114***
			[0.0378]			[0.0351]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.89	9.89	9.89	9.87	9.87	9.87
Adjusted R^2	0.0011	0.0066	0.0080	0.0021	0.0068	0.0085
N	80,402	80,413	80,435	80,402	80,413	80,435

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses.

Here I propose a novel approach to account for potential biases in ratings taking advantages of the multiple ratings categories on Airbnb and their relationship. As documented in Section 3, submitting reviews, guests answer several questions about their stay. Many dimensions of the lodging service are part of the guests' feedback, and not all address the effort exerted by hosts.[30] To account for confounding factors in ratings, I exploit the correlation between ratings about *check-in* and *communication*, and the rating regarding listing's *location*, that should not depend on hosts' effort. Doing so, I provide an estimation technique of hosts' effort using a control function approach. In particular, I propose the following parametric statistical model for the joint distribution of $r_{i,t}^{effort}$ and $r_{i,t}^{location}$, the average rating per snapshot for listing i, snapshot t and the category *location*:

$$r_{i,t}^{effort} = e_{i,t} + guest_{i,t}^{effort} \tag{6.1}$$

$$r_{i,t}^{location} = b_i + guest_{i,t}^{location}, \tag{6.2}$$

where b_i is the fixed quality of listing i; $e_{i,t}$ is the effort exerted by the host of listing i at snapshot t; and $guest_{i,t}^{effort}$ and $guest_{i,t}^{location}$ account for specific characteristics such as guests' attitude, or tastes regarding host's effort and listing's location.

Equation 6.1 represents the empirical analog of the theoretical mapping connecting effort to ratings. In Section 2, the monitoring is perfect with high effort ($e = 1$) producing positive rating ($r = r^+$), and low effort ($e = 0$) negative rating ($r = r^-$). Here, $r_{i,t}^{effort}$ depends on hosts' effort and an additional component, $guest_{i,t}^{effort}$, related to potential guests' biases. Similarly, in the model, hosts' quality b is perfectly revealed to guests, whereas, in Equation 6.2, $r_{i,t}^{location}$ reports the fixed quality b_i and a second guests' component, $guest_{i,t}^{location}$.

The control function approach relies on the relationship between the guests' biases regarding effort and location:

$$guest_{i,t}^{effort} = \alpha + \beta guest_{i,t}^{location} + \varepsilon_{i,t}, \tag{6.3}$$

with $E(guest_{i,t}^{location}\varepsilon_{i,t}) = 0$ and $\beta \neq 0$. Equation 6.3 assumes a common linear relationship between characteristics for all guests in the dataset. It allows guests to have different values of $guest_{i,t}^{location}$ and $guest_{i,t}^{effort}$, but a common linear relationship is always present for every guest up to the orthogonal error $\varepsilon_{i,t}$.[31]

[30] In particular, ratings can capture the total guests' utility factoring in prices, or the probability to have a match. To this extent, guests may be worse off by a reduction in the number of hosts (irrespective of the higher effort exerted by hosts) and ratings could be negatively affected. In Appendix E.1 I study the effect on competition on all other kinds of ratings.

[31] The common relationship can be relaxed allowing the parameter β to change over time-invariant group of listings. Still, all results presented in this Section do not qualitatively change when I allow for different values of β with a random coefficient approach.

Plugging Equation 6.3 into the previous system of equations, I derive the following fixed effect panel regression:

$$r_{i,t}^{effort} = \alpha - \beta b_i + \beta r_{i,t}^{location} + e_{i,t} + \varepsilon_{i,t}. \tag{6.4}$$

In Equation 6.4, $r_{i,t}^{effort}$ is regressed on $r_{i,t}^{location}$ with a constant and a listing fixed effect accounting for $\alpha - \beta b_i$. Accordingly, the host effort $e_{i,t}$ can be estimated from the residuals of a fixed effect panel regression with noise $\varepsilon_{i,t}$. To have a consistent estimate of β (and unbiased measures of effort), the following orthogonality conditions are sufficient:

$$E[r_{i,t}^{location}\varepsilon_{i,t}|b_i] = 0 \tag{OC_1}$$

$$E[r_{i,t}^{location}e_{i,t}|b_i] = 0. \tag{OC_2}$$

Condition OC_1 directly follows from assumption 6.3 and the orthogonality of the error $\varepsilon_{i,t}$ with $guest_{i,t}^{location}$. Differently, condition OC_2 imposes hosts' effort to not be correlated with deviations of $r_{i,t}^{location}$ from the fixed quality b_i. I provide empirical evidence supporting condition OC_2 studying the relationship between the effort measures $e_{i,t}^{check}$, $e_{i,t}^{comm}$, the location rating $\bar{r}_{i,t}^{location}$ and a different proxy for hosts' effort present in the dataset: hosts' response rate. This variable represents the percentage of new inquiries of lodging requests to which the host responded within 24 hours in the past 30 days before each snapshot.[32] In case of hosts with multiple listings, the variable does not adjust and it considers all new inquires received by a host. To account for this, I restrict the analysis to listings whose hosts do not manage multiple properties on Airbnb.[33] I regress the variable hosts' response rate over $e_{i,t}^{check}$, $e_{i,t}^{comm}$, and $r_{i,t}^{location}$ controlling for listing fixed effects (see Appendix Table D.2).[34] The results support condition OC_2: hosts' response rate is not significantly correlated with $r_{i,t}^{location}$, whereas it is positively and significantly correlated with effort.

I study the impact of competition on hosts' effort using the effort measures $e_{i,t}^{check}$, $e_{i,t}^{comm}$ estimated as residuals of the regression in Equation 6.4. To do so, I replicate the identification strategy presented in Section 4.[35] I present the IV estimates in Table 5.

[32]For more information regarding how the response time is computed, see the official Airbnb webpage at www.airbnb.com/help/article/430/what-is-response-rate-and-how-is-it-calculated.

[33]At each snapshot I observe listing and host identification numbers. Listings whose hosts do not manage multiple properties on Airbnb constitute the 48 percent of total amount of Airbnb listings in the dataset.

[34]The variable *hosts' response rate* takes values from 0 to 1. A higher percentage corresponds to a faster rate of host's replies.

[35]I use information regarding all listings in the dataset to compute the effort measures by Equation 6.4. To replicate the previous analysis I consider the same restrictions as in Section 5 bootstrapping standard errors to account for the fact that $e_{i,t}^{check}$ and $e_{i,t}^{comm}$ are estimated residuals. The number of observations are slightly different relative to the previous analysis since I have to exclude listings with missing information about $r_{i,t}^{location}$ to estimate the effort measures.

Table 5: IV Estimates of the Impact of Competition on the Estimated Hosts' Effort

	$e_{i,t}^{check-in}$			$e_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.126***			-0.134***		
	[0.0398]			[0.0398]		
$\ln(L_{i,t}^{1})$		-0.108***			-0.107***	
		[0.0387]			[0.0357]	
$\ln(L_{i,t}^{2})$			-0.108***			-0.103***
			[0.0322]			[0.0343]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	-0.00128	-0.00127	-0.00127	-0.000839	-0.000831	-.000830
R^2	0.00062	0.00097	0.0010	0.0004	0.00085	0.0010
N	77,640	77,650	77,671	77,640	77,650	77,671

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Bootstrap standard errors (to account for the fact that $e_{i,t}^{check-in}$ and $e_{i,t}^{comm}$ are estimated residuals) are in parentheses.

The negative relationship between the number of competitors and the estimated effort measures is statistically significant. Accordingly, the number of competitors negatively affects hosts' effort even after removing confounding factors due to guests' characteristics.

Moreover, now the magnitude of the effect is relevant also in economic terms: a 10 percent increase in the number of competitors depresses effort by around 0.012 units. This change almost accounts for the variation from the 80th percentile ($e_{i,t}^{check} = 0.0139$ and $e_{i,t}^{comm} = 0.011$) to the 20th percentile ($e_{i,t}^{check} = -0.0052$ and $e_{i,t}^{comm} - .0059$) of the effort distribution.

6.2 Competition and Hosts' Revenues

Here I present evidence supporting the other theoretical predictions proposed in Section 2.

I observe for each listing i and snapshot t the price charged per night, $p_{i,t}$, and the number of available nights to rent in the next 30 days, $available_{i,t}^{30}$. To ease the interpretation of results, I construct a proxy for the number of nights rented for listing i in next thirty days $rent_{i,t}^{30} = (30 - available_{i,t}^{30})$.[36] I use $p_{i,t}$ and $rent_{i,t}^{30}$ to study the relationship between the number of competitors and hosts' revenues. The identification of the causal relationship follows the same strategy used for the ratings regarding hosts' effort. The IV estimates are in Table 6. The price per night is not significantly affected by the number of competitors, whereas the impact of the nights rented in the next 30 days is negative

[36]Hosts may not be available to rent in some days for external reasons and not because dwellings are already booked. Accordingly, $rent_{i,t}^{30}$ may overestimate the total number of rented nights. To account for this, I do not consider listings with no single available nights in the next 90 days (3 percent of the short-term listings considered).

and significant. In particular, a 10 percent decrease in the number of competitors leads to a 1 percent increase in rented nights.

These findings are in line with the study by Lewis and Zervas (2019) showing that a rise in demand affects only partially prices and increases congestion. This may be due to the costs that non-professional hosts face in changing their prices or other behavioral motivations described by Proserpio et al. (2018). Moreover, the non-significant effect of competition on prices confirms that the matching between hosts and guests is frictional. In a frictionless market, prices serve to balance demand and supply. Thus, a great reduction in the number of hosts should determine a jump in price. Yet, on Airbnb, the number of rented nights by each host results from the market equilibrium and it acts as a further balance between demand and supply. Therefore, the increase in the number of hosts' rented nights after the settlement agreement may be interpreted as a test for the presence of frictions. Before the settlement agreement, hosts rented less than twenty nights in the next 30 nights. However, the presence of spare nights does not imply the presence of frictions. This may simply show the scarcity of guests' demand for certain hosts. Yet, in this case, a sudden decrease in the number of sellers should not significantly affect the number of matches, and the number of rented nights.[37] Therefore, results in Table 6 suggest that search frictions due to the hosts' capacity constraints are present on the platform in line with the model presented in Section 2.

To provide evidence about the correlation between the instrumental variable and unobservables affecting hosts' revenues, I conduct two event-study analyses. I consider lead-lag models in which $p_{i,t}$ and $rent^{30}_{i,t}$ are regressed over the product between γ^d_i and a full set of dummy variables for each snapshot:

$$y_{i,t} = \alpha_i + \rho_t + \sum_{\tau=Sept2016}^{Jan2019} \beta_\tau \gamma_i^d \times 1(t=\tau) + \varepsilon_{i,t}, \tag{6.5}$$

where $y_{i,t} = \{p_{i,t}, rent^{30}_{i,t}\}$. In Appendix Figures D.1, I plot the estimated β_τ of Equation 6.5 over the snapshot dates. The coefficients related to the months before September 2017 do not exhibit trends (although the full set of dummies does completely remove some seasonality effects). Then, only for the variable $rent^{30}_{i,t}$, the coefficients after January 2018 slightly increase relative to the values before the settlement agreement. This corroborates the exclusion restriction assumption: unobservables affecting prices and the number of night rented do not correlate with the instrument variable before the registration restriction's announcement. Furthermore, the positive trend after September 2017 shows that hosts' revenues (in terms of nights rented) increase when hosts face less competition.

[37] This procedure shares the same intuition with the test proposed by Brancaccio, Kalouptsidi, Papageorgiou and Rosaia (2020). When only matches between the two sides are observed, shocks in the supply side can be used to determine whether potential transactions remain unrealized because of frictions.

Table 6: IV Estimates of the Impact of Competition on Hosts' Prices and Number of Rented Nights

	$p_{i,t}$			$rent^{30}_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L^{0.5}_{i,t})$	-6.818			-1.327**		
	[4.840]			[0.598]		
$\ln(L^{1}_{i,t})$		-5.607			-1.163**	
		[4.006]			[0.537]	
$\ln(L^{2}_{i,t})$			-6.850			-2.024***
			[4.366]			[0.501]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	182.9	182.8	182.8	20.09	20.09	20.09
Adjusted R^2	0.018	0.019	0.019	0.22	0.22	0.22
N	76,306	76,317	76,339	76,381	76,392	76,414

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses.

7 Robustness Checks

7.1 Competition and Hosts' Selectivity

Having fewer competitors may affect how selective hosts are in accepting guests. This effect may confound the empirical analysis if, after the settlement, hosts are able to select guests with a higher propensity to rate positively hosts.

Changes in guests' selection have already been tackled in Section 6.1 with the effort estimation. By controlling for ratings about the listing's location, I remove confounding factors related to guests' characteristics. Moreover, in Section 6.2 I show that prices do not change after the reduction in the number of competitors. Prices may be an effective tool to select guests. Thus, the absence of an effect on prices may suggest that the profile of guests interested in renting the listings does not significantly change.

To corroborate these considerations, here I study how hosts use the tools provided by the platform to restrict and select guests that can request to book their dwellings. Airbnb allows hosts to require guests to have a verified email, or that the platform verifies their identity[38]. At the same time, hosts may choose the "instant booking" option allowing guests to rent without being accepted by the hosts.

If, after the settlement agreement, hosts are more selective, then they may use these tools, requiring

[38] To be identified, guests have to send a scan of an official document to Airbnb. See https://www.airbnb.com/help/article/1237/verifying-your-identity.

stricter conditions or deactivating the instant booking option. Yet, no single hosts among those studied change the requirements for guests in the period considered. Moreover, the instant booking option ($instant_{i,t}$) is not significantly deactivated by those hosts with fewer competitors (Appendix Table E.1) implementing the same strategy used for the ratings. These results suggest that changes in the number of competitors do not affect the selective behavior of hosts in terms of the tools they can use to screen guests allowed to rent their dwellings.

7.2 Pre-trends Analysis and the New Year's Eve Higher Demand

I provide further evidence in support of the exclusion restriction in the design proposed in Section 4: the proportion of non-registered listings affects hosts' effort only through its effects on competition.

In line with the evidence presented in Section 4, in Appendix Figures E.1 and E.2, I report the coefficients of the event studies in Equations 4.3 and 4.4 focusing only on the parameters about snapshots before the regulation enforcement. This is relevant because the presence of a trend before the settlement would go against the exclusion restriction, indicating that γ_i^d directly affects ratings. Appendix E.2 do not show trends on the response variables $r_{i,t}^{checkin}$ and $r_{i,t}^{comm}$. The coefficients' trend on ratings appears to be flat during more than a year before September 2017. The only perceivable drop is in December 2015 only for $r_{i,t}^{checkin}$.

Also Appendix Figure E.1 presents a flat trend before the settlement for what concerns the number of competitors, $\ln(L_{it}^{0.5})$. The size of those parameters significantly different from zero is ten times smaller relative to the changes occurring after the settlement (see Figure 1). These positive and negative variations occur in January and February 2017, respectively. In line with the findings by Farronato and Fradkin (2018), during the period of New Year's Eve, more Airbnb listings enter the market, responding to the demand expansion due to the winter holidays and the hotels' capacity constraints. The slight increase in the parameters associated with this period of the year before the settlement could be problematic for the identification. In particular, it may suggest that γ_i^d is correlated with San Francisco areas' attractiveness during the winter holidays period. Further evidence suggesting this relationship can be found observing the event study graph for the number of rented nights in Appendix Figure D.1. Here the parameters' values before the settlement agreement appear to be significantly different from zero during January 2017. To address this potential concern, I restrict the sample of snapshots. In particular, I remove all snapshots taken during the winter months (December, January, and February) from 2015 to 2019. Appendix Tables E.2 and E.3 show the results of the first stage and the IV, confirming a negative and significant relationship between the number of competitors and hosts' effort.

7.3 The Moscone Center Renovation

The settlement agreement between the City Council and Airbnb is not the only event influencing the San Francisco hospitality market during 2017. In April 2017, one of the major convention centers in San Francisco, the George R. Moscone Convention Center, was partially renovated. The expansion effort required significant closures and reduced activities for two years until the reopening in January 2019. According to the San Francisco Travel Association, the Moscone Center's partial closure had a significant negative impact on the number of tourists and visitors.[39] The reduction in demand due to these reduced activities affects the proposed identification strategy as long as the effects of γ_i^d are not correlated with the negative impact on demand due to this extra shock.

To show that the Moscone Center renovation does not pose a serious concern for the identification strategy, I present two pieces of evidence. First, I show in Appendix Tables E.4 and E.5 the results of the *first stage* and *reduced form* equations controlling for the product of the distance between each listing and the Moscone Center, $d_i^{Moscone}$, and the time window in which the center was partially closed (April 2017 - January 2019), $closure_{17-19}$. Appendix Table E.4 shows that the predicting power of γ_i^d remains high, and it is not affected by the presence of the other "predictor". The coefficient for $d_i^{Moscone} \times closure_{17-19}$ is positive and significant with a much smaller size relative to the instrument. In line with the intuition, during the Moscone Center's closure, fewer listings stay on the platform when their distance to the Center is lower as they are more likely to rely on its touristic appeal. The results in Appendix Table E.5 confirm that the instrument positively affects ratings about effort. However, the distance for the Moscone does not significantly impact the hosts decisions about effort. As a second piece of evidence, in Appendix Table E.6 I show the IV results removing all listings located within 1 kilometer of the Moscone Center. Doing so, the the most affected listings by the period of restructuring are not included. The negative relationship between the number of competitors and hosts' effort continues to be statistically significant with similar magnitudes relative to the results in Section 5. Thus, the negative effect of competition on effort is robust to excluding listings close to the San Francisco City Center and the Financial District (where the Moscone Center is located).

7.4 Other Robustness Checks

In Appendix E, I provide further robustness checks of the results. In Appendix E.1, I present the impact of competition on other ratings using the same identification strategy as in Section 4. The model predicts that, with fewer competitors, hosts' effort increases, but guests' ex-ante utility diminishes, and hosts can exploit a larger share of the transaction surplus. Accordingly, ratings about *value-for-money* and the *overall experience* (that should jointly capture the contrasting effects of higher effort

[39] The Center draws millions of attendees and exhibitors per year and, by its own estimation, Moscone Center is responsible for 21 percent of San Francisco's tourism industry. See https://civilgrandjury.sfgov.org/report.html.

and lower surplus) are not significantly affected by changes in the number of competitors. As a further dimension related to hosts' effort, ratings regarding *accuracy* of the webpage are affected negatively by the number of competitors; whereas rating about *cleanliness* are not. The absence of a significant effect for hosts' cleanliness activities may be due to the nature of this effort dimension and the characteristics of the identification strategy. The identification design exploits the additional reduction in the number of competitors experienced by those hosts who are "more treated" by the settlement. Yet, also the "least treated" hosts experience a significant reduction in the number of competitors and also these hosts are expected to exert more effort. Yet, cleaning activities are often a medium-term investment for hosts who may not personally clean their lodgings after every guest's stay. Bonuses may be paid for better services, but these decisions are more difficult to identify by comparing hosts with marginally fewer competitors. Finally, ratings about *location* are also negatively affected by an increase in the number of competitors in the same area. These ratings are not directly related to hosts' effort. Still, when the number of available listings reduces, listings' location may be more valuable for guests given the reduction in the number of alternatives. In Section 6.1, I illustrate an estimation technique for hosts' effort to take into account the presence of confounding effects related to variations in guests' tastes and attitude. Accordingly, the negative and significant effect of competition on hosts' effort is not solely determined by guests' valuation changes about listings' location. In Appendix E.2, I show the results using a larger radius for the number of competitors. In particular, I study variations in the number of competitors within 2 and 3 kilometers of each listing. The negative impact of competition on hosts' effort persists; the size decreases, and the statistical significance disappears. This suggests that competition's geographic dimension is relevant in determining hosts' decision in line with the theoretical assumptions and the identification design. The results are also robust once I restrict the number of snapshots considered. In Appendix E.3, I consider only snapshot dates from September 2016 (one year before the registration enforcement started to be implemented) to January 2019 (one year after the end of the enforcement implementation). The *first stage* and the IV results confirm the predicting power of the instrument and the negative significant impact of competition on hosts' effort. In Appendix E.4, I change the instrument to account for hosts' potential anticipation of the policy. In particular, the results of the *first stage* and the IV regressions are robust to anticipating the starting date for the settlement effect to September 2017; and to the use of the proportion of non-registered listings on May 2017 (when the settlement was announced). In Appendix E.5, I show that the estimated results' standard errors are consistent with different specifications. The standard errors are robust to considering a broader range of geographical correlations. In particular, I cluster standard errors at the San Francisco district level, and I allow for geographical correlation in line with Conley (1999): all results remain significant. Finally, in Appendix E.6, I account for variations in competition composition, controlling for many variables about the profile of competitors within d kilometers of listing i. All IV estimates are negative and significant with similar magnitudes relative to the coefficients in Section 5. This suggests that variations in competitors' profiles do not alter the negative relationship between effort and the number of competitors.

8 Conclusion

In this work, I provide theoretical and empirical evidence of the negative effect of competition on sellers' incentives to exert effort. First, I develop a model with reputation concerns and frictional matching where changes in entry costs impact the number of hosts in the market and their incentives to exert effort. Using data from Airbnb, I identify the causal relationship between the number of competitors and hosts' effort. To do so, I study a change in the registration enforcement of Airbnb hosts in San Francisco in September 2017. All empirical results are in line with the main prediction of the model. In particular, I observe a negative and significant impact of the number of competitors on hosts' ratings about effort. Due to the concentrated distribution of ratings, the economic effect of the competition change is hard to measure. To have a sense of the economic relevance of this effect, I provide an estimation of hosts' effort. I exploit the relationship between ratings reported by the same guests. Doing so, I account for the rating inflation that characterizes many online settings. As a result, the negative impact of a 10 percent increase in the number of competitors equals a variation from the 80th to the 20th percentile of the effort distribution.

My work's main limitation regards the structure of the dataset and the available pieces of information about transactions and effort. All proxies that I use to estimate hosts' effort are extracted from the Airbnb feedback system. Accordingly, my analysis considers only hosts' effort exerted and reported in reviewed transactions. With the hosts' effort estimation, I account for biases of ratings conditional on submission. Yet, potential biases due to selection into submitting a rating remain in place: it is a promising avenue for future research.

From a policy perspective, the results suggest that limiting competitors' number in a platform may be beneficial for services' quality. Besides the selection effect, sellers have stronger incentives to exert effort. Thus, rental restrictions such as the San Francisco Short-Term Rentals Regulation may favor local sellers without undermining their services' quality. Moreover, this work sheds light on a trade-off between quantity and quality of transactions in the context of platform design. Several platforms (Airbnb included) charge a percent fee on each transaction's total price between sellers and buyers. Platforms have incentives to lower entry costs, attract more users, and foster more exchanges. Still, my work shows that an increase in entry costs leads Airbnb hosts to rent their dwellings for more nights and exert more effort. Thus, transactions' quality increases and the total effect of an increase in entry costs on platforms' profit is ambiguous. In line with these policy implications, further research is necessary to investigate the optimal entry fee for market efficiency and platforms' profits.

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APPENDIX

"Competition and Reputation in a Congested Marketplace: Theory and Evidence from Airbnb"

A Appendix: The Model

Here I provide proofs of the Theorem and the Proposition discussed in Section 2. To do that, I start presenting the senior hosts' profit maximization; and I discuss how seniors' prices may be informative of hosts' effort. Then, I show how the probability of exerting effort for junior hosts with $c = k$ can be uniquely identified, and I present junior hosts' profit maximization. I show the existence and uniqueness of a search equilibrium with informative reviews (Theorem 1), and I conclude with the proof of Proposition 1.

Senior Hosts' Profit Maximization - Seniors post prices p_2 after observing reviews r_2. They take as given guests' utility U, and the function $\theta(p,r)$ mapping offers (p,r) to tightness levels θ with binding market utility constraint. Thus, to maximize profits, posting prices p_2 is equivalent to choosing a mapping from reviews r to tightness levels $\theta(r) = \theta(\hat{p},r) : (a\mu(r)+b-\hat{p})\frac{\alpha(\theta(\hat{p},r))}{\theta(\hat{p},r)} = U$. Accordingly, if $a\mu(r_2)+b < U$, $\theta(r_2) = 0$, and $p_2(r_2) = 0$. Otherwise, with $a\mu(r_2)+b \geq U$, the optimal tightness level $\theta(r_2)$, price $p_2(r_2)$, and profits for seniors with reviews r_2 are:

$$\alpha'(\theta(r_2)) = \frac{U}{a\mu(r_2)+b} \tag{A.1}$$

$$p_2(r_2) = a\mu(r_2)+b-\frac{\theta(r_2)}{\alpha(\theta(r_2))}U \tag{A.2}$$

$$\Pi_2(r_2) = (a\mu(r_2)+b)\big(\alpha(\theta(r_2))-\alpha'(\theta(r_2))\theta(r_2)\big).$$

With $a\mu(r_2)+b \geq U$, $\Pi_2(r_2)$ is strictly increasing in $\mu(r_2)$:

$$\begin{aligned}
\frac{\partial\Pi_2(r_2)}{\partial\mu(r_2)} &= a(\alpha(\theta(r_2))-\alpha'(\theta(r_2))\theta(r_2))+(a\mu(r_2)+b)\frac{\partial(\alpha(\theta(r_2))-\alpha'(\theta(r_2))\theta(r_2))}{\partial\theta(r_2)}\frac{\partial\theta(r_2)}{\partial\mu(r_2)}\\
&= a(\alpha(\theta(r_2))-\alpha'(\theta(r_2))\theta(r_2))-(a\mu(r_2)+b)\alpha''(\theta(r_2))\theta(r_2)\frac{\partial\theta(r_2)}{\partial\mu(r_2)}\\
&= a(\alpha(\theta(r_2))-\alpha'(\theta(r_2))\theta(r_2))+a(a\mu(r_2)+b)\alpha''(\theta(r_2))\theta(r_2)\frac{1}{\alpha''(\theta(r_2))}\frac{U}{(a\mu(r_2)+b)^2}\\
&= a\alpha(\theta(r_2)) > 0,
\end{aligned}$$

where the third passage directly follows from the properties of the derivative of the inverse function.[40]

Prices as Informative Signals - Only reviews affect guests' beliefs about hosts' effort in the main text, and prices play no role.[41] Still, prices posted by seniors may be an informative signal for the future effort choice. This is only the case when $r_2 = r_2^+$: the cost of seniors with r_2^- is always $c = k$, and they never exert effort: $\mu(p_2, r_2^-) = 0 \; \forall p_2$. Seniors with $r_2^\emptyset$ do not know their cost of effort: $\mu(p_2, r_2^\emptyset) = \pi \; \forall p_2$. Differently, seniors with r_2^+ know their cost of effort and their cost may be $c = k$, or $c = 0$. Yet, their expected profits do not depend on their cost of effort (either exerting effort is costless, or they do not exert effort), and hosts with $c = 0$ cannot implement a pricing strategy to profitably separate themselves from hosts with $c = k$. As a result, hosts with $c = k$ and $c = 0$ pool together and post the same price. This pooling strategy admits multiple equilibria depending on guests' beliefs about hosts' effort (on and off-the-equilibrium). The pooling price that maximizes hosts' profits is equivalent to the equilibrium price p_2^+ in the main text: with this price, the premium of exerting effort $\Pi_2(r_2^+)$ is maximized, and a greater measure of juniors with $c = k$ exert effort. Thus, restricting the attention on *equilibria with informative reviews* is equivalent (in terms of allocation) to focus on equilibria with informative prices and reviews such that guests' beliefs sustain the hosts' favorite allocation with the highest level of exerted effort by juniors.

Optimal Effort Decision by Junior Hosts - Junior hosts with $c = k$ may exert effort to mimic hosts with $c = 0$, and enjoy higher profits when they are seniors. The difference in discounted senior profits with r_2^+ and r_2^- represents the return of exerting effort: $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-))$. Accordingly, the probability to exert effort $\omega_1^\emptyset$ can be uniquely determined with the following steps: Consider $\omega_1^\emptyset = 1$ and calculate $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-))$. If it is greater than k, junior hosts with $c = k$ exert effort with probability $\omega_1^\emptyset = 1$. Otherwise, consider $\omega_1^\emptyset = 0$ and calculate again $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-))$. If it is lower than k, junior hosts with $c = k$ exert effort with probability $\omega_1^\emptyset = 0$. Otherwise, derive $\omega_1^\emptyset \in (0,1)$ such that $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-)) = k$. Recall that $\mu(r_2^+) = \frac{\pi}{\pi + (1-\pi)\omega_1^\emptyset}$ and $\mu(r_2^-) = 0$; and $\frac{\partial \Pi_2(r_2)}{\partial \mu(r_2)} > 0$. Thus, $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-))$ is strictly decreasing in $\omega_1^\emptyset$, and the equation $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-)) = k$ admits one and only one solution.

Junior Hosts' Profit Maximization - Before matching, junior hosts have not yet drawn their cost of effort and the review $r_1^\emptyset$ is uninformative. They maximize Π_1 as in Equation 2.2. Similarly to seniors, juniors take as given guests' utility U, and the function $\theta(p, r)$ mapping offers (p, r) to tightness levels θ with binding market utility constraint. As for seniors, to maximize profits, posting prices p_1 is equivalent to choosing a mapping from reviews r to tightness levels $\theta(r) = \theta(\hat{p}, r)$:

[40] Recall that the first derivative of the function α is invertible.

[41] Doing so, prices do not have a dual role of directing search and signaling effort as in Delacroix and Shi (2013).

$(a\mu(r)+b-\hat{p})\frac{\alpha(\theta(\hat{p},r))}{\theta(\hat{p},r)} = U$. Accordingly, the optimal tightness level $\theta(r_1^\emptyset)$, and price $p_1(r_1^\emptyset)$ are:

$$\alpha'(\theta(r_1^\emptyset)) = \frac{U}{a\mu(r_1^\emptyset)+b-k(1-\pi)\omega_1^\emptyset+\beta\Delta\Pi} \tag{A.3}$$

$$p_1(r_1^\emptyset) = a\mu(r_1^\emptyset)+b-\frac{\theta(r_1^\emptyset)}{\alpha(\theta(r_1^\emptyset))}U, \tag{A.4}$$

where $\Delta\Pi$ captures the value of a match in terms of reviews updating and it is defined as follows:

$$\Delta\Pi = \Pi_2(r_2^+)(\pi+(1-\pi)\omega_1^\emptyset)+(1-\pi)(1-\omega_1^\emptyset)\Pi_2(r_2^-)-\Pi_2(r_2^\emptyset).$$

If $a\mu(r_1^\emptyset)+b-k(1-\pi)\omega_1^\emptyset+\beta\Delta\Pi < U$, then $\theta(r_1^\emptyset)=0$ and $p_1^\emptyset(r_1^\emptyset)=0$.

Proof of Theorem 1. The existence and the uniqueness of equilibrium with informative reviews rely on the continuity and the monotonicity of junior profits Π_1 relative to U. In this case, there exists one and only one value of U^E such that the free entry condition in Equation 2.1 is satisfied. From this utility level U^E, the equilibrium allocation can be uniquely determined. Accordingly, I first show the continuity and the monotonicity with respect to U of senior profits $\Pi_2(r_2)$, and of the probability to exert effort for juniors with $c=k$, $\omega_1^\emptyset$. Then, I show the continuity and the monotonicity on U of junior profits Π_1.

Continuity and Monotonicity of $\Pi_2(r_2)$ *relative to* U - Senior profits with r_2^- and $r_2^\emptyset$ do not depend on $\omega_1^\emptyset$ (since $\mu(r_2^-)=0$ and $\mu(r_2^\emptyset)=\pi$) and their relationship with respect to U is easier to determine. In particular: for $r_2=\{r_2^-,r_2^\emptyset\}$, $\Pi_2(r_2)$ is decreasing in U if $a\mu(r_2)+b\geq U$:

$$\begin{aligned}
\frac{\partial\Pi_2(r_2)}{\partial U} &= (a\mu(r_2)+b)\frac{\partial(\alpha(\theta(r_2))-\alpha'(\theta(r_2))\theta(r_2))}{\partial\theta(r_2)}\frac{\partial\theta(r_2)}{\partial U}\\
&= -(a\mu(r_2)+b)\alpha''(\theta(r_2))\theta(r_2)\frac{\partial\theta(r_2)}{\partial U}\\
&= -(a\mu(r_2)+b)\alpha''(\theta(r_2))\theta(r_2)\frac{1}{\alpha''(\theta(r_2))}\frac{1}{(a\mu(r_2)+b)}\\
&= -\theta(r_2) < 0.
\end{aligned}$$

Senior profits with r_2^+ do depend on $\omega_1^\emptyset$ (since $\mu(r_2^+) = \frac{\pi}{\pi+(1-\pi)\omega_1^\emptyset}$). With $a\mu(r_2^+)+b \geq U$:

$$\begin{aligned}
\frac{\partial \Pi_2(r_2^+)}{\partial U} &= (a\mu(r_2^+)+b)\frac{\partial(\alpha(\theta(r_2^+)) - \alpha'(\theta(r_2^+))\theta(r_2^+))}{\partial \theta(r_2^+)}\frac{\partial \theta(r_2^+)}{\partial U} + a\frac{\partial \mu(r_2^+)}{\partial U}(\alpha(\theta(r_2^+)) - \alpha'(\theta(r_2^+))\theta(r_2^+)) \\
&= -(a\mu(r_2^+)+b)\theta(r_2^+)\alpha''(\theta(r_2^+))\frac{\partial \theta(r_2^+)}{\partial U} + a\frac{\partial \mu(r_2^+)}{\partial U}(\alpha(\theta(r_2^+)) - \alpha'(\theta(r_2^+))\theta(r_2^+)) \\
&= -\theta(r_2^+) + \theta(r_2^+)a\frac{\partial \mu(r_2^+)}{\partial U}\alpha'(\theta(r_2^+)) + a\frac{\partial \mu(r_2^+)}{\partial U}(\alpha(\theta(r_2^+)) - \alpha'(\theta(r_2^+))\theta(r_2^+)) \\
&= -\theta(r_2^+) + a\frac{\partial \mu(r_2^+)}{\partial U}\alpha(\theta(r_2^+)),
\end{aligned}$$

where $\frac{\partial \mu(r_2^+)}{\partial U} = -\frac{(1-\pi)\pi}{\pi+(1-\pi)\omega_1^\emptyset}\frac{\partial \omega_1^\emptyset}{\partial U}$. Accordingly, the relationship between $\Pi_2(r_2^+)$ and U can only be determined after $\frac{\partial \omega_1^\emptyset}{\partial U}$ is derived.

Continuity and Monotonicity of $\omega_1^\emptyset$ relative to U - The probability to exert effort by juniors $\omega_1^\emptyset$ is derived comparing the cost of effort k with the reputational benefits $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-))$. If $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-)) > k$, then $\omega_1^\emptyset = 1$ and $\frac{\partial \omega_1^\emptyset}{\partial U} = 0$. Thus, $\frac{\partial \Pi_2(r_2^+)}{\partial U} = -\theta(r_2^+) = -\theta(r_2^\emptyset)$. Similarly, if $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-)) < k$, then $\omega_1^\emptyset = 0$ and $\frac{\partial \omega_1^\emptyset}{\partial U} = 0$. Thus, $\frac{\partial \Pi_2(r_2^+)}{\partial U} = -\theta(r_2^+)$.

If $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-)) = k$, then $\omega_1^\emptyset \in (0,1)$ and $\frac{\partial \omega_1^\emptyset}{\partial U} \neq 0$. Yet, in order to satisfy $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-)) = k$, we have to impose that:

$$\begin{aligned}
\frac{\partial \Pi_2(r_2^-)}{\partial U} &= \frac{\partial \Pi_2(r_2^+)}{\partial U} \\
-\theta(r_2^-) &= -\theta(r_2^+) + a\frac{\partial \mu(r_2^+)}{\partial U}\alpha(\theta(r_2^+)).
\end{aligned}$$

In line with previous equation, if $\beta(\Pi_2(r_2^+) - \Pi_2(r_2^-)) = k$, then $\frac{\partial \Pi_2(r_2^+)}{\partial U} = -\theta(r_2^-) < 0$ and,

$$\frac{\partial \omega_1^\emptyset}{\partial U} = \frac{(\theta(r_2^-) - \theta(r_2^+))(\pi + (1-\pi)\omega_1^\emptyset)}{a(1-\pi)\pi\alpha(\theta(r_2^+))} < 0.$$

Continuity and Monotonicity of Π_1 relative to U - With the results of the maximization in Equations A.3 and A.4, the junior profit Π_1 can be written as follows:

$$\Pi_1 = [a\mu(r_1^\emptyset) + b - k(1-\pi)\omega_1^\emptyset + \beta\Delta\Pi][\alpha(\theta(r_1^\emptyset)) - \alpha'(\theta(r_1^\emptyset))\theta(r_1^\emptyset)] + \beta\Pi_2(r_2^\emptyset).$$

Accordingly, Π_1 is decreasing in U if $a\mu(r_1^{\emptyset}) + b - k(1-\pi)\omega_1^{\emptyset} + \beta\Delta\Pi > U$:

$$
\begin{aligned}
\frac{\partial \Pi_1}{\partial U} =& \big[(a-k)(1-\pi)\frac{\partial \omega_1^{\emptyset}}{\partial U} + \beta \frac{\partial \Delta\Pi}{\partial U}\big][\alpha(\theta(r_1^{\emptyset})) - \alpha'(\theta(r_1^{\emptyset}))\theta(r_1^{\emptyset})] + \\
& + [a\mu(r_1^{\emptyset}) + b - k(1-\pi)\omega_1^{\emptyset} + \beta\Delta\Pi]\big[-\alpha''(\theta(r_1^{\emptyset})\theta(r_1^{\emptyset})\frac{\partial \theta(r_1^{\emptyset})}{\partial U}\big] \\
& - \beta\theta(r_2^{\emptyset}) \\
=& \big[(a-k)(1-\pi)\frac{\partial \omega_1^{\emptyset}}{\partial U} + \beta\big((1-\pi)\frac{\partial \omega_1^{\emptyset}}{\partial U}(\Pi_2(r_2^+) - \Pi_2(r_2^-)) - \theta(r_2^-)(1-\pi)(1-\omega_1^{\emptyset}) \\
& - \theta(r_2^{\emptyset}) + (\pi + (1-\pi)\omega_1^{\emptyset})\frac{\partial \Pi_2(r_2^+)}{\partial U}\big)\big]\alpha(\theta(r_1^{\emptyset})) - \theta(r_1^{\emptyset}) - \beta\theta(r_2^{\emptyset}) < 0.
\end{aligned}
$$

Unique Definition of the Equilibrium - Since Π_1 is decreasing in U, there exist only one U such that the free entry condition $\Pi_1 \leq f$ is satisfied with equality. For this utility level U, Equations A.1, and A.2 define unique levels of $\theta(r_2), p(r_2)$ with $r_2 = \{r_2^+, r_2^-, r_2^{\emptyset}\}$, and the probability $\omega_1^{\emptyset}$. Similarly, Equations A.3, and A.4 define unique levels of $\theta(r_1^{\emptyset})$ and $p(r_1^{\emptyset})$. At this step it is possible to uniquely define the mass of junior hosts entering h_1. The mass of senior hosts with reviews r_2^+,r_2^-, and $r_2^{\emptyset}$, $h_2(r_2^+), h_2(r_2^-), h_2(r_2^{\emptyset})$, can be derived in terms of h_1 and the elements of the equilibrium allocation already (uniquely) derived: $h_2(r_2^+) = \alpha(\theta(r_1^{\emptyset}))(\pi + (1-\pi)\omega_1^{\emptyset})h_1$, $h_2(r_2^-) = \alpha(\theta(r_1^{\emptyset}))((1-\pi)(1-\omega_1^{\emptyset}))h_1$, and $h_2(r_2^{\emptyset}) = (1-\alpha(\theta(r_1^{\emptyset})))h_1$. Finally, imposing the measure of guests directing to all offers adds up to one, h_1 is uniquely derived:

$$
\begin{aligned}
1 &= g(p_1^{\emptyset}, r_1^{\emptyset}) + g(p_2^+, r_2^+) + g(p_2^-, r_2^-) + g(p_2^{\emptyset}, r_2^{\emptyset}) \\
1 &= h_1\left(\frac{1}{\theta(r_1^{\emptyset})} + \frac{\alpha(\theta(r_1^{\emptyset}))(\pi + (1-\pi)\omega_1^{\emptyset})}{\theta(r_2^+)} + \frac{\alpha(\theta(r_1^{\emptyset}))((1-\pi)(1-\omega_1^{\emptyset}))}{\theta(r_2^-)} + \frac{(1-\alpha(\theta(r_1^{\emptyset})))}{\theta(r_2^{\emptyset})}\right).
\end{aligned}
$$

□

Proof of Proposition 1. The equilibrium with higher entry costs f_H is associated with a lower equilibrium guests' utility level U^E relative to the equilibrium with f_L. This is because $\frac{\partial \Pi_1}{\partial U} < 0$ and the free entry condition is satisfied for a lower level of U^E. Then, since $\frac{\partial \Pi_2(r_2)}{\partial U} < 0$ for $r_2 = \{r_2^+, r_2^-, r_2^{\emptyset}\}$ and $\frac{\partial \omega_1^{\emptyset}}{\partial U} < 0$, seniors enjoy higher profits, and juniors exert more effort with high entry costs f_H. Finally, recalling that, in equilibrium, $\mu^E(r_2^+) = \frac{\pi}{\pi + (1-\pi)\omega_1^{\emptyset}}$, then guests' beliefs associated with r_2^+ decrease as juniors are more likely to exert effort. □

B Appendix: Empirical Setting and Dataset

B.1 The San Francisco Short-Term Rentals Regulation (February 2015)

Rentals are considered "short-term" if the properties are rented for less than 30 consecutive nights at a time. Listings present on Airbnb can be exempt from the registration requirements if they only accept guests for periods of 30 or more days; or in case they are professional structures such as hotels and B&B. The regulation is mainly composed of the following parts:

- Only San Francisco permanent residents who own or rent single-family dwellings in the city are eligible to engage in short-term rentals. In particular, hosts must reside in their dwellings for at least 275 days per year;
- Resident tenants must notify their landlords before engaging in short-term rentals.If the contract between tenant and landlord prohibits subletting, the landlord may evict the tenant. Moreover, tenants cannot charge more rent than they are paying to the landlord and rent control laws must be respected;
- Compliance to city building code requirements is necessary and Airbnb and HomeAway will regularly provide the city with information about San Francisco listings to allow for an effective enforcement of the law.
- Only the primary residence can be used for short-term rentals. When a host is absent, the dwelling can be rented for a maximum of 90 days per year;
- Hosts must obtain a permit and register at the OSTR. Every two years, they must pay a \$250 fee. Moreover, hosts are required to obtain a city business license;
- The San Francisco hotel tax must be collected from renters and paid to the cityFor Airbnb hosts, the platform automatically collects and pays such a tax for its hosts. Hosts must be covered by an insurance with a coverage of at least \$500,000. Airbnb provides hosts with 1 million in coverage;

The Short-Term Starter Kit by the San Francisco OSTR at https://businessportal.sfgov.org/start/starter-kits/short-term-rental, and the official text of the ordinance at https://sfgov.legistar.com/View provide a comprehensive analysis of all the regulation's requirements.

B.2 The Settlement Agreement: Exit, Entry, and Hosts' Selection

The Short-Term Rental Regulation has been effective since February 2015. However, as highlighted in Section 3.2, the enforcement of listings' registration at the San Francisco OSTR has proven to be difficult. The settlement agreement, effective from September 2017, addressed the enforcement difficulties of registration implementing a resolution that forced every eligible Airbnb listings to be registered before January 2018. Appendix Figure B.1 reports the percentage of Airbnb listings offering short-term lodging that displayed a registration number at each snapshot. Before September 2017, less than 15 percent of listings displays a registration number. Conversely, at the beginning of 2018, when the settlement agreement has been completely implemented, the percentage of listings offering short-term lodging with registration numbers reaches 100 percent and it stays constant afterwards.

Appendix Figures B.2 and B.5 capture the change in the total number of Airbnb listings in San Francisco at each snapshot. Appendix Figure B.2 shows the evolution of the number of Airbnb listings offering short-term lodging: from September 2016 until September 2017 the number of short-term listings remains constant between 8,000 and 9,000 units; then, when the "pass-through registration" system started to be at place, the number of listings sharply drops to 4,000 units in February 2018, when all eligible Airbnb units have to be registered. The number of short-term listings stays constant for the next months when the implementation of settlement agreement was completed. To visualize the drop in the number of listings for different areas of San Francisco after the settlement, Appendix Figures B.3 and B.4 present two maps with the location of Airbnb listings offering short-term lodging in San Francisco in September 2017 and in January 2018.

The evolution of the number of Airbnb listings that do *not* offer short-term lodging (from now on, long-term) is displayed in Appendix Figure B.5. The number of long-term listings, which are exempt from the regulation, steadily grows during the months in which the "pass-through registration" system starts to be implemented. Then, in August 2018, the number jumps from less than 1,000 units to more than 2,500 units in August 2018 and it continues to grow with more listings entering the platform without offering short-term lodging at the end of 2018 and at the beginning of 2019.

The settlement agreement determined a selection in the type of listings that continued to be present on the platform after the implementation of the registration requirements. In Appendix Table B.1, I present some summary statistics to characterize this selection process. To do so, I divide listings into four groups: *compliers*, *exiters*, *never-regulated*, *always-regulated*. *Compliers* are those listings that enter the platform before September 2017 and do not exit before January 2018, when the implementation of the settlement agreement is completed. Accordingly, at one stage of their stay on the platform, they all comply with the terms of the Short-Term Rentals Regulation. *Exiters* are those listings that enter the platform before September 2017 and exit between September 2017 and January 2018 (before the full implementation of the settlement).

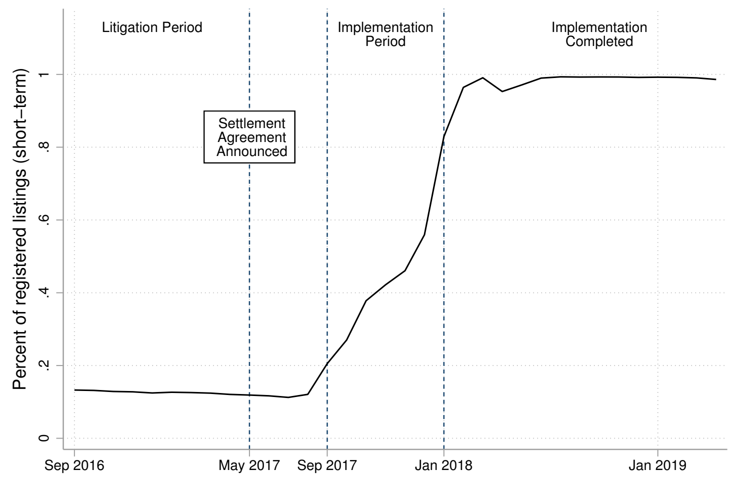


Figure B.1: Percent of Registered Airbnb Listings over Time

Note: The figure plots the percentage of Airbnb listings offering short-term lodging with a registration number in San Francisco from September 2016 to April 2019. The settlement agreement between the City Council and Airbnb was signed in May 2017 and it has been effective since September 2017. From January 2018 all eligible Airbnb listings must be registered.

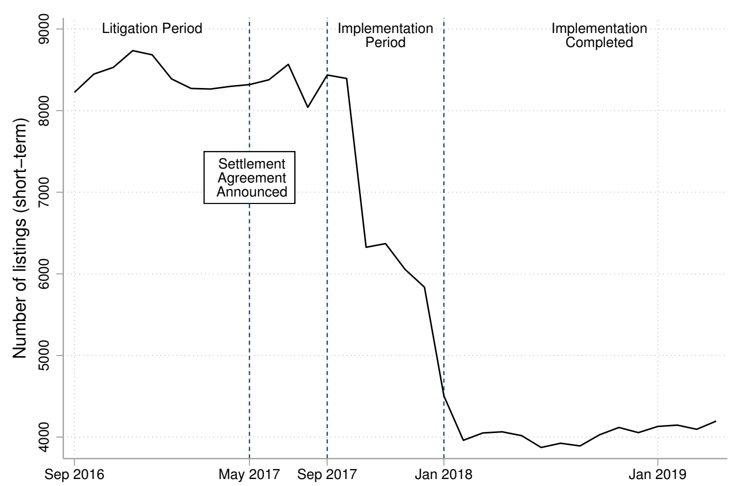


Figure B.2: Short-term Airbnb Listings over Time

Note: The figure plots the total number of Airbnb listings offering short-term lodging in San Francisco from September 2016 to April 2019. The settlement agreement between the City Council and Airbnb was signed in May 2017 and it has been effective since September 2017. From January 2018 all eligible Airbnb listings must be registered.

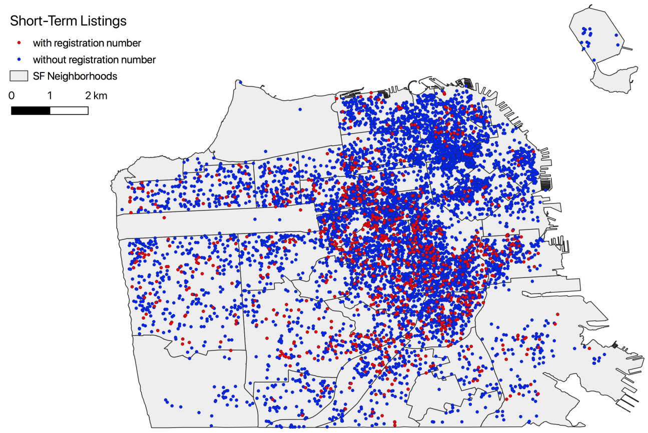


Figure B.3: Location of Airbnb Short-Term Listings in San Francisco: September 2017

Note: The map shows the location of all Airbnb listings listings offering short-term lodging in San Francisco that were present for the snapshot associated with September 2017. Blue dots correspond to generic short-term Airbnb listings; whereas red dots correspond to listings that display a registration number.

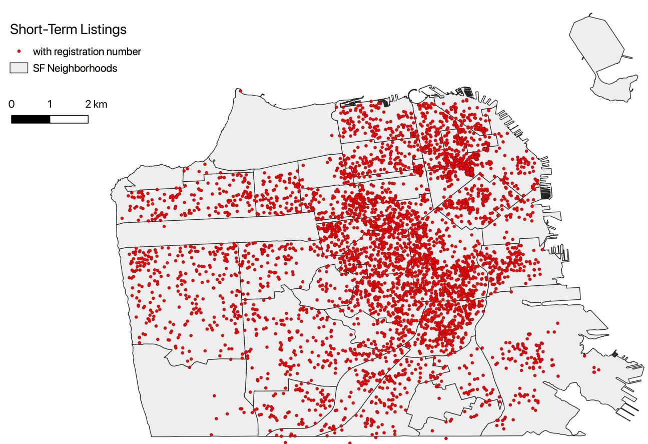


Figure B.4: Location of Airbnb Short-Term Listings in San Francisco: January 2018

Note: The map shows the location of all Airbnb listings listings offering short-term lodging in San Francisco that were present for the snapshot associated with January 2018. Red dots correspond to generic (registered) short-term Airbnb listings.

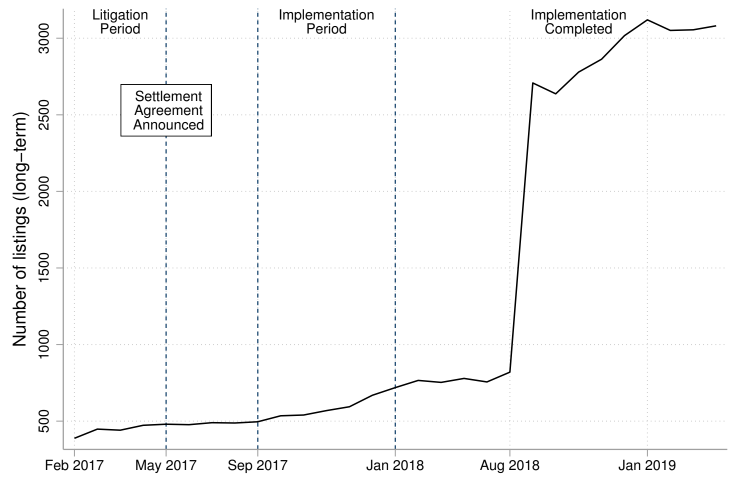


Figure B.5: Long-Term Airbnb Listings over Time

Note: The figure plots the total number of Airbnb listings that do *not* offer short-term lodging (long-term) in San Francisco over time (different snapshots) from February 2017 to April 2019. The three vertical lines regard the timing of the settlement agreement between the San Francisco City Council and Airbnb. The agreement was signed in May 2017 and it has been effective since September 2017. From January 2018 all eligible Airbnb listings should be registered.

Never-regulated listings exit the platform before September 2017, when the implementation of the settlement agreement had not started yet. Finally, *always-regulated* listings enter the platform after September 2017, so they have to register to appear on the website.

In Appendix Table B.1, Panel A compares listings that are present on Airbnb before and after the settlement agreement (*compliers*) with those that enter before September 2017 and exit during the implementation of the new regulation (*exiters*). *Compliers* require guests to stay for more consecutive nights relative to *exiters* and they charge lower prices. Still, they have a greater turnover since their number of reviews per snapshot is higher. Moreover, *compliers* have significantly higher ratings and they seem to be selected among those present on Airbnb before the settlement agreement. In Appendix Table B.2, I show statistics measured in September 2017 for *compliers* than *exiters*. In September 2017, *compliers* have, on average, almost five times more reviews than *exiters*, and enter the platform almost thirty days before. *Compliers* charge significantly lower prices than *exiters* and have higher ratings. Accordingly, other than reducing the number of listings present on the platform, the regulation enforcement of the settlement agreement may have affected hosts' effort through the selection of hosts who stay after the enforcement of the registration. To tackle this issue, in Section 5, I restrict my analysis to *compliers*.

A similar differential in the listing profiles is present in Panel B of Appendix Table B.1 where listings that are not affected by the settlement agreement (*never-regulated*) are compared with listings that enter after September 2017 (*always-regulated*). This latter group tends to engage in significantly longer rentals relative to *never-regulated* listings. In particular, *always-regulated* listings require guests to stay and rent their house for almost 20 consecutive nights, on average; whereas *never-regulated* listings require, on average, less than 5 consecutive nights. Accordingly, listings that enter after the settlement are much less likely to engage in short-term rentals than those listings that are active before September 2017. The difference in the duration of the lodging services across groups may explain other differentials in terms of prices and the total number of reviews. The price per night charged by *never-regulated* listings is significantly higher than the one charged by *always-regulated* listings: shorter rentals tend to be more expensive. In addition, longer stays mechanically produce a lower stream of reviews over time. Moreover, *always-regulated* listings tend to have significantly higher ratings than *never-regulated* listings: this may be due to the different service duration, or to an improvement in the service quality provided by hosts (in line with the model's prediction).

Table B.1: Summary Statistics: the Settlement Agreement and Listings Selection

	Compliers		*Exiters*			
	Mean	SD	Mean	SD	Δ	$p-value$
Panel A						
Days in Airbnb	1,060.05	372.51	550.95	221.89	509.10	0.0
Total number of reviews	74.08	90.91	11.38	26.43	62.70	0.0
Price per night	207.44	176.31	244.25	231.02	-36.82	0.0
Availability next 30 days	7.27	9.89	4.90	9.69	2.37	0.0
$r_{i,t}^{overall}$	94.22	6.30	92.86	9.22	1.37	0.0
$r_{i,t}^{accuracy}$	9.66	0.63	9.48	0.95	0.18	0.0
$r_{i,t}^{check-in}$	9.80	0.53	9.67	0.78	0.12	0.0
$r_{i,t}^{clean}$	9.50	0.75	9.20	1.18	0.31	0.0
$r_{i,t}^{comm}$	9.77	0.56	9.69	0.80	0.09	0.0
$r_{i,t}^{location}$	9.50	0.70	9.43	0.96	0.08	0.0
$r_{i,t}^{value}$	9.25	0.73	9.17	1.01	0.09	0.0
Minimum nights required	11.53	22.11	3.16	4.67	8.37	0.0
Short-term rentals	73%	-	99%	-	0.3	-
Registration displayed	71%	-	5%		0.7	-
Number of listings	5,406	-	3,970	-	-	-
	Never Regulated		*Always Regulated*			
	Mean	SD	Mean	SD	Δ	$p-value$
Panel B						
Days in Airbnb	148.35	174.62	203.58	164.26	-55.23	0.0
Total number of reviews	10.93	24.69	8.57	19.15	2.36	0.0
Price per night	202.05	189.53	195.69	174.65	6.35	0.0
Availability next 30 days	11.15	11.57	10.04	11.19	1.11	0.0
$r_{i,t}^{overall}$	91.16	10.68	94.90	9.09	-3.74	0.0
$r_{i,t}^{accuracy}$	9.33	1.09	9.67	0.81	-0.34	0.0
$r_{i,t}^{check-in}$	9.50	0.99	9.76	0.74	-0.26	0.0
$r_{i,t}^{clean}$	9.08	1.28	9.47	1.07	-0.39	0.0
$r_{i,t}^{comm}$	9.55	0.94	9.74	0.79	-0.19	0.0
$r_{i,t}^{location}$	9.30	1.07	9.57	0.81	-0.28	0.0
$r_{i,t}^{value}$	8.97	1.17	9.22	1.04	-0.25	0.0
Minimum nights required	4.13	12.52	19.92	26.14	-15.79	0.0
Short-term rentals	96%	-	46%	-	-0.5	-
Registration displayed	4%	-	46%	-	-0.4	-
Number of listings	11,730	-	7,146	-	-	-

Note: The two panels compare the profile of listings before and after the settlement agreement divided in four groups. *Compliers*: those that enter the platform before September 2017 and do not exit before January 2018. *Exiters*: those that enter the platform before September 2017 and exit between September 2017 and January 2018. *Never-regulated*: those that exit the platform before September 2017. *Always-regulated*: those that enter the platform after September 2017. The last two columns show the differences between the averages and the $p-value$ of the difference.

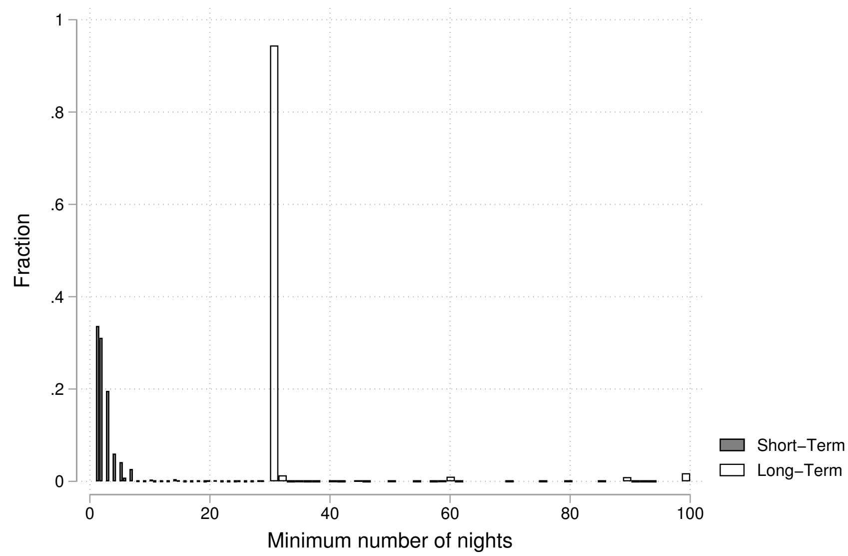
Table B.2: Summary Statistics: the Settlement Agreement and Listings Selection in September 2017.

	Compliers		*Exiters*			
	Mean	SD	Mean	SD	Δ	$p-value$
Days in Airbnb	1,061.10	376.96	552.19	221.81	508.91	0.0
Days in Airbnb before September 2017	487.19	248.97	474.76	227.14	12.44	0.0
Total number of reviews	45.45	61.38	9.77	24.46	35.68	0.0
Price per night	206.40	165.08	246.12	232.62	-39.72	0.0
Availability next 30 days	7.11	8.70	3.54	8.05	3.57	0.0
$r_{i,t}^{overall}$	94.36	6.06	93.07	9.01	1.29	0.0
$r_{i,t}^{accuracy}$	9.68	0.61	9.49	0.94	0.19	0.0
$r_{i,t}^{check-in}$	9.82	0.50	9.69	0.75	0.12	0.0
$r_{i,t}^{clean}$	9.52	0.73	9.22	1.16	0.30	0.0
$r_{i,t}^{comm}$	9.79	0.52	9.70	0.78	0.09	0.0
$r_{i,t}^{location}$	9.53	0.65	9.43	0.94	0.09	0.00
$r_{i,t}^{value}$	9.27	0.70	9.19	0.99	0.08	0.00
Minimum nights required	5.90	15.16	3.09	4.66	2.82	0.0
Short-term rentals	90%	-	0.1%	-	0.08	-
Registration displayed	19%	-	3%	-	0.16	-
Number of listings	4,574	-	3,629	-	-	-

Note: The table compare the profile of listings before and after the settlement agreement. All statistics refer to the snapshot regarding September 2017. Listings are divided in two groups. *Compliers*: those that enter the platform before September 2017 and do not exit before January 2018. *Exiters*: those that enter the platform before September 2017 and exit between September 2017 and January 2018. The last two columns provide the differences between the statistics' averages and the $p-value$ of the difference. The numbers of listings in the two groups are not equal to the ones shown in Appendix Table B.1 since not all listings in the two groups were active (present on the platform) at the date of the snapshot regarding September 2017.

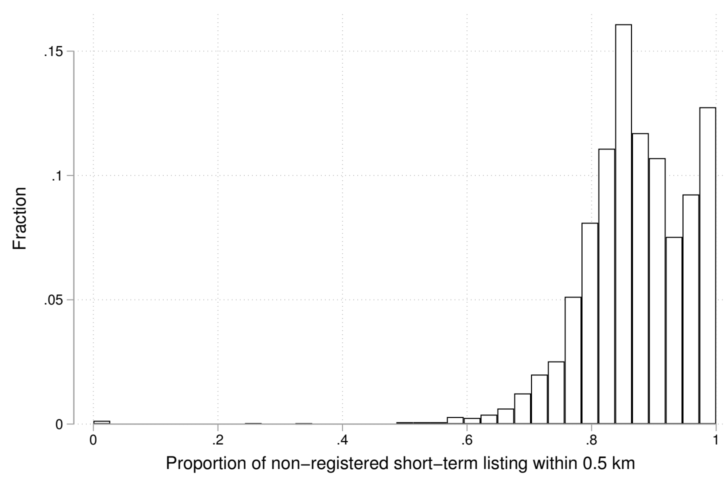
C Appendix: Identification Strategy

Figure C.1: Distribution of Minimum Number of Nights across Short-Term and Long-Term Listings



Note: The figure shows the distribution of the minimum numbers of nights hosts allow guests to stay. Hosts are divided in short-term and long-term in line with the San Francisco regulation.

Figure C.2: Distribution of $\gamma_i^{0.5}$



Note: The figure shows the distribution of values of $\gamma_i^{0.5}$ for the set of listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018.

D Appendix: Main Results and Extensions

Table D.1: OLS Estimates of the Impact of Competition on Hosts' Effort

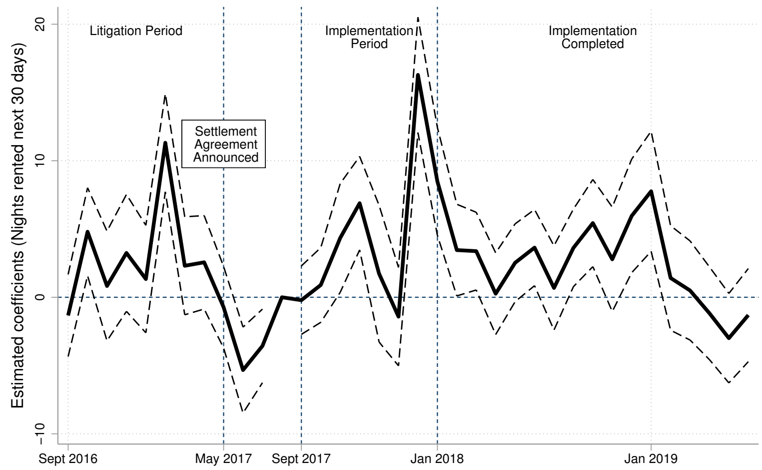
	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	0.00409			0.0163		
	[0.0118]			[0.0108]		
$\ln(L_{i,t}^{1})$		-0.0155			0.000448	
		[0.0167]			[0.0151]	
$\ln(L_{i,t}^{2})$			-0.0180			-0.00273
			[0.0209]			[0.0204]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.89	9.89	9.89	9.87	9.87	9.87
Adjusted R^2	0.0088	0.0088	0.0088	0.0091	0.0090	0.0090
N	80,402	80,413	80,435	80,402	80,413	80,435

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses.

Table D.2: Evidence Supporting Assumption OC_2: Response Rate, $\bar{r}_{i,t}^{location}$, $e_{i,t}$

	Response Rate	Response Rate	Response Rate
$\bar{r}_{i,t}^{location} \times 100$	0.0727		
	[0.0590]		
$e_{i,t}^{check} \times 100$		0.202*	
		[0.108]	
$e_{i,t}^{comm} \times 100$			0.356***
			[0.117]
Listing FE	✓	✓	✓
Mean	0.976	0.976	0.976
R-squared	0.000046	0.00051	0.00017
N	54,262	54,262	54,262

Note: Only listings whose hosts do not manage multiple properties on Airbnb are considered. The variable *Response Rate* takes values from 0 to 1. A higher percentage corresponds to a faster rate of host's replies. Standard errors clustered by listing are in parentheses.



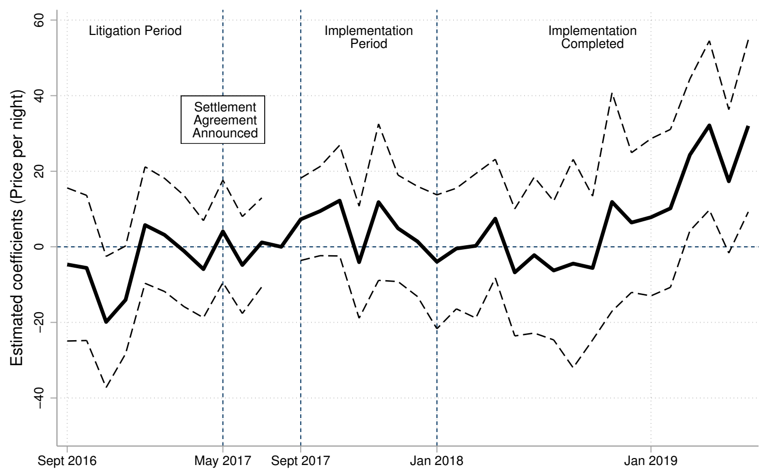


Figure D.1: Estimated Coefficients from Equation 6.5: Nights rented next 30 days and Price per night

Note: In line with Equation 6.5, $rented_{i,t}^{30}$ and $p_{i,t}$ are regressed on listing and snapshot fixed effects, and on the products between $\gamma_i^{0.5}$ and snapshot dummies. Standard errors (10%) are clustered by listing. The graph plots the estimated coefficients on these products. The values of the coefficients corresponding to August 2017 ($\hat{\beta}_{Aug2017}$) are normalized to zero. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered.

E Appendix: Robustness Checks

Table E.1: IV Estimates of the Impact of Competition on Hosts' Activation of the Instant Booking Option

	$instant_{i,t}$		
	(1)	(2)	(3)
$\ln(L_{i,t}^{0.5})$	0.0311		
	[0.0592]		
$\ln(L_{i,t}^{1})$		0.0240	
		[0.0459]	
$\ln(L_{i,t}^{2})$			0.0104
			[0.0439]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	0.32	0.32	0.32
Adjusted R^2	0.047	0.048	0.047
N	80,290	80,301	80,323

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses.

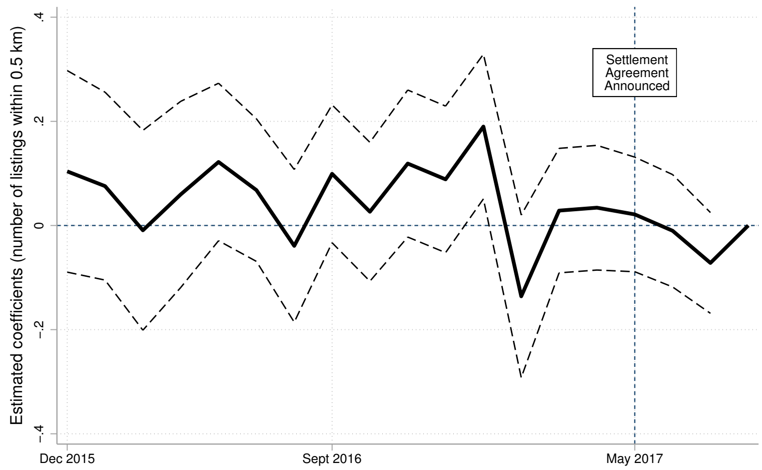


Figure E.1: Estimated Coefficients from Equation 4.3 before the Settlement: Number of Listings within 0.5 km

Note: In line with Equation 4.3, $\ln(L_{i,t}^{0.5})$ is regressed on listing and snapshot fixed effects, and on the products between $\gamma_i^{0.5}$ and snapshot dummies. Standard errors (10%) are clustered by listing. The graph plots the estimated coefficients on these products before the settlement. The value of the coefficient corresponding to August 2017 ($\hat{\beta}_{Aug2017}$) is normalized to zero. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered.

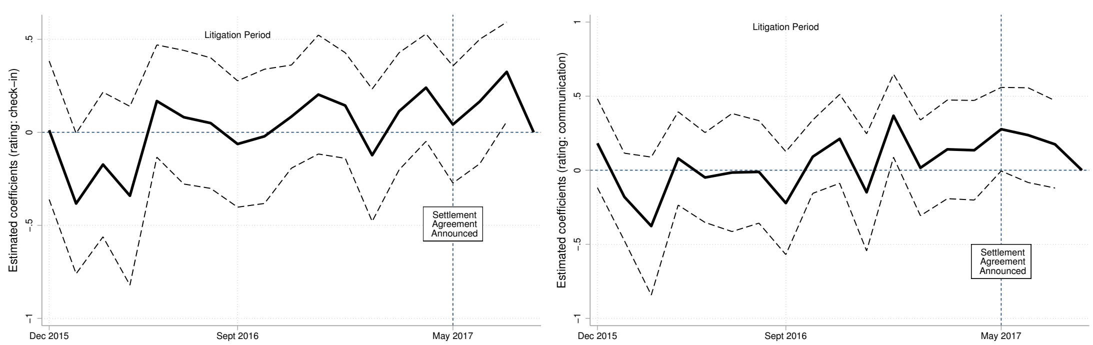


Figure E.2: Estimated Coefficients from Equation 4.4 before the Settlement: Ratings Regarding Check-in and Communication

Note: In line with Equation 4.4, $r_{i,t}^{checkin}$ and $r_{i,t}^{comm}$ are regressed on listing and snapshot fixed effects, and on the products between $\gamma_i^{0.5}$ and snapshot dummies. Standard errors (10%) are clustered by listing. The graph plots the estimated coefficients on these products before the settlement. The values of the coefficients corresponding to August 2017 ($\hat{\beta}_{Aug2017}$) are normalized to zero. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered.

Table E.2: Impact of the Settlement Agreement on Competition with No Winter Snapshots (First Stage)

	$\ln(L_{i,t}^{0.5})$	$\ln(L_{i,t}^{1})$	$\ln(L_{i,t}^{2})$
$post_{Nov2017}$	1.119***	2.063***	2.689***
	[0.0856]	[0.0888]	[0.0513]
$\gamma_i^{0.5} \times post_{Nov2017}$	-1.651***		
	[0.103]		
$\gamma_i^{1} \times post_{Nov2017}$		-2.770***	
		[0.107]	
$\gamma_i^{2} \times post_{Nov2017}$			-3.484***
			[0.0596]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	4.230	5.493	6.742
F-test	566.3	1269.3	3560.6
Adjusted R^2	0.68	0.82	0.91
N	60,652	60,658	60,676

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Snapshots taken in the months of December, January, and February are removed for the sample. Standard errors clustered by listing are in parentheses.

Table E.3: IV Estimates of the Impact of Competition on Hosts' Effort with No Winter Snapshots

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.140***			-0.135***		
	[0.0440]			[0.0424]		
$\ln(L_{i,t}^{1})$		-0.119***			-0.111***	
		[0.0378]			[0.0339]	
$\ln(L_{i,t}^{2})$			-0.112***			-0.0935***
			[0.0349]			[0.0319]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.901	9.901	9.901	9.878	9.878	9.878
Adjusted R^2	0.0052	0.010	0.011	0.0042	0.0090	
N	60,652	60,658	60,676	60,652	60,658	60,676

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Snapshots taken in the months of December, January, and February are removed for the sample. Standard errors clustered by listing are in parentheses.

Table E.4: Impact of the Settlement Agreement on Competition controlling for the distance from the Moscone Center (First Stage)

	$\ln(L_{i,t}^{0.5})$	$\ln(L_{i,t}^{1})$	$\ln(L_{i,t}^{2})$
$post_{Nov2017}$	0.988***	1.833***	2.427***
	[0.0768]	[0.0786]	[0.0473]
$\gamma_i^{0.5} \times post_{Nov2017}$	-1.490***		
	[0.0925]		
$\gamma_i^{1} \times post_{Nov2017}$		-2.497***	
		[0.0949]	
$\gamma_i^{2} \times post_{Nov2017}$			-3.176***
			[0.0545]
$d_i^{Moscone} \times closure_{17-19}$	0.0187***	0.0161***	0.0124***
	[0.00177]	[0.00135]	[0.000821]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	4.222	5.484	6.732
F-test	496.3	1142.5	3221.2
Adjusted R^2	0.68	0.81	0.91
N	80,290	80,301	80,323

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Snapshots taken in the months of December, January, and February are removed for the sample. Standard errors clustered by listing are in parentheses.

Table E.5: Impact of the Settlement Agreement on Hosts' Effort controlling for the distance from the Moscone Center (Reduced Form)

	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$post_{Nov2017}$	-0.0170	-0.0891	-0.150	-0.0545	-0.117	-0.158*
	[0.0573]	[0.0823]	[0.0948]	[0.0557]	[0.0770]	[0.0899]
$\gamma_i^{0.5} \times post_{Nov2017}$	0.214***			0.223***		
	[0.0648]			[0.0634]		
$\gamma_i^{1} \times post_{Nov2017}$		0.297***			0.295***	
		[0.0940]			[0.0877]	
$\gamma_i^{2} \times post_{Nov2017}$			0.367***			0.340***
			[0.109]			[0.104]
$d_i^{Moscone} \times closure_{17-19}$	-0.000737	-0.000478	-0.000202	-0.00289	-0.00267	-0.00248
	[0.00167]	[0.00169]	[0.00169]	[0.00187]	[0.00187]	[0.00187]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.901	9.901	9.901	9.879	9.879	9.879
Adjusted R^2	0.012	0.012	0.012	0.012	0.012	0.012
N	80,290	80,301	80,323	80,290	80,301	80,323

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses.

Table E.6: IV Estimates of the Impact of Competition on Hosts' Effort with Listings 1-km far from the Moscone Center

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.106***			-0.106***		
	[0.0376]			[0.0382]		
$\ln(L_{i,t}^{1})$		-0.0918***			-0.0836**	
		[0.0338]			[0.0333]	
$\ln(L_{i,t}^{2})$			-0.0948***			-0.0792**
			[0.0311]			[0.0315]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.913	9.913	9.913	9.898	9.898	9.898
Adjusted R^2	0.0092	0.011	0.011	0.0079	0.011	0.011
N	76,825	76,836	76,858	76,825	76,836	76,858

Note: Only listings 1-kilometer far from the Moscone Center, offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses.

E.1 Competition and the Other Ratings

In Section 5, I show how changes in competition affect the effort choices by hosts. To do so, I study ratings reported by guests about hosts' effort. Yet, guests report ratings about different dimensions and in this Appendix, I show the effect of competition on the other ratings' categories. The overall effect from a change in the number of hosts on guests' utility is ambiguous. In particular, with fewer competitors, hosts exert more effort, but guests' probability to find an available host is lower. Hosts may also charge a higher price, but this seems not to be the case as shown in Section 6.2.[42] The impact of less competition on ratings varies depending on the reported dimension of guests' utility.

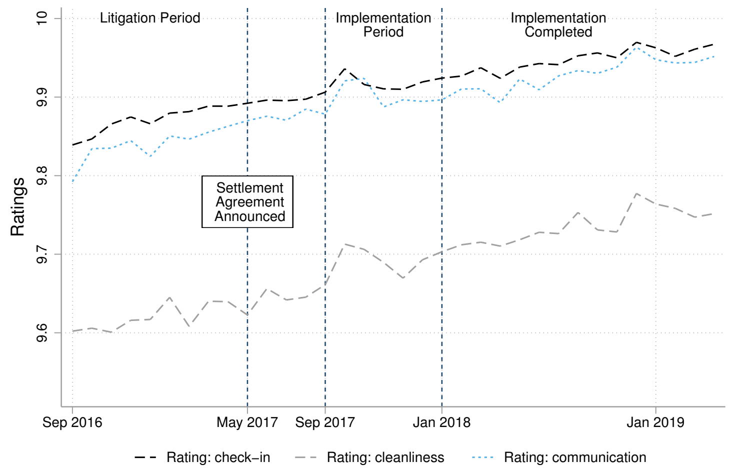
Appendix Figure E.3 shows the dynamics of all ratings' categories for the period of interest: all ratings increase over time. Appendix Table E.7 reports the IV estimates for the ratings about *accuracy* of the web page and *cleanliness*, denoted as $r_{i,t}^{accuracy}$ and $r_{i,t}^{clean}$, respectively. Both categories represent different dimensions of hosts' effort. With more competition, the effect on $r_{i,t}^{accuracy}$ is negative and significant as for the categories *check-in* and *communication*. This corroborates the results regarding the negative effect of competition on effort. Differently, $r_{i,t}^{clean}$ is not significantly affected by the number of competitors although $r_{i,t}^{clean}$ presents a clear positive trend with a similar magnitude with respect to the dynamics of $r_{i,t}^{check-in}$ and $r_{i,t}^{comm}$, as shown in the Appendix Figure E.3.

The absence of a significant effect for hosts' cleanliness activities may be due to the nature of this effort dimension and the characteristics of the identification strategy. Cleaning activities are often a medium-term investment for hosts who may not personally clean their lodgings after every guest's stay. Bonuses may be paid for better services, but these are probably decisions that are more difficult to identify comparing hosts with marginally fewer competitors. As it is suggested by Appendix Figure E.3, all hosts may clean more after a certain threshold of competitors exit the platform.

Appendix Table E.8 reports the IV estimates for the ratings about *location*: $r_{i,t}^{location}$. These ratings should not be affected by hosts' effort choice. However, variations in the number of listings in a specific area may have an effect on this dimension. In fact, it is more difficult for guests to find an available listing when the number of competitors reduces. Thus, listings' location may be more valuable for guests given the reduced number of alternatives. This story is in line with the negative an significant effect of competition on $r_{i,t}^{location}$ in Appendix Table E.8. In Section 6.1, I illustrate an estimation technique for hosts' effort to take into account the presence of confounding effects related to variations in guests' tastes and attitude. Accordingly, the negative and significant effect of competition on hosts' effort is not solely determined by changes in guests' valuation about listings' location. Finally, Appendix Table E.9 reports the IV estimates for the ratings about *value-for-money* and the *overall experience*, denoted as $r_{i,t}^{value}$ and $r_{i,t}^{overall}$, respectively. Both categories should capture hosts' effort, but also prices, and the probability to have a match. Thus, changes in the number of

[42]In the model, the resulting effect on the expected guests' utility U is negative, whereas the ex-post utility from a specific match may be greater or lower with less competition depending on the matched host's seniority.

competitors affect these ratings in multiple ways and the overall predicted effect is ambiguous. In line with this, Appendix Table E.9 shows that the impact of competition is non-significant apart from the 0.5 km specification for $r_{i,t}^{overall}$ with a positive effect significant at 10 percent. Fewer competitors may increase hosts' incentives to provide a high-quality service, but this is partially (if not completely) undo by the increased difficulty in having a match.



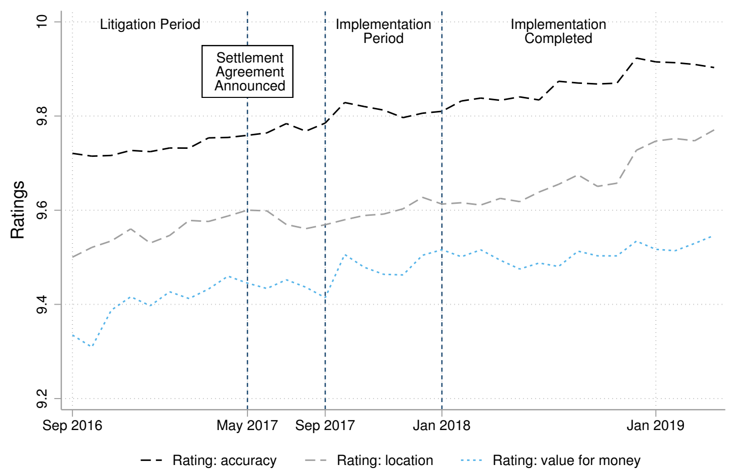


Figure E.3: Dynamics of Ratings over Time

Note: The figure plots the ratings of listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. The settlement agreement between the City Council and Airbnb was signed in May 2017 and it has been effective since September 2017. From January 2018 all eligible Airbnb listings must be registered.

Table E.7: IV Estimates of the Impact of Competition on Ratings about Accuracy and Cleanliness

	$r_{i,t}^{accuracy}$			$r_{i,t}^{clean}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.176***			0.0262		
	[0.0480]			[0.0466]		
$\ln(L_{i,t}^{1})$		-0.190***			-0.00938	
		[0.0402]			[0.0364]	
$\ln(L_{i,t}^{2})$			-0.208***			-0.0138
			[0.0378]			[0.0335]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.792	9.792	9.792	9.665	9.665	9.665
Adjusted R^2	0.012	0.016	0.018	0.010	0.010	0.010
N	78,366	78,377	78,399	78,149	78,160	78,182

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018. Standard errors clustered by listing are in parentheses.

Table E.8: IV Estimates of the Impact of Competition on Ratings about Location

	$r_{i,t}^{location}$		
	(1)	(2)	(3)
$\ln(L_{i,t}^{0.5})$	-0.172***		
	[0.0545]		
$\ln(L_{i,t}^{1})$		-0.141***	
		[0.0458]	
$\ln(L_{i,t}^{2})$			-0.0892**
			[0.0421]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	9.599	9.599	9.599
Adjusted R^2	0.024	0.027	0.030
N	77,640	77,650	77,671

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018. Standard errors clustered by listing are in parentheses.

Table E.9: IV Estimates of the Impact of Competition on Ratings about Value for Money and the Overall Experience

	$r_{i,t}^{value}$			$r_{i,t}^{overall}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	0.0366			1.446**		
	[0.0556]			[0.608]		
$\ln(L_{i,t}^{1})$		0.0359			0.716	
		[0.0487]			[0.507]	
$\ln(L_{i,t}^{2})$			0.0261			0.345
			[0.0447]			[0.475]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.440	9.440	9.440	94.10	94.10	94.10
Adjusted R^2	0.0080	0.0082	0.0081	0.00038	0.0020	0.0022
N	76,649	76,660	76,682	71,884	71,895	71,917

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018. Standard errors clustered by listing are in parentheses.

E.2 The Impact of Listings within 2 and 3 Kilometers

Here I repeat the same analysis considering variations in the number of competitors within 2 and 3 kilometers of each listing. $\ln(L_{i,t}^{2-3})$ denotes the logarithm of the number of competitor within this distance. In Appendix Table E.10, I report the IV Estimates for this distance (the instrument has been modified to compute the proportion of non-registered listings within 2 and 3 kilometers) controlling further for $\ln(L_{i,t}^{2})$. In all settings, the impact of competition is negative and non-significant, or weakly significant.

Table E.10: IV Estimates of the Impact of Competition within 2 and 3 Kilometers on Hosts' Effort

	$r_{i,t}^{check-in}$		$r_{i,t}^{comm}$	
	(1)	(2)	(3)	(4)
$\ln(L_{i,t}^{2-3})$	-0.0399	-0.0736	-0.0237	-0.0381
	[0.0264]	[0.0690]	[0.0287]	[0.0722]
$\ln(L_{i,t}^{2})$		0.0299		0.0126
		[0.0513]		[0.0507]
Listing FE	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓
Mean	9.901	9.901	9.879	9.879
Adjusted R^2	0.012	0.012	0.012	0.012
N	80,343	80,322	80,343	80,322

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered using snapshots from September 2016 to January 2019. The only instrumented variable in all regression is $\ln(L_{i,t}^{2-3})$, following the design in Section 4. Standard errors clustered by listing are in parentheses.

E.3 Restricting the Time-Window

In this Appendix, I restrict the number of snapshots I use to identify the effect of competition on effort and profits. In particular, I consider data starting from September 2016 (one year before the registration enforcement started to be implemented) to January 2019 (one year after the end of the implementation). Appendix Tables E.11, E.12, and E.13 and show the results for the *first stage*, *reduced form* and the IV regressions for ratings $r_{i,t}^{effort}$. By reducing the number of observations, the significance of the coefficients slightly decrease whereas the magnitudes do not vary.

Table E.11: Impact of the Settlement Agreement on Competition (First Stage) - September 2016 / January 2019

	$\ln(L_{i,t}^{0.5})$ (1)	$\ln(L_{i,t}^{1})$ (2)	$\ln(L_{i,t}^{2})$ (3)
$post_{Nov2017}$	0.670***	1.507***	2.145***
	[0.0678]	[0.0672]	[0.0386]
$\gamma_i^{0.5} \times post_{Nov2017}$	-1.495***		
	[0.0818]		
$\gamma_i^{1} \times post_{Nov2017}$		-2.476***	
		[0.0802]	
$\gamma_i^{2} \times post_{Nov2017}$			-3.222***
			[0.0442]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	4.229	5.490	6.739
F-test	663.8	1470.4	4062.8
Adjusted R^2	0.74	0.85	0.93
N	57,348	57,355	57,369

Note: Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered using snapshots from September 2016 to January 2019. Standard errors clustered by listing are in parentheses.

Table E.12: Impact of the Settlement Agreement on Hosts' Effort (Reduced Form) - September 2016 / January 2019

	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$post_{Nov2017}$	-0.0598	-0.139*	-0.178*	-0.0274	-0.123*	-0.118
	[0.0556]	[0.0821]	[0.0986]	[0.0520]	[0.0742]	[0.0878]
$\gamma_i^{0.5} \times post_{Nov2017}$	0.185***			0.161***		
	[0.0646]			[0.0607]		
$\gamma_i^{1} \times post_{Nov2017}$		0.276***			0.271***	
		[0.0957]			[0.0870]	
$\gamma_i^{2} \times post_{Nov2017}$			0.321***			0.265***
			[0.115]			[0.102]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.889	9.889	9.889	9.869	9.869	9.869
Adjusted R^2	0.0041	0.0042	0.0042	0.0039	0.0041	0.0039
N	57,348	57,355	57,369	57,348	57,355	57,369

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered using snapshots from September 2016 to January 2019. Standard errors clustered by listing are in parentheses.

Table E.13: IV Estimates of the Impact of Competition on Hosts' Effort - September 2016 / January 2019

	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.124***			-0.108***		
	[0.0438]			[0.0412]		
$\ln(L_{i,t}^{1})$		-0.111***			-0.110***	
		[0.0388]			[0.0353]	
$\ln(L_{i,t}^{2})$			-0.0995***			-0.0821***
			[0.0357]			[0.0318]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.889	9.889	9.889	9.869	9.869	9.869
Adjusted R^2	0.00128	0.00335	0.00415	0.00147	0.00290	0.00378
N	57,348	57,355	57,369	5,7348	57,355	57,369

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered using snapshots from September 2016 to January 2019. Standard errors clustered by listing are in parentheses.

E.4 Date Variations in the Instrumental Variable

In this Appendix, I modify the instrument measuring the effect of the shock (the dummy variable) and the expected propensity to be affected by the shock (the cross-section variation) in September 2017 and in May 2017, respectively. I denote the new dummy $post_{Sept2017}$, and the new proportion of non-registered listings γ_i^{d-May}. This may be relevant given the potential policy anticipation by hosts. Appendix Tables E.14, E.15 and E.16 show the results for the *first stage*, *reduced form* and the IV regressions for ratings $r_{i,t}^{effort}$. With this specification, the effect of the *first stage* is much lower (but still significant), in line with the event study graph in Figure 1 where the effect of the settlement starts from November 2017. Similarly, the *reduced form*'s coefficients are lower since the ratings' change between September and November 2017 (the anticipation?) is not very strong as supported by the event study in Figures 2 and Appendix Figure 3. However, due to the greater reduction in the precision of the *first stage*, the IV results are much higher with the new instrumental variable (the IV coefficients are the ratio between the *reduced form* and the *first stage* coefficients).

Table E.14: Impact of the Settlement Agreement on Competition (First Stage) - $\gamma_i^{d-May} \times post_{Sept2017}$

	$\ln(L_{i,t}^{0.5})$ (1)	$\ln(L_{i,t}^{1})$ (2)	$\ln(L_{i,t}^{2})$ (3)
$post_{Sept2017}$	0.0273	0.00785	-0.0151
	[0.0300]	[0.0249]	[0.0205]
$\gamma_i^{0.5-May} \times post_{Sept2017}$	-0.374***		
	[0.0346]		
$\gamma_i^{1-May} \times post_{Sept2017}$		-0.378***	
		[0.0288]	
$\gamma_i^{2-May} \times post_{Sept2017}$			-0.351***
			[0.0223]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	4.222	5.484	6.732
F-test	384.1	662.3	1144.9
Adjusted R^2	0.65	0.77	0.85
N	80,402	80,413	80,435

Note: Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses.

Table E.15: Impact of the Settlement Agreement on Hosts' Effort (Reduced Form) - $\gamma_i^{d-May} \times post_{Sept2017}$

	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$post_{Sept2017}$	0.0669*	0.0700*	0.0744*	0.0345	0.0358	0.0421
	[0.0359]	[0.0381]	[0.0385]	[0.0343]	[0.0364]	[0.0367]
$\gamma_i^{0.5-May} \times post_{Sept2017}$	0.122***			0.133***		
	[0.0356]			[0.0330]		
$\gamma_i^{1-May} \times post_{Sept2017}$		0.118***			0.131***	
		[0.0381]			[0.0351]	
$\gamma_i^{2-May} \times post_{Sept2017}$			0.112***			0.123***
			[0.0386]			[0.0355]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.893	9.893	9.893	9.872	9.872	9.872
Adjusted R^2	0.0092	0.0091	0.0091	0.0096	0.0095	0.0094
N	80,402	80,413	80,435	80,402	80,413	80,435

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses.

Table E.16: IV Estimates of the Impact of Competition on Hosts' Effort - $\gamma_i^{d-May} \times post_{Sept2017}$

	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.326***			-0.356***		
	[0.0992]			[0.0939]		
$\ln(L_{i,t}^{1})$		-0.311***			-0.347***	
		[0.102]			[0.0952]	
$\ln(L_{i,t}^{2})$			-0.317***			-0.350***
			[0.111]			[0.103]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.893	9.893	9.893	9.872	9.872	9.872
Adjusted R^2	0.0011	0.0066	0.0080	0.0026	0.0069	0.0087
N	80,402	80,413	80,435	80,402	80,413	80,435

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses.

E.5 Standard Errors: Clustered at District Level and Conley (1999)

In this Appendix, I demonstrate that not only the coefficients, but also the standard errors of the estimated results are consistent to different specifications. In particular, I show that our standard errors are robust to considering a broader range of geographical correlations. I present here results using clustered standard errors at San Francisco district level and allowing for geographical correlation using the exact latitude and longitude of each listing in line with Conley (1999).

Airbnb guests can select listings choosing between 60 San Francisco districts. I observe the district in which each listing is included.[43] Appendix Tables E.17, E.19, and E.21 show the results of the *first stage*, *reduced form* and IV regressions for ratings $r_{i,t}^{effort}$ clustering standard errors at the district level. Similarly, Appendix Tables E.18, E.20, and E.22 present the results with standard errors accounting for Conley (1999) spatial correlation.[44] In all specifications, standard errors inflate due to the larger correlation allowed by the cluster. Yet, the significance of all results does not change and the F statistics continues to be much higher the traditional threshold to identify weak instruments.

Table E.17: Impact of the Settlement Agreement on Competition (First Stage) - District Clustered s.e.

	$\ln(L_{i,t}^{0.5})$ (1)	$\ln(L_{i,t}^{1})$ (2)	$\ln(L_{i,t}^{2})$ (3)
$post_{Nov2017}$	1.393***	2.279***	2.902***
	[0.266]	[0.326]	[0.232]
$\gamma_i^{0.5} \times post_{Nov2017}$	-1.547***		
	[0.312]		
$\gamma_i^{1} \times post_{Nov2017}$		-2.588***	
		[0.375]	
$\gamma_i^{2} \times post_{Nov2017}$			-3.300***
			[0.259]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	4.216	5.479	6.727
F-test	1159.8	2567.6	11324.9
Adjusted R^2	0.67	0.81	0.91
N	78,412	78,423	78,445

Note: Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered. Standard errors clustered by district are in parentheses. In San Francisco there are 60 districts.

[43] Listings may "change" their reference district in the insideairbnb dataset. I consider the listing's district the one that appears more frequently over the listing stay on the platform.

[44] To compute Conley (1999) standard errors I use the method suggested by Colella, Lalive, Sakalli and Thoenig (2019).

Table E.18: Impact of the Settlement Agreement on Competition (First Stage) - Conley (1999) s.e.

	$\ln(L_{i,t}^{0.5})$ (1)	$\ln(L_{i,t}^{1})$ (2)	$\ln(L_{i,t}^{2})$ (3)
$post_{Nov2017}$	1.170	2.047	2.663
	[0.343]	[0.658]	[0.723]
$\gamma_i^{0.5} \times post_{Nov2017}$	-1.552***		
	[0.102]		
$\gamma_i^{1} \times post_{Nov2017}$		-2.592***	
		[0.178]	
$\gamma_i^{2} \times post_{Nov2017}$			-3.283***
			[0.212]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	4.222	5.484	6.732
F-test	513.8	1137.3	3043.0
Adjusted R^2	0.674	0.813	0.907
N	80,290	80,301	80,323

Note: Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered. Standard errors (in parentheses) are adjusted to reflect spatial dependence as in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 10 km (covering all San Francisco municipality).

Table E.19: Impact of the Settlement Agreement on Hosts' Effort (Reduced Form) - District Clustered s.e.

	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$post_{Nov2017}$	-0.0414	-0.111	-0.175	-0.0736	-0.146	-0.194*
	[0.0743]	[0.111]	[0.117]	[0.0783]	[0.118]	[0.114]
$\gamma_i^{0.5} \times post_{Nov2017}$	0.213**			0.236***		
	[0.0833]			[0.0867]		
$\gamma_i^{1} \times post_{Nov2017}$		0.292**			0.318**	
		[0.128]			[0.129]	
$\gamma_i^{2} \times post_{Nov2017}$			0.365**			0.373***
			[0.138]			[0.125]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.903	9.903	9.903	9.880	9.880	9.880
Adjusted R^2	0.012	0.012	0.012	0.012	0.012	0.012
N	78,412	78,423	78,445	78,412	78,423	78,445

Note: Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered. Standard errors clustered by district are in parentheses. In San Francisco there are 60 districts.

Table E.20: Impact of the Settlement Agreement on Hosts' Effort (Reduced Form) - Conley (1999) s.e.

	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$post_{Nov2017}$	-0.0731	-0.194***	-0.273***	-0.0503	-0.152**	-0.171**
	[0.0423]	[0.0671]	[0.116]	[0.0332]	[0.0728]	[0.0721]
$\gamma_i^{0.5} \times post_{Nov2017}$	0.217***			0.233***		
	[0.0394]			[0.0376]		
$\gamma_i^{1} \times post_{Nov2017}$		0.300***			0.311***	
		[0.0565]			[0.0526]	
$\gamma_i^{2} \times post_{Nov2017}$			0.368***			0.362***
			[0.0756]			[0.0684]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.901	9.901	9.901	9.879	9.879	9.879
Adjusted R^2	0.00056	0.00059	0.00063	0.00064	0.00062	0.00059
N	80,290	80,301	80,323	80,290	80,301	80,323

Note: Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered. Standard errors (in parentheses) are adjusted to reflect spatial dependence as in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 10 km (covering all San Francisco municipality).

Table E.21: IV Estimates of the Impact of Competition on Hosts' Effort - District Clustered s.e.

	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.138**			-0.153**		
	[0.0632]			[0.0659]		
$\ln(L_{i,t}^{1})$		-0.113**			-0.123**	
		[0.0531]			[0.0548]	
$\ln(L_{i,t}^{2})$			-0.111**			-0.113***
			[0.0435]			[0.0396]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.901	9.901	9.901	9.879	9.879	9.879
Adjusted R^2	0.0048	0.010	0.011	0.0024	0.0094	0.011
N	78,412	78,423	78,445	78,412	78,423	78,445

Note: Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered. Standard errors clustered by district are in parentheses. In San Francisco there are 60 districts.

Table E.22: IV Estimates of the Impact of Competition on Hosts' Effort - Conley (1999) s.e.

	$r_{i,t}^{check-in}$			$r_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.140***			-0.150***		
	[0.0251]			[0.0267]		
$\ln(L_{i,t}^{1})$		-0.116***			-0.120***	
		[0.0210]			[0.0221]	
$\ln(L_{i,t}^{2})$			-0.112***			-0.110***
			[0.0221]			[0.0224]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.901	9.901	9.901	9.879	9.879	9.879
Adjusted R^2	0.0011	0.0066	0.0080	0.0026	0.0069	0.0087
N	80,290	80,301	80,323	80,290	80,301	80,323

Note: Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered. Standard errors (in parentheses) are adjusted to reflect spatial dependence as in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 10 km (covering all San Francisco municipality).

E.6 Controlling for the Composition of Competitors

In the previous analysis, the total number of short-term listings describes the intensity of competition faced by each listing. Yet, the profile of competitors around each listing may be also relevant to determine the competitiveness of the area in which the listing is located. This point may constitute a potential threat to the identification since the enforcement of the regulation selects the profile of listings active on the platform. To partially account for variations in the composition of competition, I present the results as Section 5 controlling for the following set of variables regarding listings within d kilometers of listing i: $z_{i,t}^{d,shared}$, the ratio between short-term listings renting shared apartments and short-term listings renting entire apartments; $z_{i,t}^{d,super}$, the ratio between superhost short-term listings and non-superhost short-term listings; $z_{i,t}^{d,90/100}$, the ratio between short-term listings with rating $\bar{R}_{i,t}$ lower than 4 and short-term listings with rating $\bar{R}_{i,t}$ equal to 5; $z_{i,t}^{d,90-100/100}$, the ratio between short-term listings with rating $\bar{R}_{i,t}$ between 4 and 5 and short-term listings with rating $\bar{R}_{i,t}$ equal to 5; $z_{i,t}^{d,acc1/5}$, the ratio between short-term listings that can accommodate only one guest and short-term listings that can accommodate more than five guests; $z_{i,t}^{d,acc2/5}$, the ratio between short-term listings that can accommodate only two guests and short-term listings that can accommodate more than five guests; $z_{i,t}^{d,acc3-4/5}$, the ratio between short-term listings that can accommodate three, four or five guests and short-term listings that can accommodate more than five guests. Appendix Tables E.23 and E.24 show the results. The *first stage* coefficients in Appendix Table E.23 continue to be strongly negatively significant. The IV estimates in Appendix Table E.24 are negative and significant. Interestingly, the magnitude of the IV estimates is similar relative to the coefficients in Section 5. This suggests that variations in the profile of competitors do not alter the negative relationship between effort and the number of competitors.

Table E.23: Impact of the Settlement Agreement on Competition Controlling for Composition (First Stage)

	$\ln(L^{0.5}_{i,t})$	$\ln(L^{1}_{i,t})$	$\ln(L^{2}_{i,t})$
$post_{Nov2017}$	1.354***	2.035***	2.050***
	[0.0747]	[0.0833]	[0.0498]
$\gamma_i^{0.5} \times post_{Nov2017}$	-1.830***		
	[0.0859]		
$\gamma_i^{1} \times post_{Nov2017}$		-2.544***	
		[0.0992]	
$\gamma_i^{2} \times post_{Nov2017}$			-2.340***
			[0.0606]
$X_{i,t}$	✓	✓	✓
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	4.277	5.491	6.734
F-test	457	1203	6940
Adjusted R^2	0.71	0.84	0.94
N	78,017	80,115	80,300

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. $X_{i,t}$ includes $z_{i,t}^{d,shared}$, $z_{i,t}^{d,super}$, $z_{i,t}^{d,90/100}$, $z_{i,t}^{d,90-100/100}$, $z_{i,t}^{d,acc1/5}$, $z_{i,t}^{d,acc2/5}$, and $z_{i,t}^{d,acc3-4/5}$ where the distance d corresponds to the one used for the main independent variable. Standard errors clustered by listing are in parentheses.

Table E.24: IV Estimates of the Impact of Competition on Hosts' Effort Controlling for Composition

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.117***			-0.121***		
	[0.0339]			[0.0342]		
$\ln(L_{i,t}^{1})$		-0.0979***			-0.123***	
		[0.0367]			[0.0363]	
$\ln(L_{i,t}^{2})$			-0.0585			-0.120**
			[0.0549]			[0.0500]
$X_{i,t}$	✓	✓	✓	✓	✓	✓
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.902	9.901	9.901	9.881	9.879	9.879
Adjusted R^2	0.0031	0.00083	0.0037	0.0011	0.0000014	0.0000017
N	78,017	80,115	80,300	78,017	80,115	80,300

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. $X_{i,t}$ includes $z_{i,t}^{d,shared}$, $z_{i,t}^{d,super}$, $z_{i,t}^{d,90/100}$, $z_{i,t}^{d,90-100/100}$, $z_{i,t}^{d,acc1/5}$, $z_{i,t}^{d,acc2/5}$, and $z_{i,t}^{d,acc3-4/5}$ where the distance d corresponds to the one used for the main independent variable. Standard errors clustered by listing are in parentheses.