Web Appendix

**Regulating the Sharing Economy:
The Effects of Day Caps on Short- and Long-Term Rental
Markets and Stakeholder Outcomes**

April 20, 2024

Contents

A.1 Theoretical Model

Short-term rental market – demand. We assume that demand for short-term accommodation comes from many individuals with heterogenous preferences (e.g., in terms of characteristics of the property, its exact location,...), who, given these preferences, choose the best accommodation available to them. Anderson et al. (1992) show that (under certain assumptions) the discrete choices made by these heterogenous consumers can be captured by a representative consumer with utility function

$$U = \sum_{j=1}^{J} \beta_j \log Q_j, \quad \sum_{j=1}^{J} \beta_j = 1, \ \beta_j \geq 0, \tag{A.1.1}$$

where Q_j is an index representing aggregate consumption of short-term accommodation in area j, while β_j denotes area j's relative market size. To model demand for individual properties, we assume that consumers can choose between a large number (more precisely, a continuum of size $\mathcal{I}_j$) of differentiated properties in each area.[1] The specification of the index Q_j captures that individuals benefit both from the consumed *amount* of short-term accommodation and from having access to a larger *number of differentiated offerings*. Specifically, Q_j combines the differentiated properties in area j using a constant elasticity of substitution (CES) aggregator:

$$Q_j = \left[\int_{i \in \mathcal{I}_j} \big(q_j(i)\big)^{(\sigma-1)/\sigma} di \right]^{\sigma/(\sigma-1)}, \quad \sigma > 1. \tag{A.1.2}$$

The index thus integrates over ("sums up") the quantities of consumed short-term accommodation $q_j(i)$ over all properties i in area j, where the elasticity of substitution σ measures how differentiated properties are (larger values of σ correspond to less differentiation). In the limit when σ becomes very large, the exponents approach one and the properties become perfect substitutes (i.e., are non-differentiated). In this extreme case, $Q_j = \int_{i \in \mathcal{I}_j} q_j(i) di$ simply measures the total amount of Airbnb consumption in area j. Properties are imperfect substitutes for smaller values of σ. In this more general case, consumers benefit from the number of offerings on top of total Airbnb

[1] As will become clear below, our set up makes sure that each supplier has price setting power (i.e., market power), while still having no impact on the optimal price of competitors.

consumption. To see this, consider a special case where a total mass M of properties is consumed in equal quantities q. The index

$$\begin{aligned} Q_j &= \left[\int_0^M q^{(\sigma-1)/\sigma} di\right]^{\sigma/(\sigma-1)} \\ &= \left(Mq^{(\sigma-1)/\sigma}\right)^{\sigma/(\sigma-1)} = M^{\sigma/(\sigma-1)} q = M^{1/(\sigma-1)} \underbrace{(Mq)}_{\text{Total Quantity}} \end{aligned} \tag{A.1.3}$$

then increases in M even conditional on the total quantity. This 'love for variety'-effect becomes stronger when properties are more differentiated and is important for the welfare expressions that we derive below.

To derive the demand function for property i, first note that the upper tier Cobb-Douglas utility specification[2] implies that expenditure for short-term accommodation in area j, X_j, is a fixed share β_j of total expenditure Y, i.e., $X_j = \beta_j Y$. Utility maximization yields the following first order condition for property i in area j:

$$\frac{\sigma - 1}{\sigma}\left(q_j(i)\right)^{-1/\sigma} = \lambda p_j(i), \tag{A.1.4}$$

where λ denotes the Lagrange multiplier associated with the utility-maximization problem. Dividing the first-order condition for two properties i and k and solving for $q_j(k)$ gives

$$q_j(k) = \left(\frac{p_j(i)}{p_j(k)}\right)^{\sigma} q_j(i). \tag{A.1.5}$$

Multiplying both sides with $p_j(k)$ and integrating over all properties in area j gives the demand function for property i:

$$q_j(i) = p_j(i)^{-\sigma} \cdot X_j \cdot P_j^{\sigma-1} = A_j p_j(i)^{-\sigma}, \tag{A.1.6}$$

where $A_j = X_j \cdot P_j^{\sigma-1}$. Demand for property i depends on three components. First, its own price, where the parameter $\sigma > 1$ denotes the price elasticity

[2] U can be obtained by taking logs on a standard Cobb-Douglas utility function of the form $\tilde{U} = \prod_j Q_j^{\beta_j}$. Since taking logs is a positive monotone transformation, U and $\tilde{U}$ represent the same preference ordering.

of demand.[3] A_j is a scaling factor and consists of two components. Total expenditure X_j in area j and a price index P_j for area j, which is defined as

$$P_j = \left(\int_{i \in \mathcal{I}_j} (p_j(i))^{1-\sigma} \, di \right)^{\frac{1}{1-\sigma}}. \tag{A.1.7}$$

The price index P_j captures the impact of competition on the demand for property i and depends on the number and the prices of other offerings in area j. In particular, lower prices for a subset of properties and (ceteris paribus) a larger number of properties (i.e., a larger set $\mathcal{I}_j$) lower the index and thus scale down demand for property i.[4] Thus, the price index encapsulates the impact of competition from other hosts on host i.

Short-term rental market – supply. Each area j is populated by a set of potential Airbnb hosts. Offering short-term accommodation involves both (constant) marginal cost $c(i)$ (e.g., cleaning) and fixed cost F.

Because the following analysis is identical in all areas and for all values of $c(i)$, we drop the indices j and i in the following to ease notation. Hosts set prices to maximize profits

$$\pi = \big(p - c\big) q - F, \tag{A.1.8}$$

leading to a first order condition

$$q + \big(p - c\big) \frac{\partial q}{\partial p} = 0 \tag{A.1.9}$$

and, therefore, equilibrium price

$$p^* = \frac{c}{1 - \frac{1}{\sigma}} = \frac{\sigma}{\sigma - 1} c, \tag{A.1.10}$$

where $\sigma = (\partial q / \partial p)/(q/p)$ denotes the price elasticity of demand. Note first that the optimal price is a mark-up over marginal cost that is inversely

[3] Note that σ has a dual role as it denotes both the price elasticity of demand and the elasticity of substitution. These two elasticities are naturally related as they both measure how strongly demand responds to price increases, but they are not necessarily identical for other specification of the utility function. Note that higher values of σ imply that demand responds more sensitively to own price changes and hence indicate that properties are closer substitutes.

[4] The last point becomes apparent later when we compute P_j explicitly.

related to the price elasticity of demand, i.e., the mark-up is higher for more differentiated properties. Note also that the specification of demand implies that prices depend only on marginal cost, not the prices set by other hosts. We therefore write $p(c)$ in the following to denote the optimal price of a host with marginal cost c.

Optimal pricing implies revenue

$$r(c) = p(c)q(p(c)) = \left(\frac{\sigma - 1}{\sigma}\right)^{\sigma-1} c^{1-\sigma} \cdot X \cdot P^{\sigma-1} \tag{A.1.11}$$

and profits $V(c) = \pi(c) - F$, where variable profits $\pi(c)$ are given by

$$\pi(c) = \big(p(c) - c\big)q(p(c)) = \frac{1}{\sigma - 1} cq(p(c)) = \frac{r(c)}{\sigma} = Bc^{1-\sigma}, \tag{A.1.12}$$

where $B = \left(\frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}}\right) XP^{\sigma-1}$ can be interpreted as a shifter of market demand. Notice that variable profits are a fraction σ of revenue $(r(c))$. Intuitively, profits (and revenue) decrease in own marginal cost and increase in the price index (i.e., if for higher prices and/or a lower number of other hosts).

Each area hosts a set of potential short-term accommodation providers. To offer their property on Airbnb, potential providers have to pay a sunk entry cost F_E. By paying F_E potential providers learn about their marginal cost c, which we assume to be drawn from a cumulative distribution function $G(c)$ with upper bound $c_{\max}$ and lower bound $c_{\min}$. $g(c)$ denotes the respective density function.

Among the M_E potential hosts, all that make positive profits will offer their property on Airbnb (we call those hosts 'active' hosts). Formally, offering a property on Airbnb is optimal if

$$\pi(c) - F \geq 0 \quad \Longleftrightarrow \quad Bc^{1-\sigma} \geq F. \tag{A.1.13}$$

This condition defines a cutoff value $\hat{c}$ where $\pi(\hat{c}) = F$, such that all hosts with marginal cost below $\hat{c}$ find it optimal to become active. Note that the cutoff increases (i.e., more hosts decide to become active) if market demand B increases and fixed cost F go down.

The mass of active hosts M is $M_E G(\hat{c})$. M_E is determined by free entry, which drives expected profits down to zero. The mass of potential hosts that pay (M_E) thus adjusts until expected profits from offering on Airbnb equals F_E, i.e.,

$$\int_{c_{\min}}^{\hat{c}} (\pi(c) - F)g(c)dc = F_E. \tag{A.1.14}$$

M_E affects profits through its impact on the price index and thus market demand B. To see this note first that the price index can also be written by integrating over marginal cost values:

$$P = \left(\int_{i\in\mathcal{I}} p(i)^{1-\sigma} di\right)^{\frac{1}{1-\sigma}} = \left(\int_{c_{\min}}^{\hat{c}} p(c)^{1-\sigma} M_E g(c) dc\right)^{\frac{1}{1-\sigma}}, \tag{A.1.15}$$

where $M_E g(c)$ is the mass of hosts with marginal cost c. This yields

$$P = M_E^{\frac{1}{1-\sigma}} \left(\int_{c_{\min}}^{\hat{c}} p(c)^{1-\sigma} g(c) dc\right)^{\frac{1}{1-\sigma}}, \tag{A.1.16}$$

which reveals that the price index decreases in M_E. This reflects that given the marginal cost cutoff $\hat{c}$, a larger mass of entrants M_E increases the mass of active hosts $M = M_E G(\hat{c})$, which scales down demand and thus profit for each particular property.

To summarize, the entry decision is divided into two steps. First, the condition $\pi(c) \geq F$ determines the cutoff marginal cost $\hat{c}$. Second, the zero overall (including F_E) profit condition pins down M_E and thus $M = M_E G(\hat{c})$, the mass of active providers. Together with the optimal pricing rule and demand, this completes the description of the equilibrium in the short-term accommodation market.

Long-term rental market. The long-term rental demand function follows from a representative consumer utility function:

$$U^r = \sum_{j=1}^{J} \gamma_j \log Q_j^r, \quad \sum_{j=1}^{J} \gamma_j = 1,\ \gamma_j \geq 0, \tag{A.1.17}$$

where Q_j^r is a CES index of consumed rental properties in area j given by

$$Q_j^r = \left[\int_{k\in\mathcal{K}_j} \left(q_j(k)\right)^{(\nu-1)/\nu} dk\right]^{\nu/(\nu-1)}, \quad \nu > 1. \tag{A.1.18}$$

Thus, the structure of the long-term rental market follows the one for the short-term rental market.

As noted in the main document, supply in the long-term rental market comes from property owners who do not offer their property on Airbnb, that is, overall housing supply is assumed to be constant. Thus, long-term rental market supply is inversely related to entry into the short-term accommodation market.

Welfare of Airbnb guests. As noted in the main text, we follow two approaches to measure the welfare of Airbnb guests. Our first approach starts from the observation that the total number of Airbnb reservations is a reasonable approximation for utility if the elasticity of substitution σ is large.[5] As price comparisons are easy on platforms like Airbnb, it seems reasonable to expect rather price sensitive consumer behavior, i.e., large values for σ. Using this approximation, utility can be written as

$$U = \sum_j \beta_j \cdot \log Q_j = \sum_j \beta_j \cdot \log \bar{Q}_j, \tag{A.1.19}$$

where the index of consumed short-term accommodation in area j, Q_j, is simply the total number of Airbnb reservations in area j, $\bar{Q}_j$.

Our second approach uses that in general, consumer welfare (in area j) is proportional to $1/P_j$.[6] In order to link the price index to empirical quantities, we will now show that the price index can be written as the product of two factors: the mass of active hosts and an average price measure. To see this, recall that

$$P = M_E^{\frac{1}{1-\sigma}} \left(\int_{c_{\min}}^{\hat{c}} p(c)^{1-\sigma} g(c) dc \right)^{\frac{1}{1-\sigma}}. \tag{A.1.20}$$

[5] The approximation becomes exact if σ approaches infinity.

[6] See Melitz and Redding (2014).

In order to express the price index as a function of active hosts, we can write

$$
\begin{aligned}
P &= M_E^{\frac{1}{1-\sigma}} \left(\int_{c_{\min}}^{\hat{c}} p(c)^{1-\sigma} g(c) dc \right)^{\frac{1}{1-\sigma}} \\
&= \left(M_E G(\hat{c})\right)^{\frac{1}{1-\sigma}} \left(\int_{c_{\min}}^{\hat{c}} p(c)^{1-\sigma} \frac{g(c)}{G(\hat{c})} dc \right)^{\frac{1}{1-\sigma}} \\
&= M^{\frac{1}{1-\sigma}} \left(\int_{c_{\min}}^{\hat{c}} p(c)^{1-\sigma} \frac{g(c)}{G(\hat{c})} dc \right)^{\frac{1}{1-\sigma}}. \qquad \text{(A.1.21)}
\end{aligned}
$$

The integral is the expected value of $p(c)^{1-\sigma}$ conditional on marginal cost being below $\hat{c}$ that we denote by $\bar{p}^{1-\sigma}$ in the following.

Using this definition, we can write the price index

$$
P = M^{\frac{1}{1-\sigma}} \cdot \bar{p} \qquad \text{(A.1.22)}
$$

as the product of an inverse measure of the mass of active hosts and an average price.

As written in the main document, consumer welfare can also be linked to an average quantity measure[7]; more precisely, to the quantity demanded at the average price $\bar{p}$. To see this, consider the value of the consumption index Q_j in equilibrium:

$$
\begin{aligned}
Q_j = \left[\int_{i \in \mathcal{I}_j} \left(q_j(i)\right)^{(\sigma-1)/\sigma} di \right]^{\sigma/(\sigma-1)} &= \left(\int_{c_{\min}}^{\hat{c}} \left(A_j p(c)^{-\sigma}\right)^{(\sigma-1)/\sigma} M_E g(c) dc \right)^{\sigma/(\sigma-1)} \\
= M^{\sigma/(\sigma-1)} A_j \left(\frac{\sigma}{\sigma-1} \right)^{-\sigma} \left(\int_{c_{\min}}^{\hat{c}} c^{1-\sigma} \frac{g(c)}{G(\hat{c})} dc \right)^{\sigma/(\sigma-1)} & \\
= M^{\sigma/(\sigma-1)} q(\bar{p}) := M^{\sigma/(\sigma-1)} \cdot \bar{q}. &
\end{aligned}
$$

Welfare of Airbnb hosts and the platform. Host welfare is given by profits $\pi(c) - F$. Since fixed costs F are likely to be negligible for hosts who sublet their own apartment on a short-term basis, we can approximate welfare changes for these hosts by variable profit changes. Using that variable profit is a fraction of revenue (see above), we compute relative welfare changes for this

[7]This is not surprising as price and quantity are related through the demand function.

group by relative revenue changes. Quantifying welfare for hosts who offer properties for short-term rentals, which they do not use as own residence, is more challenging because F is likely to be substantial but unobserved. We therefore assume that long-term rental income F is a fraction ϕ of Airbnb income $\pi(c)$. Welfare for these landlords is then given by

$$(1-\phi)\pi(c) = (1-\phi)\frac{r(c)}{\sigma}, \tag{A.1.23}$$

which allows us to measure the percentage change in landlords' welfare again by relative revenue changes.

Finally, as most of Airbnb's income derives from fees that are proportional to revenue, we can also use relative revenue changes to quantify Airbnb's income changes.

Welfare of local residents. Following the same steps as in our second approach to Airbnb consumer welfare measurement, one can show that renter welfare can be decomposed into a measure of average price and the mass of providers.

Short-term rental regulations. Short-term rental regulations place restrictions on the provision of short-term accommodation. These regulations tend to increase marginal cost, in particular for hosts with many reservations, i.e., low marginal cost. Since the marginal cost increase induced by the short-term rental regulations is likely to depend on the number of reservations and thus the level of marginal cost, we model the short-term rental regulations as a shift of the marginal cost distribution towards higher values in the sense of first order stochastic dominance (as shown in Figure A.1.1). Formally, we assume $G_{\mathrm{STR}}(c) \leq G(c)$ with strict inequality for at least some values of c. Hence, the probability of observing marginal cost below any given value c decreases (weakly) after the introduction of the short-term rental regulations, i.e., the short-term rental regulations shifts probability mass towards higher marginal cost values. Our modeling strategy of short-term rental regulations encompasses cases where marginal cost increase only for the targeted group of hosts (with reservations above and hence marginal cost below some regulatory threshold), but is more general and also allows marginal cost increases for non-targeted hosts. The main document offers a detailed discussion why non-targeted hosts may experience costs increases. This might relate to enforcement measures – like registration requirements –

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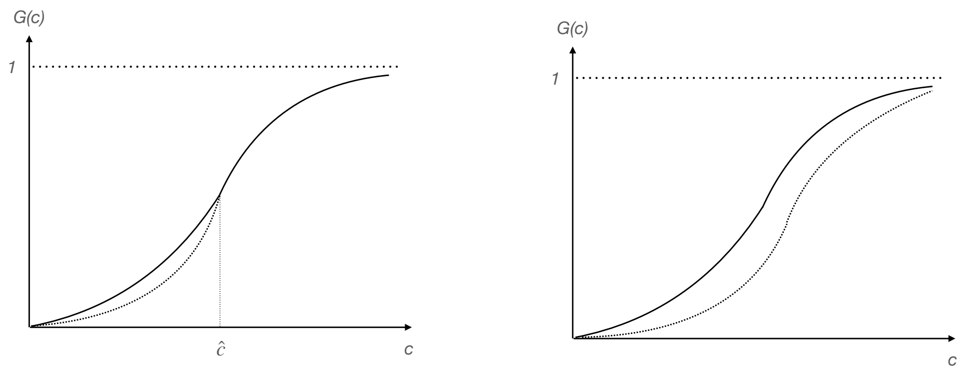


Figure A.1.1: Shifts of the marginal cost distribution induced by short-term rental regulations

Notes: Left-hand side: short-term rental regulation only increases marginal cost for targeted hosts; right-hand side: short-term rental regulation increases marginal cost for targeted and non-targeted hosts; situation before (bold line) and after (dashed line) the introduction of the short-term rental regulations.

that hit all hosts alike, non-monetary information costs (i.e., understanding the legal documents) or social costs (i.e., regulation as signal that short-term rental activity is disapproved by society).

Short-term rental regulation will affect both hosts' pricing and entry decisions. First, mark-up pricing implies that a marginal cost increase translates proportionally into price increases. Second, higher marginal cost imply that some hosts will no longer find it profitable to offer their properties on Airbnb. We characterize the entry decision again in two steps. In the first step, we show that the marginal cost cutoff increases following a regulation.

Combining both

$$\int_{c_{\min}}^{\hat{c}} (\pi(c) - F) g(c) dc = F_E \quad \text{and} \quad \pi(\hat{c}) = F \tag{A.1.24}$$

yields the following condition that characterizes $\hat{c}$:

$$\int_{c_{\min}}^{\hat{c}} \left(\frac{\pi(c)}{\pi(\hat{c})} - 1 \right) g(c) dc = \frac{F_E}{F} \quad \Longleftrightarrow \quad \int_{c_{\min}}^{\hat{c}} \left(\left(\frac{\hat{c}}{c} \right)^{\sigma - 1} - 1 \right) g(c) dc \quad = \frac{F_E}{F}. \tag{A.1.25}$$

Integrating the left-hand side by parts yields

$$\begin{aligned}
&\int_{c_{\min}}^{\hat{c}} \left(\left(\frac{\hat{c}}{c} \right)^{\sigma-1} - 1 \right) g(c) dc \\
&= \left[\left(\left(\frac{\hat{c}}{c} \right)^{\sigma-1} - 1 \right) G(c) \right]_{c_{\min}}^{\hat{c}} + (\sigma - 1)(\hat{c})^{\sigma-1} \int_{c_{\min}}^{\hat{c}} c^{-\sigma} G(c) dc \\
&= (\sigma - 1)(\hat{c})^{\sigma-1} \int_{c_{\min}}^{\hat{c}} c^{-\sigma} G(c) dc. \qquad \text{(A.1.26)}
\end{aligned}$$

Because $G_{\text{HSO}}(c) \leq G(c)$, the integral becomes smaller after regulation. For the whole expression to still equal F_E/F, the cutoff marginal cost value must therefore increase to $\hat{c}_{\text{HSO}} > \hat{c}$. As a consequence of the higher marginal cost cutoff and probability mass shifting from lower to higher marginal cost values, the average price $\bar{p}$ increases.

To determine the mass of active hosts M in the second step, we use the zero profit condition for the marginal host:

$$\pi(\hat{c}) = \tilde{\sigma} X P^{\sigma-1} (\hat{c})^{1-\sigma} = F, \qquad \text{(A.1.27)}$$

where P can again be written as $P = M^{\frac{1}{1-\sigma}} \bar{p}$. To see that M goes down following an increase in $\hat{c}$, we use that $p(\hat{c}) = \hat{c} \cdot \sigma/(\sigma - 1)$ is an upper bound for the average price $\bar{p}$[8] and so

$$\bar{P} = M^{\frac{1}{1-\sigma}} \frac{\sigma}{\sigma - 1} \hat{c} \qquad \text{(A.1.28)}$$

is an upper bound for the price index. Since variable profit increases in the price index, we have

$$F = \pi(\hat{c}) < \bar{\pi}(\hat{c}) = \tilde{\sigma} X \bar{P}^{\sigma-1} (\hat{c})^{1-\sigma} = \tilde{\sigma} X M^{-1} \left(\frac{\sigma}{\sigma - 1} \right)^{\sigma-1}. \qquad \text{(A.1.29)}$$

Note that profit of the marginal host and thus the equilibrium value of M would be unaffected by $\hat{c}$ if the price index took its maximum value and moved 1:1 with $\hat{c}$. Since the true price index is smaller, variable profit of the marginal host will be smaller than $\bar{\pi}(\hat{c})$ and thus M must be lower for the

[8]This upper bound would occur if all active hosts had marginal cost equal to the maximum marginal cost $\hat{c}$.

zero profit condition to hold. Note that higher prices (for some properties) also reduce demand leading to a reduction in the total number of Airbnb reservations.

The impact of the short-term rental regulation on welfare. Since hosts' profits are $V(c) = \pi(c) - F = \frac{r(c)}{\sigma}$, where $\pi(c)$ denotes variable profits, F are fixed cost, $r(c)$ is revenue, and σ is the elasticity of substitution, the change in hosts' welfare induced by short-term rental regulations in area j is proportional to the change in revenue, i.e.,

$$\Delta W_j^{\text{host}} = \frac{\Delta r}{\sigma} \tag{A.1.30}$$

The relative consumer welfare change induced by short-term rental regulations in area j is

$$\Delta W_j^{\text{guest}} = \log\left(\frac{W_j^{\text{HSO}}}{W_j}\right), \tag{A.1.31}$$

where W_j denotes initial consumer welfare and W_j^{HSO} denotes consumer welfare after the implementation of the regulation. Recall that our first approach to Airbnb consumer welfare measurement proxies utility with the total number of reservations. Using that utility in this case can be expressed as[9] $U = Q_1^{\beta_1} \cdot Q_2^{\beta_2} \cdot \ldots \cdot Q_J^{\beta_J} = \bar{Q}_1^{\beta_1} \cdot \bar{Q}_2^{\beta_2} \cdot \ldots \cdot \bar{Q}_J^{\beta_J}$, the regulation induced percentage utility change, i.e.,

$$\Delta W_j^{\text{guest}} = \log\left(\frac{U^{\text{HSO}}}{U}\right) = \sum_j \beta_j \log\left(\frac{\bar{Q}_j^{\text{HSO}}}{\bar{Q}_j}\right) = \sum_j \beta_j \Delta Q_j, \tag{A.1.32}$$

can be computed as a weighted average of percentage changes in total reservations.

Under our second approach, we obtain

$$\Delta W_j^{\text{guest}} = \log\left(\frac{W_j^{\text{HSO}}}{W_j}\right) = \log\left(\frac{P_j^{\text{HSO}}}{P_j}\right)^{-1} = -\log\left(\frac{P_j^{\text{HSO}}}{P_j}\right) = -\Delta P_j, \tag{A.1.33}$$

[9] This is the typical formulation for Cobb-Douglas utility functions. As noted above, our original formulation is the logarithm of this expression and captures the same underlying preference ordering.

where $\Delta W_j^{\text{guest}} = \log(W_j^{\text{HSO}}/W_j)$ is the percentage change in consumer welfare in area j. Using the decomposition of the price index in the mass of active hosts M and the average price, we can write:

$$\begin{aligned}\Delta W_j^{\text{guest}} &= -\frac{1}{1-\sigma}\log\left(\frac{M_j^{\text{HSO}}}{M_j}\right) - \log\left(\frac{\bar{p}_j^{\text{HSO}}}{\bar{p}_j}\right) \\ &= \frac{1}{\sigma-1}\Delta M_j - \Delta\bar{p} = \frac{\sigma}{\sigma-1}\Delta M_j + \Delta\bar{q}. \end{aligned} \tag{A.1.34}$$

To move from area specific to city-wide welfare changes, we use that city-wide welfare is proportional to

$$W = \frac{1}{\prod_j P_j^{\beta_j}},$$

which yields a city-wide percentage consumer welfare change equal to

$$\log\left(\frac{W^{\text{HSO}}}{W}\right) = \log\prod_j\left(\frac{P_j}{P_j^{\text{HSO}}}\right)^{\beta_j} = \sum_j \beta_j \log\Delta W_j. \tag{A.1.35}$$

The quantification of consumer welfare changes thus depends on four empirical quantities: the relative market size of area j (β_j); the percentage change in active hosts (ΔM_j); the percentage change in the average price ($\Delta\bar{p}$); and finally, the price elasticity of demand (σ).

Following the same steps yields an analogous expression for percentage renter welfare changes, which can be written as

$$\Delta W_j^{\text{resident}} = \frac{1}{\nu-1}\Delta M_j^r - \Delta\bar{p}_j^r. \tag{A.1.36}$$

The change in renter welfare thus depends on the percentage change in the mass (number) of landlords who lease their property on the long-term rental market (ΔM_j^r) and the relative change in long-term rents ($\Delta\bar{p}_j^r$).

As explained above, we quantify the percentage change in host and Airbnb welfare by relative revenue changes.

A.2 Descriptives

Table A.2.1 presents descriptive statistics for the dependent variables (the number of reservation days and the number of active properties per grid and month) used in our main empirical analysis, separately for each estimation sample (accounting for 6 months prior to the studied intervention and 12 months after the intervention). In addition, Figure A.2.1 presents the development of reservation days related to targeted and non-targeted hosts during the sample period in each city.

Moreover, Table A.2.2 depicts descriptive statistics for the rental price analysis. The observational unit is the grid per month. The sample comprises grids in the treated cities (Berlin, Hamburg and Munich) and in large control cities (Dusseldorf, Essen, Frankfurt, and Leipzig). For each grid and month, we calculate the average property rent (per square meter) of all properties offered in that grid and month on the Immoscout 24 platform. The table depicts sample statistics (mean, standard deviation, minimum, maximum and 25th, 50th, and 75th percentiles of the distribution). The last column gives the number of observations.

	Mean	Std. Dev.
Panel A: Berlin		
Reservation days (targeted hosts)	9.6416	34.9615
Reservation days (non-targeted hosts)	5.8096	22.9699
Active properties (targeted hosts)	0.5531	1.8508
Active properties (non-targeted hosts)	0.4488	1.7789
Panel B: Hamburg		
Reservation days (targeted hosts)	18.4861	77.1782
Reservation days (non-targeted hosts)	2.0386	11.1070
Active properties (targeted hosts)	1.10870	4.2712
Active properties (non-targeted hosts)	0.1951	1.0478
Panel C: Munich		
Reservation days (targeted hosts)	5.0094	18.3650
Reservation days (non-targeted hosts)	4.2420	16.1833
Active Properties (targeted hosts)	0.2997	1.0029
Active Properties (non-targeted hosts)	0.3277	1.1476

Notes: Descriptive statistics for reservation days and active properties per grid and month.

Table A.2.1: Descriptive statistics

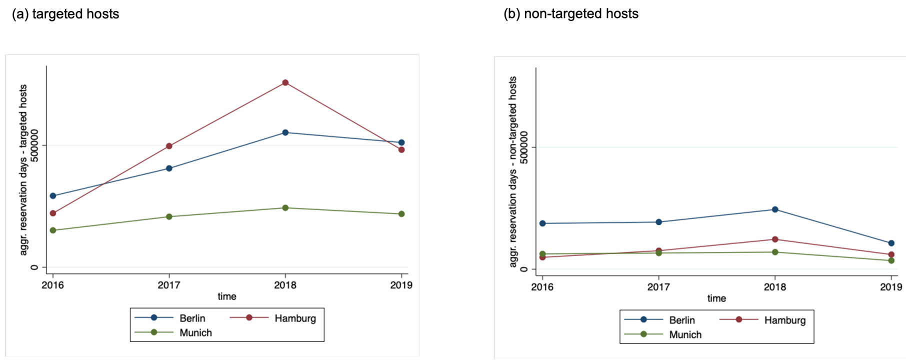


Figure A.2.1: Reservation days of targeted and non-targeted hosts

Notes: The figure shows the reservation days of (a) targeted and (b) non-targeted hosts during the sample period.

Variable	**Mean**	**Std. dev.**	**Min.**	**Percentiles**			**Max.**	**Obs.**
				25%	**50%**	**75%**		
Property rent	930.82	317.37	228.61	706.55	917.31	1143.48	2200.00	7059
Property rent per square meter	12.83	3.58	4.49	10.15	13.05	15.38	24.00	7059

Notes: The table shows descriptive statistics of the data on rental offers obtained from FDZ Ruhr of the RWI Essen (RWI 2020). The observational unit is the grid per year. The sample is restricted to grids in treated cities and large control cities (Dusseldorf, Essen; Frankfurt, and Leipzig). ‘Property rent’ is the average property rent of all rental offers on the Immoscout24 platform (in Euros) as provided by RWI in a given grid and month. ‘Rent per square meter’ is the average rent per square meter of properties offered in a given grid and month (in Euros).

Table A.2.2: Summary statistics for rental prices

A.3 Pooled estimates for all Airbnb activity

Table A.3.1 reports results for the impact of short-term rental regulations on Airbnb activity, pooling all hosts that are active on the market. The structure of the table resembles those of Table 4 in the main document.

	(1) monthly reservation days	**(2) number of active properties**
Berlin		
ATT	**-10.662*****	**-1.418*****
relative effect	-18.84%	-33.64%
Robust std. errors	(1.868)	(0.203)
R^2	0.882	0.868
Adj. R^2	0.876	0.862
Hamburg		
ATT	**-56.159*****	**-3.431*****
relative effect	-49.73%	-48.71%
Robust std. errors	(8.068)	(0.481)
R^2	0.836	0.841
Adj. R^2	0.828	0.833
Munich		
ATT	**-22.699*****	**-1.570*****
relative effect	-39.77%	-40.83%
Robust std. errors	(3.846)	(0.249)
R^2	0.832	0.855
Adj. R^2	0.820	0.844

Notes: Number of observations: Berlin = 80,517, Hamburg = 74,045, Munich = 50,475. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Difference-in-differences estimates (absolute and relative effects) for the short-term rental regulations in Berlin, Hamburg, and Munich on Airbnb activity of all hosts measured by (1) monthly reservation days (2) the number of active properties per month. ATT stands for average treatment effect on the treated. Control group consists of all grids in German cities with more than 100,000 inhabitants and no short-term rental regulations during the sample period.

Table A.3.1: DiD estimates of short-term rental regulations on Airbnb activity; all hosts

A.4 Additional estimates

A.4.1 Estimates for Berlin 2016

As mentioned in Section 4.1 in the main document, Berlin has introduced a short-term rental regulation already in 2016 that may affect results that we observe for the regulation in 2018. Table A.4.1, therefore, presents results for the short-term rental regulation in Berlin 2016 similar to the main results presented in Table 4 in the main document. When studying the effects of the regulation in Berlin in 2016, the control group only comprises the cities of Dusseldorf, Essen, Frankfurt, Hamburg, and Munich, since we lack Airbnb data for smaller cities before 2017.

	(1) monthly reservation days	**(2) number of active properties**
Panel A: Targeted properties/hosts		
ATT	**-7.507***	**-0.432***
relative effect	-48.64%	-49.98%
Robust std. errors	(1.276)	(0.073)
R^2	0.809	0.817
Adj. R^2	0.797	0.806
Panel B: Non-targeted properties/hosts		
ATT	**-4.233***	**-0.553***
relative effect	-25.19%	-31.53%
Robust std. errors	(1.078)	(0.124)
R^2	0.783	0.757
Adj. R^2	0.770	0.742

Notes: Number of observations: 31,374. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Difference-in-differences estimates (absolute and relative effects) for the short-term rental regulation in Berlin 2016 on Airbnb activity of targeted and non-targeted hosts. Airbnb activity is measured by (1) monthly reservation days (2) the number of active properties per month. ATT stands for average treatment effect on the treated.

Table A.4.1: DiD estimates of short-term rental regulation in Berlin 2016 on Airbnb activity

A.4.2 Effect of short-term rental regulations on monthly listing days

In the main document (cf. Table 4), we present results on how short-term rental regulations affect the reservation days and the number of active properties. In Table A.4.2, we show similar results using monthly listing days as output variable. While the effect on reservation days captures the effect of the short-term rental regulations on the market equilibrium, focusing on monthly listing days allows us to isolate the supply effect. We again observe a significant drop in Airbnb activity in all cities as a result of the implemented regulations.

	(1) targeted properties/hosts	**(2) non-targeted properties/hosts**
Berlin		
ATT	**-9.653*****	**-26.207*****
relative effect	-21.79%	-33.53%
Robust std. errors	(1.699)	(3.762)
R^2	0.932	0.842
Adj. R^2	0.929	0.834
Hamburg		
ATT	**-47.717*****	**-13.919*****
relative effect	-35.17%	-28.73%
Robust std. errors	(7.192)	(2.483)
R^2	0.912	0.807
Adj. R^2	0.907	0.798
Munich		
ATT	**-10.181*****	**-23.835*****
relative effect	-28.27%	-35.99%
Robust std. errors	(1.945)	(4.350)
R^2	0.920	0.812
Adj. R^2	0.915	0.797

Notes: Number of observations: Berlin = 80,517, Hamburg = 74,045, Munich = 50,475. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Difference-in-differences estimates (absolute and relative effects) for the short-term rental regulations in Berlin, Hamburg, and Munich on Airbnb activity measured by monthly listing days. ATT stands for average treatment effect on the treated. We use all grids in German cities with more than 100,000 inhabitants and no short-term rental regulations during the sample period as control.

Table A.4.2: DiD estimates of short-term rental regulations on monthly listing days of targeted and non-targeted hosts

A.5 Robustness checks

A.5.1 Different definitions of targeted hosts

As a first robustness check we alter the definition of targeted hosts. In particular, we apply the following criteria:

(i) reservation days per year exceeds the maximum number of days allowed under the city's short-term rental regulation (i.e., 90 days for Berlin; 56 days for Munich and Hamburg); or

(ii) the host lists multiple properties for short-term rental in a given city (Xu and Xu 2021); or

(iii) the property is, on average, listed as available on the Airbnb platform for more than 25 days per month in a given year (i.e., for more than 300 days annually).; or

(iv) the average monthly revenue that the host realizes on the Airbnb platform amounts to 500 Euros or more.

Criterion (i) is the one used in the main specification in the main document. The additional criteria (ii)-(iv) capture broader aspects of Airbnb activity than only the day cap stated by the short-term rental regulation.

In our *alternative definition of targeted host*, targeted hosts fulfill criteria (i)-(iv) simultaneously. Thus, the alternative definition is stricter than the definition used in our main specification. Table A.5.1 provides descriptive statistics of the number of properties classified as targeted based on the different criteria.

Table A.5.1 shows in the upper panel the total number of properties that are listed and reserved in a specific city in 2017. The lower panel states the number of Airbnb properties that are classified as targeted based on the different criteria listed above.

In Table A.5.2, we present estimates where the dependent variable captures Airbnb activity – reservation days and active properties in the market – using the alternative definition of targeted hosts. We obtain qualitatively similar results as in Table 4 in the main document.

	Berlin	Munich	Hamburg
All properties listed	13,184	7,270	7,861
All properties reserved	9,303 (70.56%)	5,060 (69.60%)	6,915 (87.97%)
Targeted properties			
(a) reservations > HSO threshold	2,399 (18.20%)	1,600 (22.01%)	3,571 (45.43%)
Additional criteria to approximate properties used solely for short-term rentals			
(i) property belonging to host with multiple properties	756 (5.73%)	384 (5.28%)	776 (9.87%)
(ii) properties continuously listed	1,800 (13.65%)	1,267 (17.43%)	1,699 (21.61%)
(iii) monthly revenues above opport. costs	1,912 (14.50%)	1,133 (15.58%)	2,168 (27.58%)
alternative definition of targeted host, i.e., at least one of criteria (a) or (i)-(iii) applies	3,972 (30.13%)	2,748 (37.80%)	4,387 (55.81%)
Non-targeted properties	9,212 (69.87%)	4,522 (62.20%)	3,474 (44.19%)

Table A.5.1: Number of Airbnb properties in 2017 that are targeted and non-targeted by short-term rental regulations

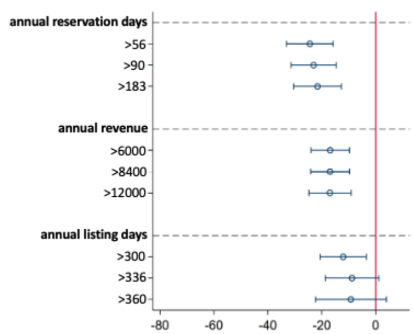
	(1) monthly reservation days	**(2) number of active properties**
Berlin		
ATT	**-4.499*****	**-0.432*****
relative effect	-13.58%	-21.24%
Robust std. errors	(1.064)	(0.078)
R^2	0.880	0.912
Adj. R^2	0.874	0.908
Hamburg		
ATT	**-49.704*****	**-2.536*****
relative effect	-49.46%	-45.02%
Robust std. errors	(7.156)	(0.359)
R^2	0.838	0.866
Adj. R^2	0.829	0.859
Munich		
ATT	**-12.705*****	**-0.744*****
relative effect	-34.74%	-34.01%
Robust std. errors	(2.397)	(0.130)
R^2	0.882	0.915
Adj. R^2	0.873	0.909

Notes: Number of observations: Berlin = 80,517, Hamburg = 74,045, Munich = 50,475. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Difference-in-differences estimates (absolute and relative effects) for the short-term rental regulations in Berlin, Hamburg, and Munich on Airbnb activity of targeted hosts where the the alternative definition of targeted host (cf. p. 19) applies. Airbnb activity is measured by (1) monthly reservation days (2) the number of active properties per month. ATT stands for average treatment effect on the treated. Control group consists of all grids in German cities with more than 100,000 inhabitants and no short-term rental regulations during the sample period.

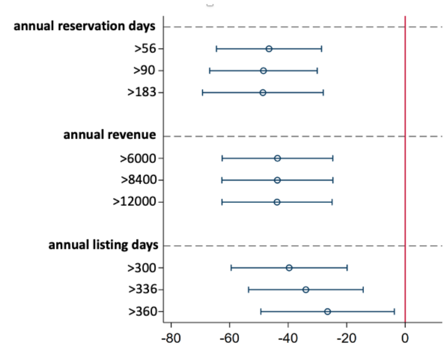
Table A.5.2: DiD estimates of short-term rental regulations on targeted Airbnb activity (alternative definition of targeted host)

A.5.2 Changes in the reservation day cut-off in the definition of targeted hosts

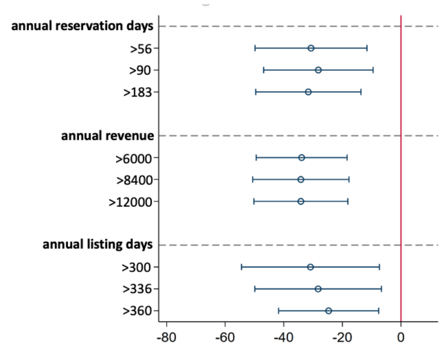
In addition, we make use only of the revenue threshold (criterion (iv) on p. 19); and only of the listing day threshold (criterion (iii) on p. 19) respectively and apply each of these criteria separately to identify 'targeted' hosts. We, furthermore, assess the robustness of the results to adjustments of the threshold values for both definitions of targeted hosts. We present results for average revenues above the threshold of 500, 700, or 1000 Euros per month in the year prior to the reform; and average monthly listing days above the threshold of 25, 28, or 30 days in the year prior to the regulation.



(a) Berlin



(b) Hamburg



(c) Munich

Figure A.5.1: Impact of short-term rental regulations on reservation days of targeted hosts (alternative definitions of targeted host; relative effects)

Figure A.5.1 reports the relative response to the short-term rental regulation – the percent change in the number of reservation days by targeted hosts per grid – when we apply different targeted host definitions. In the first panel, we present modifications of our baseline definition, where we tab properties as targeted if they are rented out for more days than allowed under the city's short-term rental regulation in the year *prior* to the reform. Specifically, we, for each of our considered regulations, apply a cap in the annual number of reservation days of 56, 90 and 183 to define targeted hosts (which corresponds to the legal threshold observed in our sample cities during our sample period). Since the confidence intervals in Figure A.5.1 overlap, estimation results do not significantly depend on how we define targeted hosts. The substantive finding is the same across all definitions depicted.

A.5.3 Variation in Airbnb intensity

In the main document, we present results for the effects of short-term rental regulations on Airbnb activity for all grids. Since Airbnb is often a local phenomenon much more present in some areas of a city than in others, measuring average effects across all gird cells may underestimate impacts in some areas of the city while overestimating the impact of the regulations in other areas. Figure A.5.2 therefore shows point estimates for the relative effects of the short-term rental regulations on monthly reservation days separately for grids with high, medium, and low Airbnb intensity prior to the regulations. For better comparison, we also include the effect including all grids as stated in Table A.5.2, that is, all estimates are based on the alternative definition of targeted hosts as mentioned above. Grids with high Airbnb intensity prior to the regulations are those grids above the 90% percentile of the Airbnb intensity distribution (prior to the respective regulation). Medium Airbnb intensity refers to Airbnb intensity between the 75th and 90th percentile of the intensity distribution, and those with an intensity below the 75th percentile are labeled as low-intensity grids.

Absolute responses are stronger when we focus on grids with a high Airbnb intensity, that is, the material responses are largely centered on high-intensity grids, which is intuitive given the difference in Airbnb presence across the three cell types. Based on Figure A.5.2, in relative terms, however, the response rates are comparable across grids with high, medium and low Airbnb intensities, indicating that targeted hosts react to short-term rental regulations in a similar way no matter where they are located.

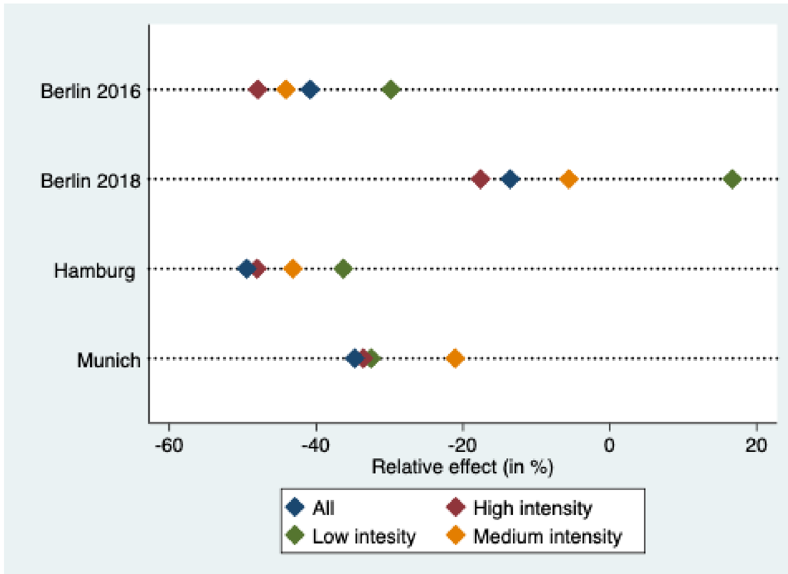


Figure A.5.2: Effects of short-term rental regulations on targeted hosts for different Airbnb intensities

Notes: The figure shows the relative effect (in %) for the DiD points estimates when grids are restricted to grids with high, medium, and low Airbnb intensity prior to the short-term rental regulations. High/medium/low Airbnb intensity refers to above the 90th/between the 75th and 90th/below the 75th percentile of the Airbnb intensity distribution.

There is also intuitive variation in the quantitative response across the studied short-term rental regulations. In Berlin, the effects are, for example, larger for the 2016 intervention than for the tightening of the regulation in 2018. This may reflect that hosts react differently to the introduction of regulations and to their modification. Some hosts may have left the market when the short-term rental regulation was initially introduced in 2016. The 2018 intervention then treated a relatively unresponsive subset of targeted hosts in the short-term rental market. Differences in responses, obviously, also relate to regulation design elements – or combinations of design elements – that vary across regulations and interventions and may differ in their impact on short-term rental supply and demand. For example, the relatively weak effects of the 2018 tightening of the short-term rental regulation in Berlin may reflect that key elements of the regulation – the registration requirement and the reservation day limit – do not pose significant (additional) hurdles to targeted hosts.

A.5.4 Alternative control groups

Short-term rental market:

	(1) monthly reservation days	(2) number of active properties
Panel A: Targeted properties/hosts		
Berlin		
ATT	**-0.097**	**-0.095**
relative effect	-0.29%	-4.66%
Robust std. errors	(1.354)	(0.101)
R^2	0.892	0.907
Adj. R^2	0.886	0.903
Hamburg		
ATT	**-44.890*****	**-2.217*****
relative effect	-44.67%	-39.35%
Robust std. errors	(7.316)	(0.372)
R^2	0.831	0.852
Adj. R^2	0.823	0.845
Munich		
ATT	**-9.407*****	**-0.635*****
relative effect	-25.72%	-29.00%
Robust std. errors	(2.501)	(0.132)
R^2	0.955	0.973
Adj. R^2	0.952	0.971
Panel B: Non-targeted properties/hosts		
Berlin		
ATT	**-2.016**	**-0.571*****
relative effect	-8.59%	-26.15%
Robust std. errors	(1.412)	(0.157)
R^2	0.807	0.743
Adj. R^2	0.798	0.731
Hamburg		
ATT	**-5.034*****	**-0.681*****
relative effect	-40.47%	-48.23%
Robust std. errors	(1.066)	(0.135)
R^2	0.642	0.602
Adj. R^2	0.623	0.582
Munich		
ATT	**-0.753**	**-0.163**
relative effect	-3.68%	-9.80%
Robust std. errors	(7.156)	(0.175)

Notes: Number of observations: Berlin = 21,692, Hamburg = 18,102, Munich = 16,577. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Difference-in-differences estimates (absolute and relative effects) for the HSOs in Berlin, Hamburg, and Munich on Airbnb activity of targeted and non-targeted hosts. Alternative definition of targeted host (cf. p. 19) is applied. Airbnb activity is measured by (1) monthly reservation days (2) the number of active properties per month. ATT stands for average treatment effect on the treated. We use all grids in very large German cities without HSOs during our sample period (i.e., Dusseldorf, Essen, Frankfurt, and Leipzig) as controls.

Table A.5.3: DiD estimates of short-term rental regulations on reservation days of targeted and non-targeted hosts (alternative definition of targeted host; very large cities as control group)

In Table A.5.3, we report results for an adjustment of the control group. In our main analysis, we included grids in all German cities with more than 100,000 inhabitants and no short-term rental regulation during our sample period in the control group to keep the set of control units as large as possible and to increase statistical power. In Table A.5.3 we restrict the control group to the largest German cities without short-term rental regulations – namely, Dusseldorf, Essen, Frankfurt, and Leipzig. We get similar substantive estimates for the ATT indicating that the choice of the exact control group is not critical.

Long-term rental market:
In Table A.5.4, we report results for the effect of the regulations on long-term rents altering the control group. While in the baseline estimation in the main document (cf. Table 8) we only use the largest German cities without regulations as control, we now included grids in all German cities with more than 100,000 inhabitants and no regulation during our sample period. As presented in A.5.4, effects are close to zero and are, therefore, similar to the results obtained in our main specification when we alter the control group.

		>90% Airbnb Exposure	
		all properties	**targeted hosts**
Berlin 2016	*ATT*	**0.033****	**0.032****
	Robust std. errors	(0.010)	(0.009)
	R^2	0.945	0.948
	Adj. R^2	0.940	0.943
	Obs.	3,582	3,284
Berlin 2018	*ATT*	**0.034*****	**0.039*****
	Robust std. errors	(0.010)	(0.011)
	R^2	0.944	0.938
	Adj. R^2	0.940	0.933
	Â *Obs.*	8,559	8,959
Hamburg	*ATT*	**-0.009**	**-0.023**
	Robust std. errors	(0.014)	(0.015)
	R^2	0.944	0.938
	Â *Adj.* R^2	0.939	0.934
	Obs.	7,701	7,657
Munich	*ATT*	**0.026***	**0.023**
	Robust std. errors	(0.011)	(0.011)
	R^2	0.944	0.939
	Adj. R^2	0.939	0.934
	Obs.	6,676	7,513

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; p-values inferred by wild bootstrap. Difference-in-differences estimates for the short-term rental regulations in Berlin 2016, Berlin 2018, Munich 2017, and Hamburg 2018 on average rental prices per grid and month. The sample is restricted to grids with high a Airbnb intensity prior to the short-term rental regulation (above the 90th percentile). The control group consists of all German cities with more than 100,000 inhabitants and without short-term rental regulations during the sample period.

Table A.5.4: DiD estimates of short-term rental regulations on average rental prices

A.6 Validity tests

A.6.1 Event study estimates

Additionally, we ran a number of robustness checks to assess the validity of our difference-in-differences design. The main threat to our empirical identification strategy and to obtaining unbiased estimates for β_d in Eq. (9) in Section 5.1 in the main document is the violation of the conditional mean independence assumption: conditional on λ_j^{ht} and θ_m^{ht}, the regressor of interest HSO_{jm}^t may be correlated with the error term ε_{jm}. If the underlying short-term rental trends systematically differ in treated grids relative to control grids, conditional mean independence is violated – or in the parlance of difference-in-differences design – there is a violation of the common-trend assumption. We address this concern in three ways.

First, we rely on event study designs to test for parallel pre-trends in the treatment and control groups. The model takes on the following form:

$$y_{jm}^{ht} = \sum_{d=-6}^{-2} \beta_d^{ht} HSO_{jm}^d + \sum_{d=0}^{11} \beta_d^{ht} HSO_{jm}^d + \lambda_j^{ht} + \theta_m^{ht} + \varepsilon_{jm}^{ht}, \tag{A.6.1}$$

where HSO_{jm}^d is a dummy variable that takes value 1 in the treated city in months with a d-month gap until the intervention's announcement date. Otherwise, the notation and the set of fixed effects correspond to those in the base specification of the difference-in-differences model (see Eq. (9)) in the main document, as does the sample frame. Since the sample is restricted to coincide with the event window (6 months prior to the regulation and 12 months after), we do not bin the deepest lag and lead. Additionally, note that concerns related to treatment effect heterogeneity in event study models (Sun and Abraham 2021) do not apply in our setting because we study the impact of one reform at a time, comparing the treated city to control cities without short-term rental regulations.

Short-term rental market - reservation days:
The event-study estimates are presented in Figure A.6.1.[10] The dependent variable is the number of targeted reservation days in grid j at time t. The yellow-shaded area depicts the intervention period (starting with the month

[10] All grids are included in the estimation. Similar result patterns, however, emerge in specifications where the sample is restricted to high-intensity grids.

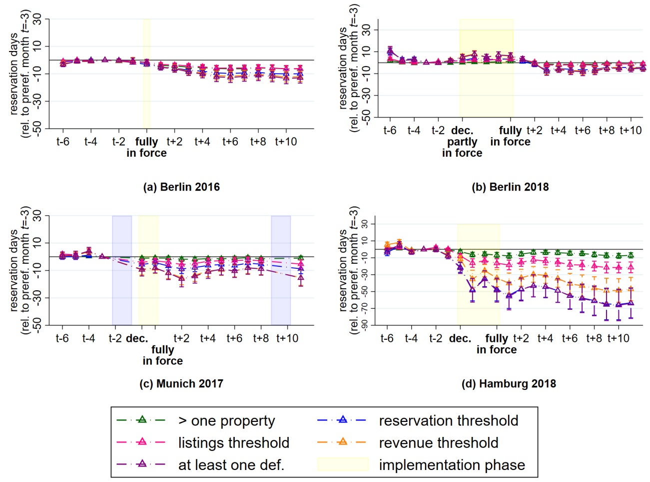


Figure A.6.1: Event-study estimates for the effects of short-term rental regulations on reservation days of targeted hosts

Notes: Event-study estimates based on Eq. (A.6.1) for the short-term rental regulations in Berlin 2016, Berlin 2018, Munich 2017, and Hamburg 2018. Dependent variable is the number of reservation days per grid and month related to targeted Airbnb activity. Targeted host is defined separately by criteria (i) 'reservation threshold', (ii) '> one property', (iii) 'listing threshold', and (iv) 'revenue threshold' (cf. p. 19). In addition, results following the alternative definition of targeted host (cf. p. 19), are shown ('at least one def.'). The estimation sample includes all grids in treated and control cities. The yellow-shaded area depicts the implementation phase of the short-term rental regulation (from the legislative decision to the implementation of the (final) legal provision). For Munich, the blue-shaded area indicates the months of Oktoberfest, when Munich experiences a large inflow of tourists not experienced by control cities.

of the legislative decision and ending when the (last element of the) legislation becomes effective).[11] The blue-shaded areas for the analysis of the Munich short-term rental regulation mark the months of September and October, where Airbnb activity in Munich is dominated by Oktoberfest attendees and deviates from that of (all potential) control cities. The respective data points are not reported. The figure, moreover, depicts estimates for alternative definitions of targeted hosts.

The result pattern is similar across the studied short-term rental regulations. For all interventions, we find no indication of significant differences in the pre-trends of reservation days of targeted hosts in treated and control grids prior to the intervention. After treatment, the reservation days

[11]Berlin 2016 is an exception in the sense that the short-term rental regulation was already passed in 2014 but came into force only in May 2016.

in treated grids quickly drop relative to those in control grids and remain stable at reduced levels thereafter. Note that the estimates depict absolute responses in the number of reservation days of targeted hosts. It is thus not surprising that the sizes of the estimated responses differ across specifications – both across different definitions of targeted hosts and across treated cities. The effect size intuitively correlates with the pretreatment number of targeted Airbnb properties (cf. Table A.5.1).

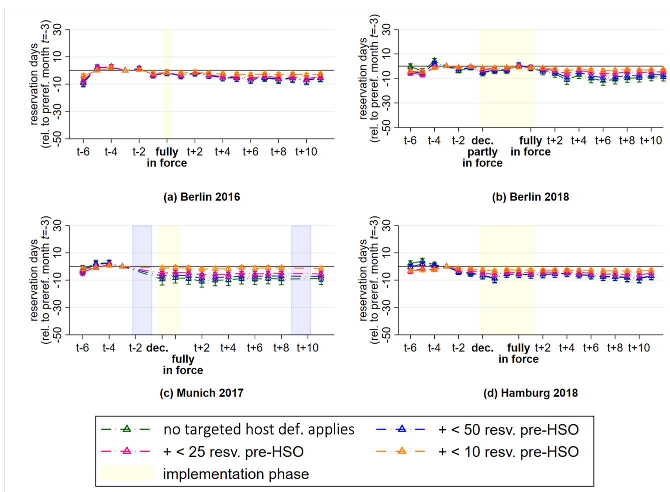


Figure A.6.2: Event-study estimates for the effects of short-term rental regulations on reservation days of of non-targeted hosts

Notes: Event-study estimates based on Eq. (A.6.1) for the short-term rental regulations in Berlin 2016, Berlin 2018, Munich 2017, and Hamburg 2018. Dependent variable is the number of reservation days per grid and month related to non-targeted Airbnb activity. A host is defined as non-targeted if none of the criteria, i.e., (i)-(iv), laid out on p. 19 applies ('no targeted host definition applies'). Additionally, the figure presents results where a non-targeted host is defined as a host with a property that is booked fewer than 50, 25 or 10 days in the year prior to the short-term rental regulation. The yellow-shaded area depicts the implementation phase of the short-term rental regulation (from the legislative decision to the implementation of the (final) legal provision). For Munich, the blue-shaded area indicates the months of Oktoberfest, when Munich experiences a large inflow of tourists not experienced by control cities

Figure A.6.2 presents analogous event-study estimates for the effect of the short-term rental regulations on the Airbnb activity of non-targeted hosts, measured by the number of reservation days related to occasional properties per grid and month.

Short-term rental market - monthly revenue:
The analysis in the main document identifies a negative impact of short-term rental regulations on hosts' revenue (cf. Table 9 in the main document). Figures A.6.3 and A.6.4 present event study estimates to these baseline difference-in-differences specifications, which again show a broadly comparable evolution of outcomes prior to treatment while effects gradually emerge in the post-treatment period.

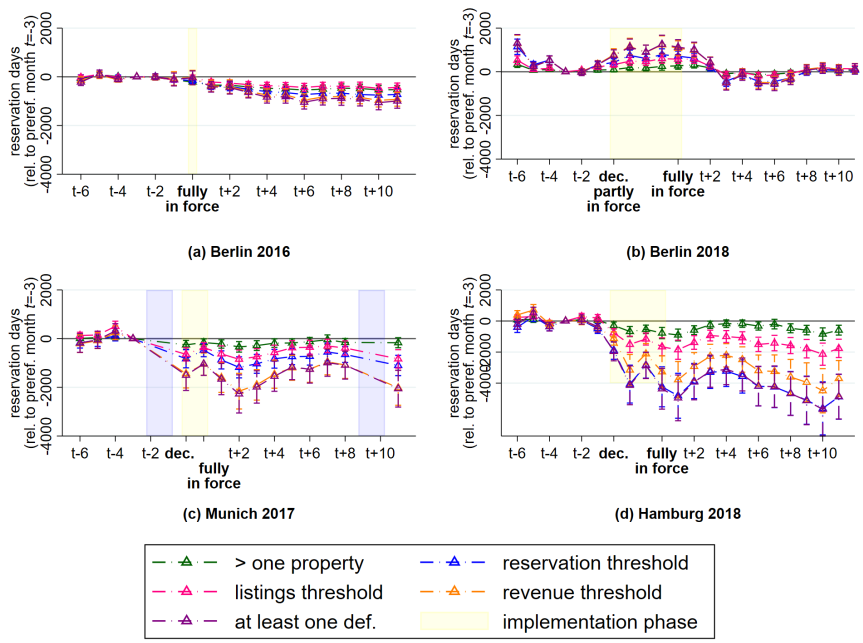


Figure A.6.3: Event-study estimates for the effect of the short-term rental regulations on monthly revenue of targeted hosts

Notes: Event-study estimates based on Eq. (A.6.1) for the short-term rental regulations in Berlin 2016, Berlin 2018, Munich 2017, and Hamburg 2018. Dependent variable is monthly revenue of targeted hosts. Targeted host is defined separately by criteria (i) 'reservation threshold', (ii) '> one property', (iii) 'listing threshold', and (iv) 'revenue threshold' (cf. p. 19). In addition, results following the alternative definition of targeted host (cf. p. 19), are shown ('at least one def.'). The estimation sample includes all grids in treated and control cities. The yellow-shaded area depicts the implementation phase of the short-term rental regulation (from the legislative decision to the implementation of the (final) legal provision). For Munich, the blue-shaded area indicates the months of Oktoberfest, when Munich experiences a large inflow of tourists not experienced by control cities.

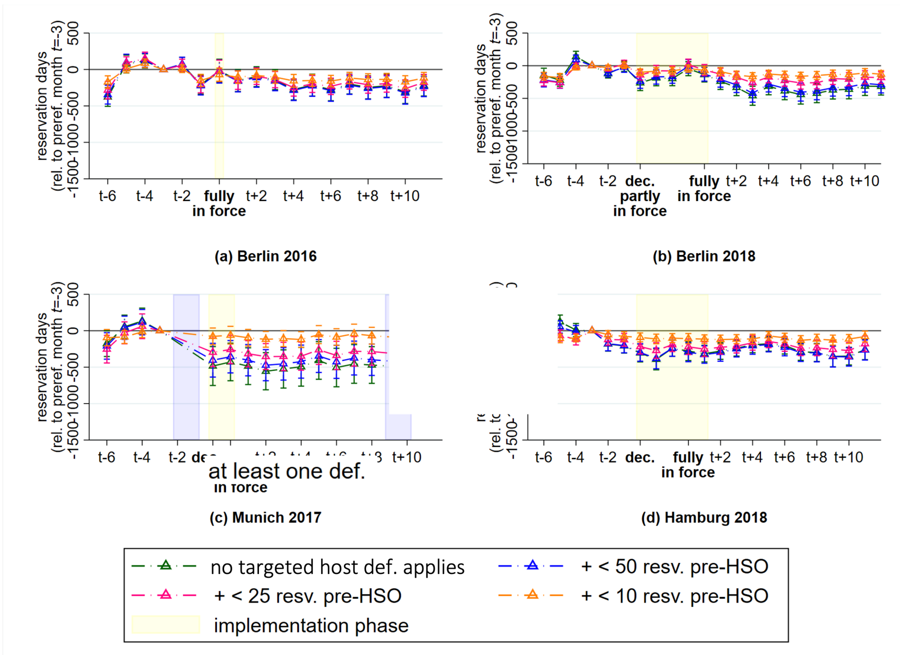


Figure A.6.4: Event-study estimates for the effect of the short-term rental regulations on monthly revenue of non-targeted hosts

Notes: Event-study estimates based on Eq. (A.6.1) for the short-term rental regulations in Berlin 2016, Berlin 2018, Munich 2017, and Hamburg 2018. Dependent variable is the short-term rental price per grid and month. A host is defined as non-targeted if none of the criteria, i.e., (i)-(iv), laid out on p. 19 applies ('no targeted host definition applies'). Additionally the figure presents results where a non-targeted host is defined as a host with a property that is booked fewer than 50, 25 or 10 days in the year prior to the short-term rental regulation. The yellow-shaded area depicts the implementation phase of the short-term rental regulation (from the legislative decision to the implementation of the (final) legal provision). For Munich, the blue-shaded area indicates the months of Oktoberfest, when Munich experiences a large inflow of tourists not experienced by control cities.

Short-term rental market - short-term rental prices:
Finally, analogous to the previous analyses, Figure A.6.5 present event study estimates to these baseline difference-in-differences specifications, which again show a broadly comparable evolution of outcomes prior to treatment while effects gradually emerge in the post-treatment period.

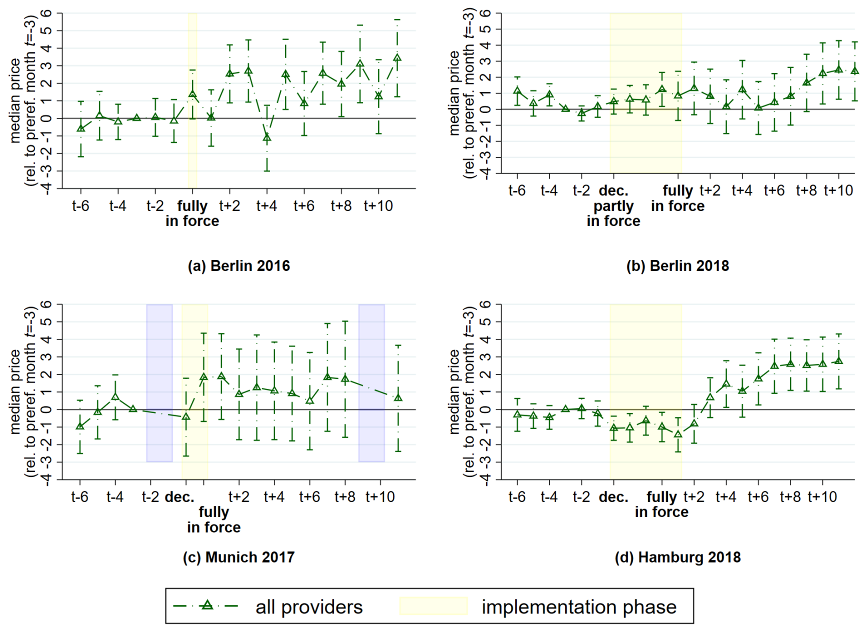


Figure A.6.5: Event-study estimates for the effects of short-term rental regulations on short-term rental prices

Notes: Event-study estimates based on Eq. (A.6.1) for the short-term rental regulations in Berlin 2016, Berlin 2018, Munich 2017, and Hamburg 2018. Dependent variable is the short-term rental price per grid and month. The yellow-shaded area depicts the implementation phase of the short-term rental regulation (from the legislative decision to the implementation of the (final) legal provision). For Munich, the blue-shaded area indicates the months of Oktoberfest, when Munich experiences a large inflow of tourists not experienced by control cities.

Long-term rental market:
Figure A.6.6 depicts event-study estimates for the short-term rental regulations in Berlin 2016 and 2018, in Munich 2017, and in Hamburg 2018. The dependent variable is the average rental price of offered properties in a given grid and month. The sample is restricted to grid with a high Airbnb intensity (in treated and control cities), defined as grids above the 90th percentile of the Airbnb intensity distribution. The figure applies different definitions of Airbnb intensity: In the base definition, we define Airbnb intensity by the number of properties in the grid listed at least once on Airbnb in the year prior to the short-term rental regulation over all properties in the grid. In addition, we apply definitions of Airbnb intensity that focus on targeted Airbnb hosts where we follow the alternative definition of targeted host, i.e., any of the criteria defined on p. 19 applies ('at least one def.'). Analogously, we present estimates for subsamples where targeted hosts are defined based on one specific criterion of targeted Airbnb activity at a time: (i) properties with more reservation days in the year prior to the short-term rental regulation than the number specified by the day cap ('reservation threshold'); criterion (ii), i.e., properties related to hosts who offer more than one property ('> one property'); criterion (iii), i.e., properties listed as available on the Airbnb platform on average more than 25 days in the year prior to the short-term rental regulation ('listing threshold'); and criterion (iv), i.e., properties that on average earned more than 500 Euros per month on the Airbnb platform in the year prior to the reform ('revenue threshold'). The yellow-shaded area depicts the implementation phase of the short-term rental regulation (from the legislative decision to the implementation of the (last) legal provisions).

The results suggest that the trend in rental prices did not significantly differ prior to the short-term rental regulations. As in the difference-in-differences estimations presented in Table 8 of the main document, we, however, again find no indication of a systematic shift in rental prices after HSOs are introduced or tightened.

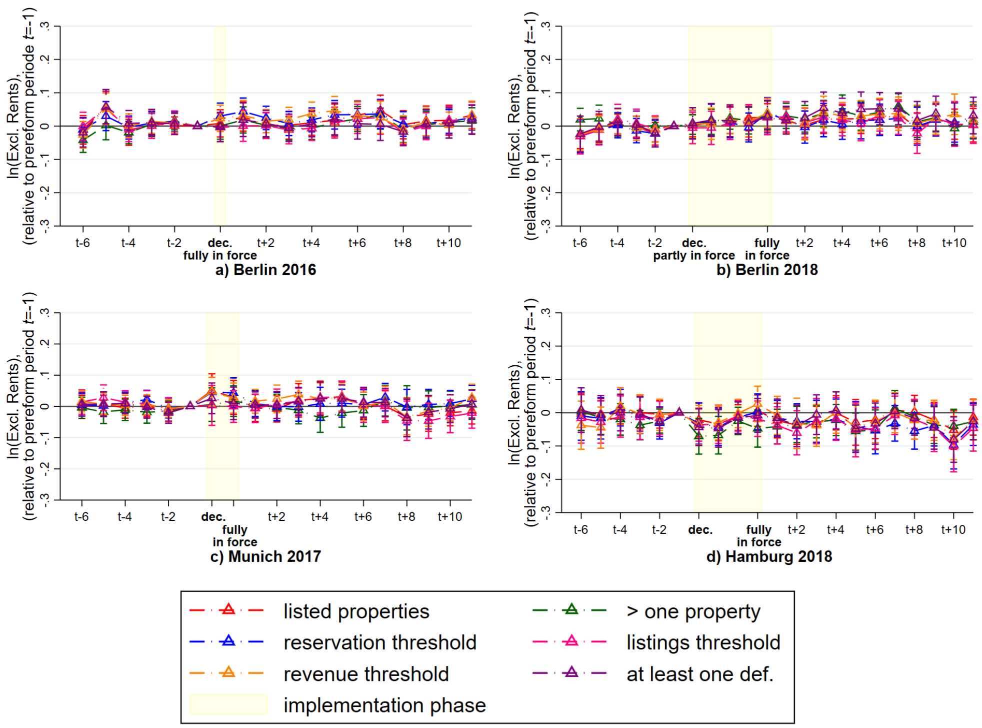


Figure A.6.6: Event-study estimates for the effects of short-term rental regulations on average rental prices

Notes: Event-study estimates based on Eq. (A.6.1) for the short-term rental regulations in Berlin 2016, Berlin 2018, Munich 2017, and Hamburg 2018. Dependent variable is the average rental price per grid and month. Sample restricted to grids with a high Airbnb intensity (above the 90th percentile). The figure applies different definitions of Airbnb intensity. In the baseline definition ('listed properties'), Airbnb intensity is defined by the number of properties in the grid listed at least once on Airbnb in the year prior to the short-term rental regulation over all properties in the cell. Alternative definitions of Airbnb intensity focus on targeted Airbnb activity (as defined on p. 19), i.e., criterion (i) applies ('reservation threshold'); criterion (ii) applies ('> one property'); criterion (iii) applies ('listing threshold'); criterion (iv) applies ('revenue threshold'), and any of the criteria (i), (ii), (iii), or (iv) applies ('at least one def.'). The yellow-shaded area depicts the implementation phase of the short-term rental regulation (from the legislative decision to the implementation of the (final) legal provision).

A.6.2 Treatment and control grids differ in underlying characteristics

As discussed in Section 6.1.4, we, moreover, run specifications, where we model differences in observed grid characteristics and interact them with a full sets of time fixed effects. This flexibly and non-parametrically controls for differences in outcome trajectories across grids with different underlying characteristics. We thereby account for socio-economic characteristics of the grid in the year prior to the considered short-term rental regulation: the age structure (specifically the fraction of young adults in the population, aged between 18 and 35), the unemployment rate, the income as proxied by the fraction of high end cars (Mercedes, BMW or Audi), the grid's position in the cities' population distribution and the pre-reform Airbnb intensity. We determine the quartiles of each of these socio-economic characteristics and interact these quartiles with a full set of month fixed effects. The results are reported in Column (1) of Table A.6.1 and are comparable to our baseline estimates.

Following our argumentation in Section 6.1.4, we, furthermore, run additional robustness checks where we rely on coarsened exact matching (CEM) to reduce the imbalance between observed characteristics of treatment and control grids. The analysis draws on the socio-economic characteristics explained in the prior paragraph and again, for each characteristic, defines four categories, grouping grids according to their realizations of the considered characteristics. Treatment and control grids are then exactly matched based on the coarsened data (see main text and Iacus et al. 2012). The estimates are presented in Column (2) of Table A.6.1 and again resemble our baseline findings (cf. Table 4 in the main document).

While the analysis so far accounted for potential socio-economic differences between treatment and control grids, we also ran analyses that additionally account for potential differences in property characteristics across grids. Our data offers two types of information on Airbnb properties: first, the size of the property as measured by the number of bedrooms; second, the quality of the property. There are two quality indicators in the data: the property's rating by Airbnb customers and the status of the host as a super hosts (which are awarded if a host (1) had at least 10 trips or 3 reservations that total at least 100 nights, (2) maintained a 90% response rate or higher, (3) maintained a 1% cancellation rate or lower, and (4) maintained a 4.8 overall rating). We use this information by determining the fraction of

	(1) Controls	(2) CEM (baseline)	(3) CEM (enhanced set of matching criteria)
Panel A: Targeted properties/hosts			
Berlin			
ATT	**-5.706*****	**-5.884*****	**-5.785*****
relative effect	-20.79%	-21.40%	-21.03%
Robust std. errors	(0.940)	(1.078)	(1.081)
R^2	0.903	0.885	0.886
Adj. R^2	0.898	0.879	0.880
Hamburg			
ATT	**-39.833*****	**-49.611*****	**-50.000*****
relative effect	-40.88%	-50.82%	-50.99%
Robust std. errors	(5.144)	(7.036)	(7.067)
R^2	0.866	0.832	0.833
Adj. R^2	0.859	0.823	0.824
Munich			
ATT	**-4.500*****	**-6.087*****	**-6.030*****
relative effect	-22.83%	-30.81%	-30.42%
Robust std. errors	(1.135)	(1.419)	(1.430)
R^2	0.875	0.878	0.882
Adj. R^2	0.866	0.869	0.873
Panel B: Non-targeted properties/hosts			
Berlin			
ATT	**-6.860*****	**-7.314*****	**-7.135*****
relative effect	-29.24%	-26.60 %	-25.94%
Robust std. errors	(0.855)	(1.077)	(1.082)
R^2	0.813	0.803	0.805
Adj. R^2	0.803	0.794	0.796
Hamburg			
ATT	**-5.492*****	**-6.645*****	**-6.691*****
relative effect	-44.16%	-53.35%	-53.56%
Robust std. errors	(0.751)	(1.007)	(1.011)
R^2	0.648	0.626	0.628
Adj. R^2	0.628	0.607	0.609
Munich			
ATT	**-3.474****	**-7.258*****	**-6.912*****
relative effect	-16.95%	-36.74%	-34.87%
Robust std. errors	(1.487)	(2.261)	(2.299)
R^2	0.623	0.585	0.582
Adj. R^2	0.594	0.555	0.552

Notes: Effect (absolute and relative) of short-term rental regulations in Berlin, Hamburg, and Munich on Airbnb activity of targeted and non-targeted hosts. The dependent variable is the sum of targeted properties' monthly reservation days per grid and year. ATT stands for average treatment effect on the treated. Column (1) presents difference-in-differences estimates including controls for socio-economic characteristics of the grid in the year prior to the considered short-term rental regulation. Column (2) reports results of coarsened exact matching (CEM) based on the socio-economic characteristics as in Column (1). Column (3) presents results of coarsened exact matching (CEM) with an enhanced set of characteristics including characteristics related to the size and quality of the property.

Table A.6.1: Effects of short-term rental regulations on reservation days (estimates with control variables and CEM matching) properties per grid offered on Airbnb with one-bedrooms and two bedrooms in the year prior to the short-term rental regulation respectively and add it to the set of matching variables. This controls for potential differences in Airbnb trends for apartments of different size. Analogously, we determine the fraction of 'high quality' Airbnb properties per grid in the year prior to the short-term rental regulation as measured by an average rating during that time frame above the sample average (which is 4.7., conditional on having a non-missing rating) or the status of a super host. Again, we determine the fraction of high-quality Airbnb properties among all properties in a given grid in the year prior to the short-term rental regulation and add this variable to the matching characteristics. This controls for potential difference in Airbnb trends of short-term rental offers of different quality. The results with the enhanced set of matching criteria are presented in Column (3) of Table A.6.1 and again turn out similar to our baseline results.

A.6.3 Placebo test

As a final test, we run a placebo analysis, where we assume that the treatment of Munich and Hamburg – whose short-term rental regulations were introduced by the end of 2017 and in 2018 respectively – occurred at the time of the introduction of the short-term rental regulation in Berlin in May 2016, and thus prior their actual treatment dates.[12] The sample is as in our base specification for the 2016 Berlin treatment but grids in Berlin are dropped from the analysis and grids in Munich and Hamburg are defined as treated instead of as control units. Reestimating the model in Eq. (9) in the main document yields an estimate for the β-coefficient of 0.419 (p-value: 0.779) when the dependent variable is the number of reservation days of targeted properties (defined as in the main analysis; relative to actual treatment effects of -6.707 (p-value: 0.000) and -48.495 (p-value: 0.000) for Munich and Hamburg) and 1.655 (p-value: 0.286) when the dependent variable is the number of active properties; (defined as in the main analysis; relative to actual treatment effects of -0.382 (p-value: 0.000) and -2.339 (p-value: 0.000) for Hamburg and Munich).

[12] Note that, in the presence of treatment effect dynamics, placebo periods must be prior to actual treatment (for the full post-period in the placebo analysis). Otherwise, treatment effect dynamics might be misinterpreted as failure of the placebo test.

A.7 Computation of the number of redirected properties

The number of properties that are redirected from short-term rental to long-term rental use are calculated based on a simple back-of-the-envelope analysis. The analysis draws on the estimated response of the number of targeted properties in the market to a given short-term rental regulation. The definition of targeted properties thereby follows the alternative definition of targeted hosts on p. 19, where we aim to capture properties that are solely used for short-term rental activity. We empirically differentiate between the estimated decline in the number of these properties in grids with a high Airbnb intensity and the estimated decline in grids with an intermediate and low Airbnb intensity (cf. A.5.2). Under the assumption that all targeted properties that leave the Airbnb platform are redirected to the long-term residential market, the number of long-term residential housing units increases in the wake of a given regulation by sum $\beta^{\text{targeted,z}} * g^z$, where g^z is the number of grids of type z in the considered treated city and z indicates grids with high, intermediate, and low Airbnb intensity in the treated city. $\beta^{\text{targted},z}$ is the estimated response in grids of type z.

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