Online Appendix: Inferring Tax Compliance from Pass-through: Evidence from Airbnb Tax Enforcement Agreements

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Appendix A A Model of Imperfect Competition

Now suppose that hosts on Airbnb provide renters with differentiated listings and compete on price. For simplicity, suppose that each host is a single-unit lister. If host i complies with the tax, then a potential compliance cost ($C_i \geq 0$) exists for filing taxes. In addition, host i incurs a marginal cost c_i and a fixed cost F_i. Thus, the total profit for host i when complying is:

$$\Pi_i(\text{comply}) = (p_i - c_i - t)q(p_i, X_i; \mathbf{p}_{-i}, \mathbf{X}_{-i}) - F_i - C_i,$$ [1]

where p_i is price, X_i are the characteristics of unit i, $\mathbf{p}_{-i}$ is the vector of prices of competing units, and $\mathbf{X}_{-i}$ is the vector of characteristics of other units.[2]

If host i chooses to evade the tax, then they do not incur the compliance cost. However, evading hosts may face the risk of being caught and penalized. Let R_i denote the expected penalty associated with evading the tax. Thus, the total profit for host i when evading is:

$$\Pi_i(\text{evade}) = (p_i - c_i)q(p_i, X_i; \mathbf{p}_{-i}, \mathbf{X}_{-i}) - F_i - R_i.$$

To solve the pre-enforcement problem for host i, note that host i takes $X_i, \mathbf{p}_{-i}$, and $\mathbf{X}_{-i}$ as given when making pricing and compliance decisions. Thus, we first evaluate each profit maximization problem and then compare the profits from evading and complying at their respective optimal prices.

Solving the first-order conditions for profit maximization implies that:

$$p_i = \underbrace{c_i + \eta}_{\text{Marginal Cost}} + \underbrace{\frac{q(p_i)}{-q'(p_i)}}_{\text{Markup}}.$$

Setting $\eta = t$ yields host i's optimal price when complying, p_i^C, and setting $\eta = 0$ yields host

[1] Alternatively, for an ad valorem sales tax we have $(1-t)p_i$ instead of $p_i - t$. We use a unit tax for simplicity.

[2] This framework maps into a model of monopolistic competition by simply letting $\mathbf{p}_{-i}$ instead denote the pricing index corresponding to the average Airbnb market price.

i's optimal price when evading (call it p_i^E). In equilibrium we have that $\Pi_j(p_j^E) \geq 0$ and $\Pi_j(p_j^E) \geq \Pi_j(p_j^C)$ for all j who evade, and we have that $\Pi_i(p_i^C) \geq 0$ and $\Pi_i(p_i^C) \geq \Pi_i(p_i^E)$ for all i who comply. Note that $p_i^E \in [p_i^C - t, p_i^C]$ as long as demand is not too convex.[3] Thus, if host i remits taxes, then some portion of the tax, σ_i, is passed through to renters. That is, the profit-maximizing price when complying is $\sigma_i t$ greater than the profit-maximizing price when evading: $p_i^C = p_i^E + \sigma_i t$.[4]

Next, consider how booking prices change with an Airbnb enforcement agreement that guarantees taxes are paid at the point of sale by renters. The profit-maximizing price set by a host that evades pre-enforcement falls by $(1-\sigma_j)t$, such that it equals the pre-enforcement tax-exclusive complier price $p_j^C - t$. The price renters pay for that host's property increases by $\sigma_j t$ to the pre-enforcement tax-inclusive complier price p_j^C. For compliers, neither the profit-maximizing prices they receive nor the prices renters pay change following an Airbnb enforcement agreement; there is only a change in who bears the statutory burden of the tax.

Altogether, with λ compliers and $1-\lambda$ evaders, the average decrease in the booking price paid to hosts, which is tax-inclusive before enforcement and tax-exclusive after enforcement, across all listings is given by:

$$\Delta p = \lambda t + (1-\lambda)(1-\sigma)t,$$

where $\sigma \in (0,1)$ is the average pass-through rate. Solving for λ implies that

$$\lambda = \frac{\Delta p - (1-\sigma)t}{\sigma t}.$$

[3]That is, the markup is decreasing in p so that the complier bears some of the tax burden when $q''(p_i) < \frac{(q'(p_i))^2}{q(p_i)}$. Weyl and Fabinger (2013) show that pass-through can be greater than one if demand is sufficiently convex. In this case, a tax would increase the tax-exclusive price. We ignore this extreme possibility and focus on the case where pass-through, on average, is between zero and one.

[4]Because we maintain general demand functions, a closed-form solution for the pass-through rate cannot be reached. However, this pass-through rate is generated by the equilibrium pricing function above. Comparing $p_i^C = c_i + t + \frac{q(p_i^C)}{-q'(p_i^C)}$ to $p_i^E = c_i + \frac{q(p_i^E)}{-q'(p_i^E)}$ reveals how σ_i is determined. Clearly, the marginal cost when complying is larger. However, markup is smaller when complying because $\frac{q(p_i^C)}{-q'(p_i^C)} < \frac{q(p_i^E)}{-q'(p_i^E)}$ when $p_i^C > p_i^E$. Combined, these differences generate the pass-through rate $\sigma_i \in (0,1)$ such that $p_i^C = p_i^E + \sigma_i t$.

Comparing this compliance rate to the proposed upper bound estimate, $\overline{\lambda}$ in Equation (1), we have that $\lambda < \overline{\lambda}$ if and only if $\sigma \in (0, 1)$.[5] Thus, the proposed upper bound on pre-enforcement compliance when hosts are price-takers, $\overline{\lambda}$ from Equation (1), is also an upper bound on pre-enforcement compliance in imperfectly competitive environments.

A.1 Entry and Exit

Now consider the case where an enforcement agreement results in hosts entering and exiting the market. After an enforcement agreement is implemented, marginal hosts are induced to enter if the pre-enforcement compliance costs (C_i) or the expected penalty for evading (R_i) is large enough. If marginal hosts enter post-enforcement, price competition generates downward pressure on prices. It is also possible that marginal evaders are no longer profitable after enforcement and exit the market. Let the net price effect from host exit be denoted by ϕ. In this case, the average change in booking price across all listings is given by:

$$\Delta p = \lambda t + (1 - \lambda)(1 - \sigma)t - \phi.$$

Solving for λ implies that

$$\lambda = \frac{\Delta p - (1 - \sigma)t + \phi}{\sigma t}.$$

Comparing this compliance rate to the proposed upper bound estimate, $\overline{\lambda}$ in Equation (1), we have that $\lambda < \overline{\lambda}$ if and only if:

$$\phi < (t - \Delta p)(1 - \sigma).$$

This shows that our estimate of $\overline{\lambda}$ is valid if net exit ($\phi > 0$) is not too large. In fact, we find in Section 5 that, if anything, enforcement has a net entry effect ($\phi < 0$).

[5]When $\sigma = 1$ we have that $\lambda = \overline{\lambda}$. In addition, $\frac{\partial \lambda}{\partial \sigma} > 0$, which implies that $\lambda < \overline{\lambda}$ for all $\sigma \in (0, 1)$.

Appendix B Compliance in the Case of Use Taxes

In many online markets, the statutory tax burden falls on consumers rather than producers even in the absence of enforcement agreements. For example, before the June 2018 Supreme Court decision in South Dakota v. Wayfair (585 U.S. ___, 2018), consumers in many states were obligated to self-report use taxes when purchasing goods from online retailers or platforms. After full enforcement is implemented by law or a collection agreement, consumers pay the applicable tax at the point of sale. In this example, unlike Airbnb, the effective statutory burden is imposed on the same side of the market (consumers) before and after enforcement. In this appendix, we show that researchers can estimate an upper bound on pre-enforcement compliance in this scenario as well. We also show that the price elasticity of supply is point identified, and that we can estimate a lower bound on the magnitude of the price elasticity of demand.

For simplicity, consider this case under the assumption that suppliers are price-takers. Suppose there are three periods. In period 0, there are no use tax obligations associated with online purchases. In the first period, individual hosts bear the burden of collecting and remitting applicable use taxes but are able to evade relatively easily. In the second period, the statutory burden again falls on consumers while evasion is no longer possible.

Consider first the consumers that comply with the tax as introduced in period 1. For these consumers, demand is given by $D^C(P+t)$ where P denotes the price paid to the seller and t denotes the tax remitted by the consumer. Now consider the consumers that evade taxes. The demand from evading consumers is given by $D^E(P+R)$ where $R \geq 0$ denotes the costs associated with evading. Suppose that the demand curves are linear, the mass of consumers is one, and $\lambda \in [0,1]$ denotes the proportion of tax-compliant consumers in period 1. This implies that market demand is given by $D = (1-\lambda)D^E + \lambda D^C = D(P+\lambda t+(1-\lambda)R)$.

The first period equilibrium is given by the equilibrium tax-exclusive price, $P = P_1$, that satisfies $S(P) = D(P+\lambda t+(1-\lambda)R)$. Thus, the price paid by consumers in the first period is $P_1 + \lambda t + (1-\lambda)R$ and the average price received by sellers is P_1. In the second period, the tax is automatically applied to each transaction at the point of sale. In this case, evasion is impossible. Thus, the second period equilibrium tax-exclusive price, $P = P_2$, satisfies $S(P) = D(P+t)$. In this case, consumers pay P_2+t and sellers receive P_2. This is displayed graphically in Figure B1, where D_0 is demand in period 0, D_1 is demand in period 1, and D_2 is demand in period 2.

If all consumers comply in the first period (i.e. $\lambda = 1$), then demand and the equilibrium price that sellers receive is the same across the periods 1 and 2: $D_1 = D_2$ and $P_1 = P_2$. However, when some consumers evade in the first period (i.e. $\lambda < 1$), then tax enforcement shifts demand further downward. This further reduces equilibrium quantity and the price received by sellers, and increases the average price paid by consumers.

When λ and R are unobserved, researchers can use the extreme case of perfectly elastic demand to derive an upper bound on pre-enforcement compliance. Figure B2 highlights that the largest possible shift in the demand curve from period 0 to 1 is the distance between P_1 and $P_2 + t$, which occurs only when demand is perfectly elastic. This implies that $\lambda t \leq P_2 + t - P_1$. Thus, one can estimate the following upper bound on pre-enforcement compliance λ:

$$\lambda \leq \frac{P_2 + t - P_1}{t} = \frac{t - \Delta p}{t} \equiv \hat{\lambda}. \tag{1}$$

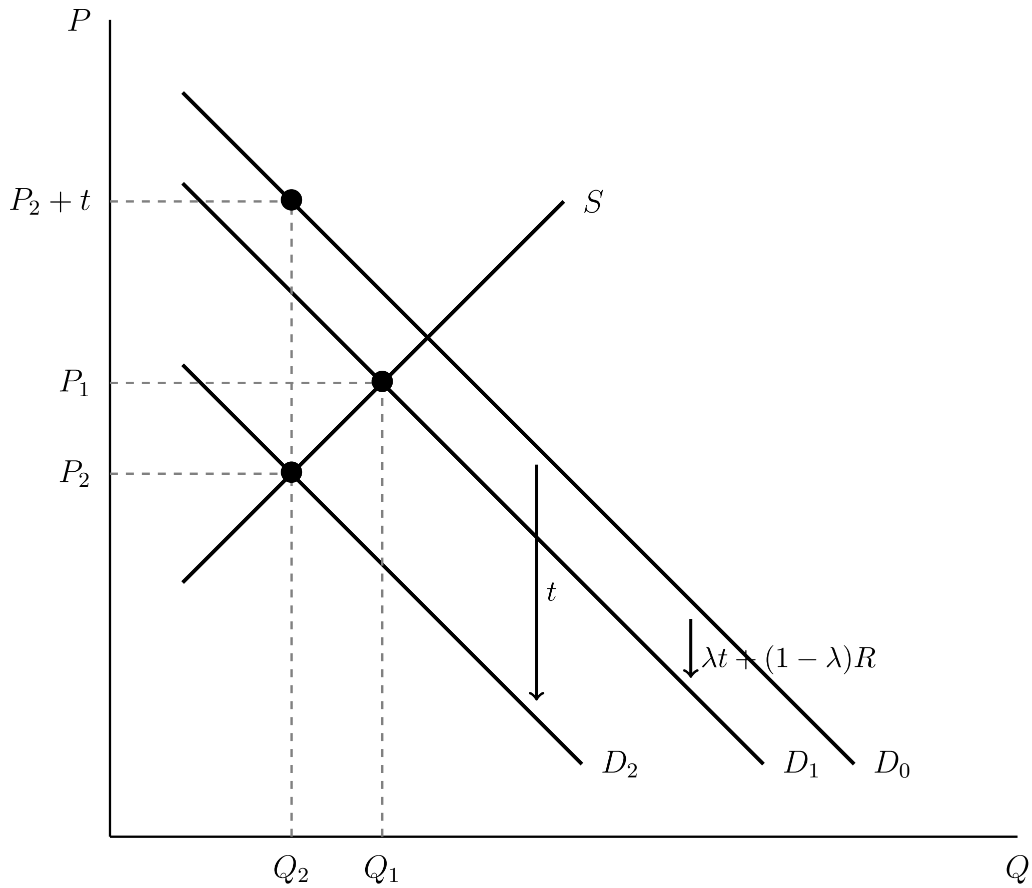
Note that this upper bound differs from the Airbnb case where the statutory burden shifts from hosts to consumers. Here, the compliance upper bound is such that:

$$\hat{\lambda} \equiv = \frac{t - \Delta p}{t} = 1 - \overline{\lambda}, \tag{2}$$

where $\overline{\lambda}$ is the upper bound from the Airbnb case. While the upper bounds differ depending on how enforcement affects the statutory burden of taxation, the fact that each upper bound is derived from the pass-through rate is consistent across contexts. This reinforces that the power of this approach is its simplicity, as it only requires the practitioner to observe the tax magnitude along with market prices under partial and full compliance.

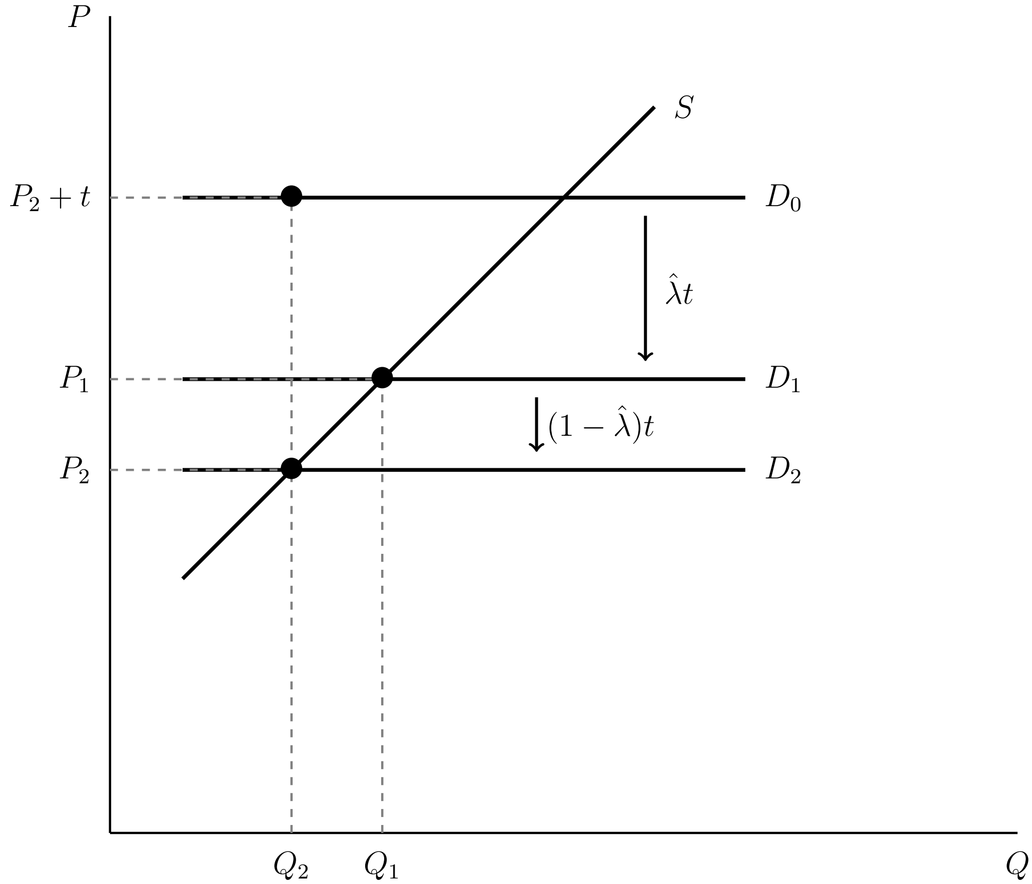
In the use tax case, the researcher can point identify the price elasticity of supply using the change in equilibrium between periods 1 and 2. The researcher can also derive a lower bound on the magnitude of the price elasticity of demand. That is, the price elasticity of demand cannot be less elastic than when $\lambda = 0$, as shown graphically in Figure B3. In this case, there is no shift in demand from period 0 to 1, meaning that tax enforcement in period 2 results in a downward demand shift by the full amount of the tax. Thus, we can trace out the steepest possible demand curve using the observed pre- and post-enforcement quantities and tax-inclusive prices to derive a lower bound on the magnitude of the price elasticity of demand.

Figure B1: Impact of Use Tax Enforcement



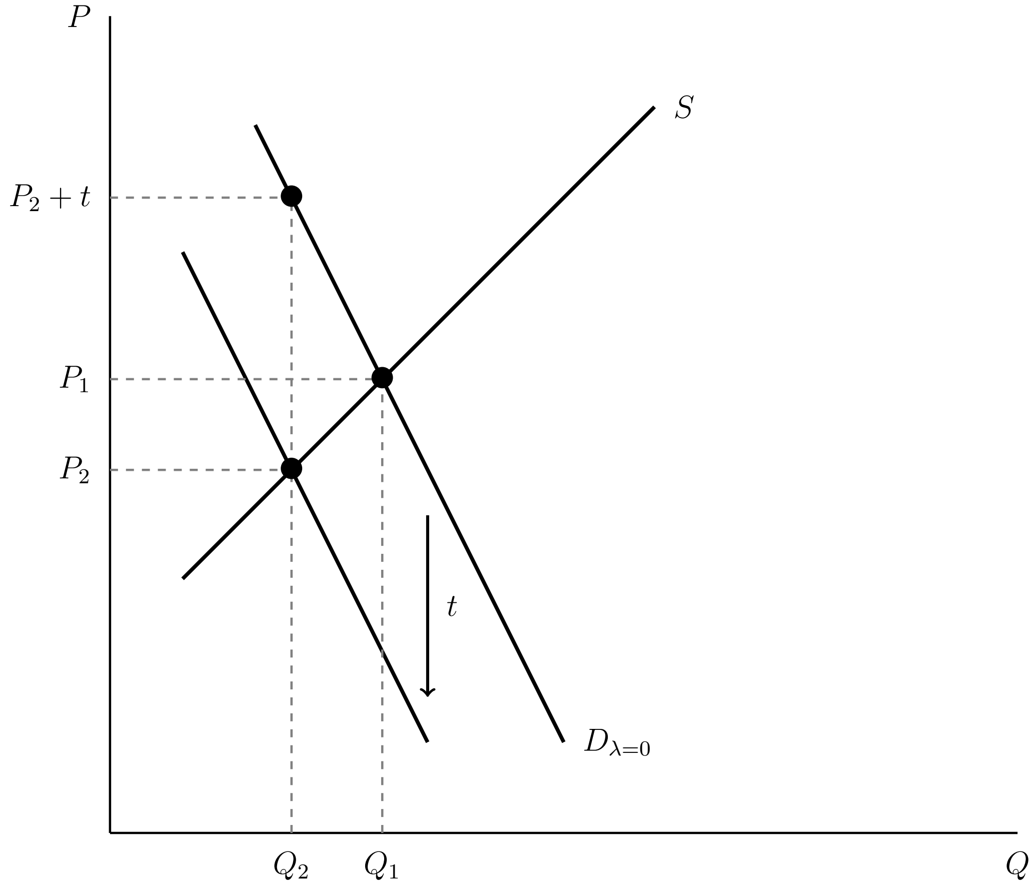
Note: Bold dots (•) represent observed equilibria.

Figure B2: The Use Tax Compliance Rate Upper Bound



Note: Bold dots (•) represent observed equilibria.

Figure B3: The Use Tax Demand Elasticity Upper Bound



Note: Bold dots (•) represent observed equilibria.

Appendix C Data Appendix - Sample Restrictions

In this appendix, we outline our process for determining which tax jurisdictions remain in our main estimation sample. Tax enforcement agreements occur between Airbnb and city, county, or state governments. Thus, the intersection of those three geographic units, which we refer to as a unique tax jurisdiction, is the level at which treatment varies. Then, using the reported coordinates, we assign all properties in our sample to their respective tax jurisdictions. To give an overview, our jurisdiction-inclusion process consists of the following four steps.

1. Consider the 105 largest jurisdictions based on average monthly property counts across the sample period.

2. Exclude jurisdictions that we find to have potentially confounding factors, such as new regulations, varying self-enforcement activity, and bans.

3. Add some sufficiently large jurisdictions outside of the largest 105 that provide additional useful within metro-month-year treatment variation.

4. Exclude jurisdictions in metropolitan areas completely lacking any within metro-month-year treatment variation.

To elaborate on the first step, we start by considering the 105 largest tax jurisdictions based on average monthly property count over our sample period. The largest 105 jurisdictions contain the majority of properties. The largest jurisdiction, New York City-New York County-New York, has a property count of nearly 30,000 in an average month. The 105th jurisdiction, Alameda City-Alameda County-California, has 208 properties listed in an average month. Although our data include properties in smaller jurisdictions, we find it useful to focus on this subset of large jurisdictions for several reasons. First, we want to avoid comparing tiny jurisdictions to large jurisdictions. Second, very large jurisdictions are more likely to resemble competitive markets where hosts are price-takers. Third, tax enforcement agreements are more likely to be reached with the larger jurisdictions. Fourth, given the second step of our process where we evaluate each jurisdiction independently to determine whether there are any potentially confounding factors, narrowing to the largest jurisdictions makes this process more tractable. There is also the added benefit that policy information on the largest jurisdictions is more readily available and reliable.

Turning to the second step, we exclude jurisdictions where there are potentially-confounding regulations introduced, increased enforcement of existing policies, and/or outright bans. We are primarily concerned with confounding policies that negatively affect Airbnb supply, since the presence of such confounders threatens our bounding argument. Policies that positively affect Airbnb supply are only of secondary concern, as their presence implies that our estimated compliance upper bound is more conservative than necessary. Among the largest 105 jurisdictions, 51 implemented an enforcement agreement during our sample period. We exclude 17 of these, which are listed in Panel A of Table C1 along with the specific problematic confounder(s). Of the remaining 54 control jurisdictions, we exclude 23, which are listed in Panel B of Table C1.

After excluding jurisdictions with confounding issues, we are left with several metropolitan areas that do not have any within metro-month-year variation in tax policies. This is problematic because we use metro-month-year fixed effects in our preferred specifications to control for location-specific idiosyncratic shocks, meaning there must be at least two jurisdictions from each metro in our estimation sample that are different in terms of tax enforcement or tax rates. In order to include as many metropolitan areas as possible to increase the amount of identifying variation, we consider useful jurisdictions outside of the largest 105. We add 13 jurisdictions without any apparent confounding factors, 2 untreated and 11 treated, which we list in Table C2.

Adding these extra jurisdictions allows us to retain New York, Washington D.C., Cleveland, New Orleans, Denver, and Chicago in our estimation sample. The jurisdictions added in Salt Lake City and Seattle provide additional treatment variation, but were not strictly necessary for their retention. There are several metro areas that we are unable to remedy: Anchorage, Atlanta, Austin, Boston, Charlotte, Dallas, Houston, Indianapolis, Minneapolis, Nashville, and Philadelphia. For example, the enforced agreements in Texas come from a single state-wide agreement, meaning there is no within-state variation in tax enforcement timing or tax rates, which rules out Austin, Dallas, and Houston. Charlotte is excluded because there are no sufficiently large jurisdictions outside of the city of Charlotte itself.[6] The full list of jurisdictions that we are forced to exclude due to a complete lack of within metro-month-year treatment variation is presented in Table C3. At the end of this process, there are 61 jurisdictions included in our main estimation sample, 38 treated and 23 untreated, which are listed in Table C4. These are the jurisdictions used to produce our main results presented in Table 3.

To test the robustness of our main results to these jurisdiction restrictions, we re-estimate them using all of the top 105 jurisdictions and the 13 additional jurisdictions from Table C2. Table C5 presents the results of this robustness check. Note that the estimated effect on price is still negative and statistically significant at the 1% level, but smaller in magnitude than our main estimates. The estimate produced by our preferred specification including property fixed effects and metro-month-year fixed effects is -0.16, which implies an upper bound on pre-enforcement compliance of 16%, while the analogous estimate from our main results in Table 3 implies a more conservative upper bound of 24%. The estimated quantity effect is also attenuated when using the full set of jurisdictions. Using our preferred specification, the estimated effect of the enforced tax rate on nights booked per month is -0.13 and statistically insignificant, compared to -0.36 and significant at the 10% level when using the restricted set of jurisdictions.

[6]The next largest jurisdiction is Mooresville-Iredell County-North Carolina, with a property count of only 37 in an average month.

Table C1: Jurisdictions Excluded Due to Confounders

City	County	Metro	State	Confounding Factor
Panel A: Treated Jurisdictions				
Aurora	Arapahoe	Denver	CO	Strict laws on operation/taxation in 12/2016.
Aventura	Miami-Dade	Miami	FL	Ban on short-term rentals. Date unclear.
Boca Raton	Palm Beach	Miami	FL	Strict zoning, residential short-term rentals not allowed. Increased enforcement efforts in late 2016.
Chicago	Cook	Chicago	IL	Several strict regulations rolled out in 2016-17.
Cleveland	Cuyahoga	Cleveland	OH	Clarified laws on short-term rentals same time as tax agreement.
Denver	Denver	Denver	CO	Passed ordinance regulating short-term rentals in 6/2016. Active enforcement in 1/2017.
Doral	Miami-Dade	Miami	FL	Ban on short-term rentals, concentrated enforcement effort in Spring 2017.
Fort Lauderdale	Broward	Miami	FL	Introduced expensive registration requirement in 8/2015.
Hallandale Beach	Broward	Miami	FL	Registration requirement introduced 10/2016.
Hollywood	Broward	Miami	FL	Registration requirement introduced 2/2016.
Miami	Miami-Dade	Miami	FL	Attempted enforcement of local ban, amidst battles between local and state government over legality of ban.
Miami Beach	Miami-Dade	Miami	FL	Strict enforcement efforts starting mid-2016.
Philadelphia	Philadelphia	Philadelphia	PA	Restricted rentals in residential areas same time as tax agreement.
Pompano Beach	Broward	Miami	FL	Changes in registration requirements 12/2015, again in mid-2017.
San Francisco	San Francisco	Oakland	CA	Early tax intro and legal battles between SF and Airbnb.
San Jose	Santa Clara	SanJose	CA	Strict regulation introduced 11/2014.
Tacoma	Pierce	Seattle	WA	Introduced strict regulations in late 2016.
Panel B: Untreated Jurisdictions				
Anaheim	Orange	LosAngeles	CA	Moratorium on short-term rental permit applications from 9/2015 through 5/2017.
Berkeley	Alameda	Oakland	CA	Technically banned before 7/2016. Afterward, cap on nights per year (90) and property must be owner-occupied.
Burbank	Los Angeles	LosAngeles	CA	Technically banned, but enforcement unclear. Regulation introduced in 2014, but was still being discussed as of 5/2015.
Carlsbad	San Diego	SanDiego	CA	Increased regulatory enforcement twice, 5/2015 and 5/2017.
Encinitas	San Diego	SanDiego	CA	Increased enforcement of existing regulations in 2016.
Franklin	Williamson	Nashville	TN	Amended short-term rental ordinance in 2015. Requires license to operate.
Hermosa Beach	Los Angeles	LosAngeles	CA	Banned short-term rentals in 5/2016.
Irvine	Orange	LosAngeles	CA	Increased enforcement of regulations in 2015-16 (warnings, fines issued).
Laguna Beach	Orange	LosAngeles	CA	Banned short-term rentals in 9/2016.
Louisville	Jefferson	Louisville	KY	Introduced registration requirements in 8/2016.
Manhattan Beach	Los Angeles	LosAngeles	CA	Banned short-term rentals in 6/2015.
Nashville	Davidson	Nashville	TN	Passed ordinance regulating short-term rentals in 7/2015.
New York	New York	NewYork	NY	Banned short-term rentals in 10/2016.
New York	Bronx	NewYork	NY	Banned short-term rentals in 10/2016.
New York	Kings	NewYork	NY	Banned short-term rentals in 10/2016.
New York	Queens	NewYork	NY	Banned short-term rentals in 10/2016.
New York	Richmond	NewYork	NY	Banned short-term rentals in 10/2016.
Newport Beach	Orange	LosAngeles	CA	Increased enforcement of existing laws in 2016-17.
Redondo Beach	Los Angeles	LosAngeles	CA	Banned short-term rentals in 3/2016.
San Clemente	Orange	LosAngeles	CA	Implemented and enforced strict registration and zoning regulations in 2016.
Sunnyvale	Santa Clara	SanJose	CA	Introduced registration requirement in 9/2015.
Union City	Hudson	NewYork	NJ	Banned short-term rentals in 12/2015.
West Hollywood	Los Angeles	LosAngeles	CA	Banned short-term rentals in 10/2015, increased enforcement 7/2016.

Table C2: Additional Jurisdictions From Outside Top 105

City	County	Metro	State	Rank
Panel A: Untreated Jurisdictions				
West New York	Hudson	NewYork	NJ	107
Newark	Essex	NewYork	NJ	115
Panel B: Treated Jurisdictions				
Silver Spring	Montgomery	DC	MD	120
Cleveland Heights	Cuyahoga	Cleveland	OH	130
Bethesda	Montgomery	DC	MD	133
University Place	Pierce	Seattle	WA	135
Richmond	Contra Costa	Oakland	CA	146
Oak Park	Cook	Chicago	IL	150
Lakewood	Cuyahoga	Cleveland	OH	157
Millcreek	Salt Lake	SaltLakeCity	UT	173
Redmond	King	Seattle	WA	191
Metairie	Jefferson	NewOrleans	LA	211
Golden	Jefferson	Denver	CO	220

Table C3: Dropped Jurisdictions - No Variation

City	County	Metro	State
Panel A: Treated Jursdictions			
Anchorage	Anchorage	Anchorage	AK
Austin	Travis	Austin	TX
Charlotte	Mecklenburg	Charlotte	NC
Dallas	Dallas	Dallas	TX
Fort Worth	Tarrant	Dallas	TX
Galveston	Galveston	Houston	TX
Houston	Harris	Houston	TX
Philadelphia	Philadelphia	Philadelphia	PA
Panel B: Unreated Jursdictions			
Atlanta	DeKalb	Atlanta	GA
Atlanta	Fulton	Atlanta	GA
Boston	Suffolk	Boston	MA
Brookline	Norfolk	Boston	MA
Cambridge	Middlesex	Boston	MA
Franklin*	Williamson	Nashville	TN
Nashville*	Davidson	Nashville	TN
Newton	Middlesex	Boston	MA
Somerville	Middlesex	Boston	MA
Indianapolis	Marion	Indianapolis	IN
Minneapolis	Hennepin	Minneapolis	MN
St. Paul	Ramsey	Minneapolis	MN

*Also dropped for potential confounding factors.

Table C4: Main Set of Jurisdictions

City	County	Metro	State	Tax Date	Tax Rate Initial	Tax Rate Max
Panel A: Treated Jurisdictions						
Bellevue	King	Seattle	WA	2015m10	12	12.4
Bethesda	Montgomery	WashingtonDC	MD	2016m6	7	7
Cleveland Heights	Cuyahoga	Cleveland	OH	2016m4	5.5	5.5
Delray Beach	Palm Beach	Miami	FL	2015m12	6	7
Evanston	Cook	Chicago	IL	2016m1	6.17	7.17
Four Corners	Lake	Orlando	FL	2015m12	7	7
Four Corners	Osceola	Orlando	FL	2015m12	7	7.5
Golden	Jefferson	Denver	CO	2016m10	3	8.43
Jersey City	Hudson	NewYork	NJ	2015m11	6	6
Kirkland	King	Seattle	WA	2015m10	10.5	11
Kissimmee	Osceola	Orlando	FL	2015m12	7	7.5
Lakewood	Cuyahoga	Cleveland	OH	2016m4	5.5	5.5
Lakewood	Jefferson	Denver	CO	2017m2	5.43	5.43
Los Angeles	Los Angeles	LosAngeles	CA	2016m8	14	14
Malibu	Los Angeles	LosAngeles	CA	2015m4	12	12
Mesa	Maricopa	Phoenix	AZ	2017m1	14.02	14.02
Metairie	Jefferson	NewOrleans	LA	2016m4	5	5
Millcreek	Salt Lake	SaltLakeCity	UT	2016m10	11.6	11.6
New Orleans	Orleans	NewOrleans	LA	2016m4	5	9
Oak Park	Cook	Chicago	IL	2016m1	6.17	11.17
Oakland	Alameda	Oakland	CA	2015m7	14	14
Orlando	Orange	Orlando	FL	2015m12	6.5	12.5
Phoenix	Maricopa	Phoenix	AZ	2015m7	5.3	12.57
Redmond	King	Seattle	WA	2015m10	10.5	11
Richmond	Contra Costa	Oakland	CA	2017m6	10	10
Salt Lake City	Salt Lake	SaltLakeCity	UT	2016m10	12.6	12.6
San Diego	San Diego	SanDiego	CA	2015m7	10.5	10.5
Sandy	Salt Lake	SaltLakeCity	UT	2016m10	13.1	13.1
Santa Clara	Santa Clara	SanJose	CA	2015m10	9.5	9.5
Scottsdale	Maricopa	Phoenix	AZ	2017m1	13.92	13.92
Seattle	King	Seattle	WA	2015m10	9.6	10.1
Silver Spring	Montgomery	WashingtonDC	MD	2016m6	7	7
Sunny Isles Beach	Miami-Dade	Miami	FL	2015m12	7	13
Tempe	Maricopa	Phoenix	AZ	2017m1	14.07	14.07
University Place	Pierce	Seattle	WA	2015m10	11.4	11.9
Vashon	King	Seattle	WA	2015m10	8.6	8.6
Washington	District of Columbia	WashingtonDC	DC	2015m2	14.5	14.5
West Palm Beach	Palm Beach	Miami	FL	2015m12	6	7
Panel B: Untreated Jurisdictions						
Alameda	Alameda	Oakland	CA	-	-	-
Alexandria	Alexandria	WashingtonDC	VA	-	-	-
Arlington	Arlington	WashingtonDC	VA	-	-	-
Beverly Hills	Los Angeles	LosAngeles	CA	-	-	-
Costa Mesa	Orange	LosAngeles	CA	-	-	-
Culver City	Los Angeles	LosAngeles	CA	-	-	-
Daly City	San Mateo	Oakland	CA	-	-	-
Fremont	Alameda	Oakland	CA	-	-	-
Glendale	Los Angeles	LosAngeles	CA	-	-	-
Hoboken	Hudson	NewYork	NJ	-	-	-
Huntington Beach	Orange	LosAngeles	CA	-	-	-
Long Beach	Los Angeles	LosAngeles	CA	-	-	-
Menlo Park	San Mateo	Oakland	CA	-	-	-
Milpitas	Santa Clara	SanJose	CA	-	-	-
Mountain View	Santa Clara	SanJose	CA	-	-	-
Newark	Essex	NewYork	NJ	-	-	-
Oceanside	San Diego	SanDiego	CA	-	-	-
Pasadena	Los Angeles	LosAngeles	CA	-	-	-
Redwood City	San Mateo	Oakland	CA	-	-	-
Rowland Heights	Los Angeles	LosAngeles	CA	-	-	-
San Mateo	San Mateo	Oakland	CA	-	-	-
Weehawken	Hudson	NewYork	NJ	-	-	-
West New York	Hudson	NewYork	NJ	-	-	-

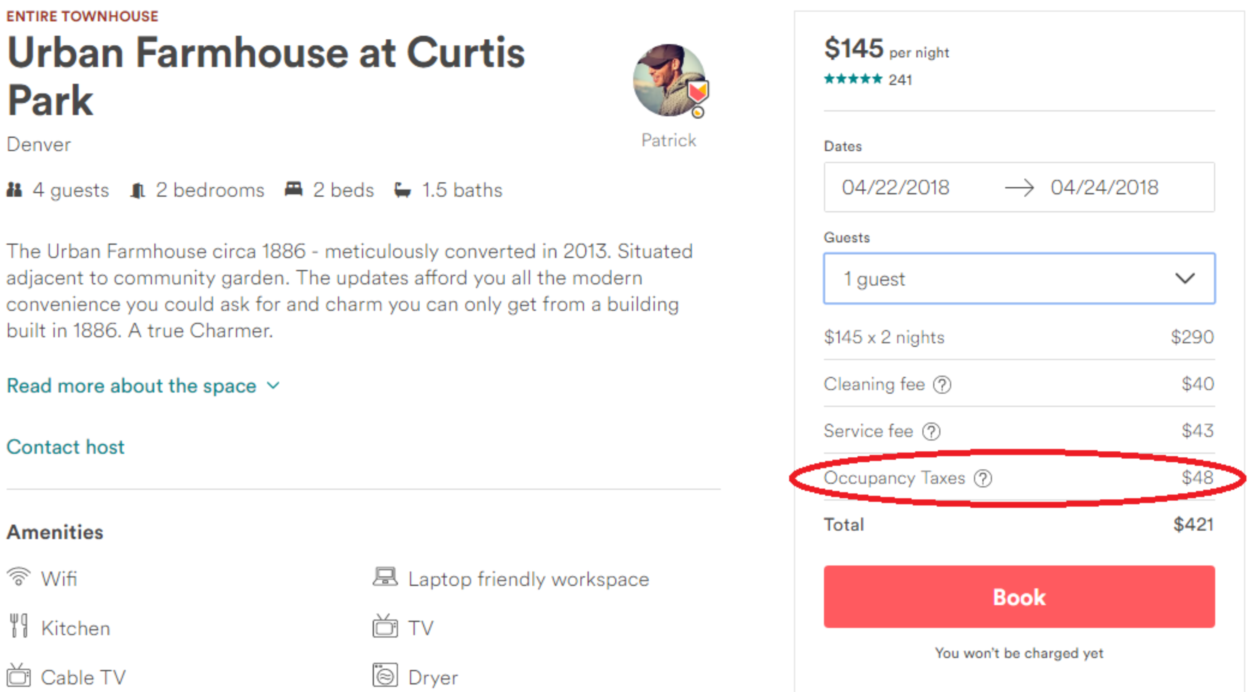
Table C5: Tax Enforcement, Bookings, and Book Price (Compare to Table 3)

	Panel A: ln(Booking Price)					
ln(1 + tax)	-0.165***	-0.211***	-0.184**	-0.226***	-0.213***	-0.184*
	(0.037)	(0.058)	(0.074)	(0.037)	(0.044)	(0.102)
Observations	2,412,690	2,412,689	2,412,690	2,498,773	2,498,772	2,498,773
	Panel B: ln(1+Nights Booked)					
ln(1 + tax)	-0.132	-0.304	-0.084	-0.205	-0.163	0.107
	(0.148)	(0.200)	(0.269)	(0.130)	(0.145)	(0.242)
Observations	7,420,780	7,420,780	7,420,780	7,432,852	7,432,852	7,432,852
Property FE	✓	✓	✓	-	-	-
Tax Jurisdiction FE	-	-	-	✓	✓	✓
Property-level Controls	-	-	-	✓	✓	✓
Metro-Month-Year FE	✓	-	-	✓	-	-
County-Month-Year FE	-	✓	-	-	✓	-
Month-Year FE	-	-	✓	-	-	✓

Notes: Main results using the full sample, before omitting jurisdictions with confounding factors and metros lacking any within-month treatment variation. Regressions of the natural log of booking price (Panel A) and the number of bookings (Panel B) on our treatment variable. Each outcome is estimated using four different specifications. Column 1 includes property fixed effects and metro-month-year fixed effects. Column 2 includes property fixed effects and county-month-year fixed effects. Column 3 includes property fixed effects and month-year fixed effects. Columns 4-6 repeat the three specifications replacing property fixed effects with tax jurisdiction fixed effects, and including controls for property level characteristics. Estimates for booking price are weighted by the number of bookings contributing to the average monthly booking price observations. As in our main results, this sample omits shared-room listings and listings with average asking prices falling in the top and bottom 10% of their jurisdiction's asking price distribution. Standard errors are robust to clustering at the tax jurisdiction level. *** p<0.01, ** p<0.05, * p<0.10.

Appendix D Additional Tables and Figures

Figure D1: Airbnb Screenshot



Source: `https://www.airbnb.com/rooms/12365447`, accessed 4/16/2018.

Table D1: Pre-Enforcement Differences in Outcomes

	Full Sample	Treated	Untreated	(Treated - Untreated)	
Booking Price	127.91	129.50	123.11	8.044	3.197
	(70.55)	(70.66)	(69.99)	(7.911)	(7.730)
ln(Booking Price)	4.73	4.75	4.68	0.063	0.041
	(0.48)	(0.47)	(0.50)	(0.056)	(0.061)
Nights Booked	6.47	6.64	6.01	0.481	0.345
	(12.51)	(12.60)	(12.22)	(0.366)	(0.328)
ln(1 + Nights Booked)	0.97	0.99	0.90	0.057	0.006
	(1.35)	(1.35)	(1.32)	(0.049)	(0.041)
Asking Price	131.56	132.48	128.90	0.937	-0.396
	(79.07)	(77.56)	(83.27)	(9.435)	(9.320)
ln(Asking Price)	4.75	4.77	4.71	0.032	0.024
	(0.49)	(0.47)	(0.53)	(0.062)	(0.070)
Observations	870,028	636,861	233,167		
Month-Year FE				✓	-
Metro-Month-Year FE				-	✓
Property-level Controls				-	✓

Notes: The first three columns present sample means and standard deviations for the full, treated, and untreated samples in the months preceding a tax enforcement agreement. The last two columns present tests for whether being in a treated jurisdiction is correlated with outcomes in the pre-enforcement months. Each estimate is from a regression of the outcome variable on an indicator for whether that listing is in an eventually-treated jurisdiction. The sample excludes listings for shared rooms, properties that have >4 bedrooms, properties that have a >12 guest limit, or properties for which average asking price falls in bottom or top decile of the jurisdiction's distribution. Standard errors are robust to clustering at the tax jurisdiction level. *** p<0.01, ** p<0.05, * p<0.10.

Table D2: Pre-Enforcement Differences in Jurisdiction Characteristics

	Full Sample	Treated	Untreated	(Treated - Untreated)	
Panel A: Jurisdiction Characteristics					
Number of Properties	459.4	588.4	138.7	484.9**	1,466.0
	(1,083.0)	(1,259.0)	(91.3)	(200.8)	(915.9)
Total Nights Available	9,085.0	11,669.0	2,662.0	9,638**	28,916.0
	(21,850.0)	(25,403.0)	(1,731.0)	(4,028.0)	(18,592.0)
Total Nights Booked	2,683.0	3,458.0	757.5	2,555**	8,150.0
	(7,278.0)	(8,486.0)	(726.0)	(1,174.0)	(5,151.0)
Proportion Properties Booked	0.359	0.359	0.361	-0.026	-0.015
	(0.130)	(0.138)	(0.106)	(0.023)	(0.021)
Median Book Price	99.70	99.96	99.05	3.12	9.85
	(33.20)	(36.11)	(24.57)	(7.21)	(16.76)
Book Price 25th Pctile	75.06	74.47	76.52	0.41	7.73
	(23.42)	(25.40)	(17.53)	(5.45)	(12.03)
Book Price 75th Pctile	139.60	140.70	137.00	5.62	26.03
	(56.96)	(63.70)	(34.94)	(10.67)	(33.51)
Panel B: Changes in Jurisdiction Characteristics					
Number of Properties (% chg)	0.111	0.111	0.110	0.017	-0.016
	(0.126)	(0.122)	(0.136)	(0.013)	(0.011)
Total Nights Available (% chg)	0.116	0.119	0.110	0.025	-0.010
	(0.196)	(0.195)	(0.200)	(0.017)	(0.013)
Total Nights Booked (% chg)	0.726	0.853	0.410	0.295*	-0.079
	(4.571)	(5.324)	(1.513)	(0.153)	(0.080)
Proportion of Properties Booked (chg)	-0.006	-0.005	-0.009	-0.001	0.001
	(0.112)	(0.116)	(0.100)	(0.003)	(0.004)
Median Book Price (% chg)	0.014	0.016	0.008	0.008	-0.006
	(0.164)	(0.184)	(0.100)	(0.007)	(0.005)
Book Price 25th Pctile (% chg)	0.006	0.007	0.005	0.000	-0.001
	(0.122)	(0.135)	(0.083)	(0.004)	(0.004)
Book Price 75th Pctile (% chg)	0.029	0.033	0.019	0.011	-0.002
	(0.278)	(0.310)	(0.174)	(0.014)	(0.008)
Observations	760	542	218		
Month-Year FE				✓	-
Metro-Month-Year FE				-	✓

Notes: The first three columns present sample means and standard deviations for all jurisdictions, treated jurisdictions, and untreated jurisdictions in the months preceding the first enforced tax in the metro area. The last two columns present tests for whether eventual treatment is correlated with jurisdiction-month level characteristics. Each estimate is from a regression of the jurisdiction characteristic on an indicator for whether that jurisdiction is eventually treated. The sample excludes listings for shared rooms, properties that have >4 bedrooms, properties that have a >12 guest limit, or properties for which average asking price falls in bottom or top decile of the jurisdiction's distribution. Standard errors are robust to clustering at the tax jurisdiction level. *** p<0.01, ** p<0.05, * p<0.10.

Table D3: Robustness Checks, Booking Price and Nights Booked

	No Property Restrictions	Omit Cheapest & Most Expensive 5%	Omit Cheapest & Most Expensive 25%	Unweighted	Drop Never-Booked	Drop First Post-Tax Month	Drop First Post-Tax & Last Pre-Tax Months
	Panel A: ln(Booking Price)						
ln(1 + tax)	-0.218***	-0.229***	-0.259***	-0.235***	-	-0.273***	-0.288***
	(0.060)	(0.056)	(0.063)	(0.067)	-	(0.063)	(0.063)
Observations	1,200,885	1,054,683	633,574	935,691	-	911,595	888,661
	Panel B: ln(1+Nights Booked)						
ln(1 + tax)	-0.389*	-0.334	-0.316	-	-0.462**	-0.262	-0.228
	(0.217)	(0.221)	(0.253)	-	(0.223)	(0.219)	(0.221)
Observations	3,508,692	2,977,353	1,720,593	-	2,270,804	2,530,149	2,477,541

Notes: Regressions of the natural log of booking price (Panel A) and the number of bookings (Panel B) on our treatment variable. All regressions use the preferred specification, which includes property fixed effects and metro-month-year fixed effects. Column 1 presents the results when removing all the property-characteristic restrictions imposed in our central estimates: exclude if listing is for a shared room, property has >4 bedrooms, property has >12 guest limit, or average asking price falls in bottom or top decile of the jurisdiction's distribution. Columns 2-7 retain these restrictions, except for the varying price restrictions in columns 2 and 3, which test the robustness of the asking price restriction using the top and bottom 5th percentile and 25th percentile as cutoffs, respectively. Estimates for booking price are weighted by the number of bookings contributing to the average monthly booking price observations, except in column 4 which presents the unweighted version of the preferred booking price estimate from column 6 of Table 3. Column 5 presents the nights booked estimate after excluding properties that have never been booked from the sample. Columns 6 and 7 test for strategically-timed booking behavior among consumers by excluding observations of the first post-enforcement and last pre-enforcement months among properties in treated jurisdictions. Standard errors are robust to clustering at the tax jurisdiction level. *** p<0.01, ** p<0.05, * p<0.10.

Table D4: Tax Enforcement, Bookings, and Book Price (Compare to Table 3)

	Panel A: ln(Booking Price)					
ln(1 + tax)	-0.234***	-0.315***	-0.119***	-0.226***	-0.226***	-0.107**
	(0.077)	(0.082)	(0.034)	(0.056)	(0.064)	(0.052)
Observations	762,813	762,806	762,813	786,022	786,015	786,022
	Panel B: ln(1+Nights Booked)					
ln(1 + tax)	-0.270	-0.244	-0.332***	-0.373	-0.235	-0.319***
	(0.269)	(0.318)	(0.076)	(0.233)	(0.212)	(0.107)
Observations	2,115,987	2,115,987	2,115,987	2,119,875	2,119,875	2,119,875
Property FE	✓	✓	✓	-	-	-
Tax Jurisdiction FE	-	-	-	✓	✓	✓
Property-level Controls	-	-	-	✓	✓	✓
Metro-Month-Year FE	✓	-	-	✓	-	-
County-Month-Year FE	-	✓	-	-	✓	-
Month-Year FE	-	-	✓	-	-	✓

Notes: Main results using the full sample, after omitting jurisdictions with ambiguous legal obligation before tax enforcement. Regressions of the natural log of booking price (Panel A) and the number of bookings (Panel B) on our treatment variable. Each outcome is estimated using four different specifications. Column 1 includes property fixed effects and metro-month-year fixed effects. Column 2 includes property fixed effects and county-month-year fixed effects. Column 3 includes property fixed effects and month-year fixed effects. Columns 4-6 repeat the three specifications replacing property fixed effects with tax jurisdiction fixed effects, and including controls for property level characteristics. Estimates for booking price are weighted by the number of bookings contributing to the average monthly booking price observations. As in our main results, this sample omits shared-room listings and listings with average asking prices falling in the top and bottom 10% of their jurisdiction's asking price distribution. Standard errors are robust to clustering at the tax jurisdiction level. *** p<0.01, ** p<0.05, * p<0.10.

Table D5: Restricting to Largest Jurisdiction in Each Metro

	Metros in Main Sample (15)		*All Metros (26*)*	
	ln(Booking Price)	ln(1+Nights Booked)	ln(Booking Price)	ln(1+Nights Booked)
ln(1 + tax)	-0.158	-0.584***	-0.214*	-0.470***
	(0.101)	(0.182)	(0.115)	(0.201)
Observations	712,316	1,935,251	976,112	2,790,279

Notes: All specifications include property fixed effects and month-year fixed effects. The comparable booking price estimate from column 3 of Table 4 is -0.196 (s.e. 0.087), and the comparable nights booked estimate is -0.522 (s.e. 0.138). The first two columns present booking price and nights booked results when keeping only the largest jurisdiction from each metro included in our main estimation sample (15 jurisdictions). The third and fourth columns present booking price and nights booked results when using the largest jurisdiction from each of our 26* metros (excluding Louisville due to confounding regulation). Standard errors are robust to clustering at the tax jurisdiction level. *** p<0.01, ** p<0.05, * p<0.10.

Table D6: Heterogeneity Estimates

	Listing Type		Asking Price Quartiles			
	Entire Home	Private Room	Bottom Quartile	Second Quartile	Third Quartile	Top Quartile
	Panel A: ln(Booking Price)					
ln(1 + tax)	-0.289***	-0.124***	-0.165***	-0.232***	-0.266***	-0.267**
	(0.084)	(0.037)	(0.040)	(0.056)	(0.099)	(0.105)
Observations	838,380	328,363	284,709	322,597	315,013	244,486
	Panel B: ln(1+Nights Booked)					
ln(1 + tax)	-0.446	-0.063	-0.377	-0.522*	-0.118	-0.320*
	(0.276)	(0.144)	(0.261)	(0.278)	(0.318)	(0.176)
Observations	2,329,361	1,047,633	792,078	861,504	862,029	863,933

Notes: Regressions of the natural log of booking price (Panel A) and the number of bookings (Panel B) on our treatment variable. All regressions use the preferred specification, which includes property fixed effects and metro-month-year fixed effects. The estimation samples are not restricted by number of bedrooms, guest limit, or price before the split-sample heterogeneity analyses are performed. As in our main estimation sample, we do omit shared-room listings. Columns 1-2 present the results when splitting the sample into entire home listings and private room listings, respectively. Columns 3-6 present the results when splitting the sample into jurisdiction-based quartiles of average asking prices. Estimates for booking price are weighted by the number of bookings contributing to the average monthly booking price observations. Standard errors are robust to clustering at the tax jurisdiction level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table D7: Hypothetical No-Tax Equilibria and Deadweight Loss Per Property-Month

λ	ϵ_{supply}	No-Tax Eqm. Price	No-Tax Eqm. Quantity	Total DWL post-enforcement	Total DWL counterfactual	Consumer Tax Incidence
0	1.5	\$140.69	6.14	\$1.84	\$0.00	76%
0.07	2.16	\$139.77	6.16	\$1.98	\$0.01	82%
0.24	∞	\$137.00	6.21	\$2.42	\$0.14	100%