DEPARTMENT OF ECONOMICS
WORKING PAPER SERIES

2018-06

McMASTER UNIVERSITY

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

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February 1, 2018

Abstract

Tax enforcement can be prohibitively costly when market transactions and participants are difficult to observe. Evasion among market participants may reduce tax revenue and provide certain types of suppliers an undue competitive advantage. Whether efforts to fully enforce taxes are worthwhile depends on the rate of compliance in the absence of such efforts. In this paper, we show that an upper bound on pre-enforcement tax compliance can be obtained using market data on pre- and post-enforcement periods. To do this, we estimate the pass-through of tax enforcement agreements between the largest online short-term housing rental platform and state and local governments, which achieve full compliance at the point of sale. Using transaction-level data on Airbnb listings across a number of U.S. metropolitan areas, as well as variation in enforcement agreements across time, location, and tax rate, we estimate that taxes are paid on no more than 23 percent of Airbnb transactions prior to enforcement. We also provide insight on demand- and supply-side responses to taxation in online and sharing economy marketplaces, as well as the potential associated inefficiencies.

Keywords: Tax compliance, evasion, enforcement, short-term housing rentals, sharing economy, Airbnb

JEL Codes: H20, H22, H26, L10

1 Introduction

Online marketplaces such as Amazon, eBay, Craigslist, and Airbnb have transformed industries by increasing competition and reducing transaction costs. However, one issue with the rise of online marketplaces is that tax obligations are often ambiguous or difficult to enforce. For example, states generally must rely on the self-reporting of residents to collect use taxes on goods purchased online from out-of-state sellers.[1] Since government agents cannot fully observe key details of online transactions, enforcing the applicable taxes is infeasible without formal agreements or laws to induce online platforms to cooperate. Thus, individual market participants, who may simply be unaware of their tax obligations, are able to evade with low probability of detection.[2]

To overcome this problem, policymakers are working to shift the burden of tax collection and remittance onto online platforms and retailers.[3] Such an approach can increase tax revenue if online platforms and retailers are less able or willing to evade.[4] Traditional suppliers also face incentives to promote enforcement to mitigate competitive advantages enjoyed by online suppliers.[5] However, whether these efforts are effective or wasteful crucially depends on the rate of compliance among individuals in the absence of formal enforcement.

In this paper, we develop an approach to bound pre-enforcement tax compliance using market data from pre-enforcement (partial compliance) and post-enforcement (full compli-

[1]See Quill Corp. v. North Dakota, 504 U.S. 298 (1992), which ruled that states cannot enforce use taxes on sales that are made to residents of that state by sellers without a presence in that state.

[2]According to Manzi (2015), in the 27 states that provide for use tax reporting on one's income tax return, approximately 2 percent of income tax returns reported any use tax in 2012.

[3]Amazon is a prominent example, where states have cited physical presence, passed laws, or entered agreements with the company to enforce the collection of sales taxes (Baugh, Ben-David and Park, Forthcoming). Note, however, that these efforts still fall short as they do not extend to third-party sellers on Amazon Marketplace.

[4]While the conventional principle of tax-collection invariance states that economic tax incidence and tax revenues do not depend on who bears the statutory tax burden, Kopczuk et al. (2016) demonstrate that this principle is violated when one or more sides of the market differ in their ability to evade. Bruce, Fox and Luna (2009) conservatively projected that foregone e-commerce state tax revenue would be $11.4 billion in 2012 alone.

[5]See, for example, lobbying groups such as the American Hotel and Lodging Association (Benner, 2017), Alliance for Main Street Fairness (`www.standwithmainstreet.com/content.aspx?page=efairness`), and Retail Industry Leaders Association (`www.rila.org/Public-Policy/Fairness/E-Fairness/Pages/default.aspx`).

ance) periods. This approach relies only on observed tax magnitudes and the reduced-form effect of enforcement on price.[6] Airbnb offers a particularly attractive setting. In jurisdictions with legislated taxes on hotels and other short-term housing rentals (STRs), but no formal enforcement agreements with platforms such as Airbnb, governing bodies must either rely on hosts (suppliers) to collect and remit the applicable taxes or pay exorbitant enforcement costs to locate and penalize evaders.[7] Since 2014, however, Airbnb has entered into over 250 agreements with cities, counties, and states across the U.S. to enforce sales, hotel, transient, and other taxes.[8] Once an agreement is reached, Airbnb becomes the tax remitter and collects taxes on every applicable transaction from renters (consumers) at the point of sale, increasing tax compliance to 100% in those jurisdictions.

To estimate the effect of tax enforcement on price, we use a difference-in-differences estimation strategy that exploits variation in Airbnb tax enforcement across time, location, and tax rate, combined with data derived from Airbnb.com. We estimate that the enforcement of a 10% tax reduces the price hosts receive by 2.3% and increases the price renters pay by 7.7%. This estimate yields an upper bound of 23% compliance pre-enforcement; that is, at least 77% of transactions evade taxation. This result suggests that tax jurisdictions can increase compliance substantially by entering an enforcement agreement.

Using the same estimation strategy, we find that the enforcement of a 10% tax reduces nights booked by 4.0%. Taken together, the estimated effects of tax enforcement on the price hosts receive and nights booked imply an average price elasticity of demand of -0.52. If we assume perfect competition, these results suggest that the negative demand shock caused by an Airbnb tax enforcement agreement dominates any contemporaneous positive supply shock. This is consistent with at least partial pre-enforcement evasion; in the absence of

[6]This is true given a perfectly competitive setting. In the appendix, we relax the perfect competition assumption and show that the bounding argument holds for imperfect competition as well, provided that price complementarity between hosts is small enough.

[7]Indeed, anecdotal evidence suggests that, in the absence of formal enforcement, compliance among Airbnb hosts is low (Tuttle, 2013; Cohn, 2016; Bruckner, 2016).

[8]See `https://www.airbnbcitizen.com/airbnb-tax-collection-program-expands-has-already-collected-110-million-for-governments/` and `https://www.airbnbcitizen.com/airbnb-tax-facts/`

evasion, quantity should remain unchanged and the price should fall by exactly the amount of the tax. Furthermore, assuming perfect competition, our estimates imply a lower bound on the price elasticity of supply of 1.75, suggesting that suppliers are relatively price-sensitive and that consumers bear a larger share of the economic tax incidence.[9]

1.1 Related Literature

While there is a well-established literature on tax evasion and compliance, our paper contributes to a more recent strand of research focusing on tax compliance across different market structures and tax regimes.[10] Perhaps the most related paper is Kopczuk et al. (2016), which shows that the textbook principle of tax-collection invariance can fail in the presence of evasion. Specifically, the authors find that economic tax incidence and tax revenues in the diesel fuel market depend on which part of the supply chain bears the statutory tax burden. Their results can be explained by the presence of heterogeneous evasion ability throughout the supply chain, though due to data limitations the authors are unable to estimate the extent of evasion.

Using an experimental approach, Doerrenberg and Duncan (2014) show that the benefits of evasion are shared with the side of the market that cannot evade. Our study provides an empirical confirmation of their findings, as our estimated negative effect of enforcement on quantity suggests that both hosts and renters benefit when tax enforcement is limited. In their work studying a local church tax in Germany, Dwenger et al. (2016) find that 20% of taxpayers are intrinsically motivated to comply in the absence of deterrence. Thus, our estimated 23% upper bound on pre-enforcement tax compliance appears to be reasonable.

Our paper also contributes to the growing sharing economy literature, where Airbnb has received recent attention. The most closely related paper is Wilking (2016), which finds that hosts reduce asking prices in response to tax enforcement agreements, but do so by less than

[9]This estimated lower-bound is consistent with the price elasticity of supply of 2.16 estimated by Farronato and Fradkin (2017), which they find to be twice as large as the price elasticity of supply of hotel rooms.

[10]See Slemrod (2016) for an overview of recent research on the economics of tax evasion and enforcement.

the full amount of the tax. This finding suggests that, indeed, some hosts do not comply pre-enforcement which means that tax enforcement agreements increase the after-tax prices faced by Airbnb renters. While this result is quite interesting, the author relies on estimates on asking prices to provide trace evidence of evasion and insight on incidence. In our paper, we are able to provide estimates of tax incidence and evasion by analyzing the effects of tax enforcement on actual booking price and quantity.

In addition, two studies suggest that Airbnb is successfully competing with the hotel industry and increasing consumer surplus. Farronato and Fradkin (2017) find that, while an increase in the prevalence of Airbnb reduces hotel revenue, at least 70% of Airbnb bookings are "new" in that they would not have resulted in hotel bookings in the absence of Airbnb. Zervas, Proserpio and Byers (2014) provide additional evidence, finding that an increase in Airbnb prevalence is associated with lower hotel prices and revenues. These studies also find that consumers appear to benefit most from the flexible supply of STRs through Airbnb during periods of high demand when hotels are likely to reach capacity.[11]

Broadly speaking, our work also contributes to the growing literature on the relationship between taxes, tax enforcement, and online shopping. One of the first papers in this literature finds that consumers facing higher local sales taxes are more likely to make (untaxed) purchases online and that taxing online purchases could significantly reduce the number of internet purchases, see Goolsbee (2000). Other economists have also studied this relationship using different online shopping data and find similar results: Alm and Melnik (2005); Ballard and Lee (2007); Scanlan (2007); Ellison and Ellison (2009); Anderson et al. (2010); and Einav et al. (2014).

[11] The additional option for homeowners to earn revenue from housing capital on Airbnb is also impacting the housing market, see Barron, Kung and Proserpio (2017).

2 Conceptual Framework

In this section, for simplicity, we illustrate the impact of tax enforcement policies in perfectly competitive markets.[12] Suppose there are two periods. In the first period, individual hosts bear the burden of collecting and remitting any applicable sales and lodging taxes with the possibility of evading. In the second period, the statutory burden of the tax shifts away from hosts towards Airbnb who collects and remits all applicable taxes from consumers at the point of sale. Neither hosts nor renters can evade under this regime.

Given the perfectly competitive assumption that hosts are price-takers, let the supply of accommodations be given by $S(P)$ and let the demand for accommodations be given by $D(P)$. The first period equilibrium is given by the equilibrium gross price, $P = P_1$, that satisfies $S(P-\lambda\cdot t) = D(P)$, where $\lambda \in [0,1]$ denotes the proportion of tax-compliant listings and t denotes the per-unit tax.[13] Thus, the price paid by renters in the first period is P_1 and the average price received by hosts is $P_1-\lambda\cdot t$. In the second period, the tax is automatically applied to each transaction by Airbnb with the statutory burden falling on consumers. Thus, the second period equilibrium gross price, $P = P_2$, satisfies $S(P) = D(P+t)$. In this case, renters pay P_2+t and hosts receive P_2.

If all hosts comply in the first period (i.e. $\lambda = 1$), then the equilibrium price that hosts receive is the same across the two periods: $P_1 - t = P_2$. When some hosts evade in the first period (i.e. $\lambda < 1$), an Airbnb enforcement agreement increases the price paid by consumers and decreases the average price received by hosts. If λ is observed, then the entire deadweight loss triangle is determinable, as well as total tax revenue, marginal deadweight loss from Airbnb enforcement, and the local slopes of the supply and demand curves. However, λ is unobserved in our setting, meaning that both the magnitude of the supply shift and the slope of the supply curve are unknown. This is displayed graphically in

[12] In the appendix, we consider our results in the context of imperfect competition, and also account for compliance costs and the possibility of entry.

[13] Although sales, hotel, and use taxes are ad valorem, we model the problem using a per-unit tax throughout the paper for simplicity.

Figure 1.

Although λ is unobserved in our setting, we can use the extreme case of perfectly elastic supply to infer an upper bound on compliance. Notice that the largest possible shift in the supply curve is the distance between the two observed equilibrium prices, P_1 and P_2, which occurs when supply is perfectly elastic (see a graphical representation of this in Figure 2). This implies that $\lambda \cdot t \leq P_1 - P_2$. Thus, we can estimate the following upper bound of the pre-enforcement compliance rate λ:

$$\lambda \leq \frac{P_1 - P_2}{t} \equiv \overline{\lambda}. \tag{1}$$

The power of this approach is its simplicity, as it only requires the practitioner to observe the tax magnitude along with gross prices under partial and full compliance.[14] In practice, we estimate this directly using the reduced form elasticity of gross price with respect to tax enforcement. A smaller difference between P_1 and P_2 implies a larger portion of the enforced tax is passed through to consumers, which correspondingly reduces the estimated upper bound on pre-enforcement compliance.

We also consider the other extreme, in which there is no compliance (i.e. $\lambda = 0$), to infer a lower bound on the elasticity of supply. This case is displayed in Figure 3. The tax enforcement agreement does not induce a supply shock when pre-enforcement compliance is 0%, implying that any change in gross price and quantity is fully attributable to a demand curve shift. Thus, we can trace out the steepest possible supply curve using the observed pre- and post-enforcement gross prices and quantities, as shown in Figure 3, and thus infer a lower bound on the price elasticity of supply. This exercise produces two key insights. First, as the price elasticity of supply approaches the lower bound, the implied point estimate of pre-enforcement compliance approaches 0%. Second, as the lower bound of the price elasticity of supply approaches infinity, the upper bound of pre-enforcement compliance approaches 0%.

[14] In Appendix A, we show that $\overline{\lambda}$ is a valid upper bound estimate of the pre-enforcement compliance rate for a variety of imperfectly competitive markets.

3 Data

We combine two sources of data to implement our empirical strategy. We start with information derived from Airbnb.com on STR listings including daily price, daily availability, daily bookings, and various property-specific characteristics (e.g., number of bedrooms, number of bathrooms, maximum number of guests, cleaning fee, security deposit, and reported location).[15] These data cover 27 major metropolitan areas across the United States and include over 860,000 properties that were active from at any time from August 2014 to September 2017.[16] We supplement these data with information on implementation dates and tax magnitudes for all the tax enforcement agreements made between Airbnb and the relevant state/local governments.[17]

The complete dataset consists of more than 4,800 unique tax jurisdictions. We restrict our sample to the largest jurisdictions (i.e. those with the most listings) for several reasons.[18] First, there is considerable heterogeneity across jurisdictions; in particular, larger jurisdictions are much more likely to be treated. Second, the largest jurisdictions are the most relevant for welfare analyses given the size of the markets and the higher likelihood of entering into an Airbnb tax enforcement agreement. Finally, the larger jurisdictions are likely to be more competitive given their denser concentration of other STR listings and lodging options. This is important because, although our reduced-form estimates do not rely on an assumption of perfect competition, we use those results to provide additional insights on the Airbnb market using the perfectly competitive framework. To this end, we also restrict our sample to listings that represent reasonably close substitutes to more traditional lodging alternatives. In particular, we drop shared room listings (3.8% of the sample), properties

[15]Derived data from Airbnb.com were obtained from a third-party company that frequently scrapes property, availability, host, and review information from the website.

[16]The 27 metros are Anchorage, Atlanta, Austin, Boston, Charlotte, Chicago, Cleveland, Dallas-Fort Worth, Denver, Houston, Indianapolis, Los Angeles, Louisville, Miami, Minneapolis-St. Paul, Nashville, New Orleans, New York City, Oakland, Orlando, Philadelphia, Phoenix, Salt Lake City, San Diego, San Jose, Seattle, and Washington, D.C.

[17]Note that we drop Palo Alto, CA due to ambiguity in their tax implementation date.

[18]We also include some jurisdictions outside of the top 100, provided they are large enough to be comparable to the other jurisdictions in the sample, to introduce additional within-metro tax variation.

with more than 4 bedrooms (2.9%), listings that allow more than 12 guests (1.5%), and listings with an average asking price in the bottom or top 10 percentile of their jurisdiction.

Table 3 displays summary statistics of several property and property-month characteristics, including our treatment variable and outcomes of interest. The average enforced tax rate from Table 3 is 5%. However, this rate includes many property-month observations that are not affected by a tax enforcement agreement. The average maximum tax rate enforced across all properties is 7.2%; conditional on being subject to any non-zero tax, this average increases to 12.4%. The maximum tax rate enforced in any jurisdiction is 21.4%, which is the current total tax rate on bookings in the city of Chicago.

Our key outcomes of interest are number of nights booked per property-month and average booking price. Bookings are not directly observed, but rather inferred from observed changes in availability between scrapes taken every 1 to 3 days. Table 3 shows that the average number of nights booked per month is 5.6. Note that this variable represents the number of nights that were reserved for any future stay. Thus, the maximum observed value of 293 means that, in the course of one month, 293 nights of future stays were booked for a particular property. We use this measure, rather than the number of nights for which a listing was booked during a particular month, because Airbnb enforces the tax on all transactions made on or after the agreement's implementation date.[19] Table 3 also shows that the average booking price in our sample is roughly $133 per night. Note, however, that there is considerable variation and a wide range from $1 per night to $3,200. As expected, average booking price and its associated variance are a little lower than the observed average asking price of $136 and ranging from $1 to $10,000.

Figure 4 shows the changes over time in the number of nights booked per month, and average price of those bookings across all of the estimation sample jurisdictions. This figure highlights how the size of the market grew substantially over the sample period, from around

[19] For example, the tax enforcement agreement in Los Angeles, CA went into effect in August of 2016. A booking made in July 2016 for a stay in October 2016 would not be taxed through the website, but a booking made in September 2016 for a stay in October 2016 would.

200,000 nights booked per month in August 2014 to about 1 million nights booked per month by January 2016. Note that the decline in nights booked and average price at the end of the sample period is an artifact of the data format. Since we aggregate to the month that bookings were made, we cannot observe bookings made during our sample period that reserve dates outside of the sample period.

Looking further at Table 3, we see an average availability of 18.4 nights per property-month with a standard deviation of 13.3 and the expected range of 0 to 31 nights. This variable measures the number of nights per property-month that the listing is booked or available to be booked.[20] In future work, estimating the effect of tax enforcement on availability per month will provide insight on intensive margin supply responses to tax enforcement. Table 3 also presents additional summary statistics of interest to provide a fuller picture of the additional costs associated with Airbnb bookings, the substitutability between hotels and Airbnb listings, and the extent to which hosts use Airbnb as a platform to support a multi-property rental business. The average security deposit is \$153.57, the average cleaning fee is \$48.1, and the average extra person fee is \$9.2. The average Airbnb rental has 1.27 bedrooms, 1.25 bathrooms, supports up to 3.3 guests, and requires a 3.9 night minimum stay. Roughly 12% percent of Airbnb listings are classified "business-ready" and 14% of properties are listed by "superhosts".[21]

4 Estimation

Our primary goal is to estimate the effects of tax enforcement agreements on nights booked per property-month and booking prices. We aggregate our data from the property-day level to the property-month level. Although Airbnb tax enforcement policies vary at the tax jurisdiction level, we use property as our cross-sectional unit of observation to control for

[20]As opposed to being marked unavailable by the host.

[21]The requirements for a property to be classified "business-ready" are outlined here: https://www.airbnb.com/help/article/1185/what-makes-a-listing-business-travel-ready. The requirements to be a "superhost" are outlined here: https://www.airbnb.com/help/article/828/what-is-a-superhost.

variation across jurisdictions in property characteristics. Consider the following difference-in-differences specification:

$$ln(Y_{ijmt}) = \alpha_j + \gamma \cdot ln(1 + \tau_{ijmt}) + \Gamma \cdot X_{ijmt} + \delta_{mt} + \epsilon_{ijmt}. \tag{2}$$

In Equation (2), Y_{ijmt} is the outcome of interest for property i in tax jurisdiction j and metro m in month-year t. Our treatment variable is τ_{ijmt}, which is the size of the tax enforced directly through Airbnb.com for property i at time t. This variable equals zero in the absence of a formal tax enforcement agreement, and becomes positive after an agreement is implemented. We estimate a log-log specification so we can interpret the effects of tax enforcement on the equilibrium outcomes as elasticities with respect to the enforced tax rate. We also include property specific controls, X_{ijmt}, which include variables such as number of bedrooms, number of bathrooms, property rating, any additional applicable fees, and cancellation policy. In all specifications, we include tax jurisdiction level fixed effects, α_j, to control for time-invariant unobserved/omitted jurisdiction-specific characteristics. We also include flexible time effects to control for time-specific shocks to a particular area; Equation (2) represents our preferred specification, which includes metro-month-year fixed effects δ_{mt}.[22]

The parameter of interest, γ, represents the elasticity of Y with respect to the tax enforced through the platform. As long as supply and demand have some non-zero and finite slope, and there is less-than-full compliance pre-enforcement, then our conceptual framework yields unambiguous predictions on our three main variables of interest: the elasticity of nights booked (γ_Q) is negative, the elasticity of booking prices that hosts receive (γ_{Ps}) is negative, and the elasticity of booking prices paid by consumers (γ_{Pd}) is positive. Note that the two price elasticities, γ_{Ps} and γ_{Pd}, must sum to one because the gap between the gross and net-of-tax prices necessarily equals the size of the tax enforced.

[22] In an alternate specification, we use county-month-year fixed effects and find similar results. However, the inclusion of county-month-year fixed effects is more restrictive since fewer tax jurisdictions are part of counties that exhibit within-county variation in tax enforcement and magnitude.

To alleviate concerns about endogenous treatment, we eliminate treatment and control jurisdictions with potentially confounding regulations and unilateral enforcement imposed during the sample period.[23] Including metro-month-year fixed effects allows us to control for metro-specific seasonality as well as idiosyncratic demand shocks. For example, agreements in Cleveland, OH and Santa Clara, CA preceded large sporting events. In those cases, the metro-month-year fixed effects absorb the demand shock that affected jurisdictions close to those events.

Our resulting estimation sample includes properties from 79 jurisdictions: 49 treated jurisdictions with initial agreements across 16 different treatment dates, and 30 jurisdictions that were never treated in the sample. Table 1 lists the 49 treated jurisdictions with their treatment dates, initial tax rates, and maximum tax rates. The treatment date and initial tax rate refer to the first agreement that was put in place for that particular jurisdiction. Some jurisdictions entered or were affected by subsequent agreements that further increased the tax rate enforced through the site. The measured enforced tax rate, τ_{ijmt}, changes accordingly to account for new agreements.[24]

The treated jurisdictions vary in geographic location, with at least one treatment jurisdiction in twelve different states.[25] Treatment dates span from February 2015 to June 2017, and have initial tax rates ranging from 4.5% to 14.07%. Table 2 lists sample jurisdictions that were never treated in the sample period. There are 30 jurisdictions spanning four states and six metro areas that were never treated during our sample period.[26] However, note that we exploit variation in location *and* timing of tax enforcement. Thus, many treated jurisdictions also serve as controls in some months. Moreover, we exploit variation in the tax rate that is enforced, which also contributes to identification even in cases where there

[23]To name a few: Santa Monica, CA; San Francisco, CA; Miami Beach, FL; Union City, NJ.

[24]For example, although the initial agreement in Chicago enforced a 4.5% tax starting in February 2015, Chicago, Cook County, and Illinois entered subsequent agreements that eventually increased the enforced rate to over 21% for the Chicago City - Cook County - Illinois tax jurisdiction. These changes are reflected in τ_{ijmt}.

[25]These states include Arizona, California, Colorado, District of Columbia, Florida, Illinois, Louisiana, Maryland, New Jersey, Ohio, Utah, and Washington.

[26]Those states include California, New Jersey, New York, and Virginia

is no within-metro variation in location or timing of treatment.

To further lend credibility to our empirical strategy, we estimate the pre-treatment differences in the outcomes of interest between the treatment and control jurisdictions. In Table 4, we report sample averages by treatment status and test statistics for the estimated pre-enforcement differences. To obtain these results, we use a restricted sample including only pre-treatment property-month observations. We then regress the outcome variables of interest on a dummy variable that indicates whether a property is in an eventually-treated tax jurisdiction.[27] We report tests under two specifications. The first includes only month-year fixed effects. The second uses metro-month-year fixed effects and property-level controls. Using both specifications allows us to informally test the effectiveness of using metro-month-year fixed effects and property-level characteristics, which we consider to be important for identification, to control for observable differences between treatment and control jurisdictions.

Focusing on the tests that include metro-month-year fixed effects, which are analogous to our preferred main specification, the estimated difference in log bookings is -0.007 (see last column of Table 4). This is a relatively precise zero, as the standard error is 0.017. The estimated difference in log price is -0.04 with a standard error of 0.055. These tests suggest that, conditional on the included controls, neither bookings nor prices predict an eventual tax enforcement agreement. However, without metro-month-year fixed effects and property-level controls, we reject the null hypotheses that average pre-treatment bookings and supply are the same across treatment and control jurisdictions.

5 Results

Insofar as a tax enforcement agreement shifts any existing sales and hotel tax burden away from Airbnb hosts, we expect the shock to lead to a rightward shift of the supply curve.

[27]Note that we cannot condition on tax jurisdiction fixed effects in these tests since the dummy variable of interest does not vary within jurisdiction.

In addition, because the enforcement imposes the statutory sales and hotel tax burden on consumers, we expect demand to shift left. The combination of these two effects results in an unambiguous decrease in the average booking price received by hosts. Such a result may be driven by a mix of two behavioral responses: consumers substituting toward lower-priced accommodations, and hosts reducing their asking price in order to retain consumers who would have otherwise substituted toward a different option.[28]

Table 5 presents our main results on bookings and booking price received by hosts, where each estimate can be interpreted as the elasticity of price/quantity with respect to the enforced tax rate. For each outcome of interest, we present three estimates. The first is a naive estimate that only includes tax jurisdiction fixed effects and month-year fixed effects. We consider this a naive estimate because it does not control for idiosyncratic shocks/trends or differences in seasonality across metros and time. Next, we present the results from two specifications that allow for such location-time-specific idiosyncrasies. These include county-month-year fixed effects and metro-month-year fixed effects. One limitation of using county-month-year fixed effects is that it effectively omits a lot of useful variation since several counties in our sample do not contain two or more large enough tax jurisdictions exhibiting within-county variation in Airbnb tax enforcement.[29] For this reason, we prefer the results from the specification using metro-month-year fixed effects, which do not limit our estimation sample as drastically.[30]

Focusing on our preferred specification using metro-month-year fixed effects, we find that the elasticity of the gross price (i.e. booking price received by hosts) with respect to the enforced tax rate is -0.23 and statistically significant. This implies that a 10% tax reduces gross price by 2.3%. This means that the majority of the tax - the remaining 7.7% of a 10% tax rate - is passed through to renters following implementation of an Airbnb tax agreement.

[28]In addition, the marginal bookings, the bookings that are no longer taking place in this market after the tax is imposed, may tend to be more expensive.

[29]Of the 33 counties that in our final estimation sample, 14 of them contain a single tax jurisdiction.

[30]Estimates with county-month-year fixed effects are still included in the table for comparison. The estimates are remarkably similar to the metro-month-year fixed effect specification, despite the considerable differences in which jurisdictions contribute to identification.

We estimate that the elasticity of nights booked with respect to the enforced tax rate is -0.4 and statistically significant, suggesting that the enforcement of a 10% tax rate reduces nights booked by 4%. This significant quantity reduction suggests that the negative demand-side response to tax enforcement dominates the contemporaneous positive supply-side response.[31]

Interpreting our result, we measure the upper bound of pre-enforcement compliance given by Equation (1): $\overline{\lambda} \equiv \frac{P_1 - P_2}{t} = \frac{\Delta P}{t} = \frac{\Delta P/P_1}{t/P_1} \approx \frac{\Delta P/P_1}{\tau} \approx \frac{\Delta ln(P)}{\Delta ln(1+\tau)} = -\gamma_{Ps}$.[32] Thus, we estimate an upper bound of compliance of 0.23 or 23%, meaning that taxes are paid on, at most, 23% of nights booked in the absence of formal Airbnb tax enforcement agreements. Our upper bound on pre-enforcement compliance estimate is valid under perfect competition and a variety of imperfectly competitive markets, as shown in the Appendix. Combining our estimated price and quantity elasticities, keeping in mind that the gap between price paid by consumers and price received by suppliers must equal the size of the enforced tax rate, we calculate a point estimate of the average price elasticity of demand across listings: $\epsilon_{demand} = \gamma_Q/\gamma_{Pd} = \frac{-0.4}{0.77} = -0.52$.

We can gain additional insight about the Airbnb market if we interpret our results in the context of perfect competition. In particular, we can identify a lower bound on the price elasticity of supply of Airbnb listings. Given the nature of Airbnb tax enforcement agreements, the supply curve cannot be any steeper than what our reduced form estimates on gross price and quantity would imply in the hypothetical scenario that supply does not shift at all (i.e. pre-enforcement compliance is 0%).[33] In this hypothetical, our reduced

[31]This also rules out a perfectly inelastic curve on either side of the market, if considering a perfectly competitive market.

[32]The first approximation is used because taxes on Airbnb bookings are actually ad valorem (τ), not a fixed per-unit amount t as we model throughout the paper for convenience. To see why the second approximation is true, suppose that the tax rate enforced is a one percent ad valorem tax. Before enforcement, the enforced tax rate (τ) is zero. Thus, $\tau = 0.01 = \Delta\tau$, which is approximately equal to $\Delta ln(1+\tau) = ln(1.01) - ln(1) = 0.00995$.

[33]These arguments are displayed graphically in Figures 1 - 3. We also implicitly assume that any marginal compliance costs are zero. This assumption is useful; a positive marginal compliance cost may induce a larger supply shift after the tax enforcement policy because the tax regime change alleviates any costs associated with complying pre-enforcement. We believe this assumption is plausible, as the increased administrative burden to comply with taxation for an additional booking is small relative to the other costs that the supplier faces. Regardless, however, omitting compliance costs does not at all threaten our bounding strategy since compliance costs would lead to an exaggerated outward shift of supply. This means, in effect, that our

form estimates simply represent the equilibrium effects of a negative demand shock by the magnitude of the enforced tax rate, which allows us to trace out the local supply curve. If, in fact, there is any positive supply shock, using this simple approach would lead us to estimate supply to be more inelastic than it truly is. Using the ratio of the estimated elasticity of quantity and gross price with respect to the enforced tax rate, we calculate the lower bound of the price elasticity of supply to be $\epsilon_{supply} = \gamma_Q/\gamma_{Ps} = \frac{-0.4}{-0.23} = 1.75$.

6 Conclusion

In this paper, we develop a simple approach to estimate the upper bound of pre-enforcement tax compliance using market data from before and after a change from partial to full compliance. We illustrate this approach using the context of Airbnb tax enforcement agreements with state and local governments, where the statutory tax burden is shifted away from individual hosts toward consumers using the platform to achieve full enforcement. To do this, we use an difference-in-differences framework, exploiting variation in Airbnb tax enforcement agreements, to estimate the effects of tax enforcement on booking price and quantity. We find that enforcement of a 10% tax reduces the price hosts receive by 2.3% and increases the price renters pay by 7.7%. This price effect implies an upper bound of 23% compliance pre-enforcement.

We also find that enforcement of a 10% tax reduces nights booked by 4.0%, which allows us to provide insight on the price elasticity of demand and supply in the Airbnb market. Combined with the estimated effect of enforcement on price, we calculate a price elasticity of demand of -0.52. If Airbnb resembles a perfectly competitive market, we can also use these estimates to obtain a lower bound on the price elasticity of supply of 1.75. In fact, this estimate is quite close to the 2.16 price elasticity of supply estimated by Farronato and Fradkin (2017) in their study of the Airbnb market. If we assume that 2.16 is the true price elasticity of supply, our results imply that taxes are only paid on roughly 5% of Airbnb

bounds on the supply elasticity and compliance rate hold even if the marginal cost of compliance is positive.

transactions before an enforcement agreement is implemented.

Overall, these results clearly show that there is a lot of compliance to be gained by entering an enforcement agreement with Airbnb, as *at least* 77% of transactions evade taxation pre-enforcement. However, these gains must be weighed against the costs of drafting an enforcement agreement and the deadweight loss generated by taxation. The results also paint a picture where demand is less price-sensitive than supply, meaning that consumers bear the larger burden of these Airbnb tax enforcement agreements. This may actually be a desirable feature from the perspective of state and local governments, as the inefficiency associated with taxation in this setting disproportionately falls on visitors from outside the jurisdiction. That said, we are unable to precisely analyze the welfare effects since we cannot estimate consumer substitution between Airbnb and other lodging options.

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Appendix A A Model of Imperfect Competition

Now suppose that hosts on Airbnb provide consumers with differentiated listings and compete in 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 from complying is:

$$\Pi_i(\text{comply}) = (p_i - c_i - t) \cdot q(p_i, X_i; \mathbf{p}_{-i}, \mathbf{X}_{-i}) - F_i - C_i,$$ [34]

where p_i is the price choice, 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.[35]

If host i chooses to evade the tax, then they do not incur the compliance cost. However, the host faces some risk from evading the tax. Let R_i denote the expected penalty from evading the tax. Note that the penalty might be host specific or city specific; we denote it as host specific for simplicity. Thus, the total profit for host i from evading is:

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

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.

[34] 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.

[35] 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.

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

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

Setting $\eta = t$ provides firm i's equilibrium price for complying (call it p_i^C), and setting $\eta = 0$ provides firm i's equilibrium price for 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 $p_i^E \in [p_i^C - t, p_i^C]$ so long as demand is not too convex.[36] Thus, if host i complies so that the tax is remitted, then some portion of the tax, call it σ_i, is passed onto consumers. That is, the profit-maximizing price when complying is $\sigma_i \cdot t$ more than the profit-maximizing price when evading: $p_i^C = p_i^E + \sigma_i \cdot t$.[37]

Now consider how booking prices change with an Airbnb enforcement agreement that guarantees that consumers pay the tax at the point of sale. The profit-maximizing price received by a host that evades pre-enforcement falls by $(1 - \sigma_j) \cdot t$, such that it equals the pre-enforcement complier net-of-tax price $p_i^C - t$. The price consumers pay for that host's property increases by $\sigma_j \cdot t$ to the pre-enforcement complier gross price p_i^C. Of course, this total price increase ignores the possibility of price complementarity between listing prices. For now, we consider these price complementarity effects to be second order, but we explore them further in the next subsection of this appendix. For compliers, neither the profit-maximizing prices they receive nor the prices consumers pay change following an Airbnb

[36] That is, the markup is decreasing in p so that the complier bears some of the tax burden when $q''(p_i) < \frac{(q'(p_i))^2}{q(p_i)}$ (i.e., when demand is not too convex). Weyl and Fabinger (2013) show that pass-through can be greater than one, $\sigma_j > 1$, if demand is sufficiently convex. In this case, a tax increases the net price. We focus on the case where pass-through, on average, is between zero and one.

[37] Because we maintain general demand functions, a closed form solution for the pass-through, σ_i, cannot be determined. 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, p_i^C has a greater marginal cost; yet, p_i^C also has a smaller markup term since $\frac{q(p_i^C)}{-q'(p_i^C)} < \frac{q(p_i^E)}{-q'(p_i^E)}$ when $p_i^C > p_i^E$. Combined, these differences generate the pass-through rate $\sigma_i \in (0, 1)$ so that $p_i^C = p_i^E + \sigma_i \cdot t$.

enforcement agreement; there is only a change in who bears the statutory burden of the tax, meaning the gross price falls by t and the net-of-tax price increases by t.

Altogether, with λ compliers and $1-\lambda$ evaders, the average decrease in gross (booking) price across all listings is given by:

$$\triangle P \equiv P_1 - P_2 = \lambda \cdot t + (1-\lambda) \cdot (1-\sigma) \cdot t,$$

where P_1 is the average booking price in the first period, P_2 is the average booking price in the second period, and $\sigma \in (0,1)$ is the average pass-through rate. Solving for λ implies that

$$\lambda = \frac{\triangle P - (1-\sigma) \cdot t}{t \cdot \sigma}.$$

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 $\sigma \in (0,1)$.[38] Thus, the proposed upper bound estimate for pre-enforcement compliance in perfectly competitive markets, $\overline{\lambda}$ in Equation (1), is an estimate for the upper bound of the compliance rate in imperfectly competitive environments without price complementarity.

A.1 Price Complementarity

By allowing for price complementarity, tax enforcement implies that the price consumers pay for evaders' properties will increase as evaders pass through some portion of the newly-enforced tax, σ. This implies that any price complementarity effect will further increase prices for both compliers and those who evaded pre-enforcement. Let ϵ be the average increase in listing prices due to price complementarity. In this case, the average change in gross price across all listings is given by:

$$\triangle P \equiv P_1 - P_2 = \lambda \cdot t + (1-\lambda) \cdot (1-\sigma) \cdot t - \epsilon.$$

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

Solving for λ implies that

$$\lambda = \frac{\triangle P - (1-\sigma) \cdot t + \epsilon}{t \cdot \sigma}.$$

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:

$$\epsilon < (t - \triangle P) \cdot (1-\sigma).$$

Thus, the upper bound estimate on the pre-enforcement compliance rate is valid as long as the price complementarity effect is not too strong. In particular, as the pass-through rate (σ) is higher, the inequality holds as long as price complementarity (ϵ) is sufficiently small.[39]

A.2 Entry

Now consider the case where an enforcement agreement results in host entry. 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) are large enough. If marginal hosts enter post-enforcement, price competition puts downward pressure on prices. Let the average markdown from entry competition be denoted by $\phi > 0$. In this case, the average change in gross price across all listings is given by:

$$\triangle P \equiv P_1 - P_2 = \lambda \cdot t + (1-\lambda) \cdot (1-\sigma) \cdot t - \epsilon + \phi.$$

Solving for λ implies that

$$\lambda = \frac{\triangle P - (1-\sigma) \cdot t + \epsilon - \phi}{t \cdot \sigma}.$$

[39]In future iterations of this paper, we plan to estimate the extent of price complementarity (ϵ) among Airbnb listings.

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:

$$\epsilon - \phi < (t - \triangle P) \cdot (1 - \sigma).$$

Thus, host entry relaxes the condition on price complementarity that must hold in order for our pre-enforcement compliance upper bound to be valid.

Tables and Figures

Table 1: Treated Jurisdictions

					Tax Rate	
City	**County**	**Metro**	**State**	**Tax Date**	**Initial**	**Max**
Aurora	Arapahoe	Denver	CO	2017m2	4.25	4.25
Bellevue	King	Seattle	WA	2015m10	12	12.4
Bethesda	Montgomery	DC	MD	2016m6	7	7
Boca Raton	Palm Beach	Miami	FL	2015m12	6	7
Chicago	Cook	Chicago	IL	2015m2	4.5	21.4
Cleveland	Cuyahoga	Cleveland	OH	2016m4	5.5	8.5
Cleveland Heights	Cuyahoga	Cleveland	OH	2016m4	5.5	5.5
Delray Beach	Palm Beach	Miami	FL	2015m12	6	7
Denver	Denver	Denver	CO	2017m2	4	4
Doral	Miami-Dade	Miami	FL	2015m12	7	13
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
Hallandale Beach	Broward	Miami	FL	2015m12	6	11
Hollywood	Broward	Miami	FL	2015m12	6	11
Jersey City	Hudson	NYC	NJ	2015m11	6	6
Kirkland	King	Seattle	WA	2015m10	9.5	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	LA	CA	2016m8	14	14
Malibu	Los Angeles	LA	CA	2015m4	12	12
Mesa	Maricopa	Phoenix	AZ	2017m1	14.02	14.02
Metairie	Jefferson	New Orleans	LA	2016m4	5	5
Millcreek	Salt Lake City	SLC	UT	2016m10	11.6	11.6
New Orleans	Orleans	New Orleans	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
Pompano Beach	Broward	Miami	FL	2015m12	6	11
Redmond	King	Seattle	WA	2015m10	8.6	11
Richmond	Contra Costa	Oakland	CA	2017m6	10	10
Salt Lake City	Salt Lake	SLC	UT	2016m10	12.6	12.6
San Diego	San Diego	San Diego	CA	2015m7	10.5	10.5
San Jose	Santa Clara	San Jose	CA	2015m2	10	10
Sandy	Salt Lake	SLC	UT	2016m10	13.1	13.1
Santa Clara	Santa Clara	San Jose	CA	2015m10	9.5	9.5
Scottsdale	Maricopa	Phoenix	AZ	2017m1	13.92	13.92
Seattle	King	Seattle	WA	2015m10	9.6	10.5
Silver Spring	Montgomery	DC	MD	2016m6	7	7
Sunny Isles Beach	Miami-Dade	Miami	FL	2015m12	7	13
Tacoma	Pierce	Seattle	WA	2015m10	11.4	12.1
Tempe	Maricopa	Phoenix	AZ	2017m1	14.07	14.07
University Place	Pierce	Seattle	WA	2015m10	11.4	12.1
Vashon	King	Seattle	WA	2015m10	8.6	8.6
Washington	District of Columbia	DC	DC	2015m2	14.5	14.5
West Palm Beach	Palm Beach	Miami	FL	2015m12	6	7

Notes: The 49 jurisdictions that are treated over our sample period. *Tax Date* is the first month that an enforcement agreement went into place. *Tax Rate* is the rate enforced directly through the site of the first tax agreement. Some jurisdictions had subsequent agreements that increased the overall tax rate enforced through the site. Additional tax varition in cities in Seattle metro: A portion of Redmond and Kirkland are taxed at 10.5%, and a portion of Tacoma is taxed at 11.5%, all implemented in 2015m10.

Table 2: Untreated Jurisdictions

City	County	State	City	County	State
Alameda	Alameda	CA	Mountain View	Santa Clara	CA
Alexandria	Alexandria	VA	New York	Bronx	NY
Arlington	Arlington	VA	New York	Kings	NY
Beverly Hills	Los Angeles	CA	New York	New York	NY
Burbank	Los Angeles	CA	New York	Queens	NY
Costa Mesa	Orange	CA	New York	Richmond	NY
Culver City	Los Angeles	CA	Newport Beach	Orange	CA
Daly City	San Mateo	CA	Oceanside	San Diego	CA
Fremont	Alameda	CA	Pasadena	Los Angeles	CA
Glendale	Los Angeles	CA	Redwood City	San Mateo	CA
Hoboken	Hudson	NJ	Rowland Heights	Los Angeles	CA
Huntington Beach	Orange	CA	San Mateo	San Mateo	CA
Long Beach	Los Angeles	CA	Springs	Suffolk	NY
Menlo Park	San Mateo	CA	Sunnyvale	Santa Clara	CA
Milpitas	Santa Clara	CA	Weehawken	Hudson	NJ

Notes: Included jurisdictions that are not treated over our sample period.

Table 3: Summary Statistics

	Panel A: *Property-Month Level Summary*				
	Mean	St. Dev.	Min	Max	Obs
Booking Price	132.79	77.52	1	3,200	1,700,515
Days Booked / Month	5.63	11.95	0	293	5,040,836
Tax Rate	0.05	0.06	0	0.21	5,040,836
Asking Price	136.32	87.01	1	10,000	3,690,250
Supply / Month	18.44	13.31	0	31	5,040,836

	Panel B: *Property Level Summary*				
	Mean	St. Dev.	Min	Max	Obs
Bedrooms	1.27	0.82	0	4	330,650
Bathrooms	1.25	0.53	0	11	329,892
Max Guests	3.29	1.92	1	12	330,650
Rating	4.67	0.47	1	5	204,338
Security Deposit	153.57	322.03	0	12,307	330,650
Cleaning Fee	48.13	60.41	0	11,652	330,650
Extra People Fee	9.21	18.76	0	800	330,650
Minimum Stay (Days)	3.87	15.75	0	3,000	330,254
Business Ready	0.12	0.32	0	1	330,650
Superhost	0.14	0.35	0	1	301,290
Number of Photos	12.96	10.74	0	268	318,580

Table 4: Pre-Enforcement Differences in Outcomes

	Full Sample	Treated	Not Treated	Treated - Not Treated	
Booking Price	131.23	126.90	133.68	-7.748	-9.893
	(72.55)	(70.21)	(73.73)	(16.412)	(8.492)
Ln(Booking Price)	4.75	4.73	4.77	-0.058	-0.042
	(0.49)	(0.47)	(0.50)	(0.128)	(0.055)
Nights Booked / Month	5.86	6.67	5.51	0.862***	0.233
	(12.60)	(12.66)	(12.56)	(0.294)	(0.167)
Ln(Booked / Month)	0.85	1.00	0.78	0.165***	-0.007
	(1.31)	(1.36)	(1.29)	(0.038)	(0.017)
Asking Price	133.45	130.04	135.16	-7.687	-8.549
	(76.55)	(76.61)	(76.46)	(17.255)	(8.762)
Ln(Asking Price)	4.77	4.75	4.78	-0.053	-0.029
	(0.50)	(0.47)	(0.50)	(0.133)	(0.056)
Supply / Month	17.96	19.98	17.08	2.806***	0.138
	(13.28)	(12.39)	(13.56)	(0.431)	(0.420)
Ln(Supply)	2.28	2.54	2.17	0.321***	0.000
	(1.48)	(1.34)	(1.52)	(0.042)	(0.041)
Observations	2,497,109	753,035	1,744,074		
Month-Year FE				✓	-
Metro-Month-Year FE				-	✓
Property Level Controls				-	✓

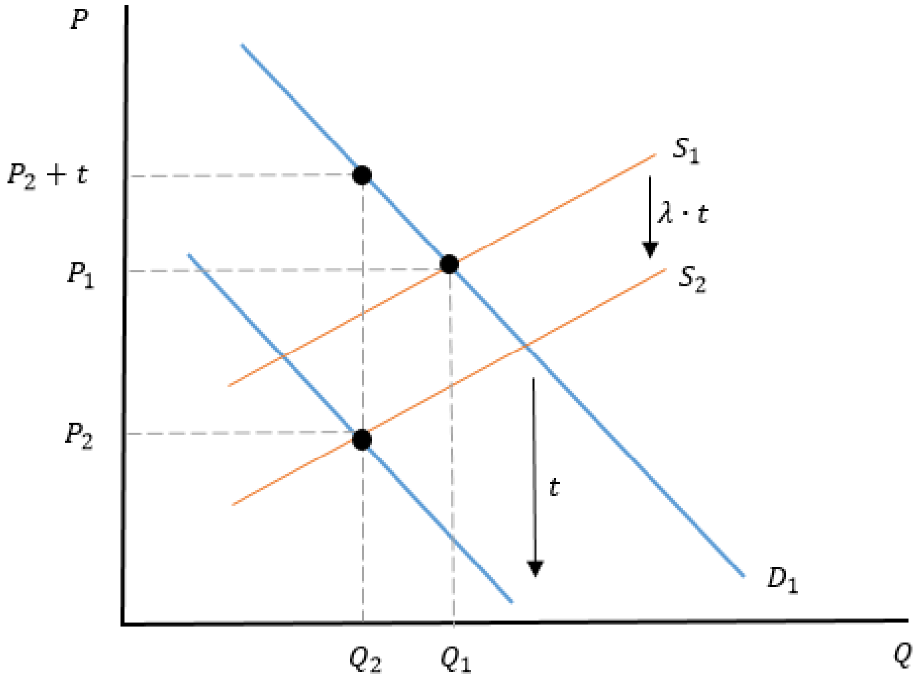
Notes: The first three columns display sample mean and standard deviations for the full, treated, and untreated samples in months when no tax enforcement agreement was in place. The last two columns display tests for whether being in a treated jurisdiction is correlated with outcomes in months with no enforcement. Each estimate is from a regression one of an outcome variables on a dummy variable for being in a jurisdictions that is eventually treated. The regressions are restricted to observations when there was no tax enforcement agreement in place.

Table 5: Tax Enforcement, Bookings, and Book Price

	Nights Booked			*Booking Price*		
	ln(B)	ln(B)	ln(B)	ln(P)	ln(P)	ln(P)
ln(1 + tax)	0.199	-0.420**	-0.402**	-0.073	-0.265***	-0.230***
	(0.312)	(0.198)	(0.159)	(0.087)	(0.056)	(0.045)
Tax Jurisdiction FE	✓	✓	✓	✓	✓	✓
Month-Year FE	✓	-	-	✓	-	-
County-Month-Year FE	-	✓	-	-	✓	-
Metro-Month-Year FE	-	-	✓	-	-	✓
Observations	5,040,836	5,040,836	5,040,836	1,700,515	1,700,514	1,700,515

Notes: All regressions also include property-specific controls. Standard errors are robust to clustering at the tax jurisdiction-level.

Figure 1: Impact of Airbnb Tax Enforcement



Note: Bold dots (•) represent observed equilibria.

Figure 2: The Compliance Rate Upper Bound

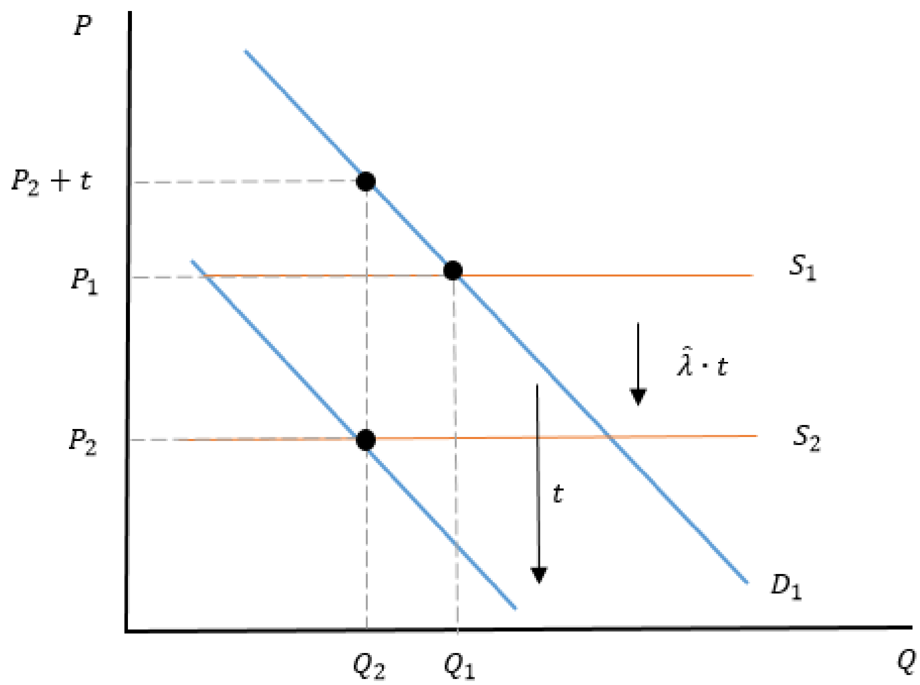


Figure 3: The Supply Elasticity Lower Bound

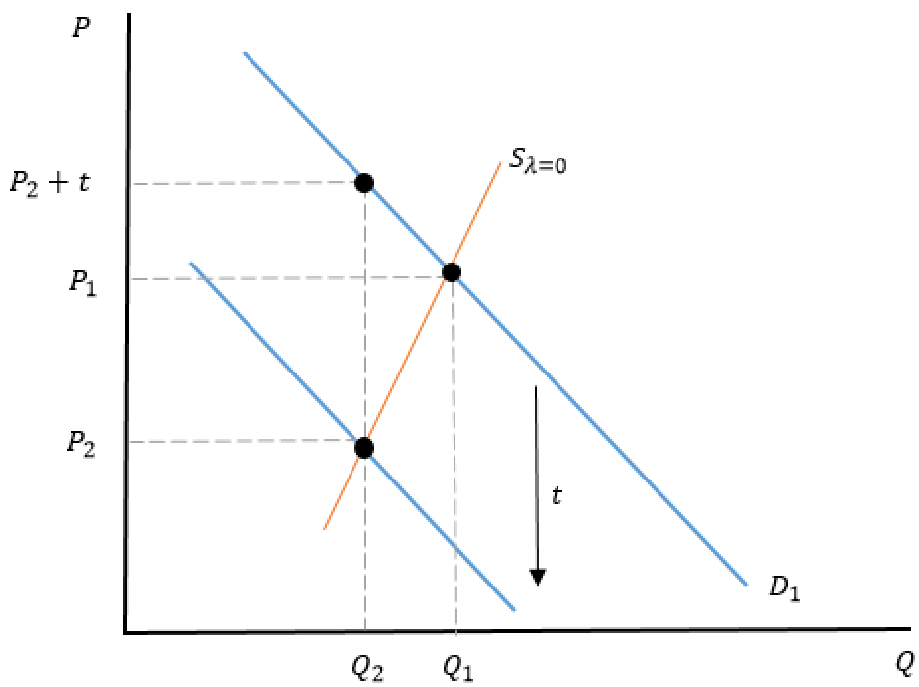
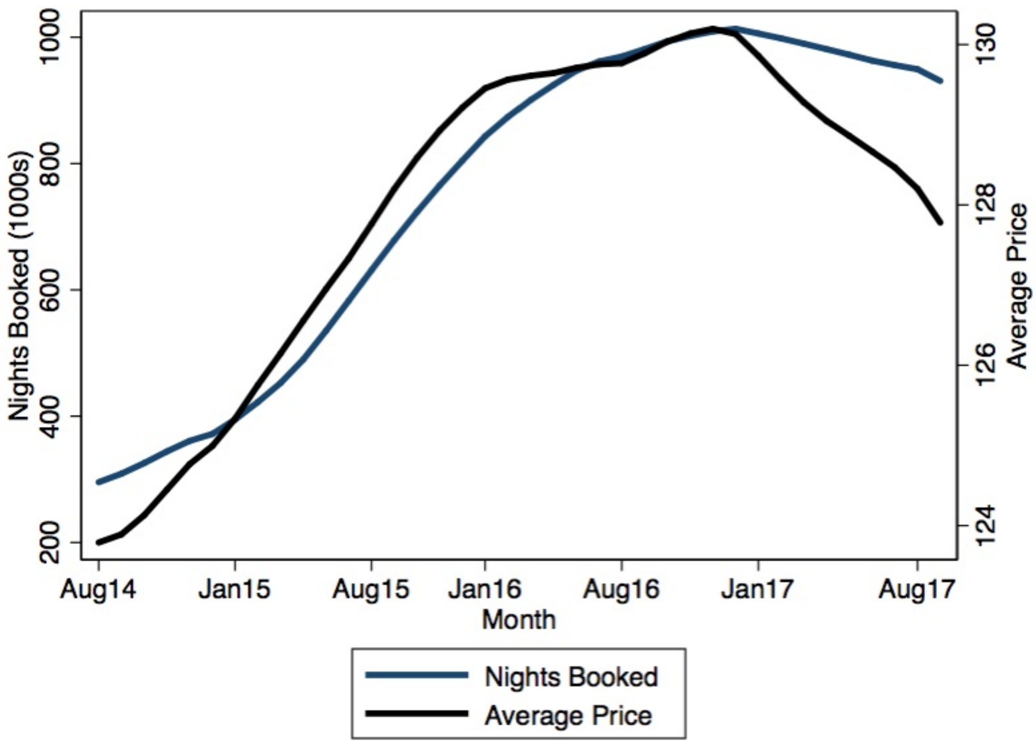


Figure 4: Airbnb Bookings and Prices



Note: Local polynomials of the total nights booked and average nightly price among estimation sample units.