

HOTEL TAX INCIDENCE WITH HETEROGENEOUS FIRM EVASION:
EVIDENCE FROM AIRBNB REMITTANCE AGREEMENTS

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ABSTRACT

How does assignment of the remittance obligation affect consumption tax incidence? In classical tax theory, the responsibility of transferring tax revenue has no effect on which party bears the economic burden of a consumption tax. I explore this prediction in the context of agreements between city governments and a large digital platform firm that shifted the obligation to remit hotel taxes from independent renters to the platform firm itself. Using variation in the location and timing of such agreements, I estimate their effect on rental prices. My results indicate that shifting the remittance obligation to the platform increases after-tax prices, suggesting that consumers bear a greater share of the tax burden when the remittance obligation is shifted to a party with fewer evasion opportunities.

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1. Introduction

The proliferation of mobile internet-connected devices has given rise to a number of firms that rely on “digital platforms” to match consumers and service providers. These firms, such as Uber, Lyft, and Airbnb, are economically significant, expanding rapidly, and often valued in the tens of billions of dollars.

Policymakers and investors wonder whether and how existing taxes and regulations should apply to platform firms. Opponents of enforcing existing rules claim they do not apply to services created out of excess capacity, and their application would stifle innovation and growth in this industry. Proponents argue instead that existing rules should be enforced on transactions of the same economic substance (e.g., regulations applying to taxicabs should apply to Uber rides). Given how differently these new firms are structured relative to their traditional counterparts, their response to such enforcement is theoretically ambiguous and thus an empirical question.

This paper examines the effect of one recent policy to enforce greater tax compliance on platform firms: bilateral tax remittance agreements between Airbnb and a number of U.S. cities. Specifically, I examine the effect that shifting responsibility for remitting hotel taxes from hosts to Airbnb has on listing prices.

2. Background and Policy

2.1 What is Airbnb?

Airbnb is the largest of several firms facilitating short-term, peer-to-peer residential space rentals through an online platform. Originally conceived as an online marketplace to connect couch surfers, Airbnb has experienced remarkable growth in recent years, expanding

exponentially in popular tourism cities around the globe.¹ Hosts on Airbnb create listings for each of their properties. Each listing includes information about the space's characteristics, such as the number of beds, kitchen availability, and whether it is a private apartment or a shared space. Hosts can designate a listing's availability and set its price for each calendar day.

2.2 *How are Airbnb transactions taxed?*

In addition to consumer safety concerns, local governments expressed frustration with Airbnb hosts' avoidance of short-term rental taxes. In cities with significant tourism, the estimated loss of occupancy tax revenue is significant. Initially, Airbnb's position was that its rentals were not subject to occupancy taxes because transactions were "peer-to-peer" rather than commercial in nature. In May 2014, the company officially retracted this view and announced that it believed its hosts were responsible for paying occupancy taxes to local governments. It also amended its "Terms of Service" agreement to inform hosts of their obligation to research and comply with applicable local taxes and regulations.²

On June 28, 2014, Airbnb announced that it had reached an agreement with the city of Portland, OR to collect an 11.5% occupancy tax on all reservations booked on its site, and to pay these taxes to the city at the end of each quarter. Crucially, the agreement explicitly prohibited Portland's city government from requiring Airbnb to disclose information related to taxable

¹ Paris is thought to have nearly 40,000 active Airbnb listings, the most of any city in the world.

² Beginning May 1, 2014, Airbnb's Terms of Service includes the following paragraph:

YOU AS A HOST UNDERSTAND AND AGREE THAT YOU ARE SOLELY RESPONSIBLE FOR

² Beginning May 1, 2014, Airbnb's Terms of Service includes the following paragraph:

YOU AS A HOST UNDERSTAND AND AGREE THAT YOU ARE SOLELY RESPONSIBLE FOR DETERMINING (I) YOUR APPLICABLE TAX REPORTING REQUIREMENTS, AND (II) THE TAXES THAT SHOULD BE INCLUDED, AND FOR INCLUDING TAXES TO BE COLLECTED OR OBLIGATIONS RELATING TO APPLICABLE TAXES IN LISTINGS. YOU ARE ALSO SOLELY RESPONSIBLE FOR REMITTING TO THE RELEVANT AUTHORITY ANY TAXES INCLUDED OR RECEIVED BY YOU. AIRBNB CANNOT AND DOES NOT OFFER TAX-RELATED ADVICE TO ANY MEMBERS.

transaction that could individually identify hosts. As part of the exchange, the Portland City Council agreed to pass a code revision that would legalize short-term home rentals if residents obtained a \$180 permit and installed fire alarms.

Between August 2014 and August 2015, similar agreements to collect and remit hotel sales taxes were signed with San Francisco, CA (14.5%), San Jose, CA (10%), Chicago, IL (4.5%), Washington, DC (14.5%), Philadelphia, PA (8.5%), Durham, NC (6%), San Diego, CA (10.5%), and Phoenix, AZ (3%), as well as several smaller municipalities. Typically, an agreement is announced two weeks before the date when Airbnb begins collecting taxes on all bookings in that jurisdiction. Airbnb notifies affected hosts of the policy change via email shortly after the announcement.

2.3 *How do taxes appear to Airbnb guests?*

When a guest searches for a rental on Airbnb, she is presented with a set of search results that includes an image, location, and tax-exclusive estimate of the nightly fee for each listing (Figure 1).³ After a guest clicks on a listing, she is shown a more detailed accounting of the rental cost, including Airbnb's service fee and any occupancy tax. Figure 2 shows examples of listings from two jurisdictions: one that has a bilateral agreement with Airbnb (Chicago, IL), and one that does not (Evanston, IL). Notice that both listings appear among same set of search results. Without clicking on a listing, it is not evident whether an occupancy tax applies to it.

3. Motivation

³ The price shown in the search results is the average cost per night of the room, excluding taxes and Airbnb's service fee. For example, if a listing's rental prices for Friday, Saturday, and Sunday are \$90, \$100, and \$110, respectively, and the listing has a \$30 cleaning fee, then the price displayed in the search results will be \$110 ($(90+100+110+30) / 3 = 110$).

In the traditional view, the economic incidence of a tax is independent of its statutory incidence. In the absence of differences in compliance and monitoring costs or evasion opportunities between the supply and demand sides of a market, shifting the remittance obligation from one to the other has no impact on which party bears the economic burden of the tax. However, recent empirical work suggests that the assignment of the remittance obligation can affect incidence in practice. I consider two potential reasons why the traditional view may not hold in the context of Airbnb’s market for short-term rentals.

3.1 Evasion technology and the point of collection

Statutory irrelevance may not hold if economic agents differ in their ability to evade taxes (Kopczuk, Marion, Muehlegger, and Slemrod forthcoming, hereafter KMMS). KMMS find that the economic incidence of a quantity tax on diesel fuel depends on the point of collection within the supply chain. As the remittance obligation moves “up” the chain from retailers to distributors and prime suppliers, the pass-through rate of diesel taxes to the retail price increases, as do tax revenues. This suggests that differential evasion opportunities afforded to these agents explain the relevance of a tax’s collection point.

The context I study differs from that of KMMS in several potentially consequential respects. First, Airbnb’s role in the provision of short-term rentals cannot be neatly confined to that of a supplier. Airbnb considers itself a “platform” or “market-maker,” rather than an upstream firm in a supply chain that provides paid lodging. Second, Airbnb hosts provide a heterogeneous product, unlike diesel fuel. Third, pre-policy remittance behavior by hosts was likely binary.⁴ Additional differences between the Airbnb and diesel fuel contexts—such as the

⁴ Although I am unable to observe pre-policy remittance behavior, based on online discussions between (anonymous) hosts and public comments by municipal tax authorities, I infer that evasion took place mainly on the

occupancy tax being ad valorem rather than specific, and the different costs of compliance and monitoring within each market—may also affect how changing the point of remittance affects the tax’s incidence, and will need to be carefully considered.

3.2 *Host sophistication in price-setting*

Classically, tax incidence is exclusively determined by market-level factors such as the level of competition and supply and demand elasticities (see, e.g., Myles 1989; Weyl and Fabinger 2013). However, there is some empirical evidence that differences in firms’ characteristics, such as managerial resources that affect price-setting strategies, can lead to variation in tax incidence within a market. For example, small, independent firms are more likely to rely on simplified pricing rules, such as round number heuristics, and may not fully incorporate tax changes into price setting behavior (Harju, Kosonen, and Skans 2015).

There is likely significant heterogeneity in host experience with, and attention to, optimal price setting. Some hosts are actually hotels, with substantial managerial resources devoted to setting prices. On the other end of the spectrum, many hosts list once or twice a year when they vacate their residences to travel, or in response to anticipated spikes in demand from local events (e.g., football games). Like consumers, hosts in the latter category may be inattentive to changes in Airbnb’s occupancy tax policies, or exhibit bounded rationality that constrains them from setting prices optimally (Chetty 2009; Finkelstein 2009).

4. **Model**

extensive margin. That is, hosts either voluntarily remitted the occupancy taxes they owed, or they paid nothing at all.

This section sets forth a simplified model of Airbnb host behavior. Hosts are divided into two types: those who remit their tax obligations, and those who do not. Prior to the enactment of any agreement, both types of host choose listing prices to maximize profit. Between two otherwise identical hosts, the one who remits sets a higher price to offset the cost of remitting the tax. Once an agreement is signed, hosts who previously set high, tax-inclusive listing prices now set low, tax-exclusive listing prices. This, combined with reduced demand by guests now faced with a tax, drives down listing prices for all hosts in equilibrium.

4.1 *Host price-setting under monopolistic competition*

Each Airbnb host supplies a product that is differentiated—by location, amenities, and so on—from those of her competitors. The market for Airbnb rentals is therefore monopolistically competitive, with each host facing a downward-sloping demand curve: $q_i = q_i(p_i, \gamma_i, p_{-i}, N)$.

This demand curve is a function of the host's own price ($\frac{\partial q_i}{\partial p_i} < 0$), the desirability of the listing ($\frac{\partial q_i}{\partial \gamma_i} > 0$), the prices set by all other hosts ($\frac{\partial q_i}{\partial p_{-i}} > 0$), and the number of other hosts ($\frac{\partial q_i}{\partial N} < 0$).

Assume that the fixed cost of entry into the Airbnb market is zero, and that the variable cost of hosting is heterogeneous across hosts and represented by $C(q_i, \delta_i)$, where $\frac{\partial C}{\partial \delta_i} > 0$. The δ_i parameter can be thought to represent a host's idiosyncratic level of inconvenience from hosting someone in their property.

Prior to the enactment of Airbnb's remittance agreements, hosts were responsible for remitting any hotel taxes owed to the municipal government. While some hosts complied, it is likely that many did not. Prior to the policy, assume hosts were one of two types: remitting or

non-remitting. The former complied fully by remitting all taxes owed, while the latter remitted nothing.⁵

All hosts must choose a listing price p_i to maximize profit:

$$\text{Remitting hosts:} \quad \pi_i^R = p_i q_i (1 - \tau) - C(q_i, \delta_i) \quad (1)$$

$$\text{Non-remitting hosts:} \quad \pi_i^{NR} = p_i q_i - C(q_i, \delta_i) \quad (2)$$

where τ denotes the hotel tax rate in the city in which the property is located.

4.2 Equilibrium

Remitting and non-remitting hosts both choose listing prices that satisfy their respective first order conditions. If two listings are equally desirable and hosts have the same cost index, then a remitting host will optimally set a higher listing price to account for the additional cost imposed by the tax remittance obligation:

$$p_i^{R*}(p_{-i}, N, \gamma_i, \delta_i, \tau) > p_i^{NR*}(p_{-i}, N, \gamma_i, \delta_i) \Big|_{\gamma_i = \gamma, \delta_i = \delta}$$

Free entry implies that the marginal host will earn zero profit in equilibrium. As a result, there exists a threshold value of δ_i that characterizes the variable cost of the marginal host. For example, conditional on listing desirability, the variable cost of the marginal remitting host is lower than the variable cost of the marginal non-remitting host:

$$\delta^{R*}(p_{-i}, N, \gamma_i, \tau) < \delta^{NR*}(p_{-i}, N, \gamma_i) \Big|_{\gamma_i = \gamma}$$

This reflects the fact that, due to the additional cost imposed by the tax remittance obligation, remitting hosts will tend to have lower idiosyncratic costs in order to remain in the market.

⁵ This model rules out evasion on the intensive margin. Remitting hosts can be thought of as those facing very large costs of evasion, such as having a neighbor who is a municipal tax officer.

In Nash equilibrium, no host can increase her profit given the prices set by other hosts. Assuming symmetric price-setting within host type and a large number of hosts, the prices charged by all other hosts, p_{-i} , can be expressed as the weighted average of the expected price set by each type of host:

$$p_{-i} = \bar{p} = \alpha^R \mathbb{E}[p_i^R | \delta_i < \delta^{R*}] + (1 - \alpha^R) \mathbb{E}[p_i^{NR} | \delta_i < \delta^{NR*}]$$

where α^R represents the share of hosts who are remitters.

4.3 *Shifting the remittance obligation to Airbnb*

Under the remittance agreements signed by Airbnb, hosts are relieved of their obligation to remit hotel taxes to municipal governments. Instead, any tax is added to the listing price set by hosts and remitted on behalf of guests by Airbnb. In the context of the model, this means that the fraction of hosts who are remitters falls to zero, and all hosts face the profit maximization in equation (2).

This change will affect a number of variables in equilibrium, starting with prices. Hosts who previously remitted, and set tax-inclusive listing prices, will now charge lower, tax-exclusive listing prices. In addition, even hosts who previously did not remit will find it optimal to lower their prices: first, because the reduced prices of previously remitting hosts will lower average prices, and second, because guests now face a tax upon check-out and will reduce their demand accordingly. The combination of these effects will lead to lower listing prices after an agreement has been signed.

In addition to affecting the average listing price, an agreement may also affect the composition of Airbnb hosts. For example, non-remitting hosts with high costs may find that they earn negative profits after the policy change, and will thus be compelled to exit the market.

4.4 *Model limitations*

This simplified model of Airbnb host behavior leaves out a number of factors that will likely govern real-world behavior. First, the decisions of hotels, direct competitors to Airbnb hosts, are left out of the model. The hotel industry, which lobbied heavily for increased tax enforcement of Airbnb hosts, will face a reduction in downward price pressure once an agreement is signed.

Second, the guest's decision problem is omitted from the model. While it may be the case that demand for temporary lodging within a city is relatively inelastic in the short run, it is almost certainly more elastic in the long run. If this is the case, then the incidence of the hotel tax will be increasingly borne by hosts in the long run, as guests have their choice of visiting cities with and without remittance agreements.

Finally, evasion is modeled here as a corner solution: a host either evades fully, or not at all. In other contexts where evasion is modeled, it is common to allow entities to choose a level of evasion (e.g., KMMS forthcoming).

5. Data

5.1 Collection

To measure the response of hosts to Airbnb's remittance agreements, I collect information on listings for selected U.S. cities and their surrounding areas between February 13 and August 30, 2015.⁶ I focus on cities that had announced, but not yet implemented, occupancy

⁶ These data are collected using an automated script or "crawler" that systematically browses Airbnb.com and collects information on listings associated with a particular geographic search

tax remittance agreements with Airbnb throughout this period: Washington, D.C.; Chicago, IL; and Phoenix, AZ. In addition, I collect data on listings in control cities that did not enact any agreements during this period: New York, NY; San Francisco, CA; and Los Angeles, CA. For each listing, I obtain its approximate geographic coordinates,⁷ price, unit type (e.g., shared, private room, entire home), number of reviews, and whether it can be booked instantly. Listings and hosts are each identified by a unique ID, facilitating the tracking of listings over time.

Data are collected in two waves, based on the implementation dates of remittance agreements. The first wave (February 13 through April 13, 2015) collects data from Washington, Chicago, New York, San Francisco, and Los Angeles. Washington and Chicago implemented remittance agreements on February 15, 2015. The second wave (June 25 through August 30, 2015) collects data from Phoenix, New York, San Francisco, and Los Angeles. Phoenix implemented a remittance agreement on July 1, 2015.

For treated cities, listings are selected in two ways. The “city” approach is to collect data on all listings returned from a search for the city name (e.g., “Chicago, IL”). In contrast, the “metro” approach is to collect data on all listings returned from a search for a specific neighborhood within the city’s metro area (e.g., “Gold Coast”, “Evanston”).

The advantage of the “city” approach is that it facilitates comparisons across cities: a listing returned in a search for “Chicago, IL” is comparable to a listing returned in a search for “New York, NY”, whereas a listing returned in a search for a specific neighborhood may not be.

term (e.g., “New York, NY”). The script mimics the browsing experience of a potential guest by clicking through each listing in the search results and obtaining its characteristics.

⁷ Geographic coordinates are purposefully offset by a small distance from the street address registered by the host for privacy. Once a listing is booked, the guest is sent an email with the exact street address. Anecdotal evidence, based on discussions by hosts on internet forums, suggests that these offsets are small (less than 1/8 mile) and, importantly, according to Airbnb’s website, offsets are done within neighborhoods.

The disadvantage of the “city” approach is that it misses many listings. Airbnb’s search algorithm returns approximately 1,000 listings per geographic search term, even if more listings exist within the city. Each time the same search is performed, a potentially different set of listings is drawn from the larger set of listings for the entire city. Searching in this manner, the fraction of a city’s total listings that are returned on any given day, and the stability of that sample from day to day, varies by city.

The advantage of the “metro” approach is that it allows for a more complete scrape of a city’s listings. Because each set of search results is limited to approximately 1,000 listings, going through a city neighborhood by neighborhood can uncover more listings than would be returned by a search for the city itself. It is also important because many of the listings returned in this manner fall outside the city’s boundaries and are located in a neighboring municipality, and are therefore not bound by the remittance agreement. For example, a search for “Chicago, IL”, and especially a search for “Evanston”, will return some listings in Evanston, IL, which are not bound by the agreement signed between Airbnb and the City of Chicago. These listings can serve as “metro” area controls, analogous to how listings in New York and San Francisco, for example, serve as controls for listings recovered via the “city” approach.

5.2 Limitations

There are several limitations to my data collection procedure that may hinder my ability to detect host response to Airbnb’s remittance agreements. First, I am only able to collect data on a city’s listings *after* a remittance agreement has been announced, but *before* it has been implemented. Typically, the time between announcement and implementation is approximately two weeks. Attentive hosts may adjust the prices of their listings during this time, possibly

before I am able to begin scraping. Relatedly, for Washington and Chicago, I began collecting data only two days before implementation, resulting in a very short “pre-period” for use in my estimates.

Second, because data collection is limited to the listings that appear in the search results, and because those results fluctuate day to day, I am unable to consistently observe a given listing over time. As a result, I may miss when a price change occurs, and have no way of knowing whether a listing’s absence is due to search behavior or because the host exited the market. One way to mitigate this problem is to increase search “depth” within a city by searching for all listings within an exhaustive set of price ranges (e.g., \$1-\$50, \$50-\$100, \$100-\$200, and so on). This partially circumvents the 1,000-listing cap on any given search, making it more likely that data on all active listings within a city will be collected. This approach was used to collect data from Phoenix and is currently being used to gather data on a broader group of cities.

5.3 Descriptive Statistics

Table 1 contains descriptive statistics for the two waves of data collected. The top panel contains information for listings in the first wave, focusing on the treated cities of Washington and Chicago, the control cities of New York, San Francisco, and Los Angeles, and additional control listings in the Washington metro area (e.g., Bethesda, Arlington) and Chicago metro area (e.g., Evanston). Columns 1-3 display statistics for all listings scraped during the collection period in each location, while columns 4-6 are limited to only those listings that appear at least once in the pre-agreement period (February 13 – February 14) and post-agreement period (February 15 – April 13).

A few points are worth noting. First, as mentioned above, cities vary in the stability of the composition of their search results. For example, during the entirety of the collection period, 2,100 unique listings were observed in Washington, while almost twice that number were observed in New York. While it is likely that New York contains more Airbnb listings than Washington, it's also likely that a listing returned in a search for New York on one day has a lower likelihood of appearing in the search results on a subsequent day than the analogous listing in Washington. Figure 3 displays the fraction of all listings for a given city on the first day it was scraped that appear on subsequent days. New York stands out relative to the other cities in the degree of turnover in its listing composition. In contrast, because of the more thorough collection procedures employed with Phoenix, turnover is relatively low for listings in that city.

Second, treated cities differ in the number of listings observed in un-treated, neighboring municipalities. For example, almost one third of listings in the Washington metro area ($=930/(930+2100)$) are located in neighboring municipalities, compared to a much smaller fraction of listings in the Chicago metro area. Phoenix is uniquely well suited for the purpose of comparing treated host behavior to that of untreated, nearby controls: more than half of the listings returned in a search for Phoenix are located in Scottsdale, Glendale, and Tempe, three municipalities that did not sign remittance agreements with Airbnb. Visual evidence of this is provided in Figure 4, which shows the spatial distribution of listings in Washington, Chicago, and Phoenix.

Figure 5 displays the cumulative fraction of listings that change price at least once in each city, limited to those listings appearing at least once in both the pre- and post-agreement

periods. On average, over 30% of listings in each city change price by the end of the data collection period.⁸

Finally, Figure 6 displays a histogram of prices across all listings under \$250 in the data. It is evident that hosts employ a number of heuristic pricing strategies, such as choosing prices in increments of \$5, as well as prices that end in 9.

6. Empirical Strategy

To measure the price-setting response of hosts to the implementation of Airbnb remittance agreements, I employ a difference-in-differences estimation strategy. Using data at the listing-date level, I estimate using OLS:

$$\log(p_{ict}) = X_i\beta + \delta_c + \delta_t + \pi Treat_c * Post_t + \varepsilon_{ict} \quad (3)$$

where i is an individual listing, c is the city, and t is the date. The parameter of interest, π , is the difference-in-differences estimator: it captures the difference in prices for listings in treated cities relative to those in untreated cities, in the post-agreement period relative to the pre-agreement period, controlling for city and time fixed effects and several listing characteristics.⁹ Standard errors are clustered to allow for non-independence at the city level. Observations spanning the pre-agreement period and up to 60 days after an agreement is implemented are used. The identifying assumption that makes the above interpretation of π valid is that any systematic

⁸ The exception is Phoenix, where fewer than 20% of listings change price by the end of data collection for Wave 2. This is due to the more thorough data collection procedure applied to Phoenix, which allows me to track more listings from the pre-agreement period to the post-agreement period, compared to the other cities sampled. As a result, a larger share of listings with no activity remain in the sample for Phoenix.

⁹ These include whether a listing can be booked “instantly,” the number of reviews, and whether it is a shared room, private room, or an entire home.

change to listing prices in treated cities relative to untreated cities in the post-agreement period is the result of the tax remittance agreement, and not any other factor.

As an alternative to using listings in untreated cities as a control for listings in treated cities, I also estimate a version of equation (3) using only listings outside the treated city's boundaries as controls. The resulting estimates have different interpretations. Listings in untreated cities are likely poor substitutes for guests interested in visiting treated cities, so the possibility of spillovers is minimal. As a result, the implementation of an agreement in Chicago is unlikely to affect the prices of listings in New York, at least in the short run. However, having only a limited number of control cities—New York, San Francisco, and Los Angeles—leaves open the possibility that price trends in these cities may systematically differ from those in treated cities. In contrast, listings in neighboring municipalities are much closer substitutes for guests visiting treated cities; indeed, a guest visiting northwest Washington may not care if her Airbnb rental is within the city limits or in neighboring Bethesda, MD. As a result, the implementation of an agreement in Washington may well produce spillover effects onto listings in Bethesda. Yet the parallel trends assumption underlying difference-in-differences estimation is likelier to hold when comparing listings in Washington and Bethesda, which are functionally a single rental market.

In addition to estimating equation (3), I also exploit the panel nature of my data to estimate the following using OLS:

$$\log(p_{ict}) = \delta_i + \delta_t + \pi Treat_c * Post_t + \varepsilon_{ict} \quad (4)$$

Because this specification includes listing fixed effects, it is estimated only on the observations of listings that appear in both the pre-agreement and post-agreement periods. In contrast to the repeated cross-sectional estimation in equation (3), the results from equation (4) fix the sample

of listings and therefore remove any composition effects of the treatment. In light of this, the estimates from equation (3) can be interpreted as the effect on average listing price in treated cities net of any changes to the sample of listings from host entry and exit, or turnover in search results. In contrast, the estimates from equation (4) isolate the effect on average listing price in treated cities, holding the sample fixed.

Finally, I also examine the effect that remittance agreements had on the variance of the listing price distribution in treated cities. To do this, I collapse the data to the city-date level, with each observation containing the standard deviation of the listing price distribution. I then estimate using OLS:

$$\log(\sigma_{ct}) = \delta_c + \delta_t + \pi Treat_c * Post_t + \varepsilon_{ct} \quad (5)$$

The parameter of interest, π , captures the effect of the remittance agreement on the standard deviation of listing prices in the treated city. Standard errors are clustered at the city level.

7. Results

Table 2 presents results obtained from estimating equation (3) using listings in the cities of New York, San Francisco, and Los Angeles as controls. The dependent variable is the log of listing price. The estimation sample is a repeated cross-section of all listings observed for each city on each day a search was performed. Column 1 reports estimates from the full sample. The estimated coefficients are all negative and statistically significant, implying that listing prices in the three treated cities fell by anywhere from 2.9% to 5.5% after the agreements were enacted, relative to listing prices in the control cities. Figure 7 provides visual evidence of price movements in treated and control cities and neighborhoods.

Recall that listing prices are tax-inclusive before an agreement is signed and tax-exclusive afterward. Therefore, a coefficient estimate of zero would imply that listing prices remain unchanged while guest prices rise by the full amount of the tax, a “pass-through” rate of 100%. In contrast, if prices adjust downward by the amount of the tax, there are two possible explanations. First, if all hosts previously remitted their tax obligations, then only the statutory, but not the economic, burden of the tax shifted, and incidence remains unchanged. Second, if all hosts were not previously in compliance, then they bear the entire burden of the tax.¹⁰

As a result, it is difficult to gauge from these estimates whether or how economic incidence was affected by this policy. For example, the magnitude of the listing price declines in Washington and Phoenix are smaller than the hotel tax amounts in both cities, implying that guest (after-tax) prices rose.¹¹ I interpret these results to suggest that the tax burden on guests in these cities rose—they are now paying higher prices for identical products. However, if some hosts were previously evading their remittance obligation, as seems likely, then their tax burden rose as well.

Columns 2 through 7 of Table 1 provide estimates separately by several measures of host sophistication. For example, hosts with multiple listings, or those who use non-heuristic pricing (e.g., not divisible by 5), or those whose listing is not a shared or private room within their own home (e.g., a separate apartment) are more likely to be sophisticated, and thus potentially more responsive to the policy. The results do not convey a consistent story: hosts with just one observed listing appear more responsive than those with multiple listings, as are hosts who rely

¹⁰ Whether the economic incidence is actually affected in this scenario is unclear. If all hosts were previously non-compliant, then the effective tax rate was zero, but may have been “borne” entirely by hosts.

¹¹ Though the estimated magnitude of the listing price decline in Chicago (5.5%) exceeds the hotel tax rate in that city (4.5%), the confidence interval is sufficiently wide for me to be unable to rule out that the two are equal.

on heuristic pricing rather than those who do not. However, shared or private room listings are not as consistently responsive as entire home listings.

Table 3 also reports estimates from equation (3), but uses listings in neighboring municipalities as controls, rather than listings in untreated cities. Both the magnitude and sign of the estimates are sensitive to the choice of control. For example, relative to listings in nearby areas like Bethesda and Arlington, the listing prices of those within the city of Washington rose by an estimated 5.7% after policy implementation, implying that the after-tax price paid by guests rose by approximately 20%. Estimates for Chicago and Phoenix are insufficiently precise to rule out no change at all, but for different reasons: there are very few listings in municipalities neighboring Chicago available to use as controls, whereas the price movements of listings within and just outside Phoenix appear very similar (see Figure 7).

One interpretation of the result in Table 3 is that the spillover effects of this policy on listings outside of a city's municipal borders are large. As made clear in Figure 1, listings in adjacent municipalities are often displayed side by side in search results, where it is unclear to a guest that one is subject to a tax upon checkout while the other is not. As a result, hosts in untreated municipalities may feel compelled to lower their prices if hosts in treated municipalities are doing the same.

Tables 4 and 5 present results analogous to those in Tables 2 and 3, but estimated using the panel specification in equation (4). Recall that, unlike the repeated cross-section results from equation (3), this approach holds constant the composition of listings to those that appeared in both the pre-agreement and post-agreement period. This reduces the sample size considerably, particularly for Washington and Chicago, reducing the precision of those estimates. Using listings in New York, San Francisco, and Los Angeles as controls (Table 4), the estimated effect

on listing prices is negative in Phoenix, and too imprecise to real out a null effect in Washington and Chicago. Using listings in neighboring municipalities as controls (Table 5), the estimates are often statistically insignificant, and occasionally positive, suggesting spillover effects may play a role here as well.

Relative to the repeated cross-section results, the magnitude of the price declines estimated by the panel specification in Table 4 are smaller. For example, a 3.8% decline in average listing prices in Phoenix (Table 2) is reduced to a 1.7% decline (Table 4). This implies that a substantial portion of the policy's effect on listing prices in Phoenix may have been caused by changes in composition. For example, if hosts previously deterred from entering the market because of the legal uncertainty surrounding their participation began listing after implementation, and if their listings were priced lower than those already on the market, then average listing prices would decline even if existing hosts failed to respond.

Finally, Tables 6 and 7 present estimates of the policy's effect on the log standard deviation of prices in treated cities, using city and metro control listings, respectively. Although each point estimate is negative, only in Chicago does the policy appear to have narrowed the distribution of prices sufficiently for the estimate to be consistently distinguishable from zero.

[need to think more about why this is the case.]

8. Conclusion

In classical economic theory, the incidence of a consumption tax is exclusively determined by market-wide demand and supply elasticities. This paper contributes to an emerging empirical literature which suggests that other factors, such as assignment of the remittance obligation, may affect incidence in practice.

I find that shifting the legal obligation to remit hotel taxes from small, independent hosts to Airbnb increases after-tax prices paid by consumers. The magnitude of this effect differs by a number of host characteristics related to sophistication. While several rationalizations of my estimates are possible, this primary result is consistent with low levels of voluntary compliance among individual hosts prior to implementation of mandatory withholding, despite the existence of a paper trail and federal information reporting on Airbnb rental transactions. This finding has potentially important implications for understanding the potential revenue and distributional consequences of taxing non-employee service transactions facilitated by digital platforms.

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Figure 1: Airbnb Search Results

The screenshot displays the Airbnb search interface for Chicago, IL, United States. The search parameters are: Dates: 12/29/2015 to 01/01/2016; 2 Guests; Room Type: Entire Home, Private Room, Shared Room; Price Range: \$10 to \$1000+.

The search results show 168 Rentals in Chicago. Two listings are highlighted:

- Charming, and cozy Evanston home.** Private room · 5.0 ★ · 3 reviews. Price: \$69.
- Guest Room in Rogers Park.** Private room · 5.0 ★ · 14 reviews. Price: \$65.

The map on the right shows the search area with various price markers ranging from \$50 to \$155. The map includes street names such as Lee St, Madison St, Oakton St, and W Fargo Ave.

Figure 2: Airbnb Listing Details in Chicago and Evanston, IL



Rebecca Sparks

\$65 Per Night

Check In	Check Out	Guests
12/29/2015	01/01/2016	2
\$65 x 3 nights		\$195
Service fee		\$23
Occupancy Taxes		\$8
Total		\$226

Request to Book

Guest Room in Rogers Park
 Chicago, IL, United States **5.0** ★ 14 Reviews

Private room 2 Guests 1 Bed

About this listing

We have a comfy guest room with a futon with a memory foam topper for a good nights sleep. Internet works great, you have your own private bathroom, and free laundry. We keep the fridge stocked for breakfast. Bus and train stops very close by for easy travel.

Chicago, IL



Christine

\$69 Per Night

Check In	Check Out	Guests
12/29/2015	01/01/2016	2
\$69 x 3 nights		\$207
Service fee		\$25
Total		\$232

Request to Book

Charming, and cozy Evanston home.
 Evanston, IL, United States **5.0** ★ 3 Reviews

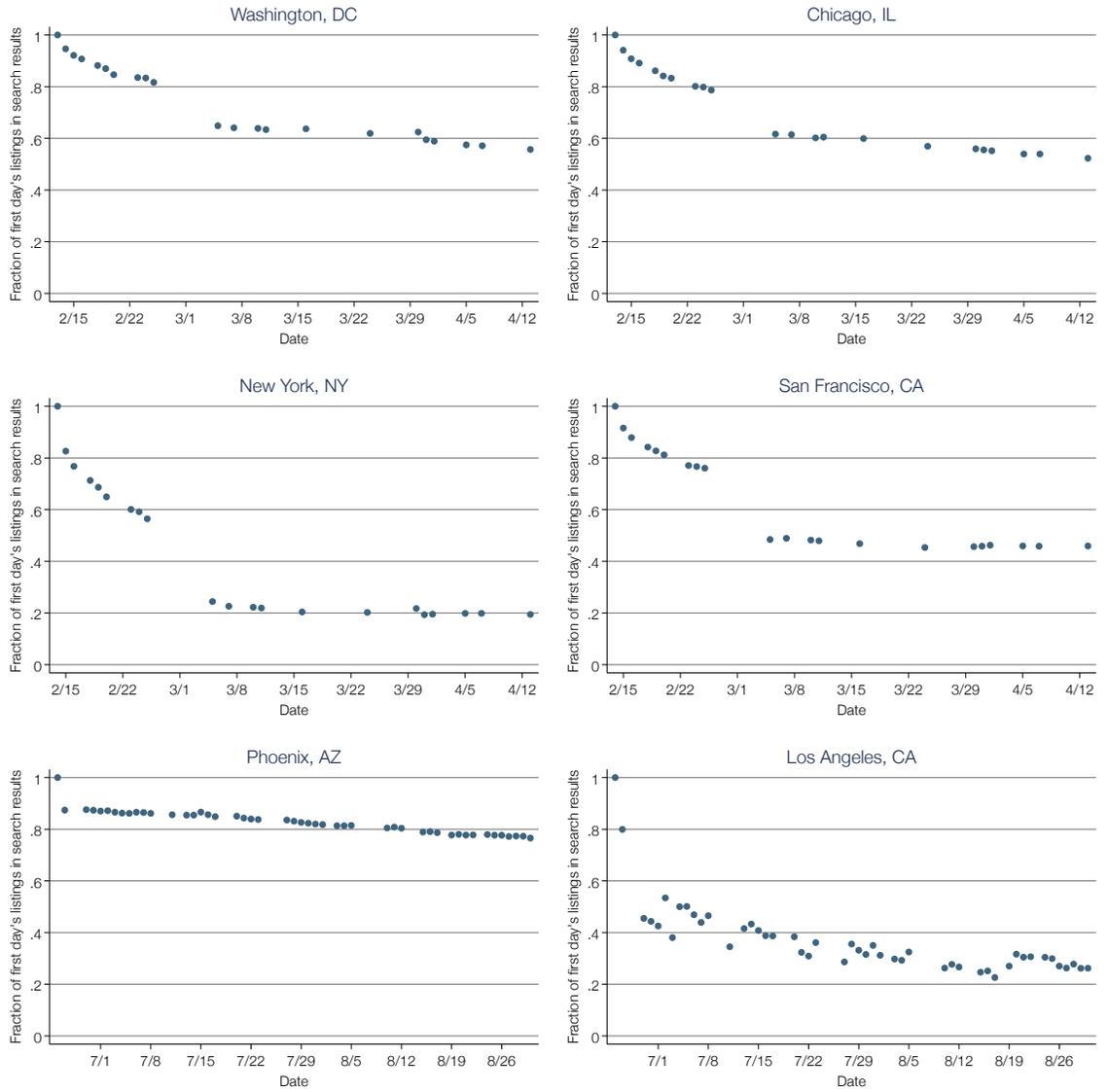
Private room 2 Guests 1 Bed

About this listing

Charming ranch home in beautiful Evanston, close to Northwestern campus, and downtown Evanston.

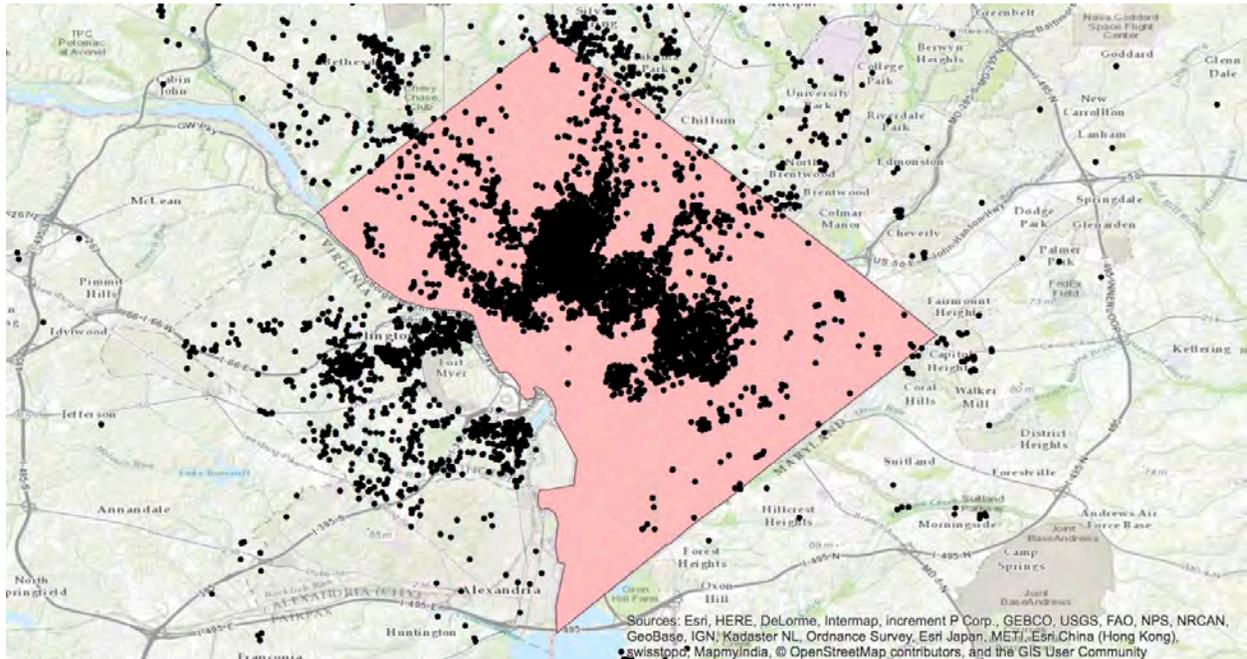
Evanston, IL

Figure 3: Listing Turnover in Search Results

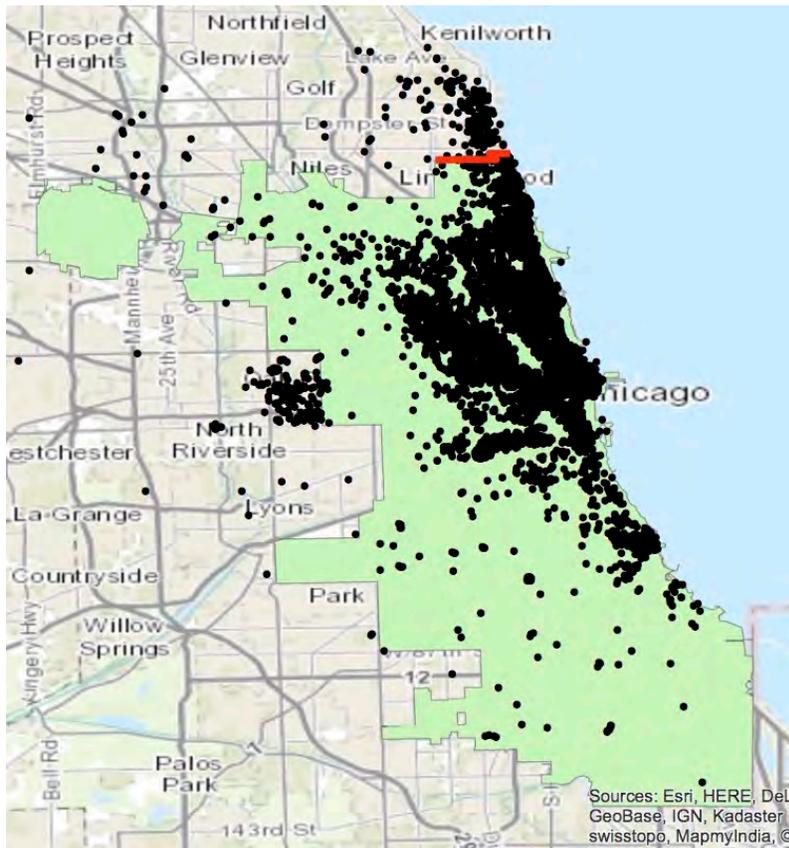


Notes: Figures display the fraction of all listings observed on the first day of data collection observed on each subsequent day that a search was performed.

Figure 4: Spatial Distribution of Listings, Relative to City Boundaries

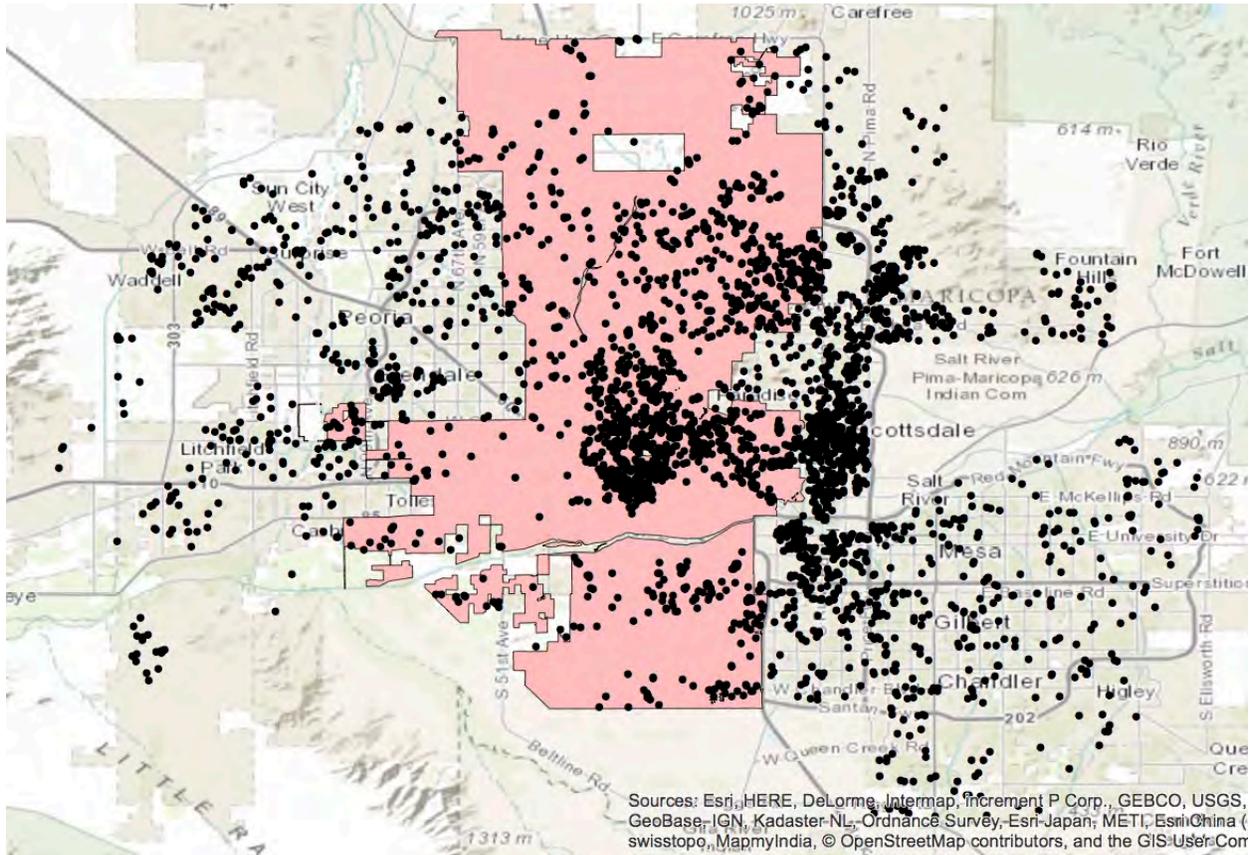


Washington, DC



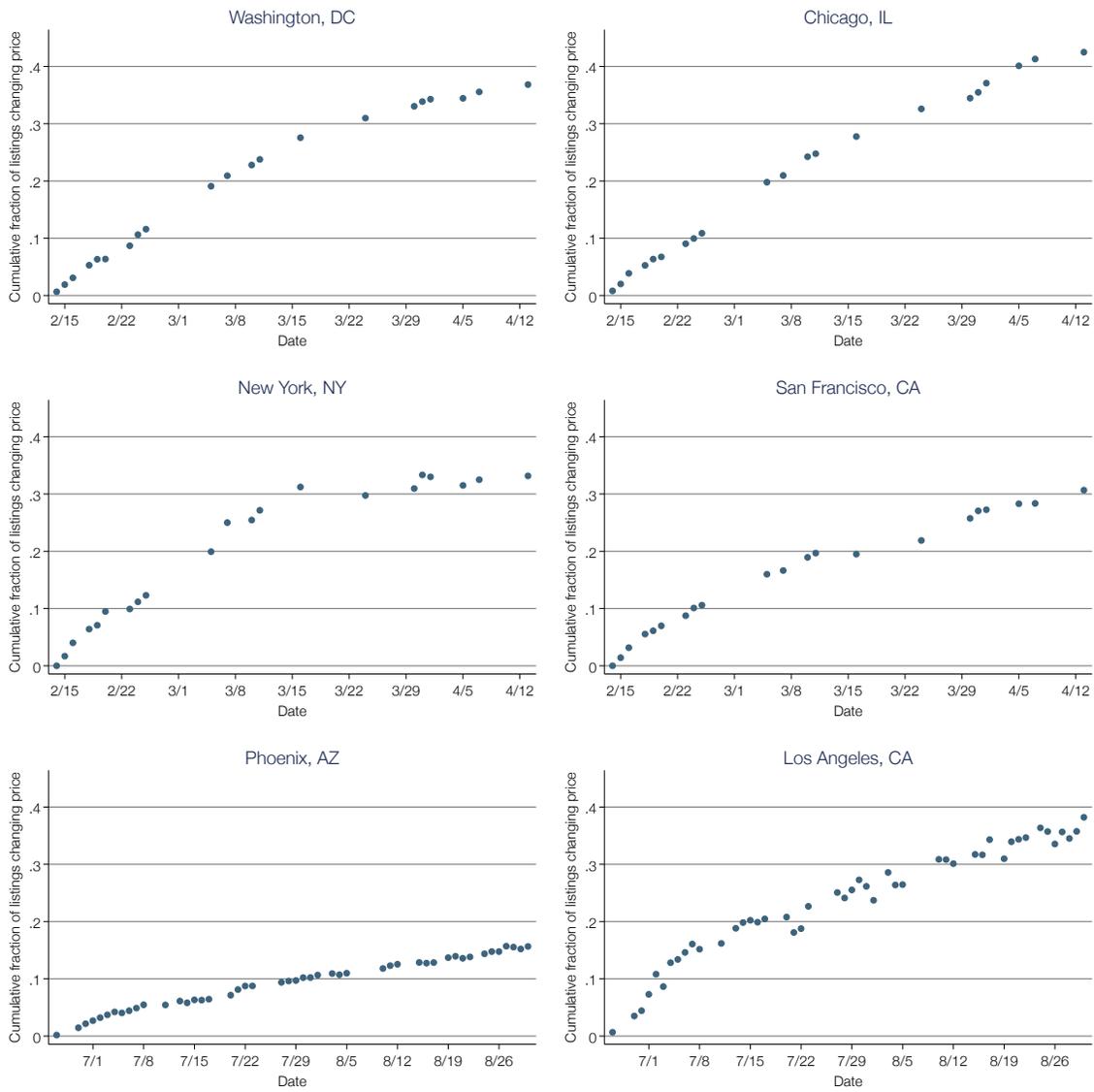
Chicago, IL

Figure 4: Spatial Distribution of Listings, Relative to City Boundaries (cont.)



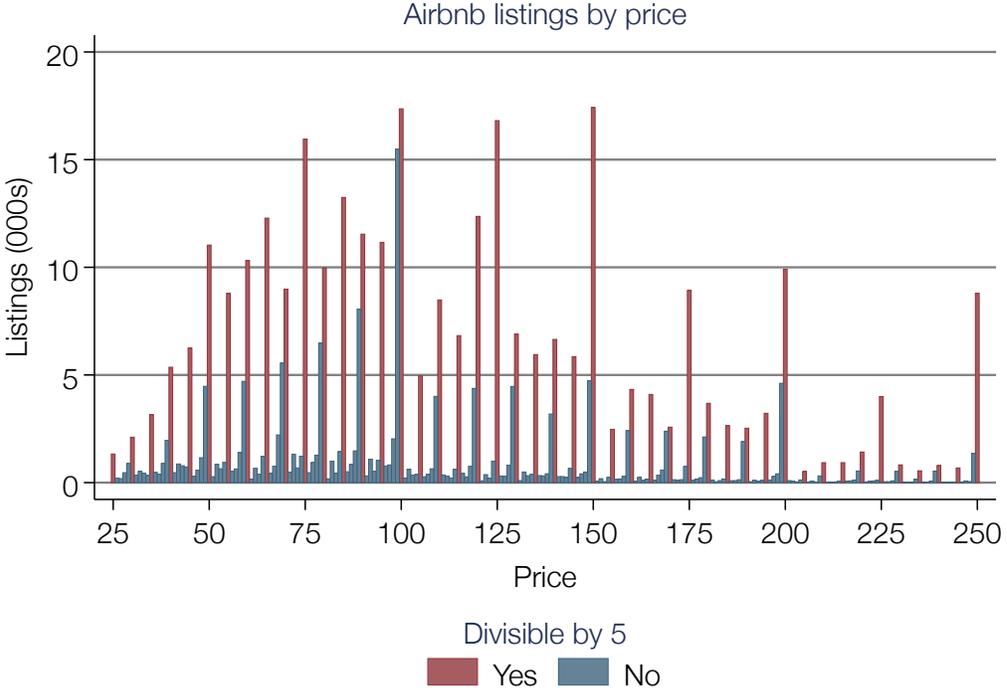
Phoenix, AZ

Figure 5: Cumulative Fraction of Listings Changing Price



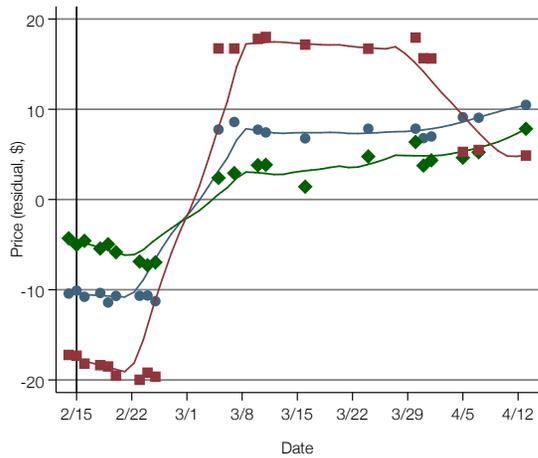
Notes: Figures display the fraction of listings appearing in both the pre- and post-agreement periods that change price at least once by the date shown.

Figure 6: Histogram of Listing Prices

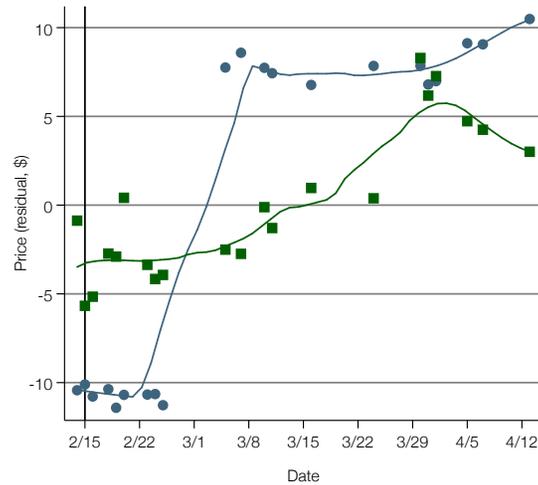


Notes: Figure displays the frequency of listings by price, for all observed listings priced under \$250.

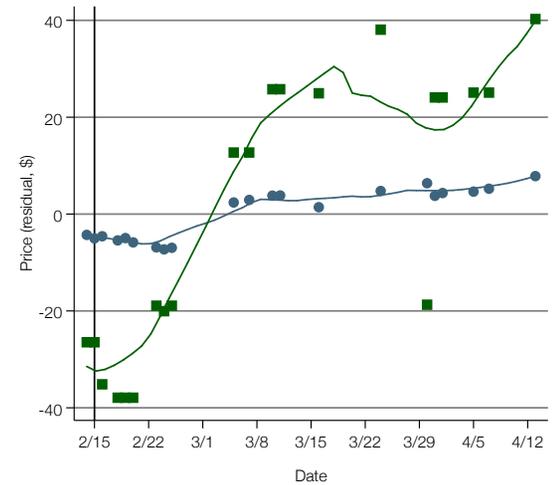
Figure 7: Price Movements in Treated and Untreated Locations



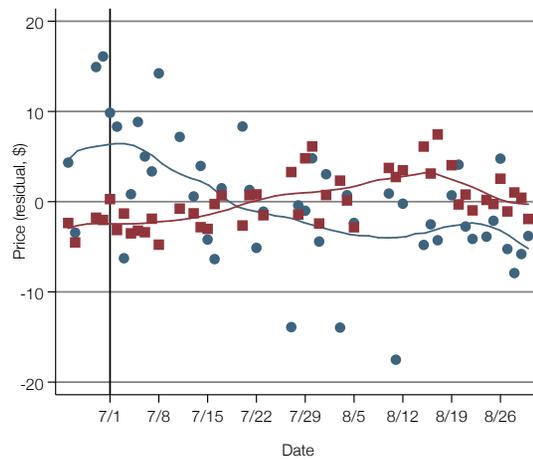
● Washington, D.C. ◆ Chicago, IL ■ New York, NY
 San Francisco, CA
 Los Angeles, CA



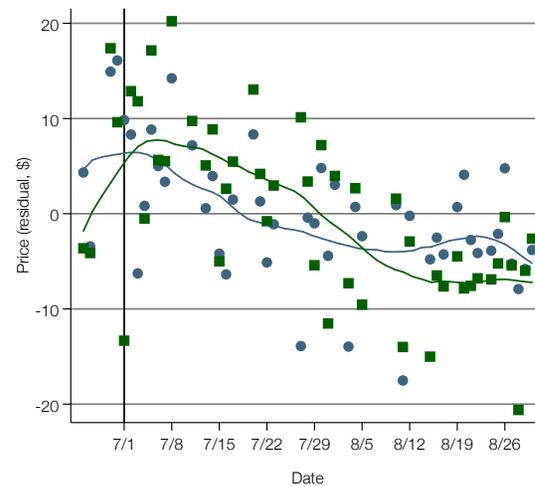
● Inside Washington, D.C. ■ Outside Washington, D.C.



● Inside Chicago, IL ■ Outside Chicago, IL



● Phoenix, AZ ■ New York, NY
 San Francisco, CA
 Los Angeles, CA



● Inside Phoenix, AZ ■ Outside Phoenix, AZ

Table 1: Summary statistics

Location	All Listings			Listings Appearing and Post-Agreement	
	Listings	% Entire Home	Average Price	Listings	% Entire Home
	(1)	(2)	(3)	(4)	(5)
<i>Wave 1: Feb. 13 - Apr. 13, 2015</i>					
Washington, D.C.	2100	.65	128	922	.634
Chicago, IL	2758	.611	129	991	.559
New York, NY	3779	.508	130	938	.494
San Francisco, CA	2185	.59	161	982	.578
Los Angeles, CA	1234	.574	125	n.a.	n.a.
Washington Metro (excl. D.C.)	930	.488	108	74	.378
Chicago Metro (excl. Chicago)	186	.366	102	7	.286
<i>Wave 2: Jun. 25 - Aug. 30, 2015</i>					
Phoenix, AZ	1534	.693	284	1311	.708
New York, NY	9253	.481	122	1443	.444
San Francisco, CA	4573	.534	166	1393	.513
Los Angeles, CA	7028	.566	115	1417	.582
Phoenix Metro (excl. Phoenix)	2025	.7	342	1716	.707

Notes: Data from Los Angeles were not collected prior to February 15.

Table 2: Difference-in-differences estimates of Airbnb remittance agreement effect on log(Price) of listings: city controls, repeated cross-section

City	All Listings (1)	Single-Listing Host		Price Divisible by 5		Shared/Private Room	
		Yes (2)	No (3)	Yes (4)	No (5)	Yes (6)	No (7)
Washington, D.C. (t = 14.5%)	-0.029* (0.011) 63,252	-0.038* (0.012) 41,047	-0.015 (0.009) 22,205	-0.042** (0.010) 43,687	0.004 (0.014) 19,565	0.001 (0.003) 26,926	-0.058 (0.025) 36,326
Chicago, IL (t = 4.5%)	-0.055** (0.011) 65,012	-0.064*** (0.010) 41,426	-0.036** (0.010) 23,586	-0.069*** (0.009) 45,227	-0.024 (0.013) 19,785	-0.036*** (0.004) 29,616	-0.070* (0.025) 35,396
Phoenix, AZ (t = 5%)	-0.038* (0.016) 199,970	-0.044** (0.014) 124,815	-0.026 (0.018) 75,155	-0.043 (0.021) 138,402	-0.003 (0.007) 61,568	-0.012 (0.018) 88,133	-0.052** (0.012) 111,837

Notes: Estimates from separate regressions of equation (3) in the text, using listings in New York, San Francisco, Los Angeles as controls. Standard errors clustered by city in parentheses. Observations below standard errors.

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 3: Difference-in-differences estimates of Airbnb remittance agreement effect on log(Price) of listings: metro controls, repeated cross-section

City	All Listings (1)	Single-Listing Host		Price Divisible by 5		Shared/Private Room	
		Yes (2)	No (3)	Yes (4)	No (5)	Yes (6)	No (7)
Washington, D.C. (t = 14.5%)	0.057*** (0.018) 40,803	0.027 (0.021) 23,719	0.077*** (0.027) 17,084	0.037* (0.020) 28,722	0.100*** (0.036) 12,081	0.036 (0.023) 16,445	0.067** (0.027) 24,358
Chicago, IL (t = 4.5%)	0.042 (0.035) 39,239	0.074 (0.054) 22,464	0.013 (0.048) 16,775	-0.005 (0.041) 27,831	0.125** (0.062) 11,408	0.021 (0.037) 16,151	0.046 (0.079) 23,088
Phoenix, AZ (t = 5%)	-0.010 (0.018) 142,137	-0.020 (0.023) 94,675	0.002 (0.027) 47,462	-0.017 (0.021) 108,140	0.044 (0.028) 33,997	0.028 (0.027) 42,348	-0.027 (0.023) 99,789

Notes: Estimates from separate regressions of equation (3) in the text, using listings in neighboring municipalities as controls. Standard errors clustered by city in parentheses. Observations below standard errors.

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 4: Difference-in-differences estimates of Airbnb remittance agreement effect on log(Price) of listings: city controls, panel

City	All Listings	Single-Listing Host		Price Divisible by 5		Shared/Private Room	
		Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Washington, D.C. (t = 14.5%)	0.000 (0.008) 35,950	0.001 (0.005) 23,534	-0.002 (0.014) 12,416	0.003 (0.007) 24,407	-0.003 (0.009) 11,543	-0.003 (0.011) 15,473	0.003 (0.004) 20,477
Chicago, IL (t = 4.5%)	0.012 (0.009) 36,226	0.014 (0.006) 23,336	0.008 (0.015) 12,890	0.010 (0.008) 24,840	0.011 (0.009) 11,386	0.004 (0.011) 16,919	0.018* (0.005) 19,307
Phoenix, AZ (t = 5%)	-0.017** (0.005) 129,673	-0.016** (0.004) 78,102	-0.019* (0.006) 51,571	-0.017** (0.004) 89,012	-0.003 (0.004) 40,661	-0.007 (0.007) 53,465	-0.020*** (0.003) 76,208

Notes: Estimates from separate regressions of equation (4) in the text, using listings in New York, San Francisco, Los Angeles as controls. Standard errors clustered by city in parentheses. Observations below standard errors.

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 5: Difference-in-differences estimates of Airbnb remittance agreement effect on log(Price) of listings: metro controls, panel

City	All Listings (1)	Single-Listing Host		Price Divisible by 5		Shared/Private Room	
		Yes (2)	No (3)	Yes (4)	No (5)	Yes (6)	No (7)
Washington, D.C. (t = 14.5%)	0.001 (0.003) 34,565	-0.003 (0.003) 20,140	0.006 (0.005) 14,425	0.002 (0.003) 24,227	-0.006 (0.006) 10,338	0.007** (0.004) 13,731	-0.002 (0.003) 20,834
Chicago, IL (t = 4.5%)	0.011** (0.005) 32,963	0.017*** (0.006) 18,795	0.005 (0.009) 14,168	0.010 (0.006) 23,264	0.014*** (0.005) 9,699	0.010 (0.007) 13,357	0.011 (0.009) 19,606
Phoenix, AZ (t = 5%)	-0.001 (0.002) 133,278	0.002 (0.002) 89,097	-0.009** (0.004) 44,181	-0.005*** (0.002) 101,527	0.009*** (0.003) 31,751	0.017*** (0.003) 39,023	-0.011*** (0.002) 94,255

Notes: Estimates from separate regressions of equation (4) in the text, using listings in neighboring municipalities as controls. Standard errors clustered by city in parentheses. Observations below standard errors.

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 6: Difference-in-differences estimates of Airbnb remittance agreement effect on $\log(\sigma_{\text{Price}})$ of listings: city controls

City	All Listings (1)
Washington, D.C. (t = 14.5%)	-0.012 (0.025) 67
Chicago, IL (t = 4.5%)	-0.190*** (0.025) 67
Phoenix, AZ (t = 5%)	-0.097* (0.039) 192

Notes: Estimates from separate regressions of equation (5) in the text, using listings in New York, San Francisco, Los Angeles as controls. Standard errors clustered by city in parentheses. Observations below standard errors. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 7: Difference-in-differences estimates of Airbnb remittance agreement effect on $\log(\sigma_{\text{Price}})$ of listings: metro controls

City	All Listings (1)
Washington, D.C. (t = 14.5%)	0.009 (0.107) 44
Chicago, IL (t = 4.5%)	-0.234** (0.096) 44
Phoenix, AZ (t = 5%)	-0.002 (0.007) 96

Notes: Estimates from separate regressions of equation (5) in the text, using listings in neighboring municipalities as controls. Standard errors clustered by city in parentheses. Observations below standard errors. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.