The Rise of the Sharing Economy:
Estimating the Impact of Airbnb on the Hotel Industry

Georgios Zervas
School of Management
Boston University

Davide Proserpio, John W. Byers
Computer Science Department
Boston University

Abstract

A number of decentralized peer-to-peer markets, now colloquially known as the sharing economy, have emerged as alternative suppliers of goods and services traditionally provided by long-established industries. A central question surrounding the sharing economy regards its long-term impact: will peer-to-peer platforms materialize as viable mainstream alternatives to traditional providers, or will they languish as niche markets? In this paper, we study Airbnb, a sharing economy pioneer offering short-term accommodation. Combining data from Airbnb and the Texas hotel industry, we estimate the impact of Airbnb's entry into the Texas market on hotel room revenue, and study the market response of hotels. To identify Airbnb's causal impact on hotel room revenue, we use a difference-in-differences empirical strategy that exploits the significant spatiotemporal variation in the patterns of Airbnb adoption across city-level markets. We estimate that in Austin, where Airbnb supply is highest, the impact on hotel revenue is roughly 8-10%. We find that Airbnb's impact is non-uniformly distributed, with lower-priced hotels, and hotels not catering to business travel being the most affected segments. Finally, we find that affected hotels have responded by reducing prices, an impact that benefits all consumers, not just participants in the sharing economy. Our work provides empirical evidence that the sharing economy is making inroads by successfully competing with, and acquiring market share from, incumbent firms.

1

1 Introduction[†]

The emergence of multi-sided technology platforms, collectively known as the "sharing economy", has enabled individuals to collaboratively make use of under-utilized inventory via fee-based sharing. Consumers have so far enthusiastically adopted the services offered by firms such as Airbnb, Uber, Lyft and TaskRabbit. The rapid growth of peer-to-peer platforms has been aided by their ability to scale supply in a near frictionless manner as well as the rich selection of goods and services they have on offer. As an example, Airbnb, a provider of travel accommodation and a pioneer of the sharing economy, has served over 30 million guests since it was founded in 2008. Although Airbnb remains privately held, its valuation of over \$10 billion now exceeds that of well-established global hotel chains like Hyatt. Yet incumbent firms, despite both facing higher marginal costs and offering less personalized products than peer-to-peer platforms, have mostly downplayed competition from platforms like Airbnb. For example, hotel executives have publicly issued largely dismissive statements regarding competitors like Airbnb, arguing that these peer-to-peer platforms are either a small niche market or that they target complementary market segments from that targeted by hotel chains. Interestingly, Airbnb appears to also espouse this latter view: according to Airbnb, "76% of Airbnb properties are outside the main hotel districts", suggesting complementarity of their offerings.

In this paper we provide empirical evidence to this debate by studying the impact of Airbnb's entry in Texas market on hotel revenues. We hypothesize that stays with Airbnb serve as a substitute for certain hotel stays, and that Airbnb has a measurable and quantifiable impact on hotel revenue in affected areas. Our study explores the relationship between Airbnb and hotels in the state of Texas by estimating monthly hotel room revenue as a func-

tion of Airbnb entry in the market. Using data we collected from Airbnb, and monthly hotel room revenue from approximately 3,000 hotels in Texas dating back to 2003, we quantify the extent to which Airbnb penetration has negatively impacted hotel room revenue. Our main result is that in areas where Airbnb is most popular the revenue of the most vulnerable hotels in our data has decreased by about 8-10% over the past five years.

To identify the causal impact of Airbnb on hotel revenue we employ a difference-in-differences empirical strategy. Specifically, due to the significant variability in both the temporal rate and the spatial density of Airbnb adoption, as well as the geographic specificity of both our hotel and Airbnb datasets, we are able to treat Airbnb market entry as a variable intervention in space and time against the hotel room revenue data. Our DD strategy identifies the Airbnb treatment effect by comparing differences in revenue for hotels in cities affected by Airbnb before and after Airbnb's entry against a baseline of differences in revenue for hotel in cities unaffected by Airbnb over the same period of time. Using this DD specification we find that, in Texas, each additional 10% increase in the size of the Airbnb market resulted in a 0.37% decrease in hotel room revenue. To calibrate the economic significance of this result, it is worth pointing out that in certain Texas municipalities (notably, Austin), Airbnb inventory has grown exponentially over the past few years, resulting in an estimated revenue impact of over 8-10% for the most vulnerable hotels in our data.

Our DD specification allows for both time-invariant differences in revenue between hotels as well as common time-varying shocks to revenue across hotels. The key threat to identification potentially arises in the form of unobservable (to the researcher) city-specific, time-varying factors that differentially affect hotel room revenue depending on the intensity of Airbnb adoption within each city at a given point in time. To test the robustness of our DD estimate, we perform a series of checks. First, we show that our estimate for Airbnb's impact on hotel room revenue is robust to a number of covariates that vary by location and over time (*e.g.*, country-specific population, unemployment rate, and total hotel room supply measured at the city level). Second, following common DD practice, we allow for

flexible city-specific trends (*e.g.*, linear, or quadratic), which can parametrically control for unobserved endogenous trends that vary by city (the same level at which we observe variation in Airbnb supply). Third, we show that the basic set of controls included in our DD specification (*i.e.*, hotel fixed effects and temporal trends) explain approximately 95% of the variation in Airbnb supply. Therefore, little variation in Airbnb supply remains unexplained by our model, and could potentially be driven by unobserved factors that also affect hotel room revenue. Fourth, we check whether Airbnb adoption is driven by hotel performance, which would be a case of our confusing cause and effect. To the contrary, we find that a wide range of pre-Airbnb demographic and market characteristics – including, for example, hotel room prices, occupancy rates, and hotel room supply per city – that are significant predictors of post-Airbnb hotel room revenue, are not correlated with the patterns of Airbnb adoption we see in our data. Finally, in a separate analysis, we combine DD with coarsened exact matching (Iacus et al. 2012) to further reduce endogeneity concerns. Specifically, we first match each hotel affected by Airbnb to unaffected hotels belonging to same price-tier and sharing the same affiliation, discarding hotels that remain unmatched. The intuition behind matching is that similar hotels (*e.g.*, an upscale Hilton in Austin where Airbnb adoption is high, and an upscale Hilton in Dallas where Airbnb penetration is low) are less likely to differ in unobserved ways. We find that our CEM DD estimate is similar to our main DD analysis. Taken together, these robustness checks provide significant support for the assumptions underlying our DD analysis.

We then move to investigate both the mechanisms behind Airbnb's impact on hotel room revenue and the market response to Airbnb entry. With respect to mechanisms, given the nature of rentals on Airbnb today, which typically provide fewer amenities and services than many hotels, we expect those hotels providing more differentiated services to be less affected. We start by examining two such cases: high-end hotels and hotels catering to business travelers, both of which provide amenities that a typical Airbnb stay does not. First, after segmenting hotels in five industry-standard price tiers (Budget, Economy, Midprice,

4

Upscale, and Luxury) we find the impact of Airbnb is gradually magnified as we move down the price tiers. Then, through a similar analysis, using conference and meeting room space as a proxy for the extent to which a hotel caters to business travel, we find that the impact of Airbnb also falls disproportionately on those hotels lacking conference facilities. Finally, we examine Airbnb's differential impact on chain versus independent hotels, expecting that chain hotels will be less affected, for reasons ranging from larger marketing budgets and stronger brands to providing predictably consistent service. In contrast, independent hotels exhibit more variability and perhaps more inconsistency, as we would also expect with Airbnb properties. Indeed, our analysis confirms that the impact of Airbnb on independent hotels is disproportionately larger. Finally, with respect to market response, we study the extent to which affected hotels react to Airbnb's market entry. Using hotel industry performance metrics, we find a statistically significant decrease in occupancy rate and an even bigger decrease in hotel room prices.[1] Notably, such a price response benefits all consumers, not just participants in the sharing economy.

1.1 Related Work

Relatively few empirical papers have yet studied the sharing economy and its interplay with incumbent firms offering similar goods or servces. A handful of studies have examined the adoption and effects of car-sharing, for example, two studies have used survey analysis methods to find that car-sharing is associated with significant decreases in miles traveled, gasoline consumption, and car ownership (Cervero et al. 2007, Martin et al. 2010). As for accommodation sharing, we find a large number of opinion pieces in the popular press and on blogs, but little in the way of academic literature. Our closest comparison point is a set of short studies, commissioned by Airbnb, which claim that the Airbnb business model is complementary to the hotel industry, but primarily focus on arguing for and quantifying the

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[1]These findings are consistent with a recent analysis conducted by Credit Suisse. See: `http://www.tnooz.com/article/airbnb-responsible-softening-new-york-revpar/`.

substantial net economic benefit to cities that Airbnb travelers provide.[2] While our work is related to these studies, we apply a more sophisticated identification strategy, methodology, and segmentation analysis, resulting in conclusions that are both different and more nuanced.

Our work contributes to the growing literature on multi-sided platform competition, as Airbnb exemplifies a two-sided platform. Much of this literature establishes the economic theory of two-sided markets, for example through structural models that establish theories of price structure and usage (Rochet and Tirole 2003, Rysman 2009, Weyl 2010), and models which connect innovations in product design to network effects (Parker and Van Alstyne 2005). Other work, more closely related to our own, contributes empirical results to the literature that seek to explain the behavior of firms and individuals in two-sided markets (Jin and Rysman 2012), including the role of multihoming (Landsman and Stremersch 2011), modeling response to regulation (Carbó Valverde et al. 2010), and understanding the supply-side labor market (Hall and Krueger 2015). Our work, in contrast to these, empirically studies a setting where a two-sided platform offers a substitute for consumer services supplied by traditional firms.

It is in this latter context that our work contributes to literature on substitution between online and offline markets, as firms like Airbnb can be viewed as providing enabling technology that facilitates suppliers of niche inventory to bring their products to market. In contrast to offline markets, Airbnb provides sufficiently low cost of revenue for individuals to profitably list remnant inventory online; moreover, Airbnb provides enhanced reach by reducing consumer search costs (Bakos 1997). As such, our study can be viewed as investigating the consequences of an online platform lowering the barrier to entry for suppliers. Related work has studied similar examples in other domains. For example, a number of recent studies have focused on the impact of Craigslist – a website featuring free online classified ads – on the newspaper industry. Seamans and Zhu (2013) estimate the effect of Craigslist's market entry on several newspaper performance metrics. They find that in the

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[2]See: https://www.airbnb.com/economic-impact/

face of increasing competition by Craigslist, newspapers with greater reliance on classified ad revenue responded by reducing their ad rates, and by increasing their subscription prices more than newspapers whose revenue were less reliant on advertising. Kroft and Pope (2014) estimate that Craigslist's entry resulted in a 7% reduction in the volume of classified ads appearing in newspapers during the period between January 2005 and April 2007. Further, they estimate that Craiglist's entry caused a decrease in the rental vacancy rate by approximately 1%. Our work shares a methodological trait with these studies: all of them rely on the temporal and geographic variation in Craigslist's entry to identify its effect. We exploit similar variation in the patterns of Airbnb adoption to measure its impact on hotel room revenue.

Finally, our work contributes to the literature studying the impact from external shocks on the tourism and the hospitality industry. Much of the prior work though, has centered on demand shocks. For example, O'Connor et al. (2008) study the impact of terrorism on tourism in Ireland; Baker and Coulter (2007) estimate the impact of the 2002 and 2005 terrorist attacks in Bali on the islands' vendors. Similarly, Kosová and Enz (2012) examine the adverse effects of the 9/11 attack and the 2008 financial crisis on hotel performance.

2   Data and the Airbnb Platform

For our study, we collect and combine data from various sources including the Airbnb website, the Texas Comptroller Office, Smith Travel Research (STR), county demographics from the U.S. Census Bureau, and the Current Population Survey (CPS) from the U.S. Bureau of Labor Statistics (BLS).

2.1   The Airbnb Platform

Much of the data used in our study is collected directly from the Airbnb website. Airbnb defines itself as *"a social website that connects people who have space to spare with those who*

are looking for a place to stay", and exemplifies a peer-to-peer marketplace in the sharing economy. Prospective hosts list their spare rooms or apartments on the Airbnb platform, establish their own nightly, weekly or monthly price, and offer accommodation to guests. Airbnb derives revenue from both guests and hosts for this service: guests pay a $9-12\%$ service fee for each reservation they make, depending on the length of their stay, and hosts pay a 3% service fee to cover the cost of processing payments. Since its launch in 2008, the Airbnb online marketplace has experienced very rapid growth, with more than one million properties worldwide and 30 million guests that used the service by the end of 2014 (18M of which was in the past year).[3]

Airbnb's business model currently operates with minimal regulatory controls in most locations, and as a result, hosts and guests both have incentives to use signalling mechanisms to build trust and maximize the likelihood of a successful booking. To reinforce this behavior, Airbnb has built an online reputation system that enables and encourages participants to rate and review each completed stay. Guests use star ratings to rate features of their stay, *e.g.*, cleanliness, location, and communication, while both guests and hosts are encouraged to post public reviews of each stay on the platform.

2.2 Airbnb Data: Listings and Market Entry

To estimate the extent of Airbnb's market entry, we collected consumer-facing information from `airbnb.com` on the complete set of users who had listed their properties in the state of Texas for rental on Airbnb.

We refer to these users as *hosts*, and their properties as their *listings*. Each host is associated with a set of attributes including a photo, a personal statement, their listings, guest reviews of their properties, and Airbnb-certified contact information. Similarly, each listing displays attributes including location, price, a brief textual description, photos, capacity, availability, check-in and check-out times, cleaning fees, and security deposits. Figures 2

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[3]See `http://www.cnbc.com/id/102389442`.

and 3 display a typical Airbnb listing and a typical Airbnb user profile, respectively. Our collected dataset contains detailed information on 10, 555 distinct hosts and 13, 935 distinct listings spanning a period from 2008 to August 2014.

We quantify Airbnb supply over time at the granularity of individual cities as follows: for a given city and date, we count the number of distinct listings that have (cumulatively) appeared on Airbnb in that city prior to that date. We approximate the unobservable entry date of individual listings by using the prominently displayed date their owners became Airbnb members. We note that instantaneous supply fluctuates continuously, as some Airbnb hosts take properties on and off the market. Nevertheless, due to Airbnb's exponential growth, at any given point in time, cumulative supply strongly correlates with instantaneous supply.

While the presence of Airbnb listings in a city clearly does not by itself impact hotels, regressing hotel room revenue on Airbnb supply produces a meaningful coefficient estimate. We interpret a statistically significant negative coefficient on Airbnb supply as indicating that Airbnb listings lead to Airbnb bookings that substitute for hotel stays and impact hotel room revenue. We interpret a coefficient that is not statistically significantly different from zero as indicating that Airbnb listings having no effect on hotels. We interpret a positive coefficient, though implausible, as indicating that Airbnb listings benefit hotels.

Separately, we must choose an appropriate level of geographic aggregation. Here, our data is suitably granular (with location accuracy to roughly 100 meters) to permit analysis at many different scales. Our choice of city-level granularity is driven by the observation that a city is the largest geographic unit within which we reasonably expect to see significant substitution patterns between hotels and Airbnb properties.

2.3   Hotel Data: Revenue, Prices, and Occupancy Rates

The main dependent variable we use in our analysis is monthly hotel room revenue, which we obtained from public records furnished by the Texas Comptroller's office, in their capacity

as auditors of state tax collection.[4] In addition to monthly hotel room revenue, the dataset includes basic information including hotel name, address, and capacity. The raw dataset spans the period between Jan. 2003 and Aug. 2014.

Interestingly, according to Texas law, "a hotel is considered to be any building in which members of the public rent sleeping accommodations for $15 or more per day."[5] For this reason, revenue from Airbnb properties (as well as various other vacation rental options) whose owners are in compliance with the Texas tax code is also reported in this dataset. This is evident from Figure 4, which plots the number of unique tax-paying properties in Austin broken down by capacity, *i.e.*, maximum occupancy. We conjecture that the rapid increase in low capacity properties starting in 2008 is related to Airbnb's entry into the Texas market at the same time. To exclude non-hotel properties from our analysis of impact on hotels, we cross-reference the Texas Comptroller dataset with the U.S. hotel census data provided to us by STR. The STR census includes all U.S. hotels and contains a rich attribute set for each hotel, including its opening date, price segment, capacity, operation type (chain vs. independent), and geographic location. In total, the STR dataset contains information on 3,747 hotels in Texas metropolitan areas. After linking the STR census dataset with the Texas tax dataset, we obtain high-confidence matches for a panel of 3,047 properties (81% of STR hotels, which account for over 90% of the revenue in our data).

Airbnb can affect hotel room revenue through lower occupancy rates, decreased hotel room prices, or a combination of these two factors, conventionally reported within the hotel and hospitality industry as RevPAR (revenue per available room), which is the product of average room price and occupancy. Because the data we obtained from the Comptroller's office does not report either occupancy rates or hotel room prices, we obtain additional data on these quantities for a subset of Texas hotels from STR. The room price (also referred to as average daily rate, or ADR in the industry) and occupancy rate data from STR covers a subset of 2,584 hotels in Texas who chose to report this information to STR over the same

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[4]Available at `http://aixtcp.cpa.state.tx.us/hotel/hotel_qtr_all_srch.php`
[5]See `http://www.window.state.tx.us/taxinfo/hotel/faqhotel.html`

time period (Jan. 2003 to Aug. 2014).

Finally, we assemble a set of control variables derived from publicly available sources. We obtain monthly unemployment data at the city level, and annual demographic information at the county level from the BLS at `bls.gov` and the U.S. Census Bureau at `census.gov`.

3 Empirical Strategy

Airbnb has seen widely varying degrees of traction within different local, regional and international markets, both with respect to initial market entry and the rate at which it has been adopted within markets. For example, consider Figure 1, which depicts the current extent of market penetration both of Airbnb properties and hotels within the state of Texas (top panels), and within the county encompassing the state capital, Austin (bottom panels). Unlike hotels, which have coverage throughout the state, and pockets of local density, such as in downtown Austin, Airbnb has spotty coverage at best throughout the state, but broader coverage across metro areas, including suburbs and exurbs. Table 1 reveals that patterns of Airbnb adoption, over the past eight years in the ten most populous cities in Texas, are themselves diverse, with several cities experiencing early adoption and rapid growth, while others experienced minimal Airbnb adoption. Our empirical strategy exploits this variability to identify the impact of Airbnb's rise on hotel room revenue using a differences in differences (DD) identification strategy. Specifically, we estimate Airbnb's impact on hotel room revenue by comparing changes in hotel room revenue before and after Airbnb enters a specific city, against a baseline of changes in hotel room revenue in cities with no Airbnb presence over the same period time.

The key identification assumption we have to make to support a causal interpretation of this DD estimate is that there are no unobserved, time-varying, city-specific factor that are correlated with *both* Airbnb entry and hotel room revenue. Stated differently, we assume that unobserved factors that could potentially jointly affect both Airbnb adoption *and* hotel

room revenue do not systematically vary *both* between different cities *and* over time. For instance, the following unobserved factors are accounted for in our estimate and do not bias our estimates: 1) city-specific time-invariant differences in adoption rates (*e.g.,* consumers in Austin overall being more likely to adopt Airbnb than consumers in Dallas); 2) factors that vary arbitrarily over time but do not vary across cities (*e.g.,* a generally increasing awareness of Airbnb shared across all consumers in Texas over time), and, 3) city-specific trends, which allow for unobserved confounders that vary both between cities and over time according to a pre-specified functional form (linear or quadratic). Our DD specification takes the following form:

$$\log \text{Hotel Revenue}_{ikt} = \beta \log \text{Airbnb Supply}_{kt} + h_i + \tau_t + X'_{ikt}\gamma + \epsilon_{ikt}. \tag{1}$$

The dependent variable is the log of monthly room revenue of hotel i in city k at time t. To implement the DD strategy, our model includes hotel fixed effects h_i, and time (year-month) fixed effects τ_t. The first difference is taken using the hotel fixed effects, which allow for time-invariant differences in hotel room revenue between treated hotels (*i.e.,* hotels in cities with an Airbnb presence) and non-treated hotels (*i.e.,* hotels in cities with no Airbnb presence). The second difference in our DD specification is taken over time using year-month fixed effects τ_t which allow for unobserved time-varying revenue differences that are common across different cities. The coefficient of interest is β, which has the usual DD interpretation: it is an estimate of the percentage change in hotel room revenue in Airbnb-adopting cities subsequent to Airbnb's entry compared against a baseline of changes in hotel room revenue over the same time period in cities where Airbnb does not have a presence.

We now discuss and motivate the specific form of the specification and the controls we use, as well as the other best-practice methodologies from the literature that we employ, in carrying out this empirical identification strategy.

First, an identification challenge we face is that increased demand for accommodation is likely correlated with increases in both Airbnb supply and hotel room supply. Concretely, it is plausible that over our decade-long observation period, hotel firms have been strategically

developing new properties in areas of anticipated high demand. This pattern of competition could bias our estimation, because city-specific increases in hotel room supply can also drive per-hotel room revenue down, while at the same time correlate with increased Airbnb adoption. To guard against this type of concern, we construct a control variable *Hotel Room Supply*$_{-ikt}$, which measures the total supply of hotel rooms in the same city as hotel i (but excluding hotel i itself, thus the $-i$ in the subscript), for each time t. This control, which we also incorporate in X_{ikt}, allows for increases in the supply of hotel rooms provided by competitors to impact the room revenue of each hotel in our data, much as we hypothesize an increase in Airbnb rooms does.

Second, as we explained earlier, our DD estimate will be biased if there exist unobserved factors that vary across cities and over time, and which jointly influence Airbnb entry and hotel room revenue. To further guard against this possibility, we allow for quadratic city-specific trends as a control in X_{ikt}. The inclusion of these trends relaxes the DD assumption of no cross-city time-varying unobservables that are correlated with both Airbnb supply and hotel revenue. A concern with the inclusion of city-specific time-trends is that they can be confounded with hotels' response to Airbnb (Wolfers 2006). Fortunately, our dataset covers a long pre-Airbnb period from 2003 to 2008, allowing us to estimate these trends on a large sample of pre-treatment observations. In addition, to ensure that our results are robust to alternative functional forms for the city-specific time trends we also estimate all subsequent models using linear instead of quadratic trends. Using linear trends, we obtain (but do not report for brevity) similar results.

A final issue that we have to deal with is that the unit of analysis is hotel monthly room revenue, but the treatment, Airbnb adoption, occurs at the city level. As is well known, this mismatch in the level at which we measure our dependent variable compared to the treatment variable can result in understating the standard error of the estimate of Airbnb's impact, because it is likely that hotel room revenue is serially correlated over time within a city. We correct for this mismatch by clustering standard errors at the city level, which

lets us account for possible serial correlation in hotel room revenue. In so doing, we follow the standard practice in the literature for analyzing panel data in a DD setting (see *e.g.*, the treatment recommended by Bertrand et al. (2004), as well as Donald and Lang (2007)). We report standard errors clustered at the city level for all subsequent regressions.

3.1 Identification checks

Before proceeding with estimation, we conduct a series of identification checks to assess whether our proposed empirical strategy can recover Airbnb's causal impact on hotel room revenue. Our DD identification strategy relies on randomness in Airbnb adoption with respect to unobserved city-specific time-varying factors (ϵ_{ikt}) that are also correlated with changes in hotel room revenue (conditional on the control variables we include). As with any study relying on observational data, there is no conclusive test of this assumption. However, we can exploit the richness of our data to check if this assumption is likely to hold in practice. Similar to Akerman et al. (2013), we perform two checks that support the basis for our key identification assumption.

First, we show that most variation in Airbnb adoption is explained by regressing (the log of) Airbnb supply on time-invariant city-specific factors, time fixed effects, and city-specific trends – all of which are part of the DD model. These factors explain 95% of variation in Airbnb adoption, suggesting that our modeling assumption has a sound basis in practice. Next, we repeat this regression with the addition of city-specific time-varying observables that could potentially be correlated with hotel room revenue: population, unemployment rate, and employment in the accommodation sector. The inclusion of these factors do not increase the explanatory power of the regression. These analyses suggests that little variation in Airbnb supply remains unexplained, and thus could potentially be correlated with the error term in our DD regression.

Second, we check whether pre-treatment city characteristics predict future Airbnb supply, where the time of treatment is taken to be 2008, when Airbnb entered the Texas market.

14

The idea behind this test is that assuming Airbnb adoption is exogenous (with respect to hotel performance), it should not be correlated with pre-treatment factors. To perform this identification check, for each city, we compute its most recent pre-treatment (2007) population, unemployment rate, employment in the accommodation sector, hotel room supply, hotel room prices, and hotel occupancy rates. We then interact these pre-determined factors ($Z_{k,2007}$) with a vector of post-treatment year-month fixed effects (τ_t), and regress them on Airbnb supply. Concretely, with the units of analysis being post-2007 city-months, we estimate:

$$\log \text{Airbnb Supply}_{kt} = \text{City}_k + (\tau_t \times Z_{k,2007})' \theta + e_{kt}. \tag{2}$$

Each coefficient in the vector of coefficients θ is interpreted as a correlation between a specific pre-treatment characteristic and Airbnb adoption in each post-treatment period (from January 2008 onwards). Figure 5 presents the estimated coefficients θ for each characteristic together with their 95% confidence intervals. The only significant association we find is between pre-Airbnb population and subsequent Airbnb adoption, and, for this reason, we include population as a control in all our specifications. Visually, there also appears to be a weak correlation with pre-Airbnb unemployment rate, possibly driven by the help Airbnb can provide to struggling or unemployed homeowners in paying their mortgage,[6] though nearly all individual correlation coefficients making up this trend are not statistically different from zero. Regardless, we also include county-level unemployment rates as a control in Equation 1. Beyond these associations, we find no other discernible trend in the remaining coefficients (whose 95% confidence intervals always include the zero point, or, no effect). It is especially reassuring that the pre-treatment hotel industry structure – as captured by hotel room supply, occupancy rates, room prices, and accommodation sector employment in 2007 – do not predict Airbnb supply from 2008 onwards.

As mentioned earlier, one cannot entirely rule out endogeneity concerns in a study using

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[6]See "How Airbnb helps users save their homes", August 2012, `http://fortune.com/2012/08/16/how-airbnb-helps-users-save-their-homes/`

observational data. Here, we have shown that various factors potentially affecting hotel room revenue, including demographic trends, as well as the structure and performance of the hospitality industry across different cities, are not correlated with local patterns of Airbnb adoption. These checks increase our confidence that the identification assumptions needed to estimate Airbnb's causal impact on hotel room revenue hold in our data.

3.2   Results and Economic Significance

We report the results of estimating Equation 1 in the first column of Table 2. We estimate the coefficient $\beta = -0.034$, or equivalently, a 10% increase in Airbnb listings is associated with a statistically significant 0.34% ($p < 0.01$) decrease in monthly hotel room revenue. As we stated earlier regarding interpretation of a negative coefficient β, this estimate indicates that Airbnb listings result in some Airbnb stays that are substitutes for hotel stays in cities with an established Airbnb presence. Then, in column 2 of Table 2 we incorporate the control variables discussed in the previous section. While the estimated coefficients for these controls have the signs and magnitudes we would expect (*e.g.*, increased hotel room supply and unemployment are both associated with decreased hotel room revenue), our estimates for the impact of Airbnb remain qualitatively unchanged, a 10% increase in Airbnb suppluy is associated with a 0.37% decrease in monthly hotel room revenue.

The economic significance of our estimates is best understood in the context of Airbnb's growth. For instance, in Austin, the city in Texas with the highest Airbnb penetration, we estimate that the impact of Airbnb over the past 5 years is rougly 10% of hotel room revenue (the calculation is based on an increase in Airbnb supply from approximately 450 listings in 2010 to over 8,500 listings in 2014 yielding a revenue impact of $1 - (8,500/450)^{-0.037} = 0.102$). Considering the high fixed costs associated with operating a hotel, this figure could represent a significant fraction of hotel profits. Another way to see the economic significance of Airbnb is through a direct comparison of Airbnb and hotel room supply. These currently substantial impacts are all the more striking in light of the fact that Airbnb continues to

16

grow rapidly, including in cities like Austin, where it already has an established presence. Furthermore, larger markets in Texas such as Houston and Dallas appear to have ample room for Airbnb growth, due to their large population, and relatively low Airbnb penetration to date. Therefore, our results suggest the risk to incumbent hotels from Airbnb as a market entrant is both measurable and increasing.

An alternative way to assess the economic significance of these results is by comparing the estimated coefficients for the impact of increased Airbnb supply and hotel room supply on hotel room revenue. Our results in the second column of Table 2 show that a 10% increase in the supply of hotel rooms in Texas is associated with a roughly 1.5% decrease in Texas hotel room revenue, while a corresponding 10% increase in Airbnb supply is associated with a smaller 0.37% decrease in Texas hotel room revenue. It makes intuitive sense that increasing Airbnb supply has a smaller impact than increasing hotel room supply, as we do not expect all Airbnb stays to substitute for a hotel room stay. Nevertheless, the two effects are surprisingly comparable in size: an increase in Airbnb supply has one fourth the negative revenue impact of a corresponding increase in hotel room supply. Taken at face value, this suggests that incremental Texas Airbnb inventory does weakly substitute for incremental hotel inventory. And, although the impact of additional Airbnb supply is not as large, the significantly higher marginal costs associated with increasing hotel room supply, makes hotels less likely to be able to expand inventory as rapidly. We explore substitution between Airbnb and specific hotel types in more detail in Section 4, where we seek to understand the mechanisms behind Airbnb's impact.

3.3   Robustness checks

To further reinforce the causal interpretation of our DD estimate, in this subsection we perform two additional checks: a matching method, which we use as a more stringent alternative in defining (otherwise similar) treated and untreated properties, and a specification test using an alternative functional form of Airbnb supply.

Since Airbnb adoption is clearly not random by design, to provide evidence in support of the DD identification assumptions, we showed that observed pre-treatment demographic and market characteristics do not correlate with the patterns of Airbnb adoption we observe in our data, which is what we would expect with exogenous Airbnb entry. Here, we combine DD with matching to further limit the potential for unobserved confounders biasing our estimates. To explain the matching approach, first recall our source of identification: roughly speaking, for each "treated" hotel, *i.e.*, a hotel affected by Airbnb competition, our DD analysis constructs a counterfactual outcome using a set of "untreated" hotels, *i.e.*, hotels unaffected by Airbnb. The intuition behind matching is that the more similar treated and untreated hotels are in their observed characteristics, the less likely they are to differ in unobserved ways, including bias-inducing factors. Matching methods aim to reduce endogeneity concerns by ensuring comparability between treated and untreated units (Heckman and Navarro-Lozano 2004). While various matching methods exist, here we use the Coarsened Exact Matching (CEM) procedure (Iacus et al. 2012), because it is intuitive and works well with categorical data (like most hotel characteristics).

CEM takes places in two steps. First, hotels are stratified based on observed characteristics; we use price segment (Budget to Luxury), operation (independent or chain), and hotel chain affiliation (*e.g.*, Hilton, or Marriott), if any. After this first step, each stratum contains hotels that are identical on the basis of these characteristics. For instance, a single stratum contains all Upscale Marriott hotels, some of which are eventually treated and some of which are not. In a setting with a binary treatment indicator, it is clear which units are eventually treated. In our case, where treatment intensity varies, we make the distinction between treated and untreated hotels by defining hotels in cities which see no Airbnb penetration by the end of our observation period as untreated, and the remaining hotels as treated. One could argue that this definition of treatment is too permissive; while we do not present these results for brevity, we found our CEM analysis to be robust to alternative definitions of treated units, such as hotels in cities that eventually have at least 100 Airbnb

listings. In the second step of CEM, we discard strata containing only treated or untreated hotels, and re-normalize weights of observations in the remaining strata to place equal weight on treated and untreated units in each stratum. Applying CEM to our data leaves us with $1,946$ hotels.[7] Finally, we re-estimate the DD specification in Equation 1 on the subset of matched hotels using the CEM weights. Conceptually, DD on the CEM sample estimates a treatment effect within each stratum of comparable treated and untreated hotels, then averages these treatment effects to arrive at a final estimate. We report this estimate in the third column of Table 2. We find that the effect of Airbnb on hotel room revenue is robust to CEM, attaining a magnitude $(-0.041, p < .01)$ that is nearly identical to our main analysis.

The second robustness check we perform guards against a functional specification concern in Equation 1: regressing the log of Airbnb supply on the log of hotel room revenue implicitly assumes a constant elasticity relationship between the two quantities. While this might be a reasonable assumption in data with limited variation in Airbnb supply, the constant elasticity assumption is likely violated in our setting, as it is implausible that doubling Airbnb supply from 1 to 2 units will have the same effect on hotel room revenue as doubling Airbnb supply from 100 to 200 units. To ensure that our results are not driven by this modeling choice, we model Airbnb supply non-parametrically using a categorical variable, which takes on one of the following (roughly log-binned) values: 0 Airbnb units, 1-99 Airbnb units, 100-999 Airbnb units, 1000+ Airbnb units. Specifically, we estimate:

$$
\begin{aligned}
\log \text{Hotel Revenue}_{ikt} =& \beta_1 \text{I(Airbnb Supply 1-99)}_{kt} + \beta_2 \text{I(Airbnb Supply 100-999)}_{kt} \quad (3) \\
& + \beta_3 \text{I(Airbnb Supply 1000+)}_{kt} + h_i + \tau_t + X'_{ikt}\gamma + \epsilon_{ikt},
\end{aligned}
$$

where the $I(.)$ are dummy indicators for the corresponding ranges of Airbnb supply.

This model allows for the effect of Airbnb to vary depending on the number of Airbnb

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[7]CEM entails a trade-off between matching granularity, and the number of discarded observations. We chose our matching criteria to strike a reasonable balance between ensuring units within each stratum are similar, and discarding too many observations. Our results our robust to alternate matching criteria.

listings present in each city during a given period. In addition, it provides easier to interpret estimates compared to the log-log estimates of Equation 1. In this model, each of three estimated coefficients associated with the three levels of the categorical Airbnb supply variable we use represents represents a percentage change in hotel revenue. We estimate this model by replacing Airbnb supply with this new categorical variable in Equation 1 using zero Airbnb units as the reference level. We present our results in the fourth column of Table 2. These estimates provide directly interpretrable estimates of Airbnb's economic impact. We find that increasing levels of Airbnb penetration have proportionally larger impacts on hotel room revenue, as we would expect. For example, at Airbnb adoption rates exceeding 1000 rooms, the estimate $(-0.083, p < .05)$, indicates (since we are now working with a log-level specification) an average impact of 8.3% on hotel room revenue. These estimates are in line with our previous estimates in Section 3.2. Moreover, it is also reassuring that we find no statistically significant effect at low levels of Airbnb supply. This robustness check suggests that we are not identifying the Airbnb treatment effect from variation at low rates of Airbnb supply, which one would expect to have a negligible impact on hotel room revenue.

3.4 How Affected Hotels Respond to Airbnb

We now turn to the question of responses by incumbent hotels to Airbnb market entry. Patterns of response and novel response mechanisms by traditional incumbents to entrants facilitated by online technology is of increasing focus (Seamans and Zhu 2013, Kroft and Pope 2014); we add to this literature.

We investigate whether hotels actively respond to Airbnb market entry through a price response. Recall that hotel room revenue is the product of two quantities: average occupancy rate within a given time period, and average daily room price (ADR) during that same period of time. We now separate the impact from Airbnb on hotel room revenue into two components: the effect due to reductions in occupancy and the effect due to pricing, as captured by changes in the average daily rate. A hotel that exerts no response to a supply

shock would exhibit a reduction in occupancy, whereas alternatively, a manager could maintain occupancy levels via a price response. A key difference between the two responses is that the latter, reduced prices, is a net benefit for all consumers seeking accommodations, whether they use Airbnb or not.

To estimate these component-wise effects, we re-estimate the DD specification in Equation 1, substituting the dependent variable first with occupancy rate, and then with the log of ADR. Similar to the room revenue analysis, these two quantities vary by hotel and by month. We report these results in the final two columns of Table 2. As reported in the fifth column of this table, we find a statistically significant ($p < 0.05$) connection between increased Airbnb listings and occupancy rate. The coefficient suggests that a 10% increase in Airbnb supply generates a modest decrease in occupancy rate of about 0.0007%. (Note that, in contrast to our other dependent variables, occupancy rate is already expressed as a percentage and therefore we do not log transform it. Therefore, the coefficient of this regression has a level-log interpretation.) In column 6, we regress against ADR, and we find that a 10% increase in Airbnb supply is associated with a statistically significant ($p < 0.01$) price decrease of 0.19%. This suggests that affected hotels experience a decrease in occupancy rate due to Airbnb entry, to which they actively respond by lowering their prices. Note that this behavior is consistent with basic hotel revenue management practices, where hotels set prices accordingly to the level of occupancy rates observed.[8] To understand the economic significance of these results we can repeat the same calculation performed in Section 3.2, which suggests that in Austin, Airbnb negatively impacted hotel prices by roughly 5.4%.

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[8]Indeed, the hospitality industry has high fixed-costs and low marginal-costs, and therefore the general thinking is that it's better to put a head in a bed – at a low price – than not at all.

4 Mechanisms and Market Response

4.1 Which hotels are most affected and why?

We have provided evidence that treating hotels homogeneously, Airbnb has a negative impact on hotel room revenue in Texas. In this section, we investigate various mechanisms through which Airbnb could exhibit heterogeneous impacts across different types of hotels. To motivate this analysis, we observe that while Airbnb can surely *sometimes* provide an alternative to hotels, one can hardly expect it to be a perfect substitute for all travel needs. As Airbnb has its roots in casual stays, including those involving shared accommodations, we expect it to be a less attractive option for those who are not on a budget. Specifically, business travelers whose hotel expenses will be reimbursed and vacationers who frequent high-end hotels are two examples of consumers we view as much less likely to substitute a hotel stay with an Airbnb stay. Moreover, business travelers make greater use of those business-related hotel amenities not typically provided by Airbnb properties. Following this logic, we further isolate the impact of Airbnb on hotel room revenue by partitioning hotels in two different ways, each dividing hotels into one class that we expect to be less vulnerable to Airbnb's entry and another class that we expect to be more vulnerable, then estimating this additional interaction effect in our original DD specification. First, we segment hotels by price tier. Recall that the STR hotel census divides hotels into five price tiers: Budget, Economy, Midprice, Upscale, Luxury. Second, we differentiate hotels by their customer base: those that target business travelers versus those that do not.

To estimate heterogeneous treatment effects, we estimate a new specification that adds an interaction effect between hotel types and Airbnb supply to the DD specification in Equation 1:

$$\log \text{Hotel Revenue}_{ikt} = \beta_1 \log \text{Airbnb Supply}_{kt} \tag{4}$$

$$+ \beta_2 \log \text{Airbnb Supply}_{kt} \times \text{Hotel Type}_i$$

$$+ X'_{ikt}\gamma + \alpha_i + \tau_t + \epsilon_{ikt}.$$

The coefficients of interest are β_2, which captures the differential impact of Airbnb on the various segmentations by hotel type that we investigate. Specifically, following the segmentations described above, we first define Hotel Type$_i$ as a categorical variable identifying each one of the hotel price segments used by STR. In the second analysis we use a binary indicator of whether hotel i has conference or meeting space.

The results of these analyses appear in first two columns of Table 3. We start with price segmentation, presented in the first column. We estimate Equation 4, interacting hotel price segments with Airbnb supply. Here, we use Luxury hotels as a reference category least unaffected by Airbnb, motivated by two factors: these hotels are least comparable to Airbnb based on price and also that these upmarket hotels provide amenities (*e.g.*, pools, conference rooms, concierge) to travelers that typical Airbnb rentals do not. Note that this choice of reference category does not affect our results.

We find the negative impact of Airbnb increasing as we step down price tiers, with statistically significant interaction coefficient estimates at the 1% level for each of the three lowest tiers (Midprice, Economy, and Budget). In contrast, we find only a small negative and insignificant effect for the Upscale and Luxury segment (the latter being the reference level, and hence being captured by the main effect). From a managerial standpoint, this result has direct import: even though lower-end hotels in Texas account for a disproportionately small amount of room revenue as compared with upmarket hotels, they nevertheless bear the brunt of the impact of the market entry of Airbnb. Our evidence suggests that consumers are increasingly substituting Airbnb stays for lower-end hotels in Texas, possibly identifying

the former as offering better value at a similar price point. While this increased competition affords consumers greater choice, it also places lower-end hotels in regions with high Airbnb penetration at greater risk.

In column two of Table 3 we report the results of the segmentation of hotels catering to business travelers. We use those hotels having conference and meeting space as the reference category. The estimated coefficient β_2 for the interaction between Airbnb supply and the absence of meeting space indicator is negative and statistically significant $(-0.015, p < .01)$, suggesting that hotels lacking business facilities are more affected by Airbnb. These results are consistent with Airbnb's marketing strategy thus far, which has primarily targeted vacation travel. However, seeing a growth opportunity in the business travel segment, Airbnb recently launched an initiative to attract more business travelers.[9] An interesting open question going forward is the extent to which business travel will continue to differentiate the impact of Airbnb on hotels.

A separate distinction that we explore, relating to hotel operation rather than consumer behavior, is between chain hotels (including franchises) and independent hotels. Unlike independent hotels, chain hotels allocate large marketing budgets to advertising, brand building, guest loyalty programs, and other tactics which should make them less vulnerable to competition. In addition, chains provide a more predictable standard of service, which further differentiates them from both Airbnb and independent hotels. We present this analysis in the third column of Table 3, using chain hotels as a reference level. The overall effect due to Airbnb remains negative and statistically significant $(-0.035, p < .01)$, suggesting that hotels of all operation structures were affected. However, the estimated interaction coefficient for independent hotels $(-0.01, p < .01)$ is also negative and statistically significant, suggesting that Airbnb has indeed had a slightly larger impact on independent hotels.

Overall, we find that independent hotels, hotels that do not cater to business travelers, and lower-end hotels are all more heavily affected by Airbnb than our respective reference

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[9]See: http://bits.blogs.nytimes.com/2014/07/28/airbnb-expands-into-business-travel/

categories, hotels without these characteristics. While these results help us better understand the most vulnerable hotel segments, and are certainly of importance to hoteliers, they also serve as a robustness check in that the heterogeneous substitution effects they reveal align with the effects we hypothesized based on the value proposition to consumers that Airbnb offers.

5 Discussion and conclusions

The sharing economy has recently emerged as a viable alternative to fulfilling a variety of consumer needs, ranging from prepared meals to cars to overnight accommodations, that were previously provided primarily by firms rather than entrepreneurial individuals. As the size of the sharing economy has grown, so has the magnitude of its economic impacts. Our work is among the first to provide empirical evidence that the sharing economy is significantly *changing* consumption patterns, as opposed to generating purely incremental economic activity, as has been argued in prior work. Focusing on the case of Airbnb, a pioneer in shared accommodations, we estimate that its entry into the Texas market has had a quantifiable negative impact on local hotel room revenue. The substitution patterns we observe strongly suggest that Airbnb provides a viable, but imperfect, alternative for certain traditional types of overnight accommodation. Our analyses pinpoint lower-end hotels, and hotels not catering to business travelers, as those that are most vulnerable to increased competition from rentals enabled by firms like Airbnb.

Our work has some limitations which could be addressed in future work. First, one must recognize that our findings are representative of the state of Texas; directly generalizing them to other markets may not be appropriate given the varying of dynamics of supply and demand for accommodation across different regional markets. Additional studies which model the impact of Airbnb across these markets could be a useful contribution.[10] A second

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[10]Indeed, following our original working paper, others have arrived at similar estimates for Airbnb's impact in different markets. For example, Credit Suisse analysts used STR data to estimate that in New

limitation of work is that we analyze properties listed only on Airbnb, but not properties available through related vacation rental platforms like HomeAway and VRBO. We do not believe that our results are significantly affected by these competitors, since these firms primarily serve the smaller vacation rental market; moreover, they have not experienced the extremely rapid growth of Airbnb. Nevertheless, one could investigate the impact of all of these firms in aggregate, or individually. A final limitation of our study pertains to the precise characterization of hotels' response: here we have analyzed two metrics, price and occupancy rate, that managers can invoke as a response in the short-term. On longer time scales, hotels have other ways of responding to Airbnb, including promotions, advertising, and even re-positioning to provide more personalized Airbnb-like services. Mapping out the shape of hotels' response remains an interesting open question.

Our results have direct implications for hotels, travelers, and policy makers. As far as hotel managers are concerned, the competition their firms face from peer-to-peer platforms has several unique features that differentiate it from competition with other firms. First, the Airbnb platform has near zero marginal cost, in that a new room can be incrementally added to (or removed from) the platform with negligible overhead. Because of this, Airbnb can scale supply in a near frictionless manner to meet demand, even on short timescales. By contrast, increasing hotel room supply involves buildout, causing significant marginal costs for hotel chains. Second, Airbnb offers a much wider range of products and services than hotels: Airbnb users can rent anything from an apartment to a yurt. More importantly, because Airbnb leverages existing housing inventory, it can potentially expand supply wherever houses and apartment buildings already exist. This is in contrast to hotels, which must be built at locations in accordance with local zoning requirements. Therefore, competition by Airbnb is potentially harder for incumbents to adapt to, compared to competition by other hotel firms.

York City, Jan. 2015 revenue per hotel room was 18.6% lower than a year ago. See "New York City hotel rooms are getting cheaper thanks to Airbnb" at `http://qz.com/341292/new-york-city-hotel-rooms-are-getting-cheaper-thanks-to-airbnb/`.

Turning to consumers, we show that hotels in areas where Airbnb has an established presence have responded to increased competition by lowering their prices, which harms their revenue, but benefits travelers, even those who do not use Airbnb. In addition to reduced prices, consumers also benefit from increased variety provided through peer-to-peer platforms. Furthermore, consumers on the supply side benefit through additional income generated by providing goods and services via peer-to-peer platforms.

Finally, our results have implications for policy makers. Municipal revenues rely in part on tax receipts from well-regulated industries such as hotels and taxicabs. With demand shifting away from these incumbent firms, and to the extent that regulation and taxation of peer-to-peer platforms proves to be more challenging, the bottom line of cities with an established Airbnb presence could be hurt in the short run. Of course, peer-to-peer platforms can also bring about increased demand, which would directly benefit cities too, making the overall impact on cities harder to measure. Quantifying the net impact of peer-to-peer platforms remains an interesting direction for future research.

Returning to the thesis that the sharing economy has the potential to transformatively increase social welfare, as evangelized by Botsman (2012) and others, we assert that a large population of individuals worldwide have indeed benefited from Airbnb: not only hosts that derive incremental income by renting properties through Airbnb, and guests who select an Airbnb rental as an alternative to a hotel stay, but also those consumers who benefit from lower prices and increased competition in the accommodation industry. More broadly, our results should be viewed from outside the confines of the accommodation industry. This more encompassing viewpoint can weigh the positive change the sharing economy can bring about not only by providing imperfect substitutes for existing products, but also, through an application of Say's Law, by generating demand that did not previously exist through the supply of new products and services. Harkening back to arguments Airbnb has made, supply of inexpensive accommodations can increase travel and tourism spend overall, and thus the sharing economy could be a net producer of new jobs. However, these positives

must be evaluated against various costs, including those estimated in this paper. Our study represents an empirical first step into understanding the complex set of issues surrounding the sharing economy. With the projected rapid growth of the sharing economy, a host of related studies will be needed to fully understand and reap its benefits.

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Table 1: Airbnb's spatial and temporal penetration. Cumulative counts of Airbnb listings per year in the ten most populous Texas cities.

(Pop.)	Houston 2.16M	San Antonio 1.38M	Dallas 1.24M	Austin 0.84M	Ft. Worth 0.78M	El Paso 0.67M	Arlington 0.38M	Corpus Christi 0.31M	Plano 0.27M	Laredo 0.24M
2008	1	9	0	25	0	0	0	0	0	0
2009	6	13	7	146	2	0	1	0	0	0
2010	39	22	23	468	10	0	3	0	1	0
2011	169	72	109	1,862	34	3	19	7	5	1
2012	425	171	271	5,158	68	8	27	24	20	1
2013	695	271	422	7,489	93	23	36	49	33	1
2014	891	346	526	8,575	114	31	52	60	44	2

Table 2: Difference-in-differences estimates of the impact of Airbnb on hotel room revenue, prices, and occupancy rates. The first four columns report estimates using data from the Texas Comptroller's office; the last two from STR.

	(1) Revenue	(2) Revenue	(3) Revenue	(4) Revenue	(5) Occupancy rate	(6) Room price
log Airbnb Supply	−0.034***	−0.037***	−0.041***		−0.007**	−0.019***
	(−3.02)	(−3.72)	(−3.56)		(−2.03)	(−2.95)
Airbnb Supply (ref. zero listings)						
1 to 99 Listings				−0.016		
				(−0.94)		
100 to 999 Listings				−0.047*		
				(−1.69)		
1000+ Listings				−0.083**		
				(−2.27)		
log Hotel Room Supply		−0.154***	−0.146***	−0.151***	−0.246***	−0.046***
		(−6.82)	(−6.28)	(−6.50)	(−8.19)	(−3.32)
Unemployment Rate		−0.060***	−0.060***	−0.058***	−0.031***	−0.009
		(−3.99)	(−3.43)	(−3.66)	(−3.20)	(−1.42)
log Population		−0.036	0.035	0.028	−0.032	0.118
		(−0.20)	(0.25)	(0.14)	(−0.39)	(1.61)
CEM Sample	No	No	Yes	No	No	No
N	266283	266283	167968	266283	256705	256705
R^2 within	0.23	0.24	0.24	0.23	0.25	0.35

Note: The dependent variable is log Hotel Revenue$_{ikt}$ in columns 1-4, Occupancy rate$_{ikt}$ in column 5 and log Hotel Room Price$_{ikt}$ in column 6. Cluster-robust t-statistics (at the city level) are shown in parentheses. All specifications include hotel and time fixed effects, and a city-specific quadratic time trend.

Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 3: Difference-in-differences estimates of heterogeneity in Airbnb's impact on hotel room revenue.

	(1) Price segment	(2) Business travel	(3) Operation
log Airbnb Supply	−0.014 (−1.28)	−0.031*** (−3.03)	−0.035*** (−3.48)
Budget × log Airbnb Supply	−0.039*** (−4.67)		
Economy × log Airbnb Supply	−0.032*** (−7.92)		
Midprice × log Airbnb Supply	−0.019*** (−4.65)		
Upscale × log Airbnb Supply	−0.008 (−1.57)		
w/o Meeting Space × log Airbnb Supply		−0.015*** (−4.16)	
Independent × log Airbnb Supply			−0.010*** (−2.91)
log Hotel Room Supply	−0.155*** (−6.96)	−0.155*** (−6.89)	−0.154*** (−6.85)
Unemployment Rate	−0.060*** (−3.96)	−0.060*** (−3.97)	−0.060*** (−3.96)
log Population	−0.001 (−0.01)	−0.027 (−0.15)	−0.038 (−0.21)
N	266283	266283	266283
R^2 within	0.24	0.24	0.24

Note: The dependent variable is log Hotel Revenue$_{ikt}$. Cluster-robust t-statistics (at the city level) are shown in parentheses. All specifications include hotel and time fixed effects, and a city-specific quadratic time trend.

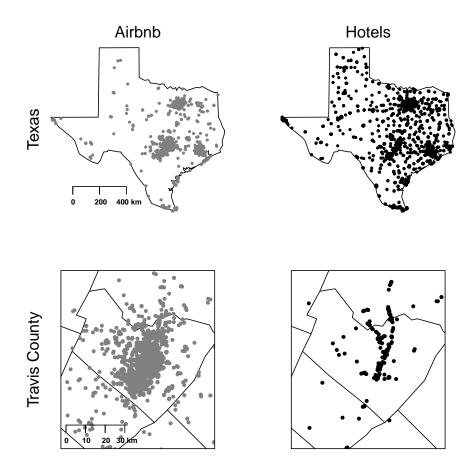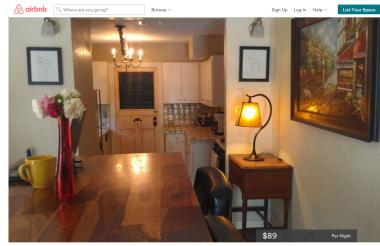*Significance levels:* * p<0.1, ** p<0.05, *** p<0.01.

Figure 1: Geographical distribution of hotels and Airbnb listings in the state of Texas (top) and in Travis County, TX (bottom) in 2013.

Figure 2: A typical Airbnb listing.

airbnb   Where are you going?   Browse ▾   Sign Up   Log In   Help ▾   **List Your Space**

Hey, I'm Sovay!

Austin, Texas, United States · Member since January 2011

I moved to Austin, Texas in January 2004 and absolutely fell in love with the city, in particular, the 78704 area. It is truly magical and the heart of the city, containing Zilker Park, South Congress (SOCO), Barton Springs Pool, Town Lake Running Trail, Umlauf Sculpture Gardens, Botanical Gardens and a walk/bike ride away from downtown. Please feel free to contact me about your upcoming stay in Austin, Texas!

479 Reviews   **4** References

Verifications

✓ Email Address
  Verified
✓ Phone Number
  ▢▢▢-▢▢ 37
✓ Reviewed
  481 Reviews

About Me

School
Old Dominion University

Work
Salon Sovay, Particular Properties

Languages
English

Listings (2)

Enchanting Zilker Cottage~Downtown
Treadwell St, Austin

SOCO ItZ bitZ Bungalow
S 1st St, Austin

Wish Lists (2)

Vacation Places
4 Listings

friends with listings
1 Listing

Reviews (479)

Reviews From Guests

Mary

We loved our stay at The SOCO ItZ bitzy Bungalow! The place is perfect size for a couple. It is in a great neighborhood, lots of yummy restaurants and cute shops. Sovay sent us a very helpful email before we arrive filled with suggestions for sight sighting and getting around. One of our best AirBnB experiences yet.

January 2015   ⌂ SOCO ItZ bitZ Bungalow

Response from Sovay:
Hi, Mary! I'm so glad to hear you two had such a wonderful time and loved your space and neighborhood :) Congratulations on your marriage proposal here in the SOCO Bungalow, that was so nice to read!!! I'm so glad to have had the opportunity to host you and you're warmly welcome back anytime!

John

The cottage is perfect. It has all the amenities you need, it's well stocked with supplies, and absolutely comfortable. I definitely will be trying to stay here again. The location is also great as well.

January 2015   ⌂ Enchanting Zilker Cottage~Downtown

Response from Sovay:
Hi, John. You were such a pleasant guest to host. You are welcome back anytime!
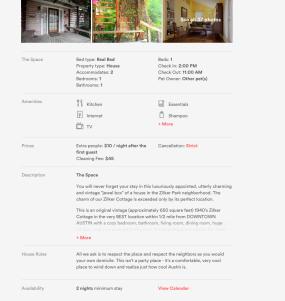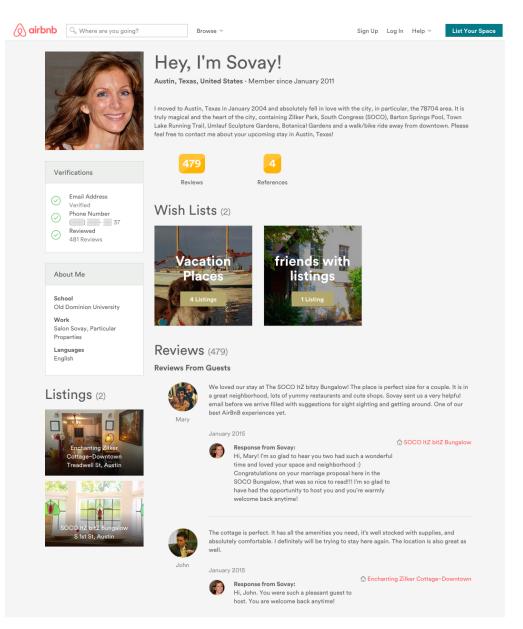
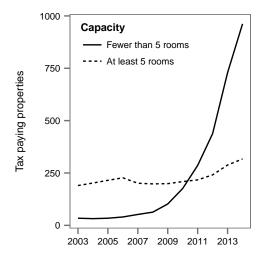Figure 3: A typical Airbnb user profile.

Figure 4: Annual counts of Austin properties that pay hotel occupancy tax, broken down by capacity.
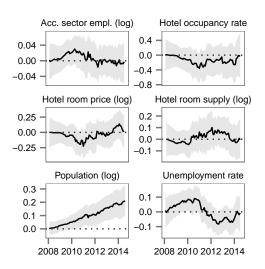

Figure 5: Correlation between Airbnb supply and pre-Airbnb (year 2007) city characteristics, with 95% confidence intervals.