Demand Interactions in Sharing Economies: Evidence from a Natural Experiment Involving Airbnb and Uber/Lyft

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Shunyuan Zhang

Harvard Business School, Harvard University

Email: szhang@hbs.edu

Dokyun Lee

Questrom School of Business, Boston University

Email: dokyun@bu.edu

Param Singh

Tepper School of Business, Carnegie Mellon University

Email: psidhu@andrew.cmu.edu

Tridas Mukhopadhyay

Tepper School of Business, Carnegie Mellon University

Email: tridas@andrew.cmu.edu

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ABSTRACT

We examine whether and how ride-sharing services influence the demand for home-sharing services. Our identification strategy hinges on a natural experiment in which Uber/Lyft exited Austin, Texas, in May 2016 due to local regulation. Using a 12-month longitudinal dataset of 11,536 Airbnb properties, we find that Uber/Lyft's exit led to a 14% *decrease* in Airbnb occupancy in Austin. In response, hosts decreased the nightly rate by $9.3 and the supply by 4.5%. We argue that when Uber/Lyft exited Austin, the transportation costs for most Airbnb guests increased significantly because most Airbnb properties (unlike hotels) have poor access to public transportation. We report three key findings: First, demand became less geographically dispersed, falling (increasing) for Airbnb properties with poor (excellent) access to public transportation. Second, demand decreased significantly for low-end properties, whose guests may be more price-sensitive, but not for high-end properties. Third, the occupancy of Austin hotels increased after Uber/Lyft's exit; the increase occurred primarily among low-end hotels, which can substitute for low-end Airbnb properties. The results indicate that access to affordable, convenient transportation is critical for the success of home-sharing services in residential areas. Regulations that negatively affect ride-sharing services may also negatively affect the demand for home-sharing services.

Keywords: Airbnb, Uber, natural experiment, geographic demand dispersion, demand interactions in sharing economy

INTRODUCTION

The sharing economy is rapidly growing and is upending entire sectors with "creative disruption." The two most prominent examples of the sharing economy are ride-sharing with private vehicles (e.g., Uber and Lyft) and home-sharing with private residences (e.g., Airbnb). A stream of recent research has investigated the impacts of sharing economy platforms on direct competitors as well as the broader economy. For example, researchers have investigated the impacts of Airbnb on apartment rental prices (Barron, Kung, and Proserpio 2017), home values (Jefferson-Jones 2015), and hotels (Li and Srinivasan 2019; Zervas, Proserpio, and Byers 2017). Other studies have investigated the impact of Uber on local entrepreneurial activities (Burtch, Carnahan, and Greenwood 2018) and drunk driving (Greenwood and Wattal 2017).

The existing literature has investigated sharing economy platforms as isolated entities and is silent on interdependencies across sharing economies. In this paper, however, we measure and quantify the impact of (the exit of) Uber and Lyft on Airbnb and investigate the mechanism behind the impact. A deeper understanding of the impact of Uber and Lyft on Airbnb demand, and vice versa, is of practical importance for two reasons. First, local governments can implement regulations that attempt to limit the growth of one sharing economy or the other.[1] Regulations include increased taxes, stricter conditions for participation in the sharing economy, hefty fines for violations, and even outright bans (Dobbins 2017). Regulations can shape the

[1] Local governments may regulate sharing economies in response to perceived negative externalities or pressure from incumbent firms. For example, the government of San Francisco, CA, regulated Airbnb by imposing liability insurance and taxes on hosts. See https://www.airbnb.com/help/article/871/san-francisco-ca.

evolution of sharing economy platforms and their ability to penetrate markets. Second, an understanding of demand interactions may enable platforms in different economies to leverage each other for future growth.

Ride-sharing and home-sharing services are obviously interdependent. Both are important parties in the travel industry. The travel journey consists of lodging (e.g., a hotel or Airbnb property) and commutes to destinations (e.g., shopping mall, convention center, airport, restaurants).[2] Ride-sharing services provide an option for local commutes, so the availability of ride-sharing services impacts local transportation costs and may have profound effects on travelers' lodging choices (Lee et al. 2010). Although Uber/Lyft offer cheaper, more convenient local transportation than taxis, it is not obvious *a priori* whether Uber/Lyft are more complementary to Airbnb than to its direct competitor, hotels. Drivers do not discriminate between Airbnb and hotels, so any traveler should have access to Uber/Lyft, regardless of the type of lodging. However, Airbnb differs from hotels in a subtle but important way: proximity to destinations. Travelers typically choose hotels that are very close to their main activities (Ellinger 1977; Wyckoff and Sasser 1981), so hotels often are clustered in areas with important destinations (Figure 1, panel 1). By contrast, Airbnb properties (Figure 1, panel 2) are geographically dispersed throughout commercial and residential areas; most properties fall outside the main hotel districts.[3]

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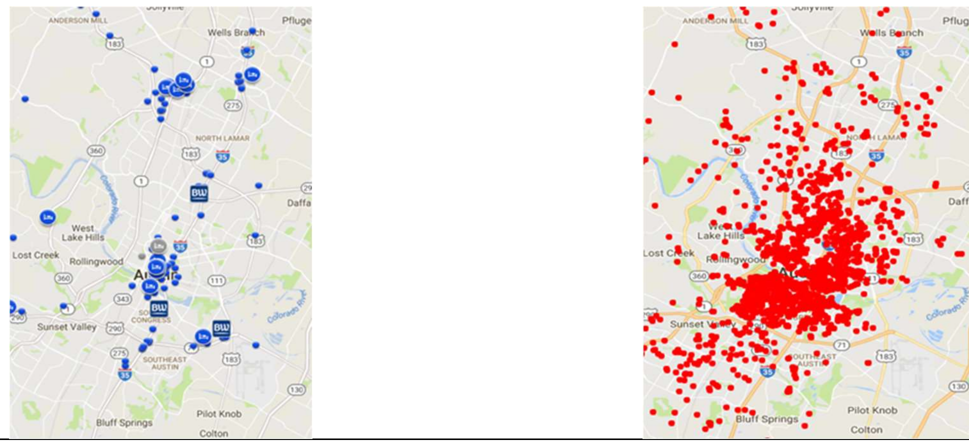
[2] A consumer survey (by Carlson Wagonlit Travel, CWT) on the usage of sharing economy apps suggests that tourists who use Uber and tourists who use Airbnb have similar customer profiles. See https://www.tourmag.com/Airbnb-and-Uber-are-tackling-Business-tourism_a76119.html

[3] 74% of Airbnb listings are outside of the main hotel districts: https://www.airbnb.com/about/about-us.

Figure 1 A Comparison of the Distributions of Hotels and Airbnb Properties

(1)	(2)
A map of the hotel distribution in Austin	A map of the Airbnb property distribution in Austin



Locations outside of the main commercial districts tend to have poorer access to both public transportation and taxi services. Since hotels are concentrated in areas with excellent transportation options, Uber and Lyft provide only marginal improvements in transportation affordability and accessibility for hotel guests. At most Airbnb properties, however, the public transportation options may be poor (e.g., long commute times, multiple transfers) or non-existent, rendering guests dependent on Uber/Lyft as the primary mode of transportation. Hence, Uber and Lyft can lessen the geographic disadvantage of (peripheral) Airbnb properties relative to (centralized) hotels, creating greater complementarity between the two sharing economies.

Demand complementarity between two products/services is established by showing that an exogenous increase in the price of one product/service leads to a decrease in the demand for the other (e.g., Gentzkow 2007; Liu, Chintagunta, and Zhu 2010; Manchanda, Ansari, and Gupta 1999; Mehta and Ma 2012). We leverage a natural experiment induced by the exit of Uber and Lyft from Austin, Texas, on May 9, 2016, in response to a local vote passed by the Austin City

Council. The Council upheld the requirement for fingerprint-based background checks for Uber and Lyft drivers, and the two ride-sharing platforms discontinued all services in Austin on the same day. (For this reason, we treat the two platforms as a single unit, "Uber/Lyft.") The exit of Uber/Lyft from Austin represents an exogenous change in the cost and convenience of local transportation and allows us to estimate the complementarity between Uber/Lyft and Airbnb.

A key question is whether the exit of Uber/Lyft *decreased the overall demand* for Airbnb properties, *redistributed the demand* across Airbnb properties, or both.[4] The exit of Uber/Lyft may have *decreased the overall demand* for Airbnb properties because guests at most Airbnb properties, located outside of the city center, suffered from increased transportation costs and wait times. If travelers prioritize transportation and convenience when planning trips, then the lodging demand in Austin should have shifted from Airbnb (generally poor access to public transportation) to hotels (generally good access). Alternatively, the exit of Uber/Lyft may have *redistributed the demand* across Airbnb properties, from those with poorer transportation access to those with good access.[5] The extent to which each outcome occurred after Uber/Lyft's exit depends on the extent to which consumers view Airbnb and hotels as horizontally differentiated.

We apply the difference-in-differences (DiD) methodology to a 12-month longitudinal panel dataset spanning 11,536 Airbnb properties across five US cities (with Austin as the treatment group and the other four cities as controls). We find that the exit of Uber/Lyft led to a 12.7% decrease in the occupancy of the average Airbnb property in Austin. We present evidence to

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[4] The exit of Uber/Lyft is unlikely to *increase* the demand for Airbnb as it worsens the location (transportation) disadvantage of Airbnb as compared to hotels.

[5] Our data show that the average Airbnb property in Austin was booked for 35% of the open days each month. Therefore, Airbnb properties had enough capacity to "absorb" the extra demand.

validate the key parallel trends assumption of the DiD analysis. The results are consistent across an extensive set of robustness analyses.

We argue that Uber/Lyft's exit indirectly affected Airbnb demand by introducing a significant *increase* in transportation costs and wait times for the guests of most Airbnb properties but not most hotels. To investigate the mechanism, we exploit each property's access to public transportation, a factor that is exogenous to Uber/Lyft's exit and yet affects the complementarity between Airbnb properties and Uber/Lyft. Specifically, we collect each property's transit score from walkscore.com. The transit score reflects how well the location is served by public transportation based on the frequency of service, type of route (e.g., rail, bus), and distance to the nearest stop on the route. We argue that Uber/Lyft, as a convenient and relatively affordable transportation option, mitigates the disadvantage of properties with lower transit scores[6]—so these properties should have the strongest complementarity with Uber/Lyft.

We investigate the underlying mechanism by decomposing the effect by the property's transit score and luxuriousness (high-end vs. low-end). Our results suggest that the exit of Uber/Lyft from Austin disproportionately affected low-end Airbnb properties. Specifically, Uber/Lyft's exit reduced the average occupancy by 34.5% for low-end Airbnb properties with minimal access to public transportation, by 17.8% for those with some access, and by 7% for those with good access; low-end Airbnb properties with excellent access had a 9.1% *increase* in the average occupancy. Hosts of low-end properties responded to the decreased demand by lowering their prices, with the steepest price reduction occurring among those with minimal access to public

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[6] Taxis, RideAustin, and car rentals are more expensive and/or inconvenient than Uber/Lyft for locations with poorer access to public transportation (see Web Appendix A). We conclude that the transit score is a reasonable proxy for access to all local transportation.

transportation. By contrast, there was no significant change in the nightly rate among the low-end properties with excellent access or among high-end Airbnb properties.

Returning to the question of whether demand shifted from Airbnb to hotels, we analyze demand data from individual hotels. We find that the average occupancy of Austin hotels increased by 0.37 reservation days per month after Uber/Lyft's exit. The increased demand disproportionately benefited midscale and economy hotels, while the more luxurious hotels had no significant change in occupancy. We argue that the demand lost from low-end Airbnb properties without excellent access to public transportation shifted overwhelmingly to hotels (98.4%) rather than to low-end properties with excellent access to public transportation (1.6%).

Why did demand fall among only the low-end Airbnb properties? The low-end and high-properties had similarly distributions of transit scores, so their guests faced similar increases in transportation costs and inconvenience (wait times) following Uber/Lyft's exit. We posit that the typical guests of low-end properties are more price-sensitive than the guests of high-end properties. The fact that the increased demand for lower-end hotels mirrors the decreased demand for low-end Airbnb properties suggests that travelers perceive low-end Airbnb properties and hotels to be reasonable substitutes for each other (Li and Srinivasan 2019; Zervas, Proserpio, and Byers 2017). Meanwhile, travelers seem to perceive high-end Airbnb properties as differentiated from higher-end hotels.

After Uber/Lyft's exit, local ride-sharing services entered the market to meet the need for affordable, convenient transportation. (The new ride-sharing services complied with the requirement of fingerprint background checks for their drivers.) The new services reduced transportation costs in Austin (Wears 2017)—at least, to some extent. If the new services had *fully* substituted for Uber/Lyft, then the effect of Uber/Lyft's exit on Airbnb demand would not have persisted through the end of 2016 (and yet it did, though the effect size decreased after September 2016). We show that the local ride-sharing services had insufficient supply, took time to scale up, and were unable to achieve the low wait times previously offered by Uber/Lyft, particularly in areas with poor transit scores.

It is not surprising, then, that when Uber and Lyft returned to Austin at the end of May 2017 (after the fingerprint requirement was overturned), the dominant local ride-sharing service, RideAustin, immediately saw a huge drop in demand (Afiune 2017), and most of the alternative ride-sharing services shut down. We take the re-entry of Uber/Lyft as another regulatory shock to the transportation cost, and we examine whether the main effect of Uber/Lyft's 2016 exit on Airbnb demand weakened in the post-re-entry period. We find that the negative effect of Uber/Lyft's exit disappeared quickly after the 2017 re-entry of both services. The re-entry analysis increases the validity of the estimated effect of Uber/Lyft's exit in 2016. It also suggests that the re-entry of Uber/Lyft closed the residual gap in the supply of convenient, affordable transportation, which the new local ride-sharing services were unable to mitigate fully.

Our research makes several contributions. First, we contribute to the marketing literature by identifying complementarities between cross-category products (e.g., Liu, Chintagunta, and Zhu 2010; Manchanda, Ansari, and Gupta 1999; Mehta and Ma 2012). Demonstrations of demand complementarity usually rely on individual-level purchase data (exploiting the change in demand for both products in response to a change in the price of one) and the assumption of constant preferences over time. Unfortunately, lodging services do not have enough repeated consumption by individual users to allow for a clean identification of preferences. However, unlike most repeatedly-consumed products, each Airbnb property is unique. We exploit heterogeneity in property location (which creates heterogeneity in access to public transportation) to characterize the complementarities between Airbnb properties and Uber/Lyft. Our analysis shows that home-sharing and ride-sharing services are interdependent, so regulations aimed at one sharing economy platform can affect the demand for another. Overall, the results show that Airbnb is vulnerable to policies and regulations that may negatively affect ride-sharing services such as Uber and Lyft. Given the important roles of both ride-sharing and home-sharing services in many local economies, policy makers should consider these complementarities when devising regulations for either service. Most Airbnb properties have poor access to both public transportation and taxis, and they incur significant losses when transportation costs increase. On a positive note, our results suggest that the damage caused by local regulations may be reversible—in Austin, the negative effects of Uber/Lyft's exit on Airbnb demand did not persist for long after re-entry.

Second, we contribute to the literature on competition between the incumbents and sharing economies (Cramer and Krueger 2016; Zervas, Proserpio, and Byers 2017). Our results show that ride-sharing services like Uber and Lyft moderate the competition between Airbnb and hotels. The presence of Uber and/or Lyft makes Airbnb properties more accessible and reduces the geographic advantage held by hotels over most Airbnb properties. We reconfirm the main finding of this stream of literature: consumers view low-end hotels and low-end Airbnb properties as less differentiated than their high-end counterparts (Li and Srinivasan 2019; Zervas, Proserpio, and Byers 2017).

Third, a related stream of literature in marketing and economics studies whether new technology-driven platforms complement or substitute for existing platforms. Examples include the relationship between online news and newspapers (Gentzkow 2007), television and newspapers (Gentzkow 2006, direct broadcast and cable TV (Goolsbee and Petrin 2004), and file-sharing services and recorded music sales (Oberholzer-Gee and Strumpf 2007). In our work, we confirm that Airbnb—a new technology-driven platform—competes with hotels (Li and Srinivasan 2019; Zervas, Proserpio, and Byers 2017), and we show how Uber and Lyft, as technology-driven platforms in a different sharing economy, may complement the demand for Airbnb properties and hotels in ways that moderate the competition between them.

Finally, our study sheds light on the difficulties faced by new entrants in technology-driven sharing economies. In Austin, even though Uber/Lyft exited the market entirely, such that they could not compete with new entrants, RideAustin and other new platforms lacked the scale and refined technology of Uber and Lyft. After almost 12 months, the new platforms had not fully replaced Uber and Lyft, and they quickly declined after Uber and Lyft returned to Austin.

RESEARCH CONTEXT AND EMPIRICAL FRAMEWORK

Interaction Between Ride-Sharing and Home-Sharing Economies

Both Airbnb and Uber boast enviable successes. Every day, nearly one million people rent accommodations from Airbnb, which offers more than five million rooms in 100,000 cities in 220 countries and regions (Airbnb 2020). In 2018, Airbnb accounted for 19% of the US lodging market. Meanwhile, Uber completed 14 million trips per day across 63 countries with 3.9 million drivers in 2018 (Uber 2020).

For travelers, local commutes between lodging and destinations constitute a significant part of the transportation cost: in 2019, ride-hailing (including ride-sharing and taxi services) accounted for the largest share (17.5%) of business travel expenses.[7] Since local transportation costs and the ease of access to local transportation are top factors that travelers consider when choosing where to stay (Lee et al. 2010), hoteliers have always understood the importance of location; most hotels are geographically concentrated in areas with the most popular travel destinations and easy access to transportation (Ellinger 1977). By contrast, most Airbnb properties are farther from the commercial core, so they lack good access to public transportation. They may also be underserved by taxi services, creating a gap that has been filled by ride-sharing services in the past decade. In Manhattan, for example, Liu, Brynjolfsson, and Dowlatabadi (2021) show that while taxi pick-ups are concentrated in the Manhattan core, Uber and Lyft pick-ups are significantly more common in the outer boroughs, where hailing a taxi is much more difficult.

Uber/Lyft services tend to be both faster and cheaper than equivalent taxi services. The pick-up data from Liu, Brynjolfsson, and Dowlatabadi (2021) reveal that more than half of the consumer surplus from ride-sharing services comes from their accessibility (shorter wait times). Brown and LaValle (2021) compared taxi services with Uber/Lyft services for 1,680 trips and found that for the same origin and destination pair, an Uber/Lyft rider paid an average of 40% less than a taxi rider and waited about one-quarter of the time.[8] We conducted our own Austin-specific cost comparison (see Web Appendix A for details) by checking the fares for a round trip via taxi, Uber, and Lyft between each Austin zip code and two popular destinations: Austin International Airport and the Austin Convention Center (downtown). We found that a taxi costs

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[7] https://www.certify.com/2020-02-06-Highlights-from-Certifys-2019-SpendSmart-Year-in-Review-Report.

[8] The price advantage of ride-sharing over taxis differs by the city and trip distance. For examples, see http://www.businessinsider.com/uber-vs-taxi-pricing-by-city-2014-10, https://www.lifewire.com/what-is-cheaper-an-uber-or-a-taxi-4157965.

$25.71 more than an Uber/Lyft for the average Airbnb property with *good* access to public transportation, $41.38 for the average property with *some* access, and $61.50 for the average property with *minimal* access.

Thus, ride-sharing services can balance the locational disadvantage of Airbnb properties (relative to centrally located hotels) by providing a convenient and affordable transportation option. Based on this mechanism, we expect that the complementarity between Uber/Lyft and Airbnb is stronger for properties with poorer access to public transportation.

Data

For our analysis, we exploit the natural experiment created by the joint exit of Uber and Lyft from Austin on May 9, 2016, which introduced an exogenous increase in the transportation costs of travelers in Austin. Our dataset for the main analysis spans 12 months (January 2016 through December 2016) and includes Airbnb properties in five US cities: Austin, Boston, Los Angeles, San Diego, and Seattle. Properties in Austin were subject to the natural experiment and hence form the treatment group, while properties in the other four cities form the control group. We exclude properties that did not have any bookings in the year prior to the treatment to address the "stale vacancies" issue (in which a property is listed, but only because the host neglected to update the listing's availability). See the Web Appendix B for more details on data construction.

We implement a two-step approach to address systematic differences between properties in Austin (i.e., the treated properties) and properties in the other four cities (i.e., the control properties). In the first step, we create a sample by matching control units with treated units based on similarities in observed characteristics; the matched sample contains 11,536 properties, of which 4,698 properties are in Austin. We calculate sample weights to balance the two groups. The matching step is critical because unmatched treatment and control groups might lead to a biased estimate. Two groups are considered "balanced" if they have negligible differences in observed characteristics (i.e., the standardized differences between the group means are < 10%). In the second step, we perform our empirical DiD analyses on the weighted sample.

Our data include property bookings and property and host characteristics, all obtained from AirDNA, a third party that specializes in collecting Airbnb data. Additionally, we use walkscore.com and each property's address to quantify its access to public transportation. We describe the components of our data below.

Property demand. Our listing-level property booking data contain, for each property in each month, the number of days that the property was reserved (i.e., booked) and blocked (made unavailable by the host without a booking). We operationalize the demand as the monthly occupancy: that is, the ratio of booked days to open days (when the property was not blocked) in a month, provided that the property was booked for at least one night that month.

Property characteristics. Many of the property characteristics are time-invariant: 1) property location (city, zip code, and street name), 2) property size (operationalized as the number of bedrooms), 3) property type (e.g., house, apartment), 4) room type (entire place or shared place), and 5) property amenities (e.g., parking, AC, gym). We also obtain time-variant property characteristics at the property-month level: 1) the average nightly rate, 2) number of guest reviews accumulated, and 3) number of property photos on the listing page.

Access to public transportation: walkscore.com. For each property, we collect information about access to public transportation, which is a key driver of lodging choices (Ellinger 1977; Wyckoff and Sasser 1981) and a key difference between hotels and most Airbnb properties. To capture the variation in transportation costs across Airbnb properties, we collect data from walkscore.com, which provides real-estate-related information regarding the areas near a given address. From our data provider, AirDNA, we obtain the GPS coordinates of each property and convert them into an address.[9] The most well-known feature provided by walkscore.com is the transit score, a numeric index (0–100) that reflects how well the address is served by public transportation (e.g., bus, light rail). The transit score algorithm sums the value of each nearby public transportation route. Value is determined by the frequency of service, the distance between the address and the nearest stop on the route (Hirsch et al. 2013), and the type of route (heavy/light rail has the highest value, followed by ferry/cable and then bus; see Web Appendix C for details). Figure 2 presents a sample transit score for a hotel in Austin (panel 1) and a geographic visualization of the transit scores of Austin Airbnb properties (panel 2). Very few properties (green dots) have an excellent transit score; they are centered in downtown Austin. Most properties (yellow, pink, or red dots) are located in the outer regions and have good, some, or minimal access to public transportation.

Ride data from RideAustin. When Uber/Lyft exited Austin, many smaller ride-sharing services entered the city (Wears 2017) and increased their supply of drivers over the next several months.[10] These services satisfied the requirement of fingerprint background checks for their drivers (the policy that drove Uber and Lyft to leave the city). We focus on the largest new service, RideAustin, which recruited about 4,000 drivers (about 75% of Austin's ride-share drivers) by December 2016. RideAustin was a viable alternative to Uber/Lyft in high-demand

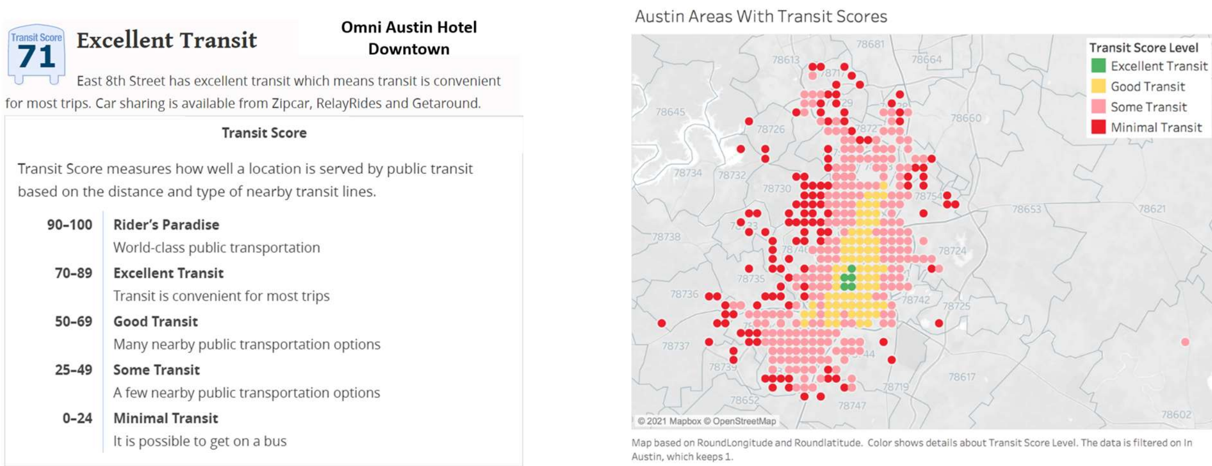
[9] For privacy, Airbnb scrambles the GPS coordinates, so the coordinates from AirDNA can be anywhere within a circle shown on the map associated with the Airbnb listing. AirDNA reports that this "perturbation" is no more than 500 meters.

[10] RideAustin reported that it took almost one month for 60–70% of its drivers to complete all the requirements: https://austinstartups.com/top-5-things-we-learned-from-our-first-million-rideaustin-rideshare-trips-1fe9f77cea63

areas (e.g., a 3–5 minute wait downtown, similar to Uber/Lyft), but the wait times in suburban areas remained substantially longer than for Uber/Lyft. Consumers also reported poor satisfaction with the ride-sharing alternatives (Hampshire et al. 2017). We obtained RideAustin data from a public source (https://data.world/andytryba/rideaustin), and we control for the monthly rides supplied by RideAustin in our main model. See Web Appendix A for details.

Figure 2 Sample Transit Score and Transit Score Map for Austin Properties

(1) (2)



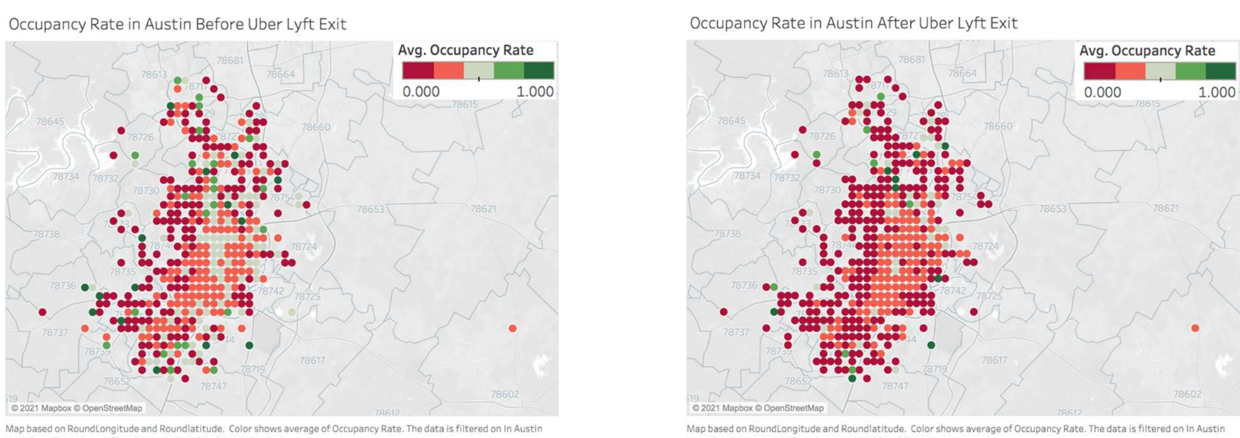
Notes: The transit score has five levels: Rider's Paradise (world-class public transportation; 0% of our sample), Excellent Transit (transit is convenient for most trips; 1.15%), Good Transit (many nearby options; 38.44%), Some Transit (a few nearby options; 55.15%), and Minimal Transit (it is possible to get on a bus; 5.26%). See walkscore.com.

Natural Experiment: Uber/Lyft's Austin Exit

A unique feature of our data is the natural experiment that occurred after Austin voters rejected Austin's Proposition 1, which would have replaced existing ordinances that required drivers of ride-sharing companies to undergo fingerprint background checks. Uber and Lyft claimed that these regulations deterred drivers and made it too costly to operate in Austin. Both companies had threatened to discontinue operations if the voters sustained the requirement, so they shut down their services in Austin on May 9, 2016. The exit of Uber/Lyft caused an increase in transportation costs in Austin because Uber/Lyft rides were generally cheaper than equivalent taxi rides.[11] By contrast, the transportation costs in the other four cities in our sample remained unchanged. We identify the interaction effect between Uber/Lyft's exit and Airbnb demand by comparing the change in occupancy before and after Uber/Lyft's exit in Austin versus in the other four cities. In Figure 3, we visualize the average demand before (panel 1) and after (panel 2) Uber/Lyft's exit. Two trends are worth noting. First, the increase in the proportion of red dots indicates a decrease in Airbnb demand after Uber/Lyft's exit. Second, green dots seem more likely to turn red (indicating a substantial decrease in demand) in the outer regions.

Figure 3 Visualizing Demand for Austin Properties Before and After Uber/Lyft's Exit

(1) (2)



Notes: The local transit scores provided by walkscore.com are categorized into four grades: 0~24 (minimal access to public transportation), 25~49 (some access), 50~69 (good access), and > 70 (excellent access).

[11] See several media reports: http://www.consumerreports.org/personal-finance/uber-vs-taxi-which-is-cheaper/. https://www.lifewire.com/what-is-cheaper-an-uber-or-a-taxi-4157965; https://money.com/the-only-3-major-airports-where-a-taxi-is-cheaper-than-an-uber/

Descriptive Statistics

Table 1 presents the summary statistics for the key variables, measured in April 2016 (immediately before the treatment) on the sample of 11,536 properties. We report the statistics by treatment (control properties in column 1; treated properties in column 2) and the difference between the groups (column 3); the treated and control units are not comparable on some variables.

An imbalanced sample may violate the critical parallel trends assumption required for DiD analysis, yielding results that might be influenced by existing differences rather than the treatment. In the next section, we describe a two-step approach to address the issue. In the first step, we match control units with treated units based on observed covariates, and we calculate sample weights to balance the groups. In the second step, we perform the DiD regressions on the weighted sample. The use of the weighting method with the DiD approach reduces the potential for false significance created by confounders.

Table 1 Summary Statistics

	(1) Austin Units		**(2) Control Units**		**(3) Mean Diff.[#]**
VARIABLES	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	
# Unique Properties	4698		6838		--
# Reservation Days	6.25	8.92	6.75	9.53	0.50**
# Blocked Days	10.00	12.76	9.85	12.54	-0.15
Occupancy Rate	0.34	0.36	0.35	0.37	0.01
Entire Home	0.63	0.48	0.57	0.50	-0.06***
House	0.72	0.45	0.68	0.47	-0.04***
# Bedrooms	1.76	1.14	1.57	1.06	-0.19***
Nightly Rate	252.90	340.52	188.78	219.81	-64.12***

# Reviews	14.98	30.58	18.08	33.19	3.10***
# Photos	16.29	11.67	17.31	12.34	1.02***
Transit Score	45.45	12.34	47.60	12.92	2.15***
AC	0.99	0.09	0.99	0.09	0.00
Breakfast	0.07	0.26	0.07	0.26	-0.00
Family-friendly	0.28	0.45	0.25	0.44	-0.03**
Gym	0.12	0.32	0.10	0.30	-0.02**
Elevator	0.06	0.23	0.09	0.28	0.03***
Laptop-friendly	0.31	0.46	0.37	0.48	0.05***
Refrigerator	0.11	0.32	0.14	0.35	0.03***
Microwave	0.10	0.30	0.13	0.34	0.03***
Washer	0.81	0.39	0.79	0.40	-0.02*
Dryer	0.86	0.35	0.86	0.34	0.00
TV	0.82	0.39	0.82	0.39	-0.00
Internet	0.97	0.17	0.97	0.16	0.00
Pool	0.24	0.43	0.19	0.39	-0.05***
Iron	0.32	0.47	0.38	0.48	0.05***
Essentials	0.49	0.50	0.54	0.50	0.05***
Smoke Detector	0.50	0.50	0.54	0.50	0.05***
Shampoo	0.42	0.49	0.45	0.50	0.04***
Beach	0.01	0.08	0.01	0.11	0.01**
Parking	0.92	0.27	0.87	0.34	-0.05***
# Supplied Days (aggregated by zip code)	9882.31	11076.14	8011.69	9192.65	-1870.62***

Notes: The group mean differences were computed without weighting the sample. As presented in Web Appendix B, the matched sample has no significant differences between the groups.

EMPIRICAL STRATEGY AND RESULTS

Difference-in-Differences (DiD) Model

Our empirical framework is based on the DiD approach (Heckman, Ichimura, and Todd 1997), which is widely applied for evaluating the effect of an intervention or treatment (in this case, Uber/Lyft's exit) on an outcome variable of interest (Airbnb property demand). This study exploits the natural experiment created by Uber/Lyft's exit from Austin to estimate the treatment effect. Specifically, the DiD analysis evaluates how demand changed among Airbnb properties in the treatment group (i.e., Austin) versus in the control group (i.e., the other four cities) after Uber/Lyft's exit.

Creating a balanced (weighted) sample for DiD analyses. We match control units with similar treated units and then calculate sample weights that reflect the frequency with which each control unit was matched with a treated unit. In the weighted sample, we expect the treatment and control groups to be comparable on a broad set of property and host characteristics.

For each property i, we estimate the propensity score, $\widehat{ps}_i$, conditional on the set of observed covariates (a broad list of variables available to us, as described in the Data section and listed in Table 1). Based on the estimated $\{\widehat{ps}_i\}_{i=1}^{I}$ for each unit i = 1, …, I, we select one or more control units that match the treated unit. We use the computed score for matching because it is effective at removing sample imbalances (Rosenbaum 2002), and it is far more efficient to match a sample using the propensity score than using all the variables (Rosenbaum and Rubin 1985). A control unit j is matched to a treated unit k if and only if $\widehat{ps}_j$ and $\widehat{ps}_k$ are similar, as determined by k-nearest neighbor matching in STATA package *psmatch2.* To avoid a bad match for treated units for which even the nearest control unit is far away, we set a caliper threshold (i.e., the maximum difference between $\widehat{ps}_j$ and $\widehat{ps}_k$) of 0.001. We allow up to four matches per treated unit.

The raw sample contains 11,605 treated properties and 48,359 control properties. The matching step leaves us with 4,698 treated properties and 6,838 control properties, and it automatically generates a weighting variable. To mitigate the concern that matching may increase the data imbalance, we iteratively check the data balance (King and Nielsen 2019) by comparing the average values of both $\widehat{ps}$ and the covariates of the treated and control units. We find that our matching strategy eliminated all significant imbalances. We provide the technical details of the matching procedure and the balance check results in Web Appendix B. In Web Appendix D, we compare the matched properties in Austin with the full sample of Austin properties, and we confirm that the matched properties are representative of Austin properties in terms of location (zip code) and accessibility (transit score). Nevertheless, the matched sample is a subsample, so the reader should interpret the estimated effects with this caveat in mind.

DiD model specification. We perform DiD regressions on the balanced (weighted) sample. The DiD method estimates the Equation (1) demand model via a weighted least squares regression (using the sample weights that were generated in the matching step):

$$DEMAND_{it} = INTERCEPT + \alpha_1 AUSTIN_i + \alpha_2 AFTER_t + \alpha_3 (AUSTIN_i \cdot AFTER_t) \qquad (1)$$
$$+ \gamma CONTROLS_{it} + PROPERTY_i + SEASONALITY_t + \varepsilon_{it}$$

where $DEMAND_{it}$ is the demand for (i.e., occupancy of) Airbnb unit i in period t. $AUSTIN_i$ equals 1 (0) if property i is in Austin (in one of the other four cities). $AFTER_t$ equals 1 (0) if period t is after (before) Uber/Lyft's exit. ε_{it} is an i.i.d. (normally distributed) random shock to $DEMAND_{it}$. $AUSTIN_i \cdot AFTER_t$ equals 1 (0) if property i was (was not) treated in period t. The key coefficient, α_3, approximates the impact of Uber/Lyft's exit on the Airbnb property demand.

The control vector, $CONTROLS_{it}$, includes time-varying variables that may correlate with property demand. For example, we obtain passenger boarding data from the US Bureau of

Transportation Statistics (BTS) and include the number of travelers visiting the city of property i in month t.[12] We also include the nightly rate, but it correlates with the demand shock (ε_{it}), so we capture $NIGHTLY\_RATE_{it}$ with four instruments: 1) the nightly rate when Proposition 1 was rejected (May 9th), 2) property characteristics (e.g., type and size), 3) the Zillow Home Value Index (ZHVI), which captures the average estimated monthly home value of properties with the same size and zip code as property i, and 4) the average monthly residential utility fees for the zip code (from OpenEI).[13] We argue that the property characteristics are exogenous (Berry et al., 1995; Nevo, 2001) because most people purchased their properties without knowing that they would become Airbnb hosts. We use the ZHVI as an indirect measure of the outside option value (i.e., listing the property for sale instead of renting it), which may influence the nightly rate (Li, Kim, and Srinivasan 2021) but should not correlate with factors on the short-term demand side.

We include property fixed effects, $PROPERTY_i$, to account for time-invariant factors (e.g., property location) that are specific to the property and may affect property demand. We also include time fixed effects, $SEASONALITY_t$, to capture seasonal patterns in demand trends. Note that $AUSTIN_i$ and $AFTER_t$ are absorbed by $PROPERTY_i$ and $SEASONALITY_t$, respectively. Hence, we rewrite our main DiD specification in Equation (2):

$$DEMAND_{it} = INTERCEPT + \alpha_3(AUSTIN_i \cdot AFTER_t) + \gamma CONTROLS_{it} + PROPERTY_i + SEASONALITY_t + \varepsilon_{it} \tag{2}$$

[12] The BTS provides market data reported by US air carriers, including the origin, destination, and number of enplaned passengers. We use the passenger boarding data as a proxy for the monthly travel demand in each city:https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/passenger/.

[13] Zillow Research provides average home values by zip code and home size: https://www.zillow.com/research/data/. The OpenEI dataset provides average residential electricity rates by zip code: https://openei.org/doe-opendata/dataset/u-s-electric-utility-companies-and-rates-look-up-by-zipcode-feb-2011.

In all main analyses, we measure property demand as occupancy: the ratio of booked days to open days in month *t*. We cluster standard errors at the individual-property level. (In Web Appendix E, we assess the robustness of our results to an alternative cluster level: the zip code.)

Validating the DiD Model: Assessing Pre-Treatment Trends

The validity of the DiD approach in Equation (2) relies on the parallel trends assumption—that the two (weighted) groups have parallel demand trends prior to the treatment (Angrist and Pischke 2008). A leads-lags relative time model is a standard method for assessing the parallel trends assumption (Autor 2003). Following the extant literature (Agrawal and Goldfarb 2008), we add a series of period dummy variables to the model by decomposing the pre-treatment periods. Specifically, we estimate the relative-time model specified in Equation (3):

$$\begin{aligned} DEMAND_{it} = INTERCEPT &+ \sum_{j} \beta_j (PRE_{it}(j) \cdot AUSTIN_i) \\ &+ \sum_{k} \beta_k (POST_{it}(k) \cdot AUSTIN_i) + \gamma CONTROLS_{it} + PROPERTY_i \\ &+ SEASONALITY_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where the added interaction term, $\Sigma_j \beta_j(PRE_{it}(j) \cdot AUSTIN_i)$, allows us to examine the possibility of falsely-significant treatment effects prior to the treatment. $PRE_{it}(j)$ is an indicator function that equals 1 if period t is j months prior to treatment. Hence, the coefficient β_j for $j = -J, -J-1, \ldots, -1, 0$ captures the pre-treatment trend in the impact of Uber/Lyft's exit on the Airbnb property demand. Similarly, $POST_{it}(k)$ is an indicator function that equals 1 if period t is k months after Uber/Lyft's exit. Hence, β_k enables us to examine dynamics in the treatment effect.

Validation of the DiD model relies on β_j, which indicates whether the estimated treatment effect began prior to the exit of Uber/Lyft. The negative estimated effect is valid only if β_j is not negative and significant. Following prior work (Agrawal and Goldfarb 2008), we set the period prior to the month of Uber/Lyft's exit as the reference period (i.e., we normalize the coefficient of April 2016 to zero) and consider the preceding three-period interval for better interpretability.

Table 2 reports the results from estimating Equation (3), and Figure 4 visualizes the estimated values of β_j for j = 2–4 (i.e., January to March; β_1 was normalized to 0). The coefficients of the pre-treatment indicators are not statistically significant, suggesting that 1) the demand for treated properties was not declining relative to the demand for control properties prior to Uber/Lyft's exit, and 2) the DiD estimation of the impact of Uber/Lyft's exit will not be falsely inflated by trends that began prior to treatment.

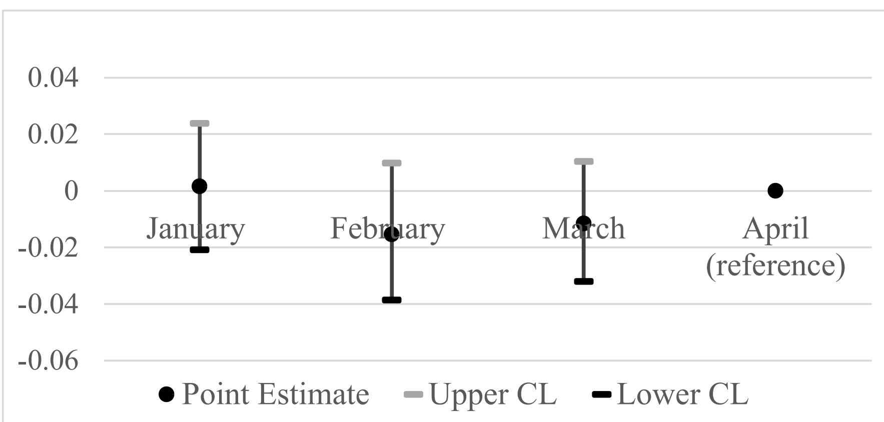
Table 2 DiD Model Validation: Relative-Time Model Assessing Pre-Treatment Trends and Post-Treatment Dynamics

VARIABLES	ESTIMATES	S.E.
Lags: Pre-Treatment Trends in Demand (Parallel Trends Validation)		
PRE_TREATMENT (-4): January	0.00149	(0.0114)
PRE_TREATMENT (-3): February	-0.0154	(0.0121)
PRE_TREATMENT (-2): March	-0.0116	(0.0107)
PRE_TREATMENT (-1): April (reference)	--	--
Leads: Post-Treatment Trends in Demand		
POST_TREATMENT (0): May	-0.0126	(0.00865)
POST_TREATMENT (1): June	-0.0820***	(0.0107)
POST_TREATMENT (2): July	-0.105***	(0.0134)
POST_TREATMENT (3): August	-0.0725***	(0.0129)
POST_TREATMENT (4): September	-0.0526***	(0.0116)
POST_TREATMENT (>4): October ~ December	-0.0293*	(0.0145)
Control Variables		
log #REVIEW	0.0468***	(0.00399)

log #PHOTO	0.0398***	(0.00990)
log NIGHTLY_RATE	-0.0581***	(0.00824)
log #SUPPLIED_DAYS (within a zip code)	0.00101	(0.00120)
log #PASSENGERS	1.108***	(0.0746)
Fixed Effect	Property	
Seasonality	Calendar Month	
Observations	67039	
R-squared	0.6675	

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties. The DV is the monthly occupancy of property *i* in month *t*. Panel *Lags: Pre-Treatment Trends in Demand (Parallel Trends Validation)* reports the estimated coefficients of the interaction terms of the treatment indicator with the period dummies in the pre-treatment months (January–April). Panel *Leads: Post-Treatment Trends in Demand* reports the estimated coefficients of the interaction terms of the treatment indicator with the period dummies in the post-treatment months (May–December). April is used as the reference period. Robust standard errors (clustered at individual-property level) are in parentheses. *p < 0.05 **p < 0.01 ***p < 0.001.

Figure 4 Plot of Estimated Coefficients in the Pre-Treatment Periods



Main DiD Model Results

After validating the parallel trends assumption, we estimated the DiD model in Equation (2). The results appear in Table 3, column 1.

Table 3 Impact of Uber/Lyft's Exit on Airbnb Property Demand

VARIABLES	(1) Main Model		(2) Controlling for RideAustin Supply	
	ESTIMATES	**S.E.**	**ESTIMATES**	**S.E.**
AUSTIN · AFTER	-0.0378***	(0.00586)	-0.0648***	(0.00689)
log #REVIEW	0.0467***	(0.00378)	0.0472***	(0.00377)
log #PHOTO	0.0400***	(0.00934)	0.0402***	(0.00932)
log NIGHTLY_RATE	-0.0604***	(0.00775)	-0.0580***	(0.00774)
log #SUPPLIED_DAYS (within a zip code)	0.000885	(0.00113)	0.00110	(0.00113)
log #PASSENGERS	1.270***	(0.0481)	1.138***	(0.0519)
RIDE_AUSTIN RIDES			0.000000307***	(4.58e-08)
Fixed Effect	Property		Property	
Seasonality	Calendar Month		Calendar Month	
Observations	67039		67039	
R-squared	0.6662		0.6662	

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties. Column (1) estimates the main DiD model (Equation 2). Column (2) controls for the supply of RideAustin, a major ride-sharing alternative that entered the market shortly after Uber/Lyft's exit. The DV is the monthly occupancy (a ratio between 0 and 1) of property *i* in month *t*. If *i* was unavailable to be booked for the entirety of *t*, then we treat the occupancy as *missing* (indefinite), and the observation for *i,t* is automatically dropped from the estimation. *SUPPLIED_DAYS* is the total number of available days among all Airbnb properties in the same zip code. *PASSENGERS* is the total number of travelers visiting the city of property *i* in *t*, computed from the passenger enplanement data reported by the BTS. *RIDE_AUSTIN RIDES* controls for the monthly rides supplied by RideAustin. The RideAustin supply is zero in the four control cities as well as in Austin prior to June 2016, when RideAustin entered the market.

Robust standard errors (clustered at the individual-property level) are in parentheses.

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

The estimated coefficient of *AUSTIN · AFTER* is negative and significant (b = -0.0378, $p <$ 0.001), suggesting that Uber/Lyft's exit reduced the overall demand for Airbnb properties in Austin. The result has economic as well as statistical significance: the average Airbnb occupancy in Austin was 0.27 in 2016, so a decrease of 0.0378 after Uber/Lyft's exit represents a 14% decrease in occupancy.

From June 2016 onward, the rapidly increasing supply of several local ride-sharing services ostensibly could have alleviated the high transportation costs caused by Uber/Lyft's exit. Travelers planning summer and fall visits might have looked for and found new, local ride-sharing alternatives (See Web Appendix I for supplementary data about travelers seeking information on ride-sharing availability and transportation costs.). Without data on all local ride-sharing services, we cannot fully tease apart the effects of Uber/Lyft's exit and the new suppliers' entries. We can, however, control for the monthly rides supplied by RideAustin, the largest supplier. The estimation results are reported in Table 3, column 2; the estimated effect size of the exit of Uber/Lyft (-0.0648) is greater than in the main model (-0.0378 in column 1). The results suggest that the decrease in Airbnb demand after Uber/Lyft's exit would have been greater without the rise of local substitutes.

EMPIRICAL EXTENSIONS: EXPLORING THE MECHANISM

Our main analyses establish a significant negative effect of Uber/Lyft's exit on the Airbnb property demand in Austin. Next, we extend our analyses to identify the mechanism by exploring heterogeneity along two key dimensions: access to public transportation and luxuriousness. We consider access to public transportation because it should moderate the impact of Uber/Lyft's exit on the convenience and cost of ground transportation for Airbnb guests. We assume that for many travelers to Austin, public transportation is a reasonable substitute for ride-sharing services; Rayle et al. (2016) found that one-third of the users of a ride-sharing service considered public transit to be the next best alternative. Then, we consider luxuriousness because it reflects the extent to which Airbnb guests have alternative lodging options. For example, low-end Airbnb properties are more likely than high-end properties to be substituted for hotels (Zervas, Proserpio, and Byers 2017). In addition, luxuriousness may capture the guest's general price sensitivity, which may correlate with their sensitivity to a surge in transportation costs.

We also analyze trends in hotel occupancy. We are most interested in determining the extent to which part of the lodging demand in Austin shifted from Airbnb to hotels following the exit of Uber/Lyft. Finally, we examine the response of Airbnb hosts after Uber/Lyft's exit in terms of the nightly rate and supply of open days.

Heterogeneous Effect by Access to Public Transportation

We investigate how transportation costs moderate the effect of Uber/Lyft's exit on the Airbnb property demand. The transportation cost associated with property i is captured by the transit score provided by walkscore.com. A low transit score implies that a property has poor access to public transportation, so a guest would have a greater need for taxi or ride-sharing services and should expect higher transportation costs. We create a categorical variable, $TRANSIT_i$, by segmenting the transit scores into four buckets (grades): grade 1 for transit score 0~24 (minimal transit), grade 2 for transit score 25~49 (some transit), grade 3 for transit score 50~69 (good transit), and grade 4 for transit score >70 (excellent transit). We estimate the moderating effect of the transit score on the treatment effect by including the interaction term of the treatment indicator and $TRANSIT_i$. Specifically, we estimate the following demand equation:

$$\begin{aligned} DEMAND_{it} = {} & INTERCEPT + \alpha_3(AUSTIN_i \cdot AFTER_t) \\ & + \rho(AUSTIN_i \cdot AFTER_t \cdot TRANSIT_i) + \eta(AFTER_t \cdot TRANSIT_i) \\ & + \gamma CONTROLS_{it} + PROPERTY_i + SEASONALITY_t + \varepsilon_{it} \end{aligned} \tag{4}$$

Note that *TRANSIT* is time-invariant and hence is absorbed by the property fixed effect term. The key coefficient, ρ, captures the moderating effect of access to public transportation.

We present the results obtained from estimating Equation (4) in Table 4. We set grade 4 as the reference category, so the coefficient of *AUSTIN·AFTER* reflects the impact of Uber/Lyft's exit on the grade 4 properties (i.e., excellent access). The coefficient of the key variable, *AUSTIN·AFTER·TRANSIT*, captures the moderating effect of access to public transportation on the Airbnb property demand after Uber/Lyft's exit. The results indicate that the exit of Uber/Lyft led to a significant *increase* in the demand for grade 4 properties and a significant *decrease* in the demand for properties in grades 1–3. Specifically, the grade 4 properties experienced an occupancy increase of 0.0410 (+9.1%, relative to the average occupancy of 0.45 among grade 4 Austin properties in 2016) after the exit of Uber/Lyft. One-sided t-tests show that the treatment effect is similar for grade 1 and grade 2 properties (p-value = 0.28), while the grade 2 properties experienced a significantly greater decrease in occupancy than the grade 3 properties (p-value = 0.029). We reason that Uber/Lyft's exit had differential effects on property demand across the transit score grades because transportation costs are a key factor in travelers' lodging choices, and in the absence of Uber/Lyft, access to public transportation is a key determinant of transportation costs. Hence, properties with poorer access to public transportation experienced a steeper decline in demand after the exit of Uber/Lyft. In a robustness test, we use an alternative gradation of the transit score, and the results are consistent (see Web Appendix F for details).

Table 4 Heterogeneous Effects of Uber/Lyft's Exit on Demand: Moderated by Access to Public Transportation

VARIABLES	**ESTIMATES**	**S.E.**
	Interaction with transportation access (transit scores grouped into grades 1–4)	
AUSTIN · AFTER (reference: grade 4)	0.0410**	(0.0153)
AUSTIN · AFTER · TRANSIT (grade 3)	-0.0628***	(0.0112)
AUSTIN · AFTER · TRANSIT (grade 2)	-0.0945***	(0.0121)
AUSTIN · AFTER · TRANSIT (grade 1)	-0.117***	(0.0315)
log #REVIEW	0.0467***	(0.00378)
log #PHOTO	0.0397***	(0.00930)
log NIGHTLY_RATE	-0.0593***	(0.00775)
log #SUPPLIED_DAYS (within a zip code)	0.000817	(0.00113)
log #PASSENGERS	1.297***	(0.0479)
Fixed Effect	Property	
Seasonality	Calendar Month	
Observations	67039	
R-squared	0.6667	

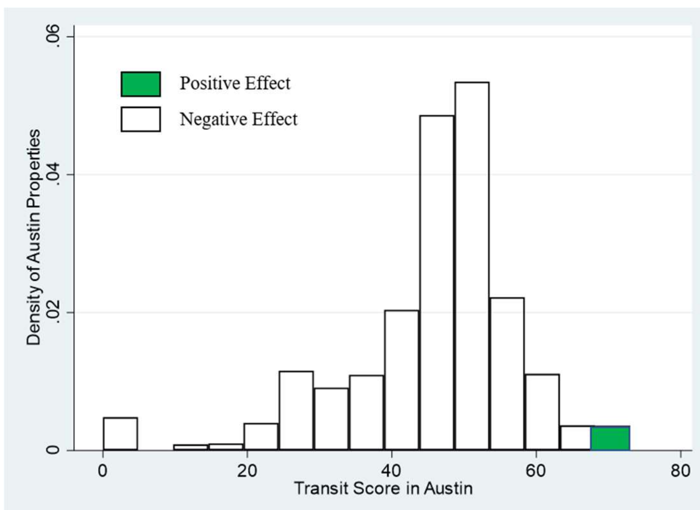
Notes: The model is estimated on the matched sample of 11,536 Airbnb properties. The DV is the monthly occupancy (a ratio between 0 and 1) of property *i* in month *t*. The local transit score grades are based on the categorization provided by walkscore.com: grade 1 is a transit score of 0~24 (minimal access to public transportation), grade 2 is 25~49 (some access), grade 3 is 50~69 (good access), and grade 4 is > 70 (excellent access). The common shift, captured in *AFTER · TRANSIT*, is controlled for and not shown.

Robust standard errors are clustered at the individual-property level.

* p < 0.05 ** p < 0.01 *** p < 0.001

Although Uber/Lyft's exit increased the demand for Airbnb properties with excellent access to public transportation, few properties fall into this category—the average transit score among Austin Airbnb properties is only 45 (grade 2). In Figure 5, we plot the distribution of transit scores in our sample. The exit of Uber/Lyft hurt all properties except for those with excellent transit scores, shaded green on the graph.

Figure 5 Distribution of Transit Scores and Positive vs. Negative Effects of Uber/Lyft's Exit on Demand for Austin Airbnb Properties



Notes: The horizontal axis is the transit score, and the vertical axis indicates the sample frequency (i.e., the number of observed units that fall in each bin).

Heterogeneous Effect by Luxuriousness

To further understand the mechanism underlying the treatment effect, we investigate heterogeneity in the effect based on property luxuriousness (high-end vs. low-end). We reason that the guests of lower-end Airbnb properties are more likely to be budget-constrained and hence more sensitive to a surge in the transportation cost. The exit of Uber/Lyft increased the transportation cost associated with all but the few central Airbnb properties because the remaining options—taxi, RideAustin, car rental, or public transportation—were more expensive and/or more inconvenient than Uber/Lyft. (See Web Appendix A for analysis and discussion). Price-sensitive guests should be more likely to switch from Airbnb properties with poor access to public transportation to lodging alternatives (e.g., economy hotels or other Airbnb properties with better access to public transportation) after Uber/Lyft's exit.

We use property nightly rates to construct a series of dummy variables that reflect luxuriousness, with the assumption that a more expensive property is more likely to be a higher-end option rather than a budget option. Using hotel prices as a reference, we define a property as "high-end" if its average nightly rate is above \$300, which is close to the average price of the top two hotel classes (explained in Table 6). We estimate the heterogeneous model (Equation 4) on the subsamples of high-end and low-end properties. As a robustness check, we repeat the analyses with a threshold of \$250, the average price of the top three hotel classes.

Table 5 reports the estimation results. First, we observe that the results are consistent between the \$300 threshold (columns 1 and 2) and the \$250 threshold (columns 3 and 4); we focus on the \$300 threshold here. The results in column 1 suggest that occupancy increased for the low-end properties with excellent access to public transportation (*reference: grade 4*: $b = 0.0454$, $p < 0.01$) while decreasing for all other low-end properties. For high-end properties (column 2), however, Uber/Lyft's exit did not affect occupancy.

Table 5 Heterogeneous Effects of Uber/Lyft's Exit on Demand: High-End vs. Low-End Airbnb Properties

VARIABLES	High-end threshold: \$300		High-end threshold: \$250	
	(1) Low-end	**(2) High-end**	**(3) Low-end**	**(4) High-end**
AUSTIN · AFTER	0.0454**	0.0144	0.0414**	0.0420
(reference: grade 4)	(0.0164)	(0.0217)	(0.0151)	(0.0310)

AUSTIN · AFTER · TRANSIT	-0.0794***	0.00740	-0.0714**	0.0482
(grade 3)	(0.0233)	(0.0201)	(0.0250)	(0.0304)
AUSTIN · AFTER · TRANSIT	-0.0897***	-0.0420	-0.0838***	-0.0270
(grade 2)	(0.0235)	(0.0228)	(0.0253)	(0.0313)
AUSTIN · AFTER · TRANSIT	-0.123***	0.00565	-0.116**	-0.0221
(grade 1)	(0.0328)	(0.0240)	(0.0387)	(0.0400)
log #REVIEW	0.0533***	-0.000854	0.0540***	0.0160
	(0.00382)	(0.0153)	(0.00394)	(0.0109)
log #PHOTO	0.0394***	0.0381*	0.0337**	0.0594**
	(0.0101)	(0.0170)	(0.0103)	(0.0220)
log NIGHTLY_RATE	-0.0650***	-0.0169	-0.0651***	-0.0500***
	(0.00898)	(0.0169)	(0.00971)	(0.0122)
log #SUPPLIED_DAYS	0.000602	0.00140	0.000296	0.00263
(within a zip code)	(0.00122)	(0.00278)	(0.00128)	(0.00237)
log #PASSENGERS	1.271***	1.198***	1.291***	1.164***
	(0.0518)	(0.139)	(0.0534)	(0.110)
Fixed Effect	Property	Property	Property	Property
Seasonality	Calendar Month	Calendar Month	Calendar Month	Calendar Month
Observations	57831	9208	52753	14286
R-squared	0.6747	0.6050	0.6716	0.5898

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties. The DV is the monthly occupancy of property *i* in month *t*. The common shift and coefficients of *AFTER · TRANSIT* are controlled for and not shown. We estimate the DiD model (Equation 2) on the subsamples of low-end (columns 1 and 3) and high-end properties (columns 2 and 4). We use two different definitions of the "high-end" nightly rate: above \$300 (the average price for the top two hotel classes) and above \$250 (the average price for the top three hotel classes). Robust standard errors (clustered at the individual-property level) are in parentheses. * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

From Table 5, we infer that after Uber/Lyft's exit, travelers who tended to stay at low-end Airbnb properties shifted toward options with better access to public transportation. Since few Airbnb properties have excellent access, we reason that these guests used low-end hotels as substitutes for low-end Airbnb properties (Li and Srinivasan 2019; Zervas, Proserpio, and Byers). By contrast, the guests of high-end properties did not seem to shift after Uber/Lyft's exit. We reason that high-end Airbnb properties might be more differentiated from hotels, so guests might have a stronger preference for Airbnb over a hotel despite the increase in transportation costs. (Our rationale is consistent with Airbnb's goal of providing authentic, novel, and interactive experiences; see Guttentag et al. 2018.) Guests of high-end properties may have used (costlier) alternatives to Uber/Lyft, perhaps renting a car or enduring the wait time for a taxi.

In summary, although all Airbnb properties with poorer access to public transportation had similar increases in the cost and inconvenience of transportation following Uber/Lyft's exit, only the low-end properties lost demand. Next, we analyze hotel occupancy to support our argument that a large fraction of that demand shifted to alternatives in more central locations.

Effect by Substitution: Analyzing Hotel Demand

So far, we have established an overall decrease in the demand for Austin Airbnb properties, relative to properties in four control cities, after the exit of Uber/Lyft. The analysis revealed that Uber/Lyft's exit primarily hurt low-end properties (but not high-end properties) and actually benefited the few properties with excellent access to public transportation. Next, we leverage hotel demand data to provide additional empirical evidence for the proposed mechanism.

Our approach is twofold. First, we investigate the main effect of Uber/Lyft's exit on the demand for Austin hotels. Second, we explore potential heterogeneity in the effects across hotels. The first analysis helps to verify the identified treatment effect—that the exit of Uber/Lyft reduced demand for Airbnb properties. Austin's popularity as a travel destination did not seem to be affected by the exit of Uber/Lyft,[14] so we assume that the total need for lodging in the city remained constant. After Uber/Lyft's exit, some travelers who otherwise would have stayed at an Airbnb property looked for alternative lodging—most likely, a (centrally located) hotel—where transportation costs would be manageable. We expect the amount of shifted demand to depend on the substitutability between the lodging alternative and the average Airbnb property.

We obtained hotel demand data from Smith Travel Research (STR) for 2015–2016. Due to privacy concerns, STR does not provide any identifying information (e.g., the hotel name, location, or name of the operator chain). At the hotel level, the data includes the city, year the hotel opened, monthly average daily rate, and monthly occupancy rate. We estimate the effect of Uber/Lyft's exit on hotel occupancy, and we examine heterogeneity by hotel class, as defined by STR: 1. Luxury Chains, 2. Upper Upscale Chains, 3. Upscale Chains, 4. Upper Midscale Chains, 5. Midscale Chains, and 6. Economy Chains. In Table 6, we present the statistics for the hotels, grouped by class.[15]

We use the class information as a moderator because a hotel's class may capture the extent to which Airbnb guests perceive it as a substitute for Airbnb properties. Zervas, Proserpio, and Byers (2017) found that travelers are more likely to use Airbnb properties as substitutes for

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[14] Two organizations, downtownaustin.com and austintexas.org, report the monthly number of visitors to Austin. The Federal Aviation Administration (FAA) and Austin-Bergstrom International Airport report monthly passenger enplanement data. All sources indicate that Austin's popularity stayed roughly the same level after Uber/Lyft's exit. The FAA reports suggest that the number of monthly visitors to Austin (from January to December) in 2016 was: 421831, 404183, 516905, 484865, 507576, 526555, 535240, 517170, 494638, 530397, 512216, 485721, respectively.

[15] There is a hotel category called "Independence," which STR assigns to hotels that do not belong to any chain. For clarity, we removed this category from the sample. The results are consistent when independent hotels are included.

cheaper hotels than for more expensive hotels. Hence, lower-end hotels should be more likely than higher-end hotels to capture demand from Airbnb properties following Uber/Lyft's exit.

Table 6 Hotel Statistics: Grouped by Hotel Class (2015–2016)

VARIABLES	Mean	Std. Dev.
Class 1 (*Luxury*), 58 unique hotels		
Occ (Occupancy Rate, %)	78.512	11.641
ADR (Average Daily Rate)	371.508	181.133
Hotel Years (# years since open)	33.441	32.943
Class 2 (*Upper Upscale*), 208 unique hotels		
Occ (%)	79.848	12.205
ADR	193.313	54.995
Hotel Years	29.841	22.984
Class 3 (*Upscale*), 381 unique hotels		
Occ (%)	79.492	13.095
ADR	154.276	39.927
Hotel Years	19.891	13.593
Class 4 (*Upper Midscale*), 420 unique hotels		
Occ (%)	74.872	15.498
ADR	120.64	30.582
Hotel Years	21.537	14.284
Class 5 (*Midscale*), 189 unique hotels		
Occ (%)	70.169	18.366
ADR	96.194	23.978
Hotel Years	29.096	14.357
Class 6 (*Economy*), 414 unique hotels		
Occ (%)	73.346	17.451
ADR	75.799	20.588
Hotel Years	31.709	14.386

Notes: The statistics are computed by hotel group and averaged across 2015–2016.

Table 7 presents the estimated average effect of Uber/Lyft's exit on hotel occupancy (column 1) and heterogeneity in the effect using the hotel class as a moderator (column 2). The hotel occupancy model includes fixed effects at the year-month level and city-month level. We also include hotel-specific linear and quadratic time trends to allow for year- and city-specific seasonal patterns as well as correlations between the hotel-specific trends and time-variant variables.

The estimated coefficient of the key variable, *AUSTIN · AFTER,* is positive and significant in column 1, indicating that the average occupancy of Austin hotels increased by 1.229% after Uber/Lyft's exit. (This coefficient translates into 1.229% * 30 ~ 0.37 days/month, given an average hotel occupancy of 75.7% and an increase of 1.229% / 75.7% = 1.62%.) The result is consistent with our prediction that hotels, as a prevalent alternative lodging option, likely captured much of the demand from Airbnb properties after Uber/Lyft's exit.

Column 2 displays the estimated coefficients of the interaction terms. We find significant positive coefficients of *AUSTIN · AFTER · Class 5* and *AUSTIN · AFTER · Class 6*, a marginally significant positive coefficient of *AUSTIN · AFTER · Class* 4 ($p < 0.1$), and insignificant coefficients of the interaction terms involving hotel classes 1, 2, and 3. These results suggest that the lower-end hotels absorbed most of the demand following the exit of Uber/Lyft, likely because travelers perceived cheaper hotels as the closest substitute for Airbnb.

A price comparison supports our theory. Among low-end (nightly rate < $300) Austin Airbnb properties, the mean per-bedroom nightly rate was $85.77 for grade 1 (minimal access to public transportation), $95.54 for grade 2, $109.58 for grade 3, and $158.73 for grade 4 (excellent access). Meanwhile, midscale hotels (class 5) charged an average nightly rate of only $96.19, and economy hotels (class 6) charged $79.80. In terms of price alone, price-sensitive guests of a low-end, grade 1–3 Airbnb property might find that the closest substitute is a lower-end hotel, not a low-end, grade 4 Airbnb property.

Table 7 Impact of Uber/Lyft's Exit on Hotel Occupancy

VARIABLES	ESTIMATES	
	(1) Base Model	(2) Interaction with Hotel Class
AUSTIN · AFTER	1.229*	-2.067
	(0.568)	(1.747)
Heterogeneous Effects Across Hotel Classes (*Luxury* as baseline)		
AUSTIN · AFTER · Class 2		3.609
(*Upper Upscale*)		(2.018)
AUSTIN · AFTER · Class 3		1.678
(Upscale)		(1.849)
AUSTIN · AFTER · Class 4		3.142
(Upper Midscale)		(1.735)
AUSTIN · AFTER · Class 5		4.673*
(Midscale)		(1.858)
AUSTIN · AFTER · Class 6		4.221*
(Economy)		(1.793)
Control Variables		
log # HOTEL_YEARS (# years since open)	14.75***	14.97***
	(1.574)	(1.577)
log #HOTELS (within a city)	-5.683	-5.884
	(12.84)	(12.84)
log Hotel Avg. ADR (within a city)	54.58***	54.66***
	(5.527)	(5.530)
log Airbnb Avg. Price (within a city)	7.767*	7.763*
	(3.393)	(3.393)

log Airbnb Tot. # Listings (within a city)	7.845***	7.864***
	(1.512)	(1.512)
Fixed Effect	Hotel	Hotel
Time Trends	Linear, Quadratic	Linear, Quadratic
Seasonality	Year-Month, City-Month	Year-Month, City-Month
Observations	38422	38422
R-squared	0.7851	0.7853

Notes: The DV is the occupancy (a ratio between 0 and 1) of hotel *i* in period *t*. The models are estimated on the monthly occupancy, reported by STR, during 2015–2016 for hotels in Austin, Boston, Los Angeles, San Diego, and Seattle. The Airbnb supply variables (*Airbnb Avg. Price, Airbnb Tot. # Listings*) are computed on all Airbnb properties (not just the matched properties) in the same city.
Robust standard errors (clustered at the individual-hotel level, identifier provided by STR as "SHARE ID") are in parentheses.
* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Strategic Response by Airbnb Hosts: Analyzing the Nightly Rate and Open Days

We examine how Airbnb hosts strategically responded to the exit of Uber/Lyft by modifying price and supply. We replicate our DiD model by regressing the logged nightly rate on the key treatment indicator, *AUSTIN · AFTER*. Results (reported in Web Appendix G) reveal a decrease of $9.3 in the average nightly rate after Uber/Lyft exited Austin. Mirroring the change in demand, the nightly rate did not change for high-end properties or for low-end properties with excellent access to public transportation, while the price for all other low-end properties decreased by 11.5% (~$12.8).

We consider whether the hosts' price response was sufficient to compensate for the increased transportation costs associated with Uber/Lyft's exit. As described earlier (and explained fully in Web Appendix A), we checked the fares for a round trip via taxi, Uber, and Lyft between each Austin zip code and two popular destinations. We found that a taxi costs much more than an

Uber/Lyft: $25.71 more for the average Airbnb property with *good* access to public transportation, $41.38 for those with *some* access, and $61.50 for those with *minimal* access.[16] A price reduction of $9.3 or $12.8 per night would not fully compensate for the surge in transportation costs in the absence of Uber/Lyft.

Next, we assess the impact of Uber/Lyft's exit on the number of days that the host made the listing available (open) to be booked. We regress the number of open days on the key dummy variable, *AUSTIN · AFTER*. Results (provided in Web Appendix G) reveal a 4.5% decrease in the Airbnb supply following the exit of Uber/Lyft. (Note that 3.7% of the listings dropped out, meaning that they had zero open days).[17] As with the nightly rate, we find a bigger drop in open days among properties with poorer access to public transportation. The results indicate that Uber/Lyft's exit hurt Airbnb revenue in two ways: by reducing demand for Airbnb properties and by prompting hosts to decrease their prices and supply.

Evolution of the Treatment Effect and Long-Term Equilibrium

Uber/Lyft's exit was a shock in Austin's transportation market, and the market responded—for example, with the entry of new ride-sharing services. We evaluate how the evolution of the transportation market aligns with the evolution of the home-sharing market (specifically, Airbnb demand, price, and supply) in May–December 2016. Examining how the treatment effect

[16] We estimated the fares by querying routes on https://www.taxifarefinder.com/ for taxis and on ride.guru for Uber/Lyft. We found the geolocation of the "centroid" of Austin properties in each zip code and estimated the fares to/from Austin's downtown and airport.

[17] We say that a property "dropped out" if it was unavailable for the whole month (as the occupancy for that month would be indefinite and automatically dropped from the regressions). Of the low-end properties with poor transit, 12.9% dropped out.

evolved over time, with consideration of market and host responses, helps us understand what the long-term equilibrium might look like.

When we estimated a relative-time model to validate the parallel trends assumption for the DiD model, we included a series of coefficients of the leads, $\sum_k POST_{it}(k)$. We use these coefficients to investigate how the treatment effect evolved over time. We also estimate analogous relative-time models on the nightly rate and supply (Web Appendix G). We find that none of the variables (occupancy, nightly rate, and supply) changed significantly in May 2016 (insignificant coefficient of *POST_TREATMENT (0)*). This is unsurprising given that Uber/Lyft did not terminate their services until May 9th, and some of the Airbnb reservations for the rest of the month likely were booked before May 9th, without knowledge of Uber/Lyft's impending exit. In June (*POST_TREATMENT (1)*), occupancy fell, and hosts decreased the nightly rate but did not change the supply. In July (*POST_TREATMENT (2)*), hosts decreased the nightly rate even more and also reduced the supply, yet occupancy still fell. In August (*POST_TREATMENT (3)*), the hosts made the biggest cut to the nightly rate and reduced the supply again, and the drop in demand was smaller than in July.

By September, new local ride-sharing services (e.g., RideAustin, see Web Appendix A) had gained a significant market presence and were mitigating the gap left by Uber/Lyft.[18] In September (*POST_TREATMENT (4)*), the decreases in both the occupancy and nightly rate were smaller than the month before, though supply decreased by a larger magnitude than in the month before. Local ride-sharing services continued to gain momentum from October through

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[18] Travelers who were planning a summer or fall visit to Austin might have looked for and found ride-sharing alternatives.

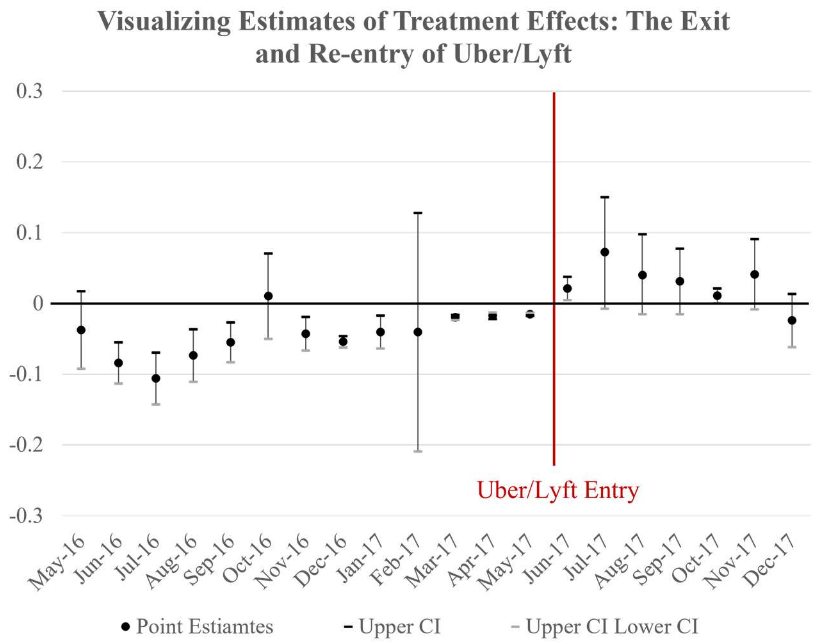
December (*POST_TREATMENT (>4)*); the decreases in the occupancy, nightly rate, and supply were all smaller than in the month before.

In sum, it appears that Airbnb hosts first tried to respond to the falling demand by reducing their prices. When this was insufficient, hosts reduced the supply as well. As local ride-sharing services gained momentum and mitigated the increased transportation costs, the Airbnb demand began to plateau, and hosts were able to reduce the price and supply to a smaller extent (though all variables remained significantly lower than before Uber/Lyft's exit).

Re-Entry of Uber/Lyft

Uber and Lyft returned to Austin in late May 2017 after Texas passed a statewide system of ride-hailing regulations (HB 100) that overruled Austin's Proposition 9. We use the 2016–2017 demand data from the same matched sample to examine the "re-entry effect," thereby increasing the validity of the estimated main effect of Uber/Lyft's exit in 2016. The analysis includes two treatments: Uber/Lyft's exit (May 2016 – May 2017) and re-entry (June 2017 – December 2017), and we decompose the treatment periods by month to examine how the coefficients evolved over time (visualized in Figure 6). Our results show that Uber/Lyft's re-entry fully negated the negative effect of Uber/Lyft's exit on Airbnb property demand in Austin. We reason that the exit of Uber/Lyft left a gap in the supply of convenient, affordable transportation, which was only partially mitigated by new local ride-sharing services. Then, the re-entry of Uber/Lyft quickly closed the residual gap, and property demand almost immediately returned to the pre-exit level. The analyses and full estimation tables are presented in Web Appendix H.

Figure 6 Plot of Estimated Coefficients in the Post-Treatment and Post-Re-Entry Periods



Robustness Checks

We verify the robustness of our main results with an extensive set of analyses. We use a matching estimation to verify that our estimation is robust to the model's specification. We use a placebo test with Airbnb data from the prior year (2015) to show that the estimated treatment effect was not due to seasonal factors that were specific to Austin in 2016. Finally, we use a Generalized Synthetic Control analysis to confirm the negative impact of Uber/Lyft's exit on the Airbnb property demand. We report these analyses in detail in Web Appendix F.

CONCLUSION

Internet-based sharing economy platforms enable individual users to monetize their excess capacities, and the platforms are becoming increasingly popular across industries. In this study, we report the demand interdependence of two popular sharing economy platforms: Airbnb (home sharing) and Uber/Lyft (ride sharing). We find that after Uber/Lyft exited Austin, the occupancy of Austin Airbnb properties decreased by 14%, providing evidence of demand complementarity. We also find that low-end Airbnb properties with poorer access to public transportation lost demand to both low-end hotels and the few low-end Airbnb properties with excellent access to public transportation.

The home-sharing economy is built around immovable shared resources. The fixed location of the resource limits the demand for the resource, particularly when the location is underserved by traditional transportation services (e.g., public transportation, taxis). By contrast, ride-sharing services involve a moveable shared resource—so ride-sharing services can alleviate transportation constraints in areas that otherwise have few transportation options. If regulators try to restrict or eliminate one sharing economy service, they may inadvertently affect others. Although policy makers in Austin likely did not intend to harm the home-sharing economy, their regulation of the ride-sharing economy ultimately hurt the demand for Airbnb properties. Likewise, we posit that the elimination of home-sharing services could hurt the demand for ride-sharing services, which face less competition from traditional transportation services in residential areas (Liu, Brynjolfsson, and Dowlatabadi 2021). If home-sharing regulations caused a decrease in the demand for travel to residential areas, then ride-sharing services may face increased competition. Our work implores regulators to consider the interdependencies among the many sharing economy services when creating restrictive legislation for one.

Our study also sheds light on the moderating role of ride-sharing services in the competition between hotels and home-sharing services. Consistent with Li and Srinivasan (2019) and Zervas, Proserpio, and Byers (2017), our results reveal that low-end hotels face competition from low-end Airbnb properties. At the high end of the price spectrum, however, customers view hotels and Airbnb as differentiated. This finding should be particularly concerning for Airbnb, as most Airbnb properties are low-end, and most do not have excellent access to public transportation. Low-end properties cater to more price-sensitive customers, so any increase in transportation costs negatively affects their demand, as shown by our analysis. As a result, Airbnb demand is particularly sensitive to the presence of ride-sharing services. Airbnb may be able to reduce this vulnerability by attracting more high-end properties and more properties in commercial districts (which generally have excellent transit scores).

Other operators in the sharing economy market could capitalize on the demand complementarity between Airbnb and Uber/Lyft. For example, Airbnb hosts and Uber drivers could provide a bundled offering for commuting to or from Airbnb properties. The principle of demand complementarity may also be applied to other industries such as retail. For example, Uber/Lyft facilitates the exploration of restaurants, shops, and other activities that are farther from the commercial core. Retailers and business owners should understand how the presence of Uber/Lyft can impact their demand, moderating the competitive landscape by reducing the locational disadvantage of peripheral retailers relative to retailers in the commercial core.

The mechanism through which ride-sharing services affect demand for home-sharing services indicates that the effect of ride-sharing services may vary based on the transportation needs of the average traveler in the city. Specifically, the treatment effect might depend on the city's attractiveness to tourists. If Austin is less appealing as a tourist destination than many other cities, then the treatment effect might not generalize well to other places. We reviewed tourism information and concluded that Austin is indeed attractive to tourists, and we also reason that the strength of the treatment effect should *increase* with the destination's attractiveness. In more popular tourist destinations, the average visitor might plan more trips from their lodging to local attractions—so local transportation costs would comprise a larger share of the travel budget. If ride-sharing services disappeared, these visitors would face a steeper increase in transportation costs and may be more likely to shift to lodging in areas with better transit scores. In Web Appendix I, we discuss Austin's attractiveness to tourists and the implications for the generalizability of our results.

As the sharing economy continues to expand, we are likely to see growing interdependence between platforms that provide related services. We note that the rise of sharing economies has generated a great deal of attention in academia and policy debates, but most prior studies have focused on the impact of one sharing economy on incumbent industries while ignoring the interactions among sharing economies. In the aftermath of policies that change the availability of high-quality ride-sharing services like Uber and Lyft, we may expect to see the rise of new, local ride-sharing services. Yet, if the new entrants cannot fully close the gap in demand for affordable, convenient transportation, then the demand for low-end lodging in peripheral areas (with poorer access to local transportation) likely will decrease as travelers shift to alternative lodging options in the city center (with better access to local transportation). In the long term, Airbnb hosts may eventually adapt fully to the shifted demand, with an increase (decrease) in the number of properties, open days, and prices in areas with better (worse) access to public transportation—just as hotels have determined their supply based on the travel demand. Our research effort is the first step in understanding the externalities between sharing economies.

This research is not without limitations. First, we do not have data on individual travelers' joint decisions regarding lodging and transportation. Individual-level data would enable a richer analysis if the data contained many within-individual repeated choices before and after Uber/Lyft's exit. Second, our robustness analyses on the prior-year data (2015) and the re-entry of Uber/Lyft (2017) suggest that the main effect in 2016 was unlikely to be driven by an annual or seasonal idiosyncratic shock, but the analyses cannot completely rule out the possibility of a shock in May 2016, specifically. Although we control for the overall travel demand (monthly passengers), we cannot verify whether there was a systematic shift in lodging preferences among travelers to Austin after May 2016. Lastly, it is possible that the travelers to cities in our sample differed systematically in their income (and, hence, they differed in their ability to afford expensive transportation options). With access to data on traveler income and demographics, future research can explore whether and how the effect of Uber/Lyft on Airbnb property demand might vary across cities.

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Web Appendix for

Demand Interactions in Sharing Economies: Evidence from a Natural Experiment Involving Airbnb and Uber/Lyft

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WEB APPENDIX A: SUPPLEMENTARY DATA ON TRANSPORTATION OPTIONS

Comparison of the Fares Charged by Ride-Sharing and Taxi Services

We compare the cost of taxi services vs. Uber/Lyft. We consider two components of cost: the monetary cost (price) and inconvenience (e.g., wait time).

Brown and LaValle (2021) conducted a formal comparison of taxi and Uber/Lyft fares in Los Angeles, based on a dataset of 1,680 trips. For the same origin-destination pair, Uber/Lyft users paid 40% less than taxi users and waited about one-quarter of the time for the ride to arrive. Greenwood and Wattal (2017) did not perform a formal comparison of fares, but the authors state that Uber X "offers significant discounts (~20% to ~30% price reductions from taxis)." Many media reports concur that Uber and Lyft are cheaper than taxis in many cities.[1] Two other papers offer explanations for why Uber/Lyft may charge lower fares than taxis. Cramer and Kruger (2016) argue that the fare discrepancy is attributable to capacity utilization: a passenger is in the car for 50% of the average Uber driver's shift but only 30% to 50% (depending on the city) of the average taxi driver's shift. Also, the construction of the fare differs between Uber/Lyft and taxi services. The standard fare components are the base fare, fare per minute, and fare per mile. Uber, relative to taxi services, charges a lower fare per mile but a slightly higher base fee, so we acknowledge that taxis may be cheaper for very short trips (less than half a mile).[2]

[1] For example, in a Business Insider report (http://www.businessinsider.com/uber-vs-taxi-pricing-by-city-2014-10), the ratio of a taxi fare (including a 20% tip) to an Uber fare was as high as 2.1 in Los Angeles and as low as 1.0 in New York. Also, see other media reports: https://www.lifewire.com/what-is-cheaper-an-uber-or-a-taxi-4157965; https://money.com/the-only-3-major-airports-where-a-taxi-is-cheaper-than-an-uber/.

[2] https://www.compare.com/ways-to-save/vehicle/uber-vs-lyft-vs-taxi

The relationship between Uber/Lyft and taxi fares differs by city, so we research the fares in Austin to provide stronger evidence that Uber/Lyft's exit from Austin increased transportation costs. We compare the estimated (average) fares of taxis, Uber, and Lyft in Austin from two sources: 1) https://www.taxifarefinder.com and 2) https://ride.guru. These sites estimate the fare for a given route (with a specified pick-up address and drop-off address).

For each zip code in our sample, we first calculate the center of the set of Airbnb properties in the zip code by averaging the latitudes and longitudes. We use the geographic center as the pick-up address, and we calculate roundtrip fares to the Austin International Airport and Austin Convention Center (downtown) for taxis, Uber, and Lyft.

Table W1 reports, for each zip code, the coordinates of the geographic center, the average transit score in the zip code, and the roundtrip taxi, Uber, and Lyft fares (without tips) to the aforementioned destinations. Then, we combine the zip codes that fall into the same transit score grade and repeat the calculations, reported in Table W2 for a roundtrip to the airport and in Table W3 for a roundtrip to downtown.

Since the Uber and Lyft fares are very similar, we will focus on the comparison between Uber and taxi services. We find that Uber is consistently cheaper. In Table W2, the difference between the taxi and Uber fares for a roundtrip to the airport is $22.86 (50%), $27.75 (50.68%), and $36.50 (51.14%) for the average pick-up address with a transit score in grade 3 (good transit), grade 2 (some transit), and grade 1 (minimal transit), respectively. In Table W3, the difference between the taxi and Uber fares for a roundtrip to downtown is $2.86 (14.49%), $13.63 (42.91%), and $25 (53.33%) for the average pick-up address with a transit score in grade 3, grade 2, and grade 1, respectively. In both tables, there is a negative relationship between the transit score and distance from the destination, and the advantage of Uber over taxis increases with the distance of the ride.

Table W1 Fare Comparison by Zip Code for a Roundtrip to Downtown and to the Airport

	Geographic Center			To Downtown (Austin Convention Center)				To Airport (AUS)			
Zip code	(mean) Latitude	(mean) Longitude	Mean Transit Score	Distance (miles)	Taxi Fare	Uber Fare	Lyft Fare	Distance (miles)	Taxi Fare	Uber Fare	Lyft Fare
78701	30.26878	-97.7436	68.5463	0.7	5	7	6	8.9	32	22	22
78702	30.26504	-97.7204	50.51378	1.8	8	8	7	8.9	30	17	16
78703	30.2844	-97.7626	43.3107	3.1	13	8	9	15.8	42	27	27
78704	30.24722	-97.7621	48.50761	2.2	10	9	9	11	31	22	22
78705	30.29339	-97.7402	59.70588	3.2	13	10	10	13.6	38	26	26
78717	30.49158	-97.7751	8.222222	22.3	54	35	35	37.2	86	55	54
78721	30.27445	-97.687	43.63158	4.7	16	12	12	10.2	29	20	20
78722	30.29002	-97.7148	51.36301	3	11	10	10	11.6	33	23	22
78723	30.3046	-97.6918	41.90345	5.5	18	13	13	14.2	38	26	26
78724	30.29562	-97.6467	30.58333	10.1	28	20	19	13.6	37	25	25
78725	30.25878	-97.6659	25.35714	6.3	20	14	15	10	28	20	20
78726	30.43052	-97.8672	2	17.2	45	29	29	28.3	68	45	45
78727	30.42853	-97.7175	24.52381	14.3	38	24	24	24.7	61	39	39
78728	30.44983	-97.688	21.18182	16.2	41	27	27	26.4	64	41	41
78729	30.45554	-97.7639	13.9	16.1	42	28	27	27.1	65	42	42
78730	30.36114	-97.8089	0.692308	11.7	32	22	22	22.7	57	38	38
78731	30.33942	-97.7593	30.53933	6.7	21	14	14	19.7	50	32	33
78732	30.40732	-97.8752	0	16.8	43	29	29	27.8	67	45	44
78733	30.32774	-97.862	0	10.3	29	21	20	19.3	50	33	33
78735	30.24705	-97.834	16.4	7.8	23	16	16	14.1	38	26	25
78736	30.2441	-97.9028	14.57143	11.9	32	22	22	18.1	47	30	30
78737	30.21716	-97.9216	4	13.8	42	25	25	20.1	51	34	34
78739	30.19018	-97.8931	8	12.5	38	22	22	18.7	42	31	31
78741	30.23551	-97.726	49.70303	2.5	10	9	9	8.5	26	19	18

78744	30.18296	-97.7395	29.95556	6.3	19	14	14	8.9	27	19	19
78745	30.2086	-97.7935	39.4188	7.5	22	16	16	11.6	33	23	23
78746	30.27588	-97.7948	20.16964	4.7	17	12	12	14.7	40	26	27
78747	30.15245	-97.7491	23.52941	10.6	34	20	20	9.6	29	20	20
78748	30.17297	-97.8182	24.38095	10.7	34	21	21	15.6	42	29	29
78749	30.21445	-97.8461	24.59091	9	26	18	18	15.2	41	27	27
78750	30.42002	-97.7971	14.35714	14.2	38	25	25	26.8	64	42	41
78751	30.31004	-97.7246	54.11364	4.7	15	12	12	13.4	37	26	25
78752	30.33224	-97.7061	49.95588	5.7	17	13	12	16.8	44	27	28
78753	30.37744	-97.6736	33.225	9.8	27	19	18	19.4	49	32	32
78754	30.3494	-97.6401	12.88889	11.3	31	21	21	21	53	34	34
78756	30.31946	-97.7402	49.33333	6.8	20	15	15	14.5	40	27	26
78757	30.34769	-97.7306	47.58065	8.8	26	18	18	19.1	49	32	32
78758	30.39011	-97.7094	40.20588	11.6	31	21	21	20.6	52	33	34
78759	30.39634	-97.7503	27.4	10.1	28	19	19	21.3	53	34	34

Notes: The latitude and longitude were converted to an address using reserved geocoding code (https://www.latlong.net/Show-Latitude-Longitude.html). The address was used as the pick-up point for the hypothetical trip to downtown or the airport.

Table W2 Fare Comparison by Transit Score Grade, Roundtrip to the Airport

Transit Score Grade	**Average Distance to Airport** (miles)	**Average Taxi Fare**	**Average Uber Fare**	**Average Lyft Fare**
3 (good access)	11.67	$68.57	$45.71	$44.86
2 (some access)	15.61	$82.50	$54.75	$54.88
1 (minimal access)	21.72	$107.88	$71.38	$71.00

Table W3 Fare Comparison by Transit Score Grade, Roundtrip to Downtown

Transit Score Grade	**Average Distance to Downtown** (miles)	**Average Taxi Fare**	**Average Uber Fare**	**Average Lyft Fare**
3 (good access)	3.09	$22.57	$19.71	$18.86
2 (some access)	7.68	$45.38	$31.75	$31.75
1 (minimal access)	13.01	$71.88	$46.88	$46.63

We also consider the second component of cost—inconvenience—and we conclude that Uber/Lyft is more convenient than a taxi.[3] Uber/Lyft's app-based services are easy for passengers to use, and the real-time ride information (e.g., the estimated arrival time) reduces uncertainty and improves reliability for the passengers. Liu, Brynjolfsson, and Dowlatabadi (2021) find that the use of GPS navigation increases transparency for Uber passengers and reduces the driver moral hazard of taking longer routes on purpose. Brown and LaValle (2021) find that, for the same origin-destination pair, the average wait time for an Uber/Lyft ride is only 25% of the wait time for a taxi.

Local Ride-Sharing Services in Austin (RideAustin)

Uber/Lyft's exit from Austin raised transportation costs for travelers, especially those with lodging outside the commercial core (as we demonstrate in the previous subsection). In the months after Uber/Lyft's exit, however, local ride-sharing services entered the market and ostensibly should have reduced transportation costs toward pre-treatment levels. If these local ride-sharing services were adequate substitutes for Uber and Lyft, then we should not expect the treatment effect to persist through 2016—and yet it did (though the effect size decreased after September 2016).

[3] https://www.ridester.com/uber-vs-taxi/.

Almost a dozen ride-sharing services entered Austin after Uber/Lyft's exit. We use RideAustin as a representative for two reasons: (1) RideAustin's data is publicly available, and (2) RideAustin became the dominant ride-sharing service in Austin after Uber/Lyft's exit; by December 2016, RideAustin acquired approximately 4,000 drivers, nearing the maximum of 5,235 drivers permitted by Austin Transportation after Uber/Lyft's exit.[4] For comparison, about 10,000 drivers worked for Uber in Austin in May 2016. (We do not have the corresponding number for Lyft.)

We find that the local ride-sharing services were able to fill part, but not all, of the gap in affordable, convenient transportation in Austin, and their impact varied by location. It took a few months for the new services to scale up their supply because of time-consuming requirements, such as the fingerprinting of drivers (the reason for Uber/Lyft's exit). For example, RideAustin began serving rides to the general public on June 16, 2016, almost a month after Uber/Lyft's exit (see Figure W1). The new services struggled to develop adequately sophisticated technology (e.g., supply-demand matching algorithms, a reliable mobile app, peak-time demand management). The ride times for the new services tended to be longer than for Uber/Lyft, and the fares were 25% higher on average. It is not surprising that once Uber/Lyft re-entered Austin, the local ride-sharing services did not survive for long.

[4] https://austinstartups.com/top-5-things-we-learned-from-our-first-million-rideaustin-rideshare-trips-1fe9f77cea63.

Figure W1 Rides per Week by RideAustin

Notes: The plot is provided in a report by Afiune (2017), which can be accessed at https://www.texastribune.org/2017/06/21/rideaustin/).

RideAustin Public Dataset

The public dataset provides the daily number of rides supplied by RideAustin in June–December 2016.[5] The dataset also provides detailed ride information. For us, the most relevant variables are the pick-up geolocation (latitude and longitude) and two timestamps (when the ride request was initiated by the rider and when the driver arrived), with which we calculate the wait time.

We aggregate the data at the month level and provide statistics in Table W4. The number of rides increased steadily after June 2016, peaked in October, and then leveled off in November and December.

Table W4 Rides Provided by RideAustin, June–December 2016

VARIABLES	MEAN	MIN	MAX
June 2016			
Driver Rating	4.868	0	5
Rider Rating	4.948	1	5

[5] https://data.world/andytryba/rideaustin

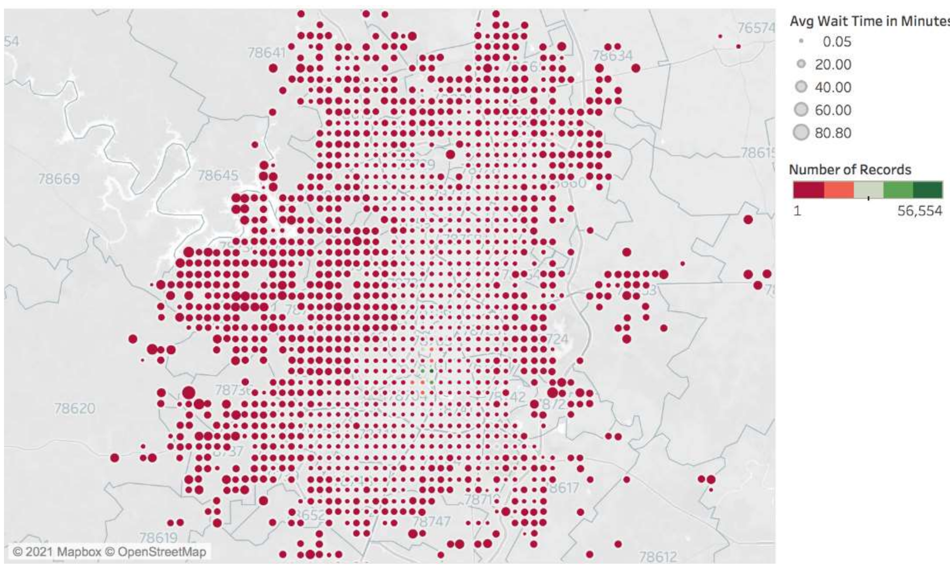
Total Rides		3745	
July 2016			
Driver Rating	4.852	0	5
Rider Rating	4.925	0	5
Total Rides		14647	
August 2016			
Driver Rating	4.822	1	5
Rider Rating	4.931	1	5
Total Rides		37785	
September 2016			
Driver Rating	4.821	1	5
Rider Rating	4.927	1	5
Total Rides		97037	
October 2016			
Driver Rating	4.81	1	5
Rider Rating	4.919	1	5
Total Rides		194539	
November 2016			
Driver Rating	4.829	1	5
Rider Rating	4.915	1	5
Total Rides		158635	
December 2016			
Driver Rating	4.824	1	5
Rider Rating	4.895	1	5
Total Rides		159853	

Notes: The statistics are computed on a daily sample and averaged at the month level.

Next, from the ride request time and driver arrival time, we compute the wait time for each ride and associate the wait time with the pick-up geolocation. In Figure W2, we visualize the wait times by pick-up location; a bigger (smaller) dot indicates a longer (shorter) wait time. We make two observations from the plot: 1) longer wait times occur in the peripheral regions (which also have poorer access to public transportation; see Figure W6), and 2) even for riders near the commercial core, the dot size indicates that the average wait time is up to 20 minutes.

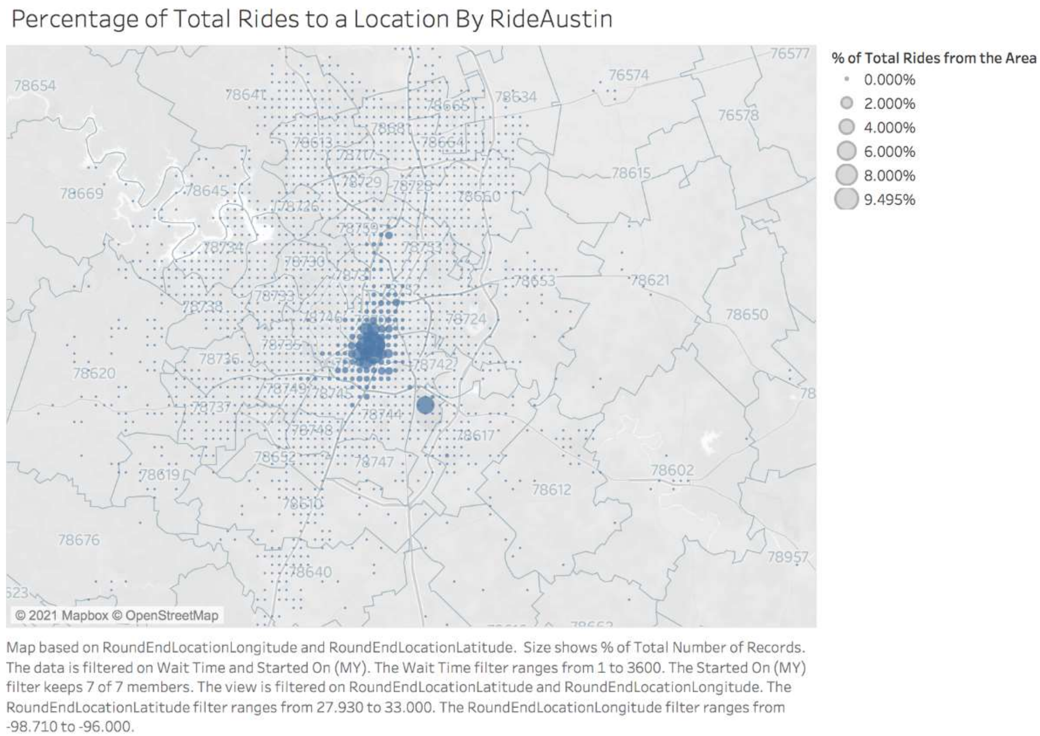
Similarly, in Figure W3, we visualize the rides supplied by RideAustin, with a bigger (smaller) dot indicating a higher (lower) percentage of the rides. The rides are concentrated in the commercial core, suggesting that the peripheral areas of Austin are underserved by RideAustin (and probably by the other local ride-sharing services).

Figure W2 Visualizing the Wait Times for RideAustin Rides



Map based on RoundLongitude and RoundLatitude. Color shows sum of Number of Records. Size shows AVG([Wait Time]/60). The data is filtered on Wait Time and Started On (MY). The Wait Time filter ranges from 60 to 56704. The Started On (MY) filter keeps 7 of 7 members. The view is filtered on RoundLatitude and RoundLongitude. The RoundLatitude filter ranges from 29.6300 to 33.0000. The RoundLongitude filter ranges from -98.2300 to -96.0000.

Figure W3 Visualizing the RideAustin Supply (Distribution of Rides)



Comparison of RideAustin and Uber/Lyft Fares

On average, rides from RideAustin were more expensive than equivalent rides from Uber/Lyft; RideAustin charged a 25% higher fare per minute and 82% higher service fee.[6] Also, RideAustin and the other new ride-sharing services were less reliable than Uber/Lyft. The apps for the new services (including RideAustin) frequently crashed during peak hours or bad weather, while the Uber and Lyft apps easily withstand these surges in demand.[7] RideAustin received significantly

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6 https://spectrumlocalnews.com/tx/austin/news/2017/05/31/comparing-price--efficiency-of-austin-s-ride-hailing-services

7 https://www.americaninno.com/austin/newsletters/the-biggest-fundings-of-february-fasten-shuts-down-rideaustin-carries-on/;https://austinstartups.com/top-5-things-we-learned-from-our-first-million-rideaustin-rideshare-trips-1fe9f77cea63.

lower consumer ratings than Uber (3.7 vs. 4.9 out of 5) because of its poor reliability.[8] As anecdotal evidence, we also observed that consumers complained about the poorer quality of service, long wait times, and unreliability of RideAustin on social media.[9]

For RideAustin, the long wait times remained a problem even after the supply of drivers increased. The typical wait time was less than 5 minutes (often just 3 minutes) for Uber[10] versus 10 minutes for RideAustin, though RideAustin riders in the suburbs waited much longer than riders in high-demand locations (e.g. downtown), as evident in Figure W2 (and explained by the ride distribution in Figure W3). Hence, while the local ride-sharing services provided a reasonable substitute for Uber/Lyft in the commercial core, they fell short in other areas.

Other Transportation Options

Travelers have other options for local transportation besides taxis and ride-sharing services. We briefly discuss two options—car rentals and public transportation—and we compare them with Uber/Lyft. The comparison helps us understand how the lodging location and traveler's characteristics affect the extent to which each option is a good alternative for Uber/Lyft.

Public transportation. Our comparison of Uber/Lyft with taxi services and RideAustin revealed that Uber/Lyft outperformed the other options in terms of both price and convenience. Between public transportation and Uber/Lyft, however, there is a different "winner" on each side. Public transportation is cheaper than Uber/Lyft; according to TripAdvisor, a single ride on Austin public transportation costs $1.25 (for the price of other options like a day pass, see

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[8] For a rating comparison, see https://knoji.com/compare/uber-vs-rideaustin/.
[9] See a Reddit thread: https://www.reddit.com/r/Austin/comments/dajq4m/why_dont_more_people_use_ride_austin_instead_of/
[10] See a report on Uber wait times: https://www.newsweek.com/exclusive-heres-how-long-it-takes-get-uber-across-us-cities-289133#:~:text=In%20fact%2C%20the%20median%20wait,markets%20in%20the%20United%20States.

https://www.capmetro.org/farechange), far less than an Uber fare. However, public transportation involves far more inconvenience than Uber/Lyft, as both the wait time[11] and the commute time tend to be longer (perhaps with the exception of trips on the rail). The inconvenience increases for travelers who stay in areas with lower transit scores, as the transit score calculation includes the route frequency (which affects the wait time). Hence, we reason that transportation costs (including price and inconvenience) surged after Uber/Lyft's exit, and more so for the properties with poorer access to public transportation.

Car rental. RideAustin, public transportation, and taxis are not very convenient for travelers staying far from the commercial core (see Figure W6). Car rentals are highly convenient and can mitigate the problem of insufficient supply (inaccessibility) for travelers with poor access to all other transportation options. However, renting a car tends to be far more expensive than the other options.

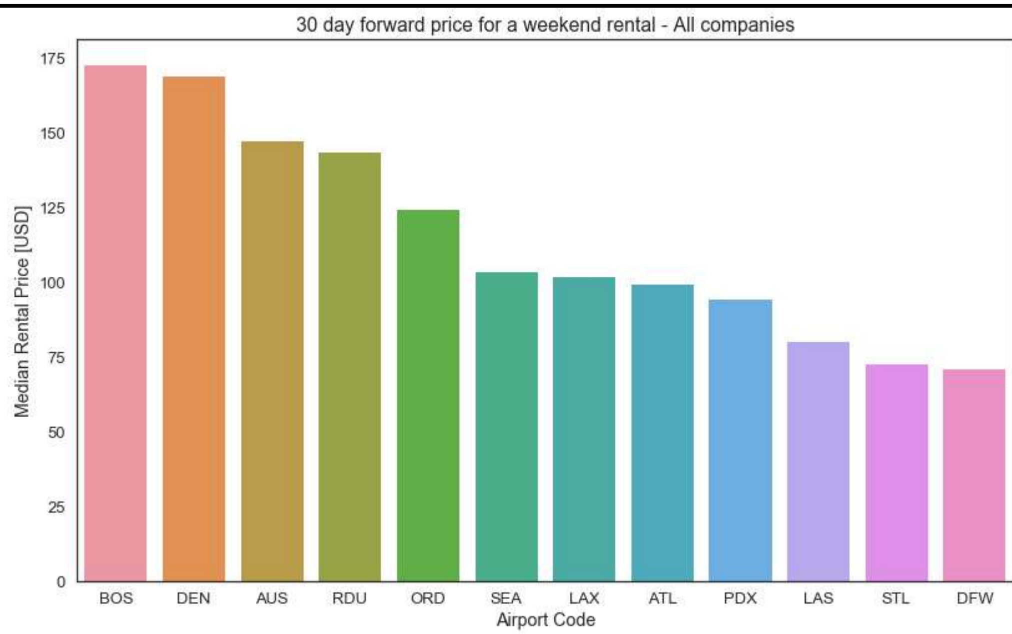
In a LinkedIn post, someone scraped a car rental website daily for three days and found that a 3-day weekend rental car costs about $150, excluding the costs of insurance, gas, and extras. As shown in Figure W4 (taken from the post), the median 3-day price for Austin (Airport Code: *AUS*) was also approximately $150. For additional Austin-specific information, we checked Priceline.com (see Figure W5 for a screenshot) and found that renting a compact sedan (with pick-up and drop-off at the Austin airport) costs $373, or about $124 per day, including taxes and fees but excluding tolls and gas.

Recall that in Austin, the average UberX/Lyft roundtrip fare is $54, so the price gap between Uber/Lyft and car rental is approximately $70 per day (though the difference would decrease if the

[11] The time between two runs for most routes can be up to 30 minutes, see https://www.tripadvisor.com/Travel-g30196-s303/Austin:Texas:Public.Transportation.html

traveler wished to take multiple roundtrips in a day). Also recall that Airbnb hosts decreased the nightly rate by an average of only $9.3, so the price reduction did not compensate for the increased cost associated with using a rental car.

Figure W4 Three-Day Car Rental Price, by Airport

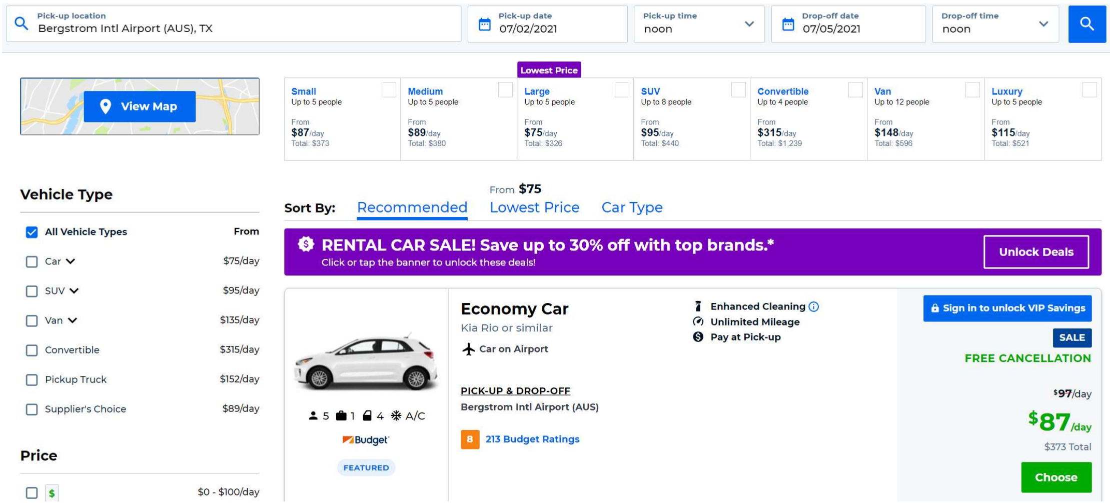


Notes: Each bar represents a city, and the vertical axis is the median car rental price for a 3-day weekend.

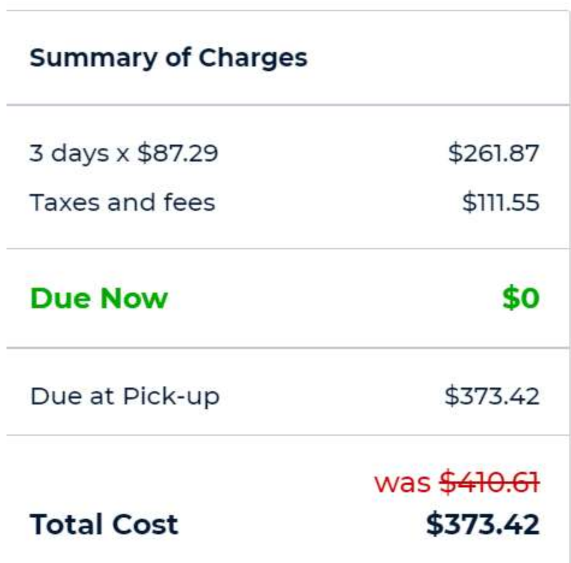
Source: https://www.linkedin.com/pulse/i-scraped-us-rental-car-prices-heres-what-found-prashanth-rajendran

Figure W5 A Screenshot of Inquired Fees for Car Rental in Austin

(a)



(b)



Notes: Panel (a) presents a screenshot of the top search result for a 3-day car rental in Austin. Panel (b) shows the total cost and breakdown of the charges for renting an economy car, excluding gas and tolls.

Source: https://www.priceline.com/

WEB APPENDIX B: MATCHING METHOD AND SAMPLE BALANCE ASSESSMENT

Constructing a Matched Sample

We create a control group by matching control units with treated units (i.e., those in Austin) based on similarities in observed covariates. The outcome is a set of matched properties and associated sample weights that reflect the frequency with which each control unit was matched with a treated unit. Then, in the weighted sample, the treatment and control groups should be comparable on a broad set of property and host characteristics.

Before conducting the matching procedure, we first removed "stale vacancies" from the sample. In a stale vacancy, the property is *listed* as available, but booking requests never get a response. Presumably, the property actually is not available, but the host neglected to update the property's status. We define a stale vacancy as a property with no booking between April 2015 (one year prior to treatment) and December 2016 (the end of the observation window; Zalmanson, Proserpio, and Nitzan 2018). Across the five cities, 19.6% of the properties meet this criterion and are excluded from further analyses.

For each property i, we compute propensity score $\widehat{ps}_i$ as a logistic function of a vector of variables, X_i, such that $\widehat{ps}_i = g(X_i\hat{\beta})$. Here, X_i includes the observed covariates presented in Table 1 and their higher-order terms.[12] The time-varying variables (e.g., # reviews) are measured

[12] We start with linear terms for the covariates and then implement a balance check. For variables on which the two groups remain unbalanced, we add interactions and higher order (squared) terms. Then, we continue under a new specification of X_i and implement another balance check, and we repeat these steps with higher orders until the sample is balanced.

in April 2016, immediately before the treatment. $\hat{\beta}$ is estimated by maximizing the sample likelihood as specified in Equation (A1):

$$L(\beta) = \prod_{i=1}^{I} g(X_i\beta) \cdot Austin_i \qquad \text{(A1)}$$

where X_i is a list of variables that measure the property and host characteristics associated with property i in the pre-treatment periods. $g(\cdot)$ takes a logit form, and $Austin_i$ is a binary variable that equals 1 (0) if i is a property in Austin (one of the other four cities).

We opt to use the propensity score for matching because it is effective at removing existing sample imbalances (Rosenbaum 2002), and it is far more efficient to match a sample on a single propensity score than on a set of variables (Rosenbaum and Rubin 1985). Note that our interest is not the estimation of $\widehat{ps}$ itself; rather, we estimate $\widehat{ps}$ because the estimation, as a reflection of the set of covariates, enables us to select control units that are likely to be comparable to treated units. We validate the matching method by comparing the matched treated and control units on the set of covariates.

Our implementation uses the STATA package *psmatch2* to approximate $\widehat{ps}$, which then is used for *k*-nearest neighbor matching (also in *psmatch2*) to identify the units with the closest $\widehat{ps}$. To avoid a bad match in which even the nearest unit is far away, we set a caliper threshold (i.e., the maximum difference between the $\widehat{ps}$ values of two units) of 0.001. We allow up to four matches per treated unit, and any treated unit without a satisfactory match is dropped from the sample.

We note that the caliper size can affect the size of the matched sample. We test our matching step with different values for the caliper and number of neighbors, and the outcomes are qualitatively consistent. Our final caliper size reflects the optimal compromise in the trade-off between the closeness of the match and the size of the final sample.

The original sample has 11,605 treated properties and 48,359 control properties. The matching step leaves us with 4,698 treated properties and 6,838 controls, along with the frequency weights generated by *psmatch2*.

Validating the Matched Sample: Covariates Balance Check

The matching step is valid only if the weighted sample (using the frequency weights) has no significant differences between the treatment and control groups on any of the observed covariates. We use the standardized difference in means (Rubin 2001, Stuart 2010), which compares, over the M-dimensional covariates, the weighted means of the treatment group, $\bar{X}_{Austin} = \frac{\sum_{i \epsilon Austin} \omega_i X_i}{\sum_{i \epsilon Austin} \omega_i}$, and the control group, $\bar{X}_{control} = \frac{\sum_{i \epsilon control} \omega_i X_i}{\sum_{i \epsilon control} \omega_i}$. For the treated units, ω_i equals 1; for the control units, ω_i is the frequency weight determined in the matching procedure. For variable X^m (m = 1, 2…, M), we compute the absolute difference in the means, normalized by the weighted sample variances, s^2_{Austin} and $s^2_{control}$:

$$d^m = \left| \frac{\bar{X}^m_{Austin} - \bar{X}^m_{control}}{\sqrt{\frac{s^2_{Austin} + s^2_{control}}{2}}} \right| \tag{A2}$$

where the weighted sample variances are:

$$
\begin{aligned}
s^2_{Austin} &= \frac{\sum_i \omega_i}{\left(\sum_i \omega_i\right)^2 - \sum_i (\omega_i)^2} \sum_i \omega_i (X_i^m - \bar{X}^m_{Austin}) && \text{if } i \text{ is in Austin} \\
s^2_{control} &= \frac{\sum_i \omega_i}{\left(\sum_i \omega_i\right)^2 - \sum_i (\omega_i)^2} \sum_i \omega_i (X_i^m - \bar{X}^m_{control}) && \text{if } i \text{ is in a control city}
\end{aligned}
\tag{A3}
$$

An absolute standardized difference below 10% (i.e., $d^m < 0.1$) is considered a negligible sample imbalance (Austin and Stuart 2015). Table W5 presents the group means in the treatment and control groups as well as the standardized differences for all observed covariates. The matching method successfully eliminated all significant imbalances from the unweighted sample.

Table W5 Validating the Matching Method: Covariates Balance Check

	Group Means in Matched Sample		**Standardized**
VARIABLES	**Austin Units**	**Control Units**	**Differences ***
# Unique Properties	4698	6838	--
Occupancy	0.32	0.29	0.081
# Reservation Days	5.56	5.49	0.008
# Blocked Days	4.01	4.29	-0.038
Entire Home	0.7	0.69	0.016
House	0.65	0.66	-0.034
# Bedrooms	1.74	1.78	-0.034
Nightly Rate	235.25	260.24	-0.087
# Reviews	18.28	17.75	0.016
# Photos	17.03	17.71	-0.054
Transit Score	45.28	44.32	0.057
AC	0.99	0.99	0.007
Breakfast	0.08	0.08	-0.018
Family-friendly	0.29	0.28	0.034
Gym	0.1	0.12	-0.057
Elevator	0.05	0.06	-0.031
Laptop-friendly	0.33	0.33	0.002

Refrigerator	0.13	0.12	0.022
Microwave	0.11	0.11	0.02
Washer	0.81	0.81	0.002
Dryer	0.86	0.87	-0.002
TV	0.82	0.84	-0.053
Internet	0.97	0.97	0.013
Pool	0.23	0.28	-0.14
Iron	0.35	0.35	0.015
Essentials	0.49	0.49	0
Smoke Detector	0.49	0.48	0.018
Shampoo	0.42	0.42	0.011
Beach	0.01	0.01	0.003
Parking	0.93	0.93	0.008
# Supplied Open Days (aggregated by zip code)	10025.79	9282.21	0.076

* A standardized difference between -0.1 and 0.1 indicates a negligible sample imbalance for that variable.

Notes: The group means and standardized differences are computed on the matched sample, using the frequency weights obtained in the matching step.

Time-varying variables are measured in April 2016, the month prior to treatment. This applies to Occupancy, # Reservation Days, # Blocked Days, Nightly Rate, # Reviews, # Photos, and # Supplied Open Days.

WEB APPENDIX C: EXPLANATION OF THE TRANSIT SCORE ALGORITHM

In our study, we used a property's access to public transportation, operationalized as the transit score from walkscore.com, to capture variation in transportation costs across Airbnb properties. The transit score is a numeric index (0–100) that reflects how well the address is served by public transportation (e.g., bus, light rail). The transit score algorithm sums the value of each nearby public transportation route; value is determined by the frequency of service, distance between the address and the nearest stop on the route (Hirsch et al. 2013), and type of route (value is weighted 2x for heavy/light rail, 1.5x for ferry/cable, and 1x bus). Then, the value is normalized between 0 and 100 to handle extremely large values (e.g., addresses in downtown Manhattan would have a very large value because of the sheer number of nearby routes that make many trips per day). The highest value of 100 is determined by the average raw transit values of five US city centers (San Francisco, Chicago, Boston, Portland, and Washington, DC). Then, the algorithm performs a logarithmic transformation of the transit values.

WEB APPENDIX D: RAW DATA PATTERN

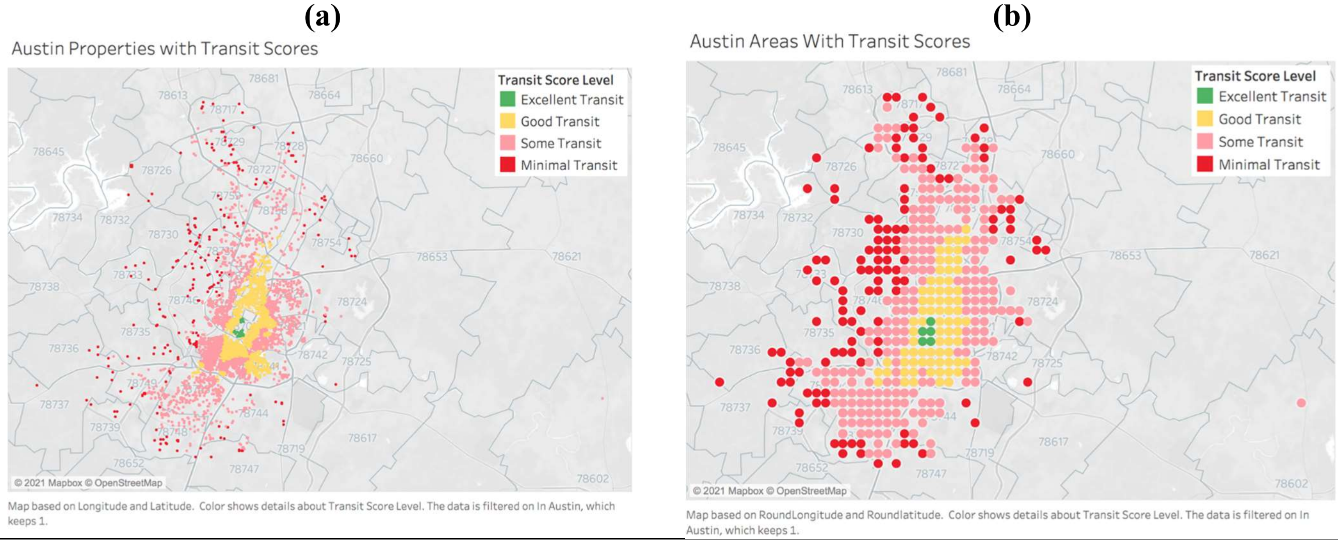
We examine the raw data patterns to provide visual evidence of the relationships between the change in demand for Airbnb properties and the location and price of the properties.

A Map of the Transit Scores (Access to Public Transportation) of Airbnb Properties

To explore geographic variation in supply and demand, in Figure W6, we visualize the distribution of transit scores (four grades, from minimal access to excellent access, as classified by walkscore.com). Plot (a) includes all Airbnb properties in the greater Austin area, while plot (b) zooms in on Austin proper. We obtain each property's geolocation (latitude and longitude) from the data provider, AirDNA. We color-code the dots such that greener (darker red) dots have better (worse) access to public transportation. Very few of the properties have excellent transit, and they all are located in the commercial core of Austin. In general, the transit scores worsen with distance from the commercial core.

Figure W6 Visualizing the Transit Score Grades of Austin Properties

(a) **(b)**



Notes: The local transit scores provided by walkscore.com are categorized into four grades: 0~24 (minimal access to public transportation), 25~49 (some), 50~69 (good), and > 70 (excellent).

Property Demand Before vs. After Uber/Lyft's Exit

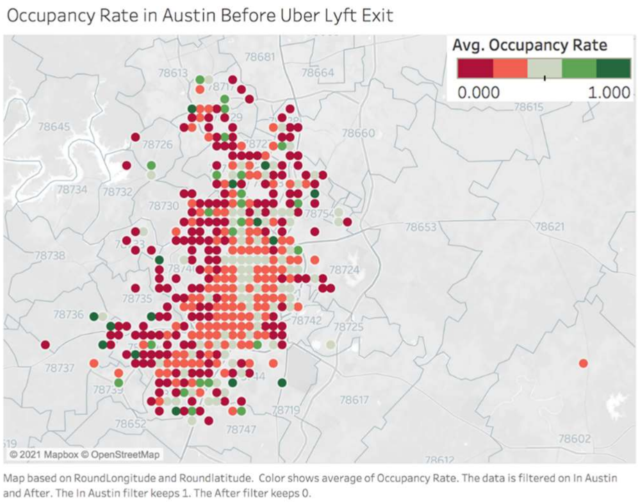
For the Austin properties, we visualize the average demand (monthly occupancy) before and after the exit of Uber/Lyft by location and luxuriousness (low-end vs. high-end)

In Figure W7, we plot the average demand (i.e., monthly occupancy) by location before Uber/Lyft's exit (plot a) and after (plot b); greener dots indicate higher occupancy, while darker red dots indicate lower occupancy. After Uber/Lyft's exit, some green dots turned red (instead of green), and some lighter red dots turned darker red, indicating a drop in occupancy. These changes are more pronounced in the outer regions; most of the remaining green dots are closer to the commercial core. This is consistent with our main argument that the properties with poorer access to public transportation (visualized in Figure W6) suffered more from the exit of Uber/Lyft.

In Figure W8, we decompose the demand visualization by luxuriousness (low-end vs. high-end). We classify a property as "high-end" if its average nightly rate in a month is above $300 (approximately the average nightly rate for the top two classes of hotels, as presented in Table 6 in the main paper). For the high-end properties, occupancy is visually similar before (plot a) and after (plot b) the exit of Uber/Lyft. By contrast, for the low-end properties, occupancy visually decreases after Uber/Lyft's exit (plot d) relative to before (plot c). As in Figure W10, the most dramatic changes in occupancy are concentrated in the outer regions, suggesting that demand fell the most for the low-end properties with the worst access to public transportation.

Figure W7 Visualizing the Effect of Uber/Lyft's Exit on Demand for Austin Properties

(a)



(b)

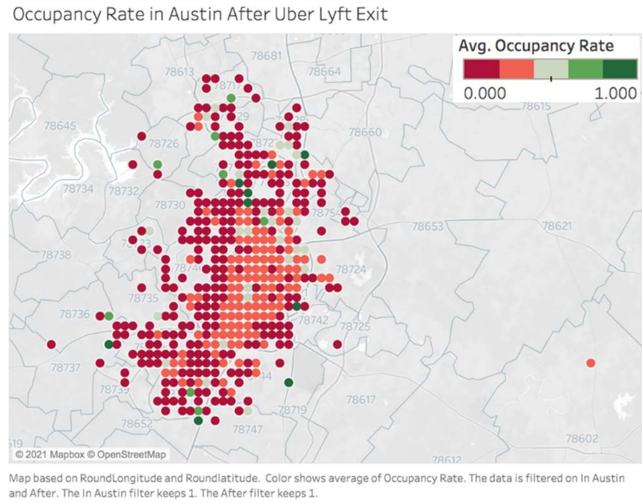
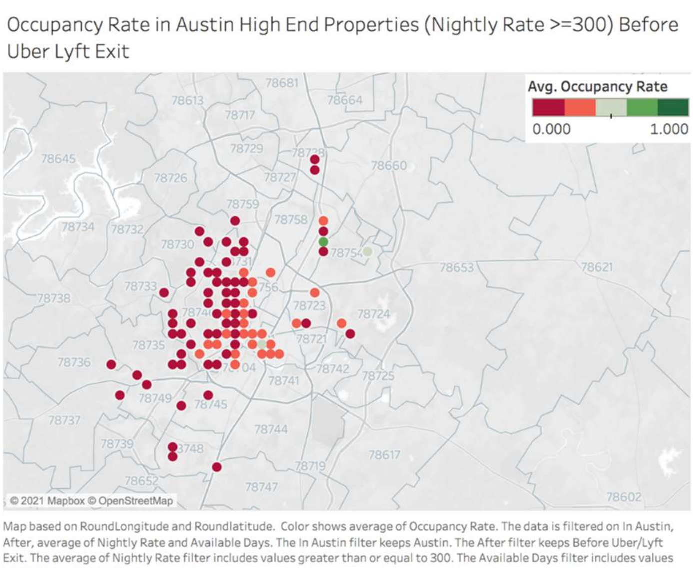
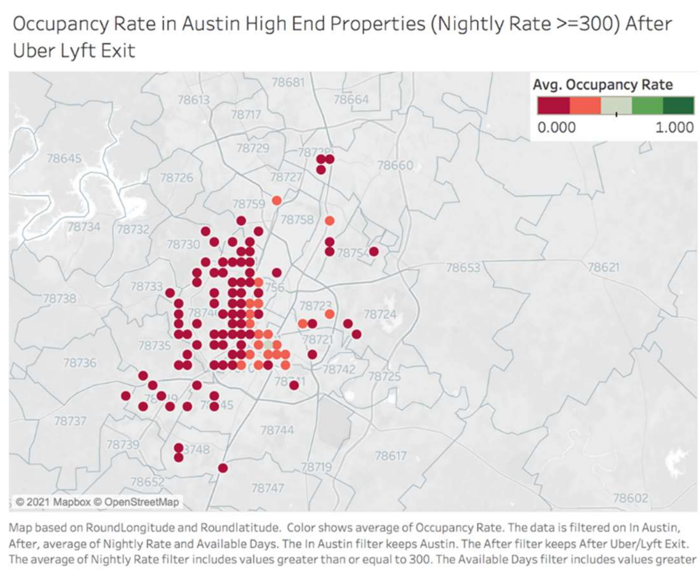


Figure W8 Visualizing the Effect of Uber/Lyft's Exit on Demand, By Luxuriousness

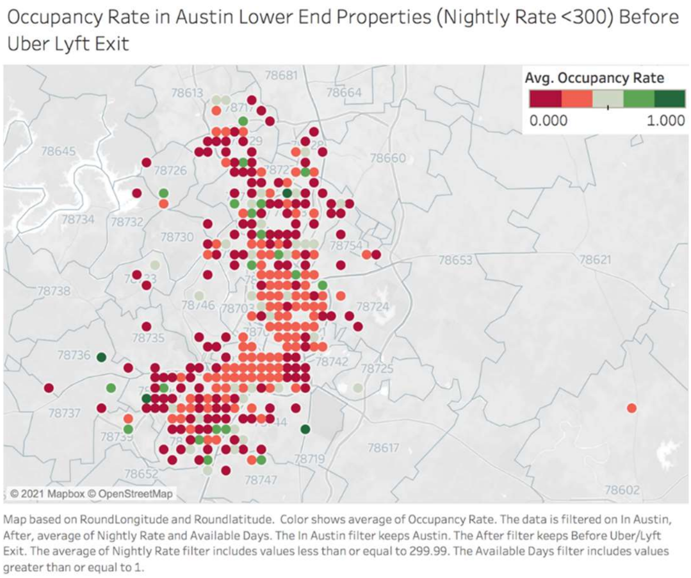
(a) High-End, Before Exit



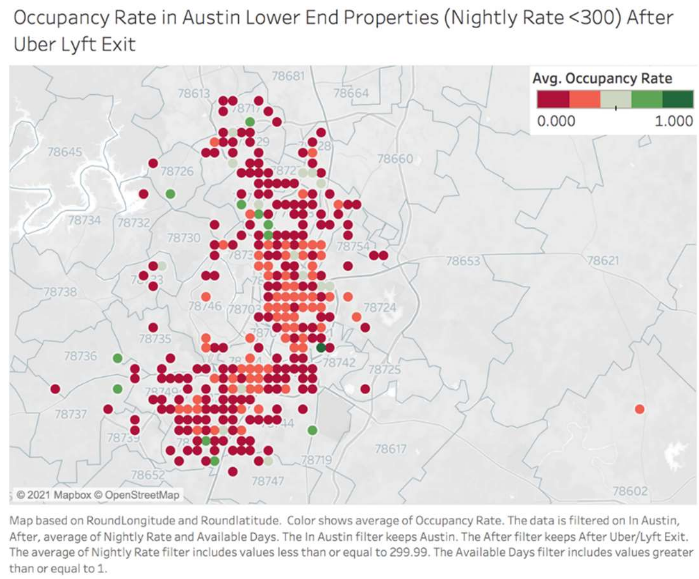
(b) High-End, After Exit



(c) Low-End, Before Exit



(d) Low-End, After Exit



Notes: We classify a property as "high-end" if its nightly rate (averaged across all periods in our observation) is above $300.

Summary Statistics on Unmatched (Dropped) Properties

Some properties in the sample were dropped during the matching step. The raw sample includes 11,605 properties in Austin and 48,359 properties in the control cities. The matching step leaves us with 4,698 properties in Austin and 6,838 properties in the control cities. In Table W6, we display the summary statistics for the matched and unmatched units, side by side.

Table W6 Summary Statistics for the Matched and Unmatched Units

	(1) Matched Units		(2) Unmatched Units	
VARIABLES	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
# Reservation Days	6.55	9.29	7.23	9.93
# Blocked Days	9.91	12.63	8.95	12.04
Occupancy Rate	0.34	0.37	0.36	0.38

Entire Home	0.69	0.46	0.64	0.48
House	0.59	0.49	0.33	0.47
# Bedrooms	1.65	1.10	1.32	0.93
Nightly Rate	214.89	277.21	163.50	239.48
# Reviews	16.81	32.19	13.27	26.92
# Photos	16.89	12.08	15.86	12.22
Transit Score	46.72	12.73	60.46	20.89
AC	0.99	0.09	0.99	0.12
Breakfast	0.07	0.26	0.10	0.30
Family-friendly	0.26	0.44	0.31	0.46
Gym	0.11	0.31	0.19	0.39
Elevator	0.07	0.26	0.27	0.44
Laptop-friendly	0.34	0.47	0.31	0.46
Refrigerator	0.13	0.34	0.11	0.32
Microwave	0.12	0.32	0.10	0.31
Washer	0.80	0.40	0.77	0.42
Dryer	0.86	0.35	0.83	0.38
TV	0.82	0.39	0.77	0.42
Internet	0.97	0.17	0.95	0.21
Pool	0.21	0.41	0.21	0.41
Iron	0.35	0.48	0.31	0.46
Essentials	0.52	0.50	0.41	0.49
Smoke Detector	0.52	0.50	0.40	0.49
Shampoo	0.44	0.50	0.34	0.47
Beach	0.01	0.10	0.02	0.14
Parking	0.89	0.31	0.53	0.50
# Supplied Open Days (aggregated by zip code)	8773.50	10044.27	6856.24	7966.24

Notes: The group mean differences were computed on all matched units (column 1) and all unmatched units (column 2), without weighting the sample.

Representativeness of the Matched Properties in Austin

We examine whether the matched (subsample) properties are representative of the full sample in Austin. Specifically, we consider geographic representativeness (transit score and zip code), and we find that the matched properties are representative of the full sample in Austin.

Distributions of zip codes. In Table W7, we present the distribution of properties by location (zip code) for the full sample (column 1) and for the matched sample (column 2). As can be seen, the distributions are similar. For example, for both groups, the most frequent zip code is 78704 (about one-quarter of the properties). The other most frequent zip codes are 78702, 78741, 78703, and 78705, all of which contain similar proportions of the properties in columns 1 and 2. Note that there are four zip codes (78719, 78734, 78738, and 78742) for which none of the properties were selected in the matched sample. However, even the full sample had few properties in the four zip codes (0.03%, 0.06%, 0.04%, and 0.01%, respectively), so we conclude that the matched sample is sufficiently representative in terms of property location.

Table W7 Frequency of Zip Codes in the Full and Matched Samples

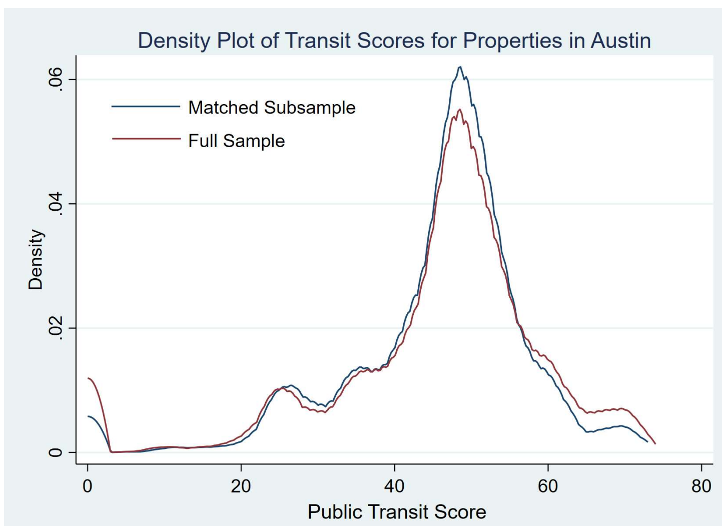
	(1)	**(2)**
Zip code	**Full Sample**	**Matched Sample**
78701	3.89	2.3
78702	12.95	15.45
78703	7.32	8.15
78704	24.89	26.59
78705	5.53	3.26
78717	0.29	0.19
78719	0.03	/

78721	1.65	1.62
78722	2.54	3.11
78723	3.15	3.09
78724	0.36	0.26
78725	0.43	0.3
78726	0.09	0.11
78727	0.56	0.45
78728	0.39	0.23
78729	0.52	0.43
78730	0.31	0.28
78731	1.56	1.89
78732	0.31	0.02
78733	0.28	0.13
78734	0.06	/
78735	0.42	0.32
78736	0.21	0.15
78737	0.32	0.11
78738	0.04	/
78739	0.17	0.11
78741	7.95	7.02
78742	0.01	/
78744	1.05	0.96
78745	4.7	4.98
78746	2.39	2.38
78747	0.32	0.36
78748	1.53	1.34
78749	0.9	0.94
78750	0.39	0.3
78751	4.33	4.68
78752	1.16	1.45
78753	0.91	0.85

78754	0.47	0.19
78756	1.31	1.53
78757	1.87	1.98
78758	1.96	1.45
78759	1.37	1.06
# Properties	11,605	4,698

Distributions of transit scores. In Figure W9, we plot the density of transit scores in the matched sample and the full sample. The two distributions are visually very similar.

Figure W9 Comparing Transit Scores Distributions



Comparing the matched and unmatched (dropped) units. This step approaches the representativeness question by computing the standardized differences between the matched/unmatched sample and the full sample of Austin Airbnb properties. A smaller absolute standardized difference $|d|$ indicates less dissimilarity ($|d|$ < 10% is considered a negligible sample imbalance). The $|d|$ between the full sample and the matched and unmatched samples are presented in columns (1) and (2), respectively, of Table W8. For 20 of the 30 covariates, the matched units are more similar (i.e., smaller $|d|$) than the unmatched units to the full sample. Of the 10 covariates (House, AC, Laptop-friendly, Refrigerator, Microwave, Washer, Dryer, TV, Shampoo, Beach) for which the unmatched sample has a smaller $|d|$ than the matched sample, only *Shampoo* has $|d| > 0.1$. We conclude that 1) the differences between the matched sample and the full sample are negligible for most of the covariates, and 2) the matched sample, relative to the unmatched sample, is more representative of the full sample of Austin properties.

Table W8 Standardized Differences Between the Matched and Unmatched Samples and the Full Sample in Austin

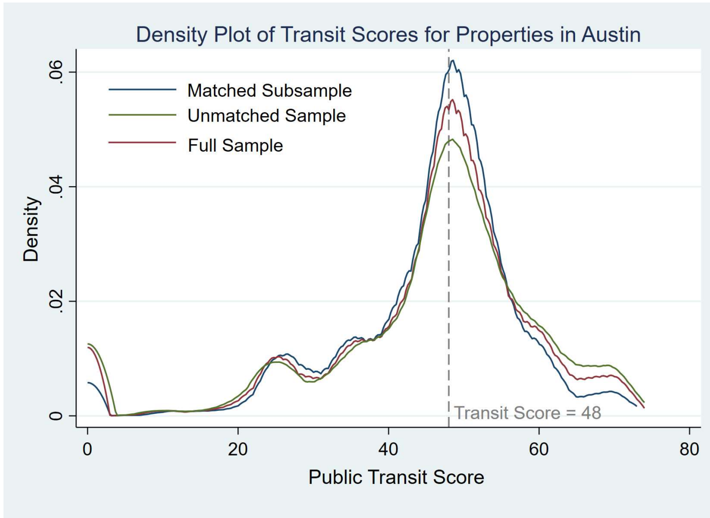
	Standardized Difference Between the Full Sample and Subsample	
	(1)	**(2)**
VARIABLES	**Matched Units**	**Unmatched Units**
# Reservation Days	0.051	0.072
# Blocked Days	0.0043	0.0058
Occupancy Rate	0.065	0.088
Entire Home	0.10	0.16
House	0.075	0.059
# Bedrooms	0.065	0.094
Nightly Rate	0.0089	0.012
# Reviews	0.15	0.37
# Photos	0.12	0.21
Transit Score	0.021	0.035
AC	0.044	0.026
Breakfast	0.064	0.10
Family-friendly	0.072	0.11
Gym	0.12	0.21

Elevator	0.099	0.17
Laptop-friendly	0.095	0.068
Refrigerator	0.080	0.060
Microwave	0.072	0.054
Washer	0.017	0.012
Dryer	0.050	0.033
TV	0.06	0.040
Internet	0.050	0.085
Pool	0.11	0.18
Iron	0.080	0.11
Essentials	0.15	0.20
Smoke Detector	0.15	0.22
Shampoo	0.18	0.13
Beach	0.029	0.025
Parking	0.11	0.33
# Supplied Open Days (aggregated by zip code)	0.041	0.056

Notes: The group mean differences were computed based on the full sample in Austin and the matched units in Austin (column 1), versus the full sample in Austin and the unmatched units in Austin (column 2), without weighting the sample.

Next, we compare the transit scores between the matched sample, the unmatched sample, and the full sample. The three distributions are visually very similar in Figure W10, though the unmatched sample has a slightly higher proportion of properties at both ends of the distribution (i.e., properties with very high or very low transit scores), while the matched sample consists of more properties with transit scores around Austin's median (48, indicated by the dashed gray line).

Figure W10 Comparing Transit Scores Among the Matched, Unmatched, and Full Samples



WEB APPENDIX E: ALTERNATIVE STANDARD ERROR CLUSTERS

In our main DiD model, standard errors are clustered at the individual-property level. We re-estimate the model with clusters at the aggregated zip code level. As shown in Table W9, the negative effect of Uber/Lyft's exit on Airbnb occupancy remains statistically significant ($p < 0.001$). Note that if we clustered at the next-highest level—the city-level—we would have only five clusters. Using fewer than 40 clusters leads to an over-rejection of the null hypothesis; the cluster-robust standard errors converge to the true standard error as the number of clusters approaches infinity (Cameron, Gelbach, and Miller 2008; Cameron and Miller 2015).

Table W9 Impact of Uber/Lyft's Exit on Property Demand: Alternative Clusters

VARIABLES	**ESTIMATES**	
AUSTIN · AFTER	-0.0378**	(0.0114)
log #REVIEW	0.0467***	(0.00322)
log #PHOTO	0.0400***	(0.00927)
log NIGHTLY_RATE	-0.0604***	(0.00839)
log #SUPPLIED_DAYS (within a zip code)	0.000885	(0.00144)
log #PASSENGERS	1.270***	(0.0909)
Fixed Effect	Property	
Seasonality	Calendar Month	
Observations	67039	
R-squared	0.6662	

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties. The DV is the monthly occupancy (a ratio between 0 and 1) of property *i* in month *t*.
Robust standard errors (clustered at the aggregated zip code level) are in parentheses.
* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

WEB APPENDIX F: ROBUSTNESS TESTS

Matching Estimator of the Effect of Uber/Lyft's Exit

One concern regarding the estimators in the main DiD analysis is that the specification of the demand model is restricted to an assumed functional form: a linear relationship between the dependent and independent variables. A violation of the assumed functional form may lead to a biased estimator. We address the issue by comparing the estimation obtained from our main analysis with the matching estimator obtained from a standard (free-form) matching analysis. Specifically, we employ a k-nearest neighbors matching method, as described in the Empirical Strategy and Results section of the main paper. We compute the average treatment effect by contrasting the difference in demand between each pair of treated and control units before and after the treatment.

Table W10 presents the average treatment effect (row "ATT" and column "Difference") of Uber/Lyft's exit on the monthly occupancy of Austin Airbnb properties. On the matched sample, the effect of Uber/Lyft's exit is significantly negative. The result is consistent with our main finding that Uber/Lyft's exit decreased the demand for Airbnb properties in Austin, so our estimation seems robust to the model's specification. It is also interesting to note that the difference in demand between the treated and control groups is greater in the unmatched sample (-0.125) than in the matched sample (-0.054). We posit that the difference in the unmatched sample captures seasonal differences between the cities, and the matching method corrects this potential bias. A full assessment of the potential false significance caused by seasonality requires replication of the main DiD analysis using the prior year's data (i.e., 2015), as we describe in the next section.

Table W10 Matching Estimator: Impact of Uber/Lyft's Exit on the Airbnb Property Demand

VARIABLE	Sample	Treated	Controls	Difference	S.E.
Property	Unmatched	0.16724	0.29265	-0.1254***	0.00652
Occupancy	**ATT**	0.17545	0.22946	**-.05401*** **	0.00843

Notes: The outcome variable is the monthly occupancy of property *i* in month *t*.
The ATT compares the change in the outcome variable between the treated properties (in Austin) and control properties (in the other four cities), before and after the exit of Uber/Lyft from Austin.
* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Placebo Test on the Prior Year's Data

The DiD estimation relies on the parallel trends assumption, which we verified in the main paper. One concern, however, is that Austin (but not the control cities) might have had an idiosyncrasy in the post-treatment periods, only. Our estimation of the treatment effect would be biased if, for example, the number of visitors to Austin suddenly dropped after May 2016 due to seasonal factors that are specific to Austin. We examine this possibility with a placebo test, modeled on Danaher and Smith (2014), that uses the same time window (January to December) during the prior year (2015 instead of 2016). We repeat our empirical steps—we create a sample by matching treated and control properties using *k*-nearest neighbor matching, and we conduct DiD regressions on the weighted sample.

Table W11 reports the results from the placebo test. The interaction term of interest is *AUSTIN* · *AFTER*, and all the variables have the same definitions as described in the main specification except that all periods are in 2015 instead of 2016. That is, *AFTER* is a dummy variable that equals 1 if *t* is after May 2015, and the coefficient of *AUSTIN* · *AFTER* captures the change in the property demand in Austin before and after May 2015, relative to the change in demand that occurred in the control cities. We expect no significant impact since Uber/Lyft's exit from Austin did not occur in 2015. As expected, the estimated coefficient of the key variable, *AUSTIN* · *AFTER*, is not significantly different from zero (b = -0.0134, $p > 0.1$).

Table W11 Placebo Test on the Prior Year's Data

	DiD model on 2015 data	
VARIABLES	**ESTIMATES**	**S.E.**
AUSTIN · *AFTER* (*AFTER* = 1 for May onward)	-0.0134	(0.0210)
log NIGHTLY_RATE	-0.0614***	(0.0163)
log #SUPPLIED_DAYS (within a zip code)	0.00424	(0.00381)
log #PASSENGERS	1.478***	(0.256)
Fixed Effect	Property	
Seasonality	Calendar Month	
Observations	36322	
R-squared	0.5979	

Notes: The model is estimated on the 2015 occupancy data from a sample of 6,646 Airbnb properties, matched following the same PSM method described in the main paper. The number of observations differs from the main analyses (using the 2016 data) because some new Airbnb listings entered the market, some existing listings were withdrawn, and other variables changed over time.

The DV is the monthly occupancy of property *i* in month *t* (in 2015). If *i* made the full month unavailable to be booked in *t*, the occupancy is computed as *missing* (indefinite), and the observation for *i,t* is automatically dropped from the estimation. Control variables such as # reviews and # photos were not incorporated because our data provider, AirDNA, did not track and collect such information before July 2015.

Robust standard errors (clustered at the individual-property level) are in parentheses.
* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Generalized Synthetic Control

In the last robustness test, we estimate the treatment effect with the synthetic control method (Abadie, Diamond, and Hainmueller 2010, 2015), which evaluates the causal effect of an intervention by forming "synthetic control units," or counterfactuals, that closely represent the treated units. Then, we compare the outcome of the treated units with the outcome of the counterfactuals; the outcomes in the pre-treatment periods should be similar.

We form a counterfactual by creating a convex combination of control properties that closely resemble the treated properties in terms of pre-treatment property demand trends. We use Generalized Synthetic Control (GSC) because it is appropriate for a large number of treated units (Xu 2017), and the synthetic control method does not work well for sparse and discrete data (i.e., many zeros in the outcome variable, which likely is true in our case at the individual-property level). We follow prior literature to aggregate individual unit data and perform GSC on the aggregated data (Guo, Sriram, and Manchanda 2020). Specifically, we compute the average demand in each zip code in each period and implement GSC at the zip code level.[13] The dependent variable is the average occupancy of properties in the same zip code. We include zip code fixed effects and time fixed effects in the demand model.

In Table W12, we report the estimation results of the GSC analysis in column 1. The estimated coefficient of the key variable, $AUSTIN \cdot AFTER$, captures the estimated treatment effect averaged across all post-treatment periods. For comparison, we report the DiD estimation

[13] We perform the estimations and inferences using the -*gsynth*- R package (Xu 2017).

results, aggregated by zip code, in column 2. The coefficient estimated by the GSC analysis is negative and significant (b = -0.065, p < 0.001), consistent with the main findings of the DiD models on the individual-level data (Table 3) and on the zip-code-level data (column 2, Table W12). Thus, the GSC analysis confirms a negative impact of Uber/Lyft's exit on the Airbnb property demand.

Table W12 Effect of Uber/Lyft's Exit on Property Demand: Generalized Synthetic Control Approach

	DV = Monthly Occupancy (zip code level)			
	(1)		**(2)**	
	GSC Analysis		**DiD Analysis**	
VARIABLES	**ESTIMATES**	**S.E.**	**ESTIMATES**	**S.E.**
	Average Treatment Effect (ATE)			
AUSTIN · AFTER	**-0.0650*****	**0.0113**	-0.0613***	(0.0101)
	Estimated Coefficient of Control Variables+			
log #REVIEW	0.0125	0.0216	-0.00410	(0.0193)
log #PHOTO	0.0671	0.0370	0.0834*	(0.0366)
log NIGHTLY_RATE	-0.0274	0.0341	-0.0760*	(0.0312)
log #SUPPLIED_DAYS	-0.0175	0.02488	-0.0118	(0.0202)
log #PASSENGERS	0.9230***	0.0720	1.059***	(0.0607)
Fixed Effect	Zip code		Zip code	
Seasonality	Calendar Month		Calendar Month	

Notes: Model (1) is estimated with a GSC model. Model (2) is estimated with a DiD model. All control variables are averaged within the zip code.

Both models treat the zip code as the unit level; there are 353 unique zip codes across the five cities and 12 periods in 2016. The DV for both models is the monthly occupancy, averaged across all properties in the same zip code.

Standard errors in the GSC model are computed with a placebo test and are bootstrapped for 1,000 samples. Standard errors in the DiD model are clustered at the zip code level.
* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Alternative Definition of the Transit Score Variable

In the main paper, we show that access to public transportation positively moderates the treatment effect of Uber/Lyft's exit on Airbnb property demand in Austin. We operationalize access to public transportation based on the transit score from walkscore.com, and we discretize the variable in the same way as walkscore.com: grade 1 for transit score 0~24 (minimal transit), grade 2 for transit score 25~49 (some transit), grade 3 for transit score 50~69 (good transit), and grade 4 for transit score >70 (excellent transit). According to Hirsch et al. (2013), the gradation is based on the convenience of public transportation: from an address in transit grade 1, it is possible to get on a bus; grade 2 has a few nearby public transportation options, and grade 3 has many nearby public transportation options; finally, from an address in transit grade 4, public transportation is convenient for most trips within the city.

To show that the results are robust to the definition of the transit score variable, we replicate the heterogeneous effect analysis with two alternative variables. First, instead of following the four-level gradation from walkscore.com, we categorize the transit score into three levels (0~33; 34~66; 67~100), with grade 3 (the top transit grade) as the reference. As shown in Table W13, the coefficient of grade 3 is positive and significant, suggesting that the exit of Uber/Lyft led to a significant *increase* in the demand for grade 3 properties. The coefficient of the key variable, *AUSTIN·AFTER·TRANSIT*, is negative and significant for both grade 2 properties (b = -0.0647, p < 0.001) and grade 1 properties (b = -0.0791, p < 0.001). The results are consistent with our main finding: properties with poorer access to public transportation lost demand after the exit of Uber/Lyft, while the few properties with the best access gained demand.

Second, we use the logged transit score as a continuous moderator (i.e., without gradation), and we present the results in Table W14. The coefficient of *AUSTIN · AFTER · TRANSIT_SCORE* is positive and significant (b = 0.0151, p < 0.05) confirming our main finding that access to public transportation positively moderates the treatment effect of Uber/Lyft's exit on Airbnb property demand in Austin.

Table W13 Heterogeneous Effects of Uber/Lyft's Exit on Demand: Alternative Gradation of the Transit Score

VARIABLES	**ESTIMATES**	**S.E.**
	Interaction with transportation access (transit scores grouped into grades 1–3)	
AUSTIN · AFTER (reference: grade 3)	0.0295*	(0.0137)
AUSTIN · AFTER · TRANSIT (grade 2)	-0.0647***	(0.0175)
AUSTIN · AFTER · TRANSIT (grade 1)	-0.0791***	(0.0132)
log #REVIEW	0.0467***	(0.00378)
log #PHOTO	0.0404***	(0.00934)
log NIGHTLY_RATE	-0.0585***	(0.00753)
log #SUPPLIED_DAYS (within a zip code)	0.000818	(0.00113)
log #PASSENGERS	1.269***	(0.0481)
Fixed Effect	Property	
Seasonality	Calendar Month	
Observations	67039	
R-squared	0.6663	

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties. The DV is the monthly occupancy (a ratio between 0 and 1) of property i in month t. The local transit score grades are based on an alternative categorization: grade 1 is a transit score of 0~33 (minimal to some access to public transportation),

grade 2 is 34~66 (some to good access), and grade 3 is 67~100 (good to excellent access). The common shift, captured in *AFTER · TRANSIT*, is controlled for and not shown.
Robust standard errors are clustered at the individual-property level.
* p < 0.05 ** p < 0.01 *** p < 0.001

Table W14 Heterogeneous Effects of Uber/Lyft's Exit on Demand: The Transit Score as a Continuous Moderator

VARIABLES	ESTIMATES	S.E.
	Interaction with transportation access (logged transit score)	
AUSTIN · AFTER	-0.0904*	(0.0387)
AUSTIN · AFTER · TRANSIT_SCORE (logged transit score used as a continuous moderator)	0.0151*	(0.00656)
log #REVIEW	0.0466***	(0.00378)
log #PHOTO	0.0402***	(0.00933)
log NIGHTLY_RATE	-0.0589***	(0.00755)
log #SUPPLIED_DAYS (within a zip code)	0.000921	(0.00113)
log #PASSENGERS	1.270***	(0.0481)
Fixed Effect	Property	
Seasonality	Calendar Month	
Observations	67039	
R-squared	0.6663	

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties. The DV is the monthly occupancy (a ratio between 0 and 1) of property *i* in month *t*. The moderator, *Transit_Score,* is a continuous variable calculated as log (transit score + 1), where the transit score has a value of 0 to 100. The common shift, captured in *AFTER · TRANSIT*, is controlled for and not shown.
Robust standard errors are clustered at the individual-property level.
* p < 0.05 ** p < 0.01 *** p < 0.001

WEB APPENDIX G: EXAMINING CHANGES IN THE AIRBNB SUPPLY

We examine dynamics on the supply side of Airbnb to assess whether hosts made adjustments—specifically, to the nightly rate and property availability—after Uber/Lyft's exit from Austin. We estimate a heterogenous effect based on access to public transportation, following the main finding that properties with poorer access to public transportation experienced a greater decrease in demand. (That is, we include an interaction term, *AUSTIN·AFTER·TRANSIT*, in the DiD regressions to examine whether the properties with lower transit scores made greater changes to the nightly rate and property availability.)

Assessing the Impact of Uber/Lyft's Exit on the Nightly Rate

We replicated our DiD model by regressing the logged nightly rate on the key treatment indicator, *AUSTIN · AFTER*. In Table W15, we report the estimated coefficients of *AUSTIN · AFTER* (the main effect, column 1) and of the interaction terms, *AUSTIN·AFTER·TRANSIT* (column 2). We find that the nightly rate decreased by 3.6% (= 1 - $\exp^{(-0.0348)}$) after Uber/Lyft exited Austin, with seasonality controlled. This translates into a decrease of $9.3 in the average nightly rate, given an average nightly rate of $257 in Austin prior to treatment (in the matched sample, among properties that were available for at least one night in a month, between January 2015 and December 2016). The insignificant coefficients of *AUSTIN·AFTER·TRANSIT* (column 2) suggest that hosts made similar adjustments to their nightly rate regardless of their property's access to public transportation.

Note that the Airbnb demand was lower after the exit of Uber/Lyft. Specifically, travelers were less likely to choose an Airbnb listing over a hotel because transportation costs rose for the average Airbnb listing (74% of which have minimal or only some access to public transportation). We posit that the average nightly rate for Austin properties dropped for two reasons: 1) Airbnb hosts noticed a drop in demand (or predicted a decrease in the demand due to the exit of Uber/Lyft), and 2) Airbnb's smart pricing algorithm reduced the recommended nightly rate for many listings based on the fall in bookings in the Austin area.[14]

Table W15 The Effect of Uber/Lyft's Exit on the Nightly Rate

VARIABLES	(1) Main Effect	(2) X Access to Public Transportation
AUSTIN · AFTER	-0.0348***	
	(0.00635)	
Interacting with the Transit Score Grade		
AUSTIN · AFTER (reference: grade 4)		-0.0602
		(0.0420)
AUSTIN · AFTER · TRANSIT (grade 3)		-0.00627
		(0.0289)
AUSTIN · AFTER · TRANSIT (grade 2)		-0.0291**
		(0.0104)
AUSTIN · AFTER · TRANSIT (grade 1)		-0.0664*
		(0.0301)
Control Variables		
log #REVIEW	0.0860***	0.0857***
	(0.00544)	(0.00545)
log #PHOTO	-0.00103	-0.00109
	(0.0195)	(0.0195)

[14] https://blog.atairbnb.com/smart-pricing/. Airbnb introduced a pricing algorithm, which is a data-driven machine learning model that computes the optimal price based on a set of factors that influence property demand, including the overall demand in the area (market and listing popularity). Hence, the algorithm should detect a decrease in local demand and calculate a lower price to adjust for the demand dynamics. Hosts choose whether to use the pricing algorithm at all; those who use it may have the algorithm either set the price automatically or suggest a price to the host.

log #BLOCKED_DAYS$_{t-1}$	0.00119	0.00119
	(0.00120)	(0.00120)
log #SUPPLIED_ DAYS$_{t-1}$ (sum in the zip code)	-0.000178	-0.000158
	(0.00108)	(0.00108)
log #NUM_HOTELS (sum in the city)	-1.025**	-1.027**
	(0.313)	(0.313)
HOTEL_OCCUPANCY (average in the city)	0.0162	0.0163
	(0.0421)	(0.0421)
HOTEL_ADR (average in the city)	0.0226	0.0227
	(0.0280)	(0.0280)
log #PASSENGERS	-0.0891	-0.0894
	(0.0558)	(0.0558)
Fixed Effect	Property	Property
Seasonality	Calendar Month	Calendar Month
Observations	67039	67039
R-squared	0.9537	0.9537

Notes: The DV is the logged average nightly rate of property *i* in period *t*. Models are estimated on observations of properties with at least one open night in month *t*; the nightly rate would not mean much if the property were blocked for all of month *t*. Possible common shifts in demand, captured in *AFTER · TRANSIT*, are controlled for and not shown.

Robust standard errors (clustered at the individual-property level) are in parentheses.

* p < 0.05 ** p < 0.01 *** p < 0.001

When Did Airbnb Hosts Start Adjusting the Nightly Rate?

Table W15 indicates that Airbnb hosts reacted to Uber/Lyft's exit by reducing their nightly rate. We estimate a relative-time model to examine the timing. Specifically, we replicate the estimation in Table W15 but replace the post-treatment periods with a series of leads. As shown in Table W16, the coefficient of the post-treatment lead is directionally negative in May, becomes significantly negative in June, is most negative in August, and then becomes progressively less negative from September through December (though the estimated coefficient of *POST_TREATMENT (4),* corresponding to October–December, is still negative and significant).

The insignificant coefficient of *POST_TREATMENT (0)* suggests that hosts did not immediately adjust their nightly rate after Uber/Lyft's exit from Austin. We note that the treatment took place in the middle of the month (May 9), and many bookings for later in the month likely were established before May 9. The pattern of an increasing treatment effect on the nightly rate in June through August resembles the evolving treatment effect on the property demand (see Table 3). We posit that hosts decreased prices to some extent early on (June) but gradually realized that the drop in demand warranted a deeper price reduction (July, August). Then, as local ride-sharing services such as RideAustin began to compensate for the loss of Uber/Lyft, the fall in demand slowed, and hosts continued to reduce the price but at a more gradual rate (in September through December). As discussed in Web Appendix A, the number of rides supplied by RideAustin increased rapidly after its launch in June 2016.

Table W16 Evolution of the Nightly Rate After Uber/Lyft's Exit

VARIABLES	ESTIMATES
Leads: Post-Treatment Trends in Property Nightly Rate	
POST_TREATMENT (0): May	-0.0108
	(0.00598)
POST_TREATMENT (1): June	-0.0226**
	(0.00750)
POST_TREATMENT (2): July	-0.0404***
	(0.0113)
POST_TREATMENT (3): August	-0.0948***
	(0.0121)
POST_TREATMENT (4): September	-0.0586***
	(0.0112)
POST_TREATMENT (>4): October ~ December	-0.0509***
	(0.0104)
Control Variables	
log #REVIEW	0.0857***
	(0.00543)
log #PHOTO	-0.00136
	(0.0194)
log #BLOCKED_DAYS$_{t-1}$	0.00122
	(0.00120)
log #SUPPLIED_DAYS $_{t-1}$ (sum in the zip code)	-0.000194
	(0.00108)
log #NUM_HOTELS (sum in the city)	-0.481
	(0.396)
HOTEL_OCCUPANCY (average in the city)	-0.00188***
	(0.000557)
HOTEL_ADR (average in the city)	0.0000875
	(0.000219)

log #PASSENGERS	0.0272
	(0.0597)
Fixed Effect	Property
Seasonality	Calendar Month
Observations	67039
R-squared	0.9538

Notes: The DV is the logged average nightly rate of property *i* in period *t*. Models are estimated on observations of properties with at least one open night in month *t*; the nightly rate would not mean much if the property were blocked for all of month *t*.
Robust standard errors (clustered at the individual-property level) are in parentheses.
* p < 0.05 ** p < 0.01 *** p < 0.001

Assessing the Impact of Uber/Lyft's Exit on the Supply of Open Days

Next, we assess whether Uber/Lyft's exit affected hosts' decisions about how many days in a month to make open for booking. We regressed the number of open days in a month on the key dummy variable, *AUSTIN · AFTER.* We used the count to capture two types of changes in the Airbnb supply: 1) a change in the availability of a property (i.e., more or fewer open nights), and 2) the decision to fully block the property for the month, making the property temporarily inactive on Airbnb.

In Table W17, we report the main estimation results (column 1) and heterogeneous effects by access to public transportation (column 2). The key coefficient of *AUSTIN · AFTER* is negative and significant, suggesting that the number of open days in a month decreased by 4.5% (= 1 - $\exp^{(-0.0462)}$) following the exit of Uber/Lyft, controlling for zip code and seasonality fixed effects. More interestingly, the set of coefficients in column 2 parallels the demand model (Table 4): the coefficient of *AUSTIN · AFTER* is *positive* and significant for properties with excellent access to public transportation (grade 4) but negative and significant for all other properties (grades 1–3).

We infer that Airbnb hosts made their properties either more or less available in response to the increase or decrease in demand. As explained in the main paper, we argue that demand increased for properties with excellent access to public transportation because the exit of Uber/Lyft increased transportation costs outside of the commercial core (main hotel discricts), making properties with excellent access to public transportation more attractive than other properties. We reason that some hosts temporarily or permanently dropped out of the Airbnb supply because they compared the short-term rental option (Airbnb listing) with the long-term rental option (e.g., monthly or yearly rental on the housing market). This conjecture is consistent with the finding that the likelihood of renting a property on the long-term rental market increases as the expected revenue from Airbnb decreases (Li, Kim, and Srinivasan 2021).

Table W17 The Effect of Uber/Lyft's Exit on the Supply of Open Days

VARIABLES	**(1) Main Effect**	**(2) X Access to Public Transportation**
UBER/LYFT'S EXIT	-0.0462*	
	(0.0184)	
Interacting with the Transit Score Grade		
AUSTIN · AFTER (reference: grade 4)		0.183*
		(0.0758)
AUSTIN · AFTER · TRANSIT (grade 3)		-0.213*
		(0.0846)
AUSTIN · AFTER · TRANSIT (grade 2)		-0.229**
		(0.0757)
AUSTIN · AFTER · TRANSIT (grade 1)		-0.235**
		(0.0752)
Control Variables		
log #REVIEW (sum within zip code)	0.0396***	0.0394***

	(0.00964)	(0.00964)
log #PHOTO (sum within zip code)	0.105***	0.106***
	(0.0246)	(0.0246)
log $\#BLOCKED\_DAYS_{t-1}$	-0.420***	-0.420***
	(0.00514)	(0.00513)
log $\#SUPPLIED\_DAYS_{t-1}$ (sum in the zip code)	0.000705	0.000669
	(0.00314)	(0.00314)
log #NUM_HOTELS (sum in the city)	-1.551	-1.551
	(0.853)	(0.853)
HOTEL_OCCUPANCY (average in the city)	-0.509***	-0.509***
	(0.141)	(0.141)
HOTEL_ADR (average in the city)	0.794***	0.794***
	(0.0950)	(0.0950)
log #PASSENGERS	0.0107	0.0107
	(0.196)	(0.196)
Fixed Effect	Property	Property
Seasonality	Calendar Month	Calendar Month
Observations	135021	135021
R-squared	0.7204	0.7204

Notes: The DV is the logged number of open days for property *i* in period *t*, i.e., log (# Open $Days_{it}$+1). The number of observations is greater than the *N* in the main analyses because the main regressions included only the properties with at least one open night in *t*, while the present model includes properties that were blocked for all of *t*. Possible common shifts in demand, captured in *AFTER · TRANSIT*, are controlled for and not shown.
Robust standard errors (clustered at the individual-property level) are in parentheses.
* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

When Did Airbnb Hosts Start Adjusting the Supply?

We estimate the relative-time model on Airbnb's supply, measured as the number of days that host *i* made open for booking in month *t*. The estimation results are reported in Table W18, column 2.

For comparison, we include the estimation results regarding the nightly rate (Table W16) in column 1. As can be seen, the treatment coefficient in column 2 became significantly negative in July ($b = -0.0453$, $p < 0.001$), suggesting that hosts were beginning to reduce the supply in response to the drop in demand caused by Uber/Lyft's exit. Note that a significant downward price correction appeared in June, as shown in column 1. It appears that hosts first tried to respond by reducing their prices, and when the price correction was insufficient to counteract the fall in demand, hosts reduced the supply as well.

Table W18 Evolution of the Supply of Open Days After Uber/Lyft's Exit

	(1)	**(2)**
VARIABLES	**DV: Nightly Rate**	**DV: # Open Days**
Leads: Post-Treatment Trends in the Supply of Open Days		
POST_TREATMENT (0): May	-0.0108	-0.0160
	(0.00598)	(0.0204)
POST_TREATMENT (1): June	-0.0226**	-0.0424
	(0.00750)	(0.0251)
POST_TREATMENT (2): July	-0.0404***	-0.0453***
	(0.0113)	(0.0118)
POST_TREATMENT (3): August	-0.0948***	-0.0607***
	(0.0121)	(0.0170)
POST_TREATMENT (4): September	-0.0586***	-0.0791**
	(0.0112)	(0.0263)
POST_TREATMENT (>4): October ~ December	-0.0509***	-0.0451***
	(0.0104)	(0.00821)
Control Variables		
log #REVIEW	0.0857***	0.0389***
	(0.00543)	(0.00922)
log #PHOTO	-0.00136	0.105***
	(0.0194)	(0.0234)

log #BLOCKED_DAYS$_{t-1}$	0.00122	-0.420***
	(0.00120)	(0.00492)
log #SUPPLIED_DAYS $_{t-1}$ (sum in the zip code)	-0.000194	0.000374
	(0.00108)	(0.00300)
log #NUM_HOTELS (sum in the city)	-0.481	-1.114
	(0.396)	(1.016)
HOTEL_OCCUPANCY (average in the city)	-0.00188***	-0.930***
	(0.000557)	(0.145)
HOTEL_ADR (average in the city)	0.0000875	1.157***
	(0.000219)	(0.108)
log #PASSENGERS	0.0272	0.332
	(0.0597)	(0.207)
Fixed Effect	Property	Property
Seasonality	Calendar Month	Calendar Month
Observations	67039	135021
R-squared	0.9538	0.7206

Notes: The DV in column 1 is the logged average nightly rate of property *i* in period *t* (among properties with at least one open night in month *t*). The DV in column 2 is the logged number of open days for property *i* in period *t*, i.e., log (# Open Days$_{it}$ + 1). There are more observations in column 2 than in column 1 because the regression in column 1 includes only the properties with at least one open night in *t*, while the regression in column 2 includes properties that were blocked for all of *t*.

Robust standard errors (clustered at the individual-property level) are in parentheses.

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Heterogeneous Effects on the Nightly Rate and Supply: Luxuriousness and Access to Public Transportation

We examine the heterogeneity in hosts' responses by luxuriousness and access to public transportation. For luxuriousness, we use the nightly rate to classify properties as high-end and low-end. For the main analysis, we use a threshold of \$300 (approximately the average rate for the top two hotel classes; see Table 6 in the main paper); we use a threshold of \$250 as a robustness check. We estimate the DiD model on the subsamples of high-end and low-end properties, and we examine the coefficients of the interaction terms, $AUSTIN \cdot AFTER \cdot TRANSIT$, using grade 4 (excellent access to public transportation) as a reference.

In Table W19, we report the estimation results for the regression on the nightly rate. First, we observe that the results are consistent between the \$300 threshold (columns 1 and 2) and the \$250 threshold (columns 3 and 4); we focus on the \$300 threshold here. The results in column 1 suggest that the average nightly rate among the low-end properties with excellent access did not change (*grade 4:* b = 0.0856*,* $p > 0.05$) after the exit of Uber/Lyft, but the average nightly rate decreased among all other low-end properties. For example, for the low-end properties with minimal access to public transportation (grade 1), the coefficient (b = -0.122) reflects a decrease in the nightly rate of 11.5% (= 1 - exp(-0.122)), which amounts to a price reduction of \$12.8 (given an average nightly rate of \$111.4 in the pre-exit period). The nightly rate fell by slightly less (11.2%) among low-end grade 2 properties (some transit) and by even less (9.15%) among low-end grade 3 properties (good transit). For high-end properties, however, the results in column 2 indicate that Uber/Lyft's exit did not affect the nightly rate.

In Table W20, we report the estimation results for the regression on the supply (the logged number of open days in a month). The results show a similar pattern: After Uber/Lyft's exit, the supply significantly decreased among low-end properties in grades 1–3. The supply did not change significantly among high-end properties in any of the transit score grades.

Table W19 Heterogeneous Effects of Uber/Lyft's Exit on the Nightly Rate, By Luxuriousness and Access to Public Transportation

VARIABLES	ESTIMATES			
	Threshold: \$300 nightly rate		Threshold: \$250 nightly rate	
	(1) Low-end	**(2) High-end**	**(3) Low-end**	**(4) High-end**
AUSTIN · AFTER	0.0856	-0.0630	0.0982	-0.0491
(reference: grade 4)	(0.0475)	(0.0977)	(0.0503)	(0.0771)
AUSTIN · AFTER · TRANSIT	-0.0964*	0.116	-0.113*	0.0869
(grade 3)	(0.0479)	(0.100)	(0.0463)	(0.0789)
AUSTIN · AFTER · TRANSIT	-0.119*	0.111	-0.130*	0.0779
(grade 2)	(0.0481)	(0.0997)	(0.0509)	(0.0791)
AUSTIN · AFTER · TRANSIT	-0.122*	-0.0215	-0.135*	0.00216
(grade 1)	(0.0528)	(0.170)	(0.0557)	(0.118)
log #REVIEW	0.0863***	0.0809***	0.0861***	0.0857***
	(0.00524)	(0.0196)	(0.00511)	(0.0170)
log #PHOTO	-0.00265	0.00884	-0.00309	0.00587
	(0.0164)	(0.0779)	(0.0171)	(0.0590)
log #BLOCKED_DAYS$_{t-1}$	0.00191	-0.00205	0.00134	0.000915
	(0.00114)	(0.00361)	(0.00118)	(0.00276)
log #SUPPLIED_DAYS	0.0000461	-0.000806	0.000195	-0.000947
(within a zip code)	(0.00108)	(0.00290)	(0.00112)	(0.00230)
log #NUM_HOTELS (sum in	-1.150***	0.591	-1.199***	0.319
the city)	(0.313)	(0.924)	(0.315)	(0.771)
HOTEL_OCCUPANCY	-0.0135	0.237*	-0.0227	0.188*
(average in the city)	(0.0405)	(0.109)	(0.0422)	(0.0882)
	0.0871**	0.0620	0.0842**	-0.0544

HOTEL_ADR (average in the city)	(0.0293)	(0.0615)	(0.0312)	(0.0519)
log #PASSENGERS	-0.110	0.0559	-0.118	-0.111
	(0.0690)	(0.164)	(0.0791)	(0.143)
Fixed Effect	Property	Property	Property	Property
Seasonality	Calendar Month	Calendar Month	Calendar Month	Calendar Month
Observations	57831	9208	52753	14286
R-squared	0.9213	0.8574	0.9090	0.8741

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties. The DV is the logged average nightly rate of property i in period t. Models are estimated on observations of properties with at least one open night in month t; the nightly rate would not mean much if the property were blocked for all of month t. The four grades refer to the transit scores from walkscore.com, as described in the main paper. The common shifts, captured in the coefficients of *AFTER · TRANSIT,* are controlled for and not shown. In columns 1 and 2, the DiD model is estimated on the subsamples of low-end and high-end properties, respectively. A property is considered "high end" if its nightly rate is above \$300, which is the average price for the top two classes of hotels. Columns 3 and 4 are analogous but use a threshold of \$250, which is the average price for the top three classes of hotels.
Robust standard errors (clustered at the individual-property level) are in parentheses.
* p < 0.05 ** p < 0.01 *** p < 0.001

Table W20 Heterogeneous Effects of Uber/Lyft's Exit on the Supply of Open Days, By Luxuriousness and Access to Public Transportation

VARIABLES	**ESTIMATES**			
	Threshold: \$300 nightly rate		Threshold: \$250 nightly rate	
	(1) Low-end	**(2) High-end**	**(3) Low-end**	**(4) High-end**
AUSTIN · AFTER	0.301*	0.168	0.312*	-0.0487
(reference: grade 4)	(0.126)	(0.217)	(0.121)	(0.228)
AUSTIN · AFTER · TRANSIT	-0.382*	0.178	-0.392**	0.0443
(grade 3)	(0.172)	(0.229)	(0.144)	(0.233)
	-0.384**	0.187	-0.398*	0.0444

AUSTIN · AFTER · TRANSIT	(0.148)	(0.223)		
(grade 2)			(0.170)	(0.244)
AUSTIN · AFTER · TRANSIT	-0.404**	0.0578	-0.402**	-0.0841
(grade 1)	(0.148)	(0.220)	(0.144)	(0.231)
log #REVIEW	0.0451***	0.0196	0.0425***	0.0375
	(0.0103)	(0.0266)	(0.0107)	(0.0222)
log #PHOTO	0.0952***	0.121*	0.102***	0.0998*
	(0.0255)	(0.0563)	(0.0275)	(0.0468)
log #BLOCKED_DAYS$_{t-1}$	-0.425***	-0.403***	-0.424***	-0.408***
	(0.00538)	(0.0128)	(0.00559)	(0.0108)
log #SUPPLIED_DAYS	0.00158	-0.00290	0.000829	-0.000362
(within a zip code)	(0.00345)	(0.00695)	(0.00365)	(0.00587)
log #NUM_HOTELS (sum in the	-3.349***	-0.795	-3.781***	-0.615
city)	(0.866)	(2.200)	(0.897)	(1.835)
HOTEL_OCCUPANCY	-0.376*	-0.849**	-0.314	-0.874**
(average in the city)	(0.154)	(0.306)	(0.161)	(0.266)
HOTEL_ADR	0.583***	1.358***	0.596***	1.151***
(average in the city)	(0.105)	(0.216)	(0.109)	(0.185)
log #PASSENGERS	0.0665	0.0947	0.00129	0.212
	(0.204)	(0.492)	(0.214)	(0.408)
Fixed Effect	Property	Property	Property	Property
Seasonality	Calendar Month	Calendar Month	Calendar Month	Calendar Month
Observations	107363	27658	97426	37595
R-squared	0.7108	0.7504	0.7061	0.7491

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties. The DV is the logged number of open days for property *i* in period t, i.e., log (# Open Days$_{it}$ + 1). There are more observations than in the main analyses because the main regressions included only the properties with at least one open night in *t,* while the present model includes properties that were blocked for all of *t*. The four grades refer to the transit scores from walkscore.com, as described in the main paper. The common shifts, captured in the coefficients of *AFTER · TRANSIT,* are controlled for and not shown. In columns 1 and 2, the DiD model is estimated on the subsamples of low-end and high-end properties, respectively. A property is considered “high end” if its nightly rate is above $300, which is the average price for the top two classes of hotels. Columns 3 and 4 are analogous but use a threshold of \$250, which is the average price for the top three classes of hotels.

Robust standard errors (clustered at the individual-property level) are in parentheses.

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

WEB APPENDIX H: ANALYZING THE RE-ENTRY OF UBER/LYFT IN AUSTIN

Uber and Lyft returned to Austin in late May 2017 after Texas passed a statewide system of ride-hailing regulations (HB 100) that overruled Austin's regulations.[15] We take the re-entry of Uber/Lyft as another regulatory shock to the transportation cost and examine whether the main effect weakened or even disappeared in the post-re-entry period.

In our re-entry model, we include two treatment indicators in the DiD regression and estimate the following demand model with the data from 2016–2017:

$$DEMAND_{it} = INTERCEPT + \beta_1 \cdot AUSTIN{\cdot}AFTER1_{it} + \beta_2 \cdot AUSTIN{\cdot}AFTER2_{it}$$
$$+ CONTROLS_{it} + SEASONALITY_t + PROPERTY_i + \varepsilon_{it}$$

where the treatment indicators $AUSTIN{\cdot}AFTER1_{it}$ and $AUSTIN{\cdot}AFTER2_{it}$ capture the exit of Uber/Lyft and the return of Uber/Lyft, respectively. More specifically, we segment the two-year periods into three segments: Jan. 2016 – April 2016 (pre-exit period), May 2016 – May 2017 (exit period), and June 2017 – Dec. 2017 (post-re-entry period). That is, $AUSTIN{\cdot}AFTER1_{it} = 1$ if property i is in Austin and period t is in the exit period (i.e., when Uber and Lyft were not available in Austin); $AUSTIN{\cdot}AFTER2_{it} = 1$ if property i is in Austin and period t is in the return period (i.e., after Uber/Lyft resumed operations in Austin).

The key coefficient β_1 captures the effect of the exit of Uber/Lyft on Austin Airbnb demand. In this analysis, however, we are more interested in the "re-entry effect" on Austin Airbnb demand, captured by β_2. Note that both β_1 and β_2 are estimated with the pre-treatment period (i.e., before Uber/Lyft's exit) as the reference.

[15] https://archive.curbed.com/2017/5/18/15657684/uber-lyft-austin-texas-ridehailing-state-law

Table W21 presents the estimation results. The key coefficient of the re-entry indicator, *AUSTIN · AFTER2,* is statistically insignificant (b = 0.0232, p > 0.1), indicating that the Airbnb demand in Austin was similar after Uber/Lyft's re-entry and before Uber/Lyft's exit. In other words, the negative effect of Uber/Lyft's exit on the Airbnb demand disappeared after re-entry. We reason that the surge in the transportation cost due to Uber/Lyft's exit was partially but not fully mitigated by new local ride-sharing services, so the re-entry of Uber/Lyft closed the residual gap in the supply of convenient, affordable transportation.[16]

In addition, we break down the two treatment periods (*AFTER1*, *AFTER2*) by month and examine how the coefficients evolved over time. In Table W22, the *Treatment Two: Return of Uber/Lyft* panel documents the difference in the Airbnb demand after Uber/Lyft's re-entry (relative to the pre-exit period), compared to the control cities. The post-re-entry demand was similar to the pre-exit demand (the coefficients are insignificant) in all months except for June and October 2017 (the coefficients are significantly positive).

We conduct an analogous regression on the Airbnb price (i.e., average nightly rate) and supply (i.e., open days in a month). In Table W23, we present the estimation results. In the *Treatment Two: Return of Uber/Lyft* panel, column 1, the trend in the price aligns with the trend in demand (in Table W22): the coefficients are insignificant for all months in the post-re-entry period.[17] In

[16] https://techcrunch.com/2017/03/12/austin-is-fine-without-uber-and-lyft-until-it-isnt/

[17] Note that the estimated coefficients have larger standard errors in the post-re-entry period than in the exit period. (Of the full matched sample of 11,536 properties, 11,084 properties remained in Jan 2017; by June 2017, only 10,184 remained. The decrease in sample size may partly explain why the standard errors were larger.) One may wonder whether the negative effect of Uber/Lyft's exit on Airbnb demand persisted in the return period, and the insignificant result is a false null effect due to the larger standard errors. However, note that the coefficients for the post-re-entry periods are positive (except for the last period, December 2017). Hence, we believe the weaker focal effect was not a false insignificance due to larger standard errors. We would be more concerned if the estimated coefficients in the post-re-entry period remained negative, which is the direction of the estimated effect of the exit of Uber/Lyft.

column 2, the coefficients are negative and significant for the first two months in the post-re-entry period (June and July 2017) and then are insignificant in August 2017 onward. Thus, Table W23 suggests that hosts relaxed the downward price correction promptly after demand returned to pre-exit levels, but it took longer for the supply to return to pre-exit levels.

Table W21 DiD Model of Uber/Lyft's 2017 Re-Entry on Property Demand

VARIABLES	Main Model	
	ESTIMATES	**S.E.**
AUSTIN · AFTER1 (Uber/Lyft's exit in 2016)	-0.0437***	(0.00607)
AUSTIN · AFTER2 (Uber/Lyft's return in 2017)	0.0232	(0.0149)
log #REVIEW	0.0356***	(0.00281)
log #PHOTO	0.0613***	(0.00803)
log NIGHTLY_RATE	-0.0593***	(0.00725)
log #SUPPLIED_DAYS (within a zip code)	0.000251	(0.00129)
log #PASSENGERS	0.926***	(0.0264)
Fixed Effect	Property	
Seasonality	Year-Month	
Observations	160528	
R-squared	0.5946	

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties across two years (24 periods): 2016 and 2017. The model contains two treatment indicators, one for Uber/Lyft's exit (2016) and one for Uber/Lyft's return (2017). The DV is the monthly occupancy (a ratio between 0 and 1) of property *i* in month *t*. If *i* was unavailable to be booked for the entirety of *t*, then we treat the occupancy as *missing* (indefinite), and the observation for *i,t* is automatically dropped from the estimation. SUPPLIED_DAYS is the total number of open days in month *t* among all Airbnb properties in the same zip code. PASSENGERS is the total number of travelers who visited Austin by plane in *t*, computed from passenger enplanement data reported by the Bureau of Transportation Statistics (BTS).

Robust standard errors (clustered at the individual-property level) are in parentheses.

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table W22 DiD Model of Uber/Lyft's Re-Entry on Airbnb Demand: A Breakdown by Month

VARIABLES	ESTIMATES	S.E.
Treatment One: Exit of Uber/Lyft		
May (2016)	-0.0374	(0.0280)
June	-0.0840***	(0.0148)
July	-0.106***	(0.0187)
August	-0.0736***	(0.0189)
September	-0.0550***	(0.0143)
October	0.0103	(0.0307)
November	-0.0430***	(0.0121)
December	-0.0542***	(0.00403)
January (2017)	-0.0406***	(0.0119)
February	-0.0404	(0.087)
March	-0.0198***	(0.00185)
April	-0.0173***	(0.00238)
May	-0.0154***	(0.00102)
Treatment Two: Return of Uber/Lyft		
June	0.0213*	(0.00840)
July	0.0724	(0.0397)
August	0.0402	(0.0295)
September	0.0312	(0.0236)
October	0.0108*	(0.0053)
November	0.0412	(0.0253)
December	-0.0241	(0.0192)
Control Variables		
log #REVIEW	0.0469***	(0.00398)

log #PHOTO	0.0681***	(0.0113)
log NIGHTLY_RATE	-0.0548***	(0.00780)
log #SUPPLIED_DAYS (within a zip code)	0.00100	(0.00120)
log #PASSENGERS	1.029***	(0.0739)
Fixed Effect	Property	
Seasonality	Year-Month	
Observations	160528	
R-squared	0.5950	

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties across two years (24 periods): 2016 and 2017. The model contains two treatment indicators, one for Uber/Lyft's exit (2016) and one for Uber/Lyft's return (2017). The DV is the monthly occupancy (a ratio between 0 and 1) of property *i* in month *t*. If *i* was unavailable to be booked for the entirety of *t*, then we treat the occupancy as *missing* (indefinite), and the observation for *i,t* is automatically dropped from the estimation. SUPPLIED_DAYS is the total number of open days in month *t* among all Airbnb properties in the same zip code. PASSENGERS is the total number of travelers who visited Austin by plane in *t*, computed from passenger enplanement data reported by the BTS.

Robust standard errors (clustered at the individual-property level) are in parentheses.

* p < 0.05 ** p < 0.01 *** p < 0.001

Table W23 DiD Model of Uber/Lyft's Re-Entry on Host Responses: A Breakdown by Month

	(1) DV: Nightly Rate		**(2) DV: Supply (# Open Days)**	
VARIABLES	**ESTIMATES**	**S.E.**	**ESTIMATES**	**S.E.**
Treatment One: Exit of Uber/Lyft				
May (2016)	-0.00321	(0.00680)	-0.0322	(0.0310)
June	-0.0163*	(0.00679)	-0.0484	(0.0282)
July	-0.0369***	(0.00878)	-0.0386*	(0.0161)

August	-0.0816***	(0.00987)	-0.0572***	(0.0084)
September	-0.0563***	(0.00866)	-0.0886**	(0.0286)
October	-0.0293*	(0.0144)	-0.0587**	(0.0227)
November	-0.0595***	(0.00966)	-0.0518	(0.0329)
December	-0.0556***	(0.00840)	-0.045**	(0.0173)
January (2017)	-0.0500***	(0.00989)	-0.0352**	(0.0135)
February	-0.0334***	(0.00938)	-0.0367***	(0.00587)
March	-0.0506***	(0.00932)	-0.0303	(0.0456)
April	-0.0364***	(0.00765)	-0.0359*	(0.0164)
May	-0.0291**	(0.0108)	-0.0334**	(0.0110)
Treatment Two: Return of Uber/Lyft				
June	-0.0157	(0.0118)	-0.0333*	(0.0139)
July	-0.0254	(0.0286)	-0.0313*	(0.0155)
August	0.00175	(0.00370)	-0.0377	(0.0272)
September	-0.0269	(0.0364)	-0.0329	(0.0418)
October	-0.0270	(0.0318)	0.0304	(0.0289)
November	-0.0210	(0.0321)	-0.00663	(0.0351)
December	-0.0108	(0.0286)	-0.0109	(0.0227)
Control Variables				
log #REVIEW	0.0856***	(0.00544)	0.0395***	0.00966
log #PHOTO	-0.00145	(0.0195)	0.103***	0.0245
log $\#BLOCKED\_DAYS_{t-1}$	0.00116	(0.00120)	-0.420***	0.00515
log #SUPPLIED_DAYS (within a zip code)	-0.000313	(0.00108)	0.00403	0.00314
log #NUM_HOTELS (sum in the city)	-1.108**	(0.368)	-1.848**	0.650
HOTEL_OCCUPANCY (average in the city)	0.00308	0.00407	-0.287**	0.101
HOTEL_ADR (average in the city)	0.0287	0.0164	0.698***	0.149
log #PASSENGERS	0.0618	0.0429	0.124	0.0807
Fixed Effect	Property		Property	

Seasonality	Year-Month	Year-Month
Observations	160528	247119
R-squared	0.9690	0.7195

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties across two years (24 periods): 2016 and 2017. The model contains two treatment indicators, one for Uber/Lyft's exit (2016) and one for Uber/Lyft's return (2017). The DV in column 1 is the logged average nightly rate of property *i* in period *t* (among properties with at least one open night in month *t*). The DV in column 2 is the logged number of open days for property *i* in period *t*, i.e., log (# Open Days_{it} + 1). There are more observations in column 2 than in column 1 because the regression in column 1 includes only the properties with at least one open night in *t*, while the regression in column 2 includes properties that were blocked for all of *t*.

Robust standard errors (clustered at the individual-property level) are in parentheses.

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

WEB APPENDIX I: SUPPLEMENTARY DATA ON TRAVELERS TO AUSTIN

Location and Transportation

Our main analyses suggest that Uber/Lyft's exit from Austin caused a shift in demand from Airbnb to hotels and from Airbnb properties with poorer access to public transportation to Airbnb properties with excellent access. Our proposed mechanism assumes that guests 1) evaluated Airbnb listings based on their proximity to destinations and public transportation, 2) were aware of Uber/Lyft's exit and possible substitutes for transportation in Austin.

For the first assumption, we do not have data to prove that guests had full knowledge of the transportation costs, but we can provide anecdotal evidence to strengthen our argument that at least some travelers were considering transportation before deciding on the location of lodging. Airbnb makes it easy for travelers to consider location and transportation by providing three types of information on every property page (illustrated in Figure W11): guest ratings of the location, a map of the surrounding area with public transportation information embedded, and a detailed list of destinations and transit options near the property (written by the host). Most hotel-booking websites (e.g., Expedia, TripAdvisor) provide similar information for travelers.

For the second assumption, we explore trends in Google searches for relevant keywords. Figure W12 (a)–(c) shows a surge in searches for "prop 1 Austin," "Uber Austin," "Uber in Austin," and "Lyft in Austin" in May and June 2016. In panel (d), we decompose the plot for "Austin Uber" into the top five cities of origin of Austin visitors, and we find a similar surge.[18] Lastly, in panel

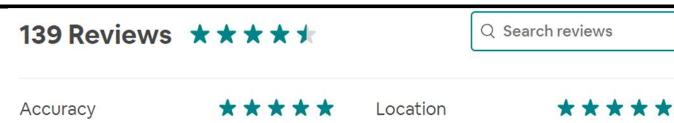
[18] We obtained passenger boarding data provided by the BTS. The dataset contains the origin, destination, and number of enplaned passengers for all flights operated by US air carriers. For Austin, the top five origin cities are Dallas (TX), Atlanta (GA), Houston (TX), Denver (CO), and Chicago (IL).

(e), we present an example of a traveler seeking information about possible substitutes for Uber/Lyft in Austin on Tripadvisor.com, suggesting that some travelers were aware of Uber/Lyft's exit and thus searched for substitutes while planning their trip.[19]

Figure W11 An Example of an Airbnb Property Page, With Detailed Information About Location & Transportation Options

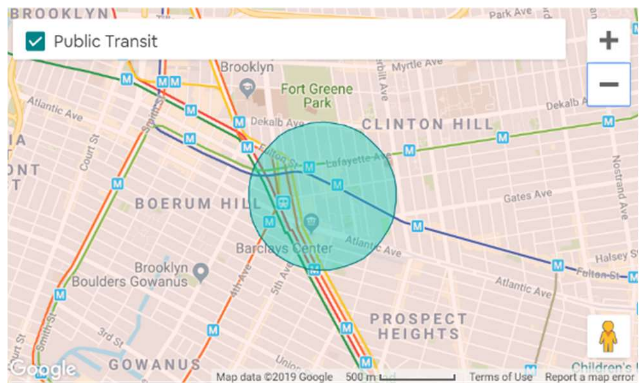
(1)

Guest ratings of the location



(2)

Google-provided map indicating the geographic location and nearby public transportation options



(3)

Description of the neighborhood and transportation options (written by the host)

Getting around

Only 2-3 blocks to the following:
- Path train to NYC
- Path train to Hoboken
- Ferry to NYC
- Light Rail to Jersey City, Bayonne, Weehawken, North Bergen
- Starbucks is steps away
- Hyatt Regency Jersey City is steps away

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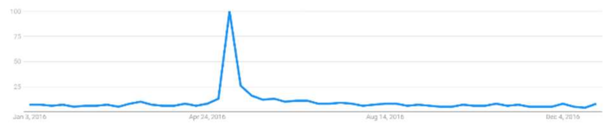
[19] https://www.tripadvisor.com/ShowTopic-g30196-i229-k10066576-Uber_alternatives-Austin_Texas.html

Figure W12 Evidence of Travelers' Awareness of Uber/Lyft's Exit

(a)

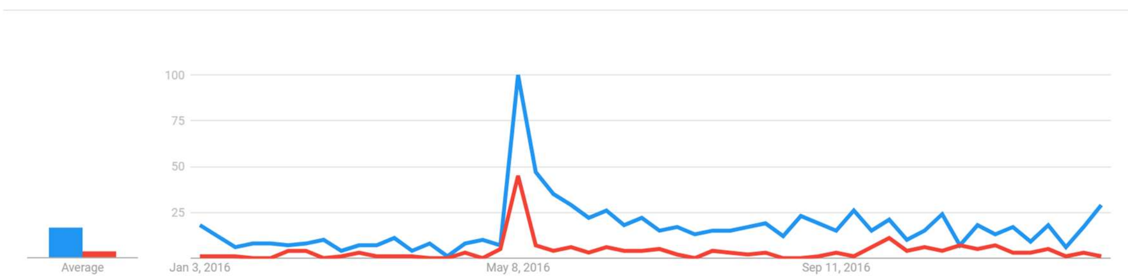
keyword: *prop 1 Austin*

(b)



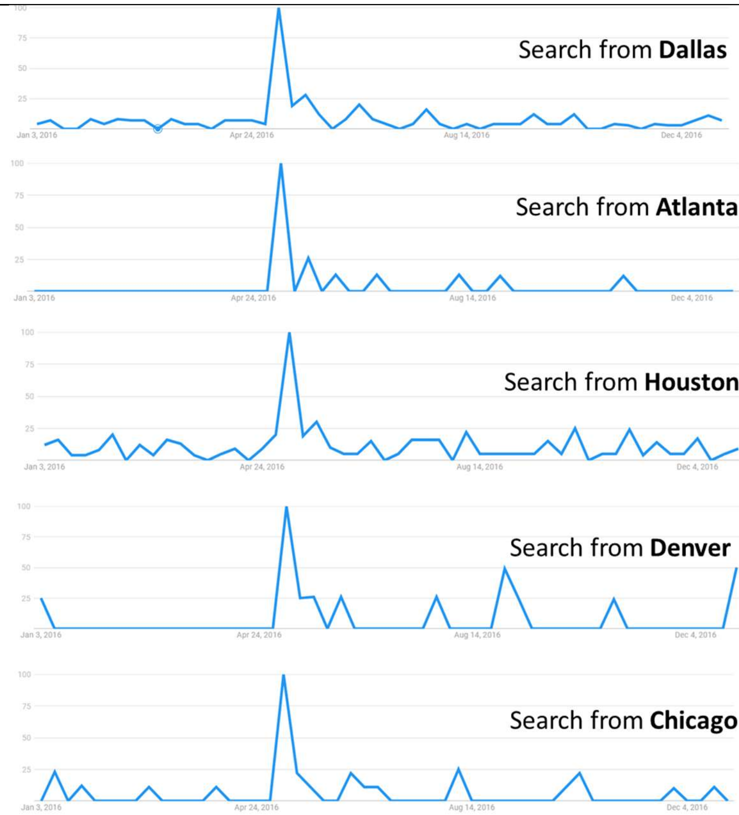
keyword: *Uber Austin*

(c)



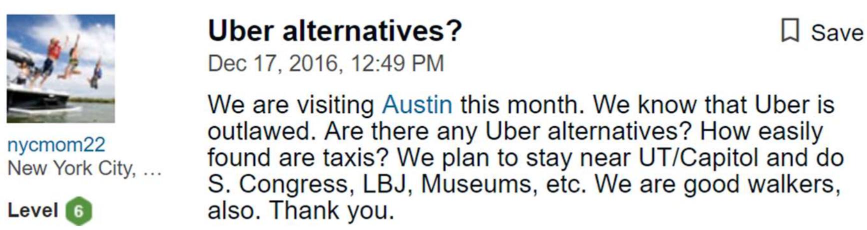
An overlay of two keywords: *Uber in Austin* (blue) and *Lyft in Austin* (red)

(d)



keyword: **Austin Uber**

(e)



A screenshot of a traveler aware of the absence of Uber/Lyft in Austin and asking for Uber alternatives (Dec. 2016)

Note for the Google Trends plots: Numbers represent the search interest relative to the highest point on the chart for the given region and time (assigned a value of 100). Thus, a value of 50 means that the term was half as popular as its peak popularity. A score of 0 means there was not enough data for the term.

Passenger Enplanement Data

From the Bureau of Transportation Statistics (BTS), we obtain passenger enplanement data to examine 1) the number of passengers visiting Austin (specifically, the Austin-Bergstrom International Airport) each month and 2) the composition of those passengers.

The BTS provides market data reported by US air carriers; the data include the origin, destination, and number of enplaned passengers on all flights.[20] We use the passenger boarding data as a proxy for the overall monthly travel demand in each of the five cities in our main sample. In Table W24, we present the total number of passengers visiting each city in each month of 2016.

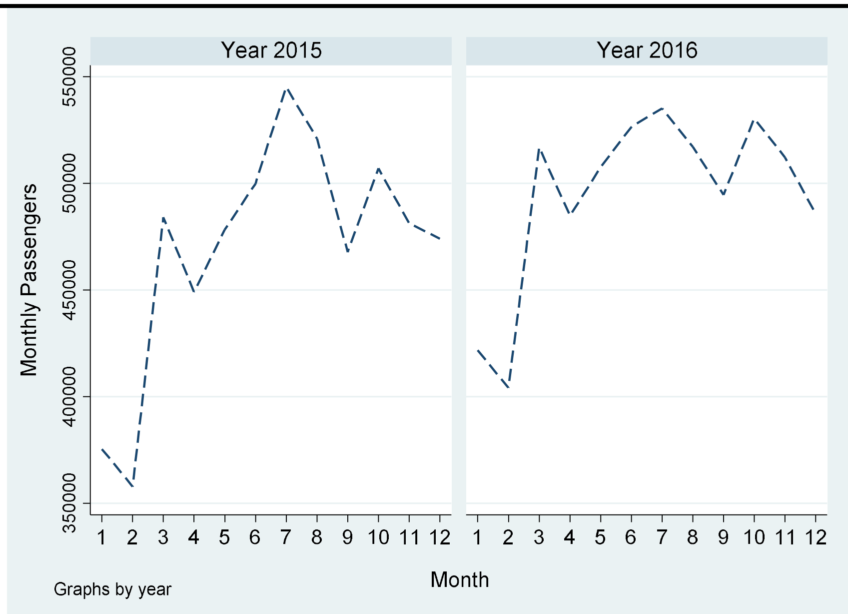
In Figure W13, we plot the monthly number of passengers for Austin alone in 2015 (left plot) and 2016 (right plot). The patterns are visually similar in 2015 and 2016.

Lastly, we examine whether the composition of passengers arriving in Austin changed significantly before and after the exit of Uber/Lyft in May 2016. Specifically, it is possible that travelers to Austin before May 2016 had a different preference for Airbnb vs. hotels than travelers after May 2016, such that Airbnb demand decreased in the post-treatment period for reasons other than Uber/Lyft's exit. We do not have data on each traveler's demographics or lodging preferences, but we can use the passenger enplanement data to investigate whether there were significant changes in the composition of the origin cities (i.e., where the travelers came from). We extract the origin cities from the BTS passenger enplanement data, aggregated at the month-level, for all of 2016. In Table W25, we list the top five origin cities in each month, the monthly passengers from each city, and the proportion of all passengers to Austin who came from each city. The top origin cities—Dallas (TX), Atlanta (GA), Houston (TX), Denver (CO), and Chicago (IL)—were

[20] https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/passenger/.

consistent throughout 2016, though the rank order varied from month to month. The same five cities also ranked at the top of 2015 (data not shown). In addition, there is overlap between the major origin cities of the travelers who visited Austin and those who visited the four control cities in 2016.[21]

Figure W13 Enplaned Passengers to Austin by Month in 2015 and 2016



Notes: The vertical axis indicates the number of passengers arriving at the Austin airport, as reported by the enplanement data. The horizontal axis indicates the month (1 = January; 12 = December).

[21] Specifically, in the control cities, the shared top cities of origin were Chicago and Denver for visiting Seattle; Dallas, Atlanta, Houston, and Denver for visiting Los Angeles; Chicago and Atlanta for visiting Boston; and Chicago, Dallas, and Denver for visiting San Diego.

Table W24 Number of Monthly Enplaned Passengers Visiting Each City in 2016

	MEAN	SD	MIN	MAX
City: Austin				
	494774.75	41651.779	404183	535240
City: Boston				
	1229347.8	148481.5	963929	1404750
City: Los Angeles				
	2371433.8	236545.88	1941918	2786921
City: San Diego				
	827971.5	64024.731	696258	930572
City: Seattle				
	1633438.8	249217.25	1258258	2039888

Table W25 Top Origin Cities of Travelers Visiting Austin in 2016

Origin City	Rank	# Passengers to Austin	Total monthly visitors to Austin	Ratio from the origin city
		January		
Dallas/Fort Worth, TX	1	48922	421831	0.115975
Houston, TX	2	38868	421831	0.092141
Atlanta, GA	3	33497	421831	0.079409
Denver, CO	4	27834	421831	0.065984
Dallas, TX	5	25360	421831	0.060119
		February		
Dallas/Fort Worth, TX	1	45274	404183	0.112014
Houston, TX	2	35603	404183	0.088086
Atlanta, GA	3	31565	404183	0.078096
Denver, CO	4	28227	404183	0.069837

Dallas, TX	5	25021	404183	0.061905
March				
Dallas/Fort Worth, TX	1	48386	516905	0.093607
Atlanta, GA	2	39020	516905	0.075488
Houston, TX	3	36759	516905	0.071114
Denver, CO	4	33841	516905	0.065469
Chicago, IL	5	31921	516905	0.061754
April				
Dallas/Fort Worth, TX	1	46756	484865	0.096431
Atlanta, GA	2	39276	484865	0.081004
Houston, TX	3	34230	484865	0.070597
Chicago, IL	4	33055	484865	0.068174
Denver, CO	5	27717	484865	0.057164
May				
Dallas/Fort Worth, TX	1	49194	507576	0.09692
Atlanta, GA	2	41948	507576	0.082644
Chicago, IL	3	38489	507576	0.075829
Houston, TX	4	33837	507576	0.066664
Denver, CO	5	28396	507576	0.055944
June				
Dallas/Fort Worth, TX	1	46376	526555	0.088074
Atlanta, GA	2	42988	526555	0.08164
Chicago, IL	3	40565	526555	0.077039
Houston, TX	4	32046	526555	0.06086
Denver, CO	5	31406	526555	0.059644
July				
Dallas/Fort Worth, TX	1	47888	535240	0.08947
Atlanta, GA	2	41944	535240	0.078365
Chicago, IL	3	40469	535240	0.075609
Denver, CO	4	34646	535240	0.06473
Houston, TX	5	31868	535240	0.05954

		August		
Dallas/Fort Worth, TX	1	46987	517170	0.090854
Chicago, IL	2	41295	517170	0.079848
Atlanta, GA	3	38448	517170	0.074343
Denver, CO	4	33546	517170	0.064865
Houston, TX	5	33213	517170	0.064221
		September		
Dallas/Fort Worth, TX	1	45626	494638	0.092241
Chicago, IL	2	40305	494638	0.081484
Atlanta, GA	3	39585	494638	0.080028
Houston, TX	4	34651	494638	0.070053
Denver, CO	5	34591	494638	0.069932
		October		
Dallas/Fort Worth, TX	1	48096	530397	0.090679
Chicago, IL	2	43171	530397	0.081394
Atlanta, GA	3	43011	530397	0.081092
Houston, TX	4	38784	530397	0.073123
Denver, CO	5	36221	530397	0.06829
		November		
Dallas/Fort Worth, TX	1	45138	512216	0.088123
Atlanta, GA	2	40905	512216	0.079859
Houston, TX	3	40665	512216	0.07939
Chicago, IL	4	36941	512216	0.07212
Denver, CO	5	31822	512216	0.062126
		December		
Dallas/Fort Worth, TX	1	44573	485721	0.091767
Houston, TX	2	38927	485721	0.080143
Atlanta, GA	3	38152	485721	0.078547
Chicago, IL	4	31741	485721	0.065348
Denver, CO	5	28303	485721	0.05827

The Attractiveness of Austin as a Tourist Destination, and Implications for Generalizability

Our study finds that the exit of Uber/Lyft from Austin impacted the transportation costs in Austin and hence impacted the lodging choices of travelers who visited Austin. One may wonder 1) whether a city's attractiveness affects the extent to which the loss of ride-sharing services would affect the demand for home-sharing services, and 2) how Austin's attractiveness as a tourist destination compares to other cities.

First, we agree that the impact of the loss of ride-sharing services on home-sharing services might be moderated by the city's attractiveness to tourists. We reason that the strength of the treatment effect should *increase* with the destination's attractiveness. In more popular tourist destinations, the average visitor might plan more trips from their lodging to local attractions—so local transportation costs would comprise a larger share of the travel budget. If ride-sharing services disappeared, these visitors would face a steeper increase in transportation costs and may be more likely to shift to lodging in areas with better transit scores. That said, we expect the impact of the loss of ride-sharing services on home-sharing services to be moderated by various city-level factors, including 1) the distribution of transit scores among Airbnb properties vs. hotels, 2) the price sensitivity of the visitors, and 3) the availability of ride-sharing substitutes for Uber/Lyft in the post-exit period. For example, we would expect Uber/Lyft's exit to have a smaller effect on Airbnb demand in a city where most Airbnb properties are concentrated in the main hotel districts (where there usually is excellent access to public transportation) or in a city that is visited primarily by high-income travelers, who should be relatively insensitive to an increase in the transportation costs and can easily afford more expensive options such as car rental.

Second, based on a review of tourism information, we believe that Austin is quite attractive to tourists (though not as appealing as, say, Paris or Sydney). This seems to be the consensus among many sources. For example, Austin was the No. 1 tourist destination in the southwestern US and No. 2 in the US as a whole.[22] Thrillist ranked Austin No. 13 in a list of the cities that are "best for a three-day weekend trip."[23] TripAdvisor ranked Austin (and our four control cities) within "the 25 most popular travel destinations in the US."[24] Similarly, we find that Austin and the control cities were ranked as top tourism cities or among the most-visited cities in the US in other independent studies.[25] WalletHub ranked Austin No. 19 (and all four control cities in the top 40) among over 180 cities in the US, based on 46 key metrics that reflect the city's attractiveness to tourists (e.g., food, entertainment, recreation). Specifically, Austin's overall score was 52.4 (higher scores are better); the control cities ranked No. 8 and No. 9 (Seattle and San Diego, both with scores of 56.5), No. 15 (Los Angeles, score of 53.6), and No. 36 (Boston, score of 49.1).[26] Based on the anecdotal evidence, we are convinced that Austin is an appealing place for tourists (as are the four control cities).

Lastly, we recognize that it would be useful to have data on the travelers' demographics (e.g., income) and intention for the visit; this level of analysis would improve our ability to predict the effect of Uber/Lyft's exit on Airbnb demand in a different city. We lacked such data, but for a more qualitative approach, we analyzed the passenger boarding data provided by the BTS, and we found overlap between the major origin cities of travelers to Austin and travelers to the four control cities in 2016 (see the section titled Passenger Enplanement Data). Based on this indirect evidence, we believe that the effect documented in Austin can be generalized to other cities, and we hope

[22] https://www.statesman.com/business/20161105/report-austin-no-1-tourist-destination-in-southwest-no-2-in-us.
[23] https://www.thrillist.com/travel/nation/best-us-cities-to-spend-a-weekend-nashville-austin-charleston-providence.
[24] https://www.businessinsider.com/the-25-most-popular-travel-destinations-in-the-us-2015-3#25-austin-texas-1.
[25] https://www.bestchoicereviews.org/travel/popular-tourist-cities-us/; https://www.ranker.com/list/forbes_-traveller-list-30-most-visited-cities-in-us/travelgrrl; https://www.afar.com/magazine/best-large-cities-in-the-united-states-to-live-in-and-visit.
[26] https://wallethub.com/edu/best-cities-for-staycations/4341.

future research can obtain the detailed individual-level data required for a more robust examination.

WEB APPENDIX J: AN ALTERNATIVE MEASURE OF PRICE

In our main analysis, we measure the price as the nightly rate for the whole listing; this is the price that displays on the property's listing page on Airbnb.com. It is possible, however, that groups of guests evaluate their lodging options and plan their budgets based on the nightly rate *per person*. Hence, we replicate the main DiD analysis but operationalize the price as the nightly rate per bedroom. (We would have preferred to compute the price *per person,* but the data did not contain the number of guests associated with each booking, so we used the number of bedrooms as a proxy.[27])

We replicate the DiD model (Equation 2 in the main paper) and report the estimation results in Table W26. The estimation results are consistent with the main findings as reported in Table 3 in the main paper.

[27] The underlying assumption is that the size of group (the number of guests who stay together) is positively correlated with the size of the property (the number of bedrooms). For example, a single guest is unlikely to choose a property with four bedrooms; similarly, a group of four guests is unlikely to be accommodated at a property with only one bedroom.

Table W26 Impact of Uber/Lyft's Exit on Property Demand: Alternative Measure of Price

VARIABLES	**Main Model**	
	ESTIMATES	**S.E.**
AUSTIN · AFTER	-0.0405***	(0.00613)
log #REVIEW	0.0469***	(0.00386)
log #PHOTO	0.0404***	(0.00938)
log NIGHTLY_RATE	-0.0581***	(0.00787)
log #SUPPLIED_DAYS (within a zip code)	0.000667	(0.00116)
log #PASSENGERS	1.266***	(0.0489)
Fixed Effect	Property	
Seasonality	Calendar Month	
Observations	67039	
R-squared	0.6612	

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties. The DV is monthly occupancy (a ratio between 0 and 1) for property *i* in month *t*. If *i* made the full month unavailable to be booked in *t*, the occupancy is computed as *missing* (indefinite), and the observation for *i,t* is automatically dropped from the estimation. *SUPPLIED_DAYS* is the total number of available days among all Airbnb properties in the same zip code. *PASSENGERS* is the total number of travelers who visited Austin by plane in *t*, computed from the passenger enplanement data reported by the BTS. The price is measured as the nightly rate per bedroom instead of the nightly rate for the whole listing, as used in the main DiD analysis.

Robust standard errors (clustered at the individual-property level) are in parentheses.

* p < 0.05 ** p < 0.01 *** p < 0.001

WEB APPENDIX K: SENSITIVITY OF THE DEMAND MODEL TO THE SET OF CONTROL VARIABLES

We test the sensitivity of the estimated treatment effect to the set of control variables in the demand model. In Table W27, we report the estimations across various model specifications. We start with fixed effects only (i.e., no control variables) in column 1, and we add one control variable at a time in columns 2–6; column 6 is the full model as reported in Table 3 in the main paper. Note that the base model and all others include property fixed effects and seasonality fixed effects. We find that the estimated treatment effect is stable across the model specifications.

Table W27 Impact of Uber/Lyft's Exit on Property Demand, with Different Sets of Control Variables

VARIABLES	**ESTIMATES**					
	Control Variable Added to the Previous Column					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Base	Passengers	Supply	Price	Photo	Full
AUSTIN · AFTER	-0.0463***	-0.0383***	-0.0382***	-0.0405***	-0.0396***	-0.0378***
	(0.00334)	(0.00518)	(0.00518)	(0.00638)	(0.00637)	(0.00586)
log #REVIEW						0.0467***
						(0.00378)
log #PHOTO					0.0672***	0.0400***
					(0.00929)	(0.00934)
log NIGHTLY_RATE				-0.0520***	-0.0529***	-0.0604***
				(0.00782)	(0.00775)	(0.00775)
			0.000788	0.00106	0.000923	0.000885

log						
#SUPPLIED_DAYS						
(within a zip code)			(0.000900)	(0.00114)	(0.00114)	(0.00113)
log #PASSENGERS		1.216***	1.216***	1.268***	1.268***	1.270***
		(0.0415)	(0.0415)	(0.0482)	(0.0482)	(0.0481)
Fixed Effect	Property	Property	Property	Property	Property	Property
	Calendar	Calendar	Calendar	Calendar	Calendar	Calendar
Seasonality	Month	Month	Month	Month	Month	Month
Observations	67039	67039	67039	67039	67039	67039
R-squared	0.6491	0.6581	0.6581	0.6636	0.6642	0.6662

Notes: The model is estimated on the matched sample of 11,536 Airbnb properties. From left to right, each model specification adds one control variable to the set in the previous column; column 6 contains the full model, i.e., the main demand model specification. The DV is monthly occupancy (a ratio between 0 and 1) for property *i* in month *t*. If *i* made the full month unavailable to be booked in *t*, the occupancy is computed as *missing* (indefinite), and the observation for *i,t* is automatically dropped from the estimation. *SUPPLIED_DAYS* is the total number of available days in month *t* among all Airbnb properties in the same zip code. *PASSENGERS* is the total number of travelers who visited Austin by plane in *t*, computed from the passenger enplanement data reported by the BTS.

Robust standard errors (clustered at the individual-property level) are in parentheses.

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

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