Short-Term Rentals and Residential Rents: Evidence From a Regulation in Santa Monica

Cayruã Chaves Fonseca[†]

Universitat de les Illes Balears, Spain

WORKING PAPER VERSION

Find the published version here

Abstract

In recent years, there has been a significant increase in short-term rentals (STRs) facilitated by digital platforms such as Airbnb. This study evaluates the impacts of regulations imposed on these platforms, focusing on the Home-Sharing Ordinance implemented in Santa Monica, California. Using a Synthetic Control Method, the analysis finds that, two years after its implementation, the ordinance caused the number of Airbnb entire home listings to decrease by 60%. However, the study found no evidence that this regulation influenced long-term rental prices. Finally, suggestive evidence indicates that the ordinance did not increase the supply of houses allocated for long-term renters, potentially explaining its lack of impact on rents.

JEL Codes: R21; R31; Z30.

Keywords: Housing markets; Short-term rentals; Airbnb; Regulation.

[*] I thank Gerard Llobet for his invaluable insights and guidance. I also wish to thank Diego Puga, Pedro Mira, Manuel Arellano, Guillermo Caruana, Jose Apesteguia, Mariona Segú, Daniel Ershov, and participants of the CEMFI Firms and Markets Workshop for their valuable comments. I gratefully acknowledge funding from Spain's Ministerio de Ciencia, Innovación y Universidades (grant PRE2018-084485) and Ministerio de Economía, Industria y Competitividad (through the María de Maeztu Programme for Units of Excellence in R&D, grant MDM-2016-0684).

[†] E-mail address: cayrua.chaves@uib.es. Website: cayruachaves.github.io

1 Introduction

In recent years, there has been a significant surge in the prevalence of short-term rentals (STR) and home-sharing. Although these practices have long been common, particularly in tourist destinations during peak seasons, the advent of online peer-to-peer platforms like Airbnb has dramatically facilitated the search and information-gathering processes associated with this kind of economic activity (Einav et al., 2016).

Short-term rental platforms offer several benefits. Firstly, they allow individuals to efficiently utilize their homes by renting out unused spaces, thereby generating additional income (Filippas et al., 2020). Secondly, compared to hotels, the supply of short-term rentals can more readily adapt to demand fluctuations, resulting in lower prices during peak periods, which is advantageous for travelers (Zervas et al., 2017; Farronato and Fradkin, 2022). Moreover, advocates of home-sharing argue that short-term rentals, such as those offered by Airbnb, provide travelers with a more authentic "live like a local" experience.[1]

However, the expansion of short-term rentals and home-sharing has sparked controversy. Critics argue that the influx of tourists into residential areas can lead to various negative impacts, including a diminished sense of community, increased noise pollution, disruptions, and heightened competition for public amenities like parking spaces (Edelman and Geradin, 2015). Furthermore, platforms like Airbnb have reduced the operational costs of short-term rentals for landlords, which may incentivize some landlords to switch from renting to long-term residents to offering their properties to travelers (Cunha and Lobão, 2022). This potential shift in housing allocation, referred to as the "reallocation effect," can decrease the availability of units for long-term tenants, consequently driving up rental prices.

The rapid growth of STR platforms and the controversy surrounding their potential effects on residents has prompted many cities to enact regulations specifically designed to address short-term renting and home-sharing activities. An example of such laws is the Home-Sharing Ordinance (HSO) implemented in Santa Monica, California, which was among the first cities to regulate short-term rentals actively. Since 2015, the city has prohibited renting entire home units for short-term stays.[2]

Economic theory suggests that the impact of Santa Monica's HSO on residential rents depends on the relative magnitudes of the effects mentioned above Filippas and Horton (2023). If the HSO prompts many absentee landlords to shift their properties from the short-term to the long-term rental market, this would increase the supply of residential housing and decrease rents (Barron et al., 2021). On the other hand, by reducing tourist-related negative externalities, the HSO may improve Santa Monica's amenities as a residential location, thereby increasing housing demand and potentially increasing rents (Garcia et al., 2024).

[1] This concept of "living/traveling like a local" is actively promoted by Airbnb, as mentioned in a New York Times article (www.nytimes.com/2016/04/20).

[2] Other examples of cities that actively regulate short-term rental platforms include San Francisco, where short-term rental units cannot be rented for more than 90 days per year; Barcelona, where vacation rentals require a special tourist license that is limited to specific neighborhoods; and New York, which has recently tightened its enforcement of the rule that short-term rentals are only allowed if the host is present during the stay. Sources: blog.airdna.co/effects-airbnb-regulation and www.nytimes.com/2023/09/16/nyregion/airbnb-nyc-housing-rentals.html.

Given the uncertainty surrounding the consequences of restricting the activity of STR platforms, this paper aims to quantify the effects of Santa Monica's Home-Sharing Ordinance (HSO) on the local housing market, with particular attention to two primary outcomes. The study explicitly addresses the following research questions: (i) How has the HSO implemented in Santa Monica affected the number of homes listed on Airbnb? (ii) How has the HSO impacted rental prices in Santa Monica's long-term housing market?

To answer these research questions, I leverage a city-month panel dataset that includes information on Airbnb activity and rents. Data on Airbnb comes from Tom Slee, a sharing economy expert who collects information directly from Airbnb's website and makes it available for public use. In addition, I gather data on long-term rents from Zillow, the leading real estate marketplace in the United States. The paper's primary empirical analysis estimates how Airbnb activity and rents would have evolved in Santa Monica without the HSO by employing a Synthetic Control Method (SCM) and using cities in Los Angeles County that did not regulate short-term rentals as control units.

This study presents two main findings. First, the implementation of the HSO significantly impacted Airbnb activity in Santa Monica. Two years post-implementation, the HSO led to a 60% decrease (equivalent to 860 units) in entire home listings on Airbnb. Second, I find no evidence suggesting that the HSO impacted rental prices in Santa Monica. The robustness of this result is reinforced by a series of supplementary tests, which examined the effect of the regulation on rents for homes with varying numbers of bedrooms and rent tiers, as well as specific zip codes within the city. Furthermore, a Synthetic Difference in Differences estimation further corroborates this result and finds no evidence of a significant effect of the HSO on residential rents in Santa Monica. Lastly, using a two-way fixed-effects model, I investigate a potential mechanism behind the HSO's lack of effect on rents. Data from the American Community Survey on housing occupancy status reveals that the HSO did not increase the stock of housing allocated for long-term renters. This result suggests that part of the explanation for the HSO's ineffectiveness in lowering rents in Santa Monica is that landlords did not switch their properties to the residential rental market, at least not in the short to medium term.[3]

Related Literature. This paper contributes to empirical research on short-term rental (STR) platforms and their impact on housing markets. Early studies, such as Horn and Merante (2017) and Schäfer and Braun (2016), found that Airbnb's expansion was associated with increasing rents in cities like Boston and Berlin.

Later research, using quasi-experimental methods, further explored STRs' effects. Garcia-López et al. (2020) employed a shift-share instrumental variable approach based on tourist attractiveness and "Airbnb" Google searches and found that Airbnb caused housing prices and rents to increase in Barcelona. Cunha and Lobão (2022) exploited regulatory changes in Portugal and applied a difference-in-differences approach to show that the liberalization of STRs increased housing prices in municipalities within Portugal's two largest Metropolitan Statistical Areas. Both studies estimate the impact of STRs on housing prices in contexts where

[3]Other mechanisms might simultaneously be at work. For example, tourist-related negative externalities might have decreased due to the reduced Airbnb activity, enhancing Santa Monica's appeal as a residential location. Another contributing factor relates to challenges associated with enforcing the regulation, which saw its effectiveness in curbing Airbnb activity diminish in the second year after its enactment.

both the dependent and independent variables are on the rise. In contrast, this study examines the effects of STRs in a scenario where overall rents are increasing, but short-term rental activity is declining due to the home-sharing ordinance.

Other researchers have also investigated the impact of platforms like Airbnb by focusing on regulations that restrict short-term rentals. A notable example is the work by Koster et al. (2021), which also uses data from locations within Los Angeles County.[4] Whereas Koster et al. (2021) aimed to estimate the average effect of regulations enacted across different cities in the region for broader external validity, I have focused on a specific HSO (Santa Monica's) to overcome the complexities of aggregating regulations that may vary in scope, enforcement practices.

Furthermore, concerning methodology, Koster et al. (2021) employed a spatial discontinuity design as their primary identification strategy, which allowed them to estimate the impact of Airbnb on house prices credibly. However, they relied on a difference-in-differences strategy to assess the effect on rents, assuming parallel pre-trends. In contrast, this paper uses the Synthetic Control Method, an empirical method designed to match pre-trends. Notably, my results diverge from those reported by Koster et al. (2021). Whereas they found that HSOs across 18 cities reduced rents by an average of 2%, my analysis reveals that Santa Monica's HSO did not significantly affect rents. This divergence in results suggests that STR platforms' impact is context-dependent, a finding supported by Garcia et al. (2024), who provides empirical evidence of the heterogeneity in home-sharing ordinance effects across different Californian cities.[5]

This paper not only contributes to the literature examining the impact of Airbnb on housing costs but also relates to other studies investigating the broader implications of expanding short-term rental platforms. Bekkerman et al. (2022) finds that STR platforms like Airbnb incentivize residential real estate investment. This study's results align with these findings, as the HSO in Santa Monica appears to have increased owners' propensity to sell their housing units, indicating that restricting Airbnb makes housing a less attractive investment.

Moreover, this work also relates to the literature that studies the effects of tourists on residents. Negative externalities generated by tourists have been discussed in the media (Lieber, 2015) and academia (Filippas and Horton, 2023). Additionally, recent studies have quantified the effect of increased short-term renting activity on the composition of private consumption amenities available to locals (Hidalgo et al., 2022; Almagro and Dominguez-Iino, 2022). In light of the findings from these studies, this paper's results suggest that laws restricting short-term rentals can potentially impact the provision of local consumption amenities.

In terms of methodology, this paper relates to other studies using the synthetic control method for estimating causal effects (Abadie and Gardeazabal, 2003; Abadie et al., 2010). This method is particularly useful in comparative case studies and in examining the effects of regulations that impact entire geographical units. I contribute to this literature by applying the SCM to study Airbnb regulation, to the best of my knowledge, for the first time, and by applying an extended version of the method, the synthetic difference-in-differences (SDID),

[4]For other studies that leverage regulations on short-term rentals as a source of exogenous variation in Airbnb to estimate its effect on rents, refer to Duso et al. (2020) and Seiler et al. (2023).

[5]Mine is not the only study that does not find a positive effect of Airbnb on prices related to the housing market. For example, Jiao et al. (2022), employing very different methodologies (geographically weighted regression and a Bayesian approach), found that Airbnb activity is negatively correlated with increases in land values in Texas.

recently proposed by Arkhangelsky et al. (2021). While both methods yield the same qualitative conclusion that we cannot reject the possibility that the regulation did not affect rents, this study confirms that the SDID is less sensitive than the SCM to including specific units in the pool of potential controls.

In summary, this study's main contribution is to illustrate that the impact of Airbnb regulation varies significantly depending on the local context. By employing a quasi-experimental approach, the paper presents evidence from a setting where regulatory measures can successfully reduce Airbnb activities without affecting residential rental prices. More broadly, this finding underscores the need for further research to identify the factors that shape how short-term rental platforms impact housing markets.

The remainder of the paper is structured as follows. Section 2 overviews the Santa Monica Home-Sharing Ordinance. Data sources and summary statistics are presented in Section 3. Section 4 describes the empirical strategy, the Synthetic Control Method. The estimated effects of Santa Monica's HSO are presented in Section 5. Section 6 discusses the paper's implications and concludes.

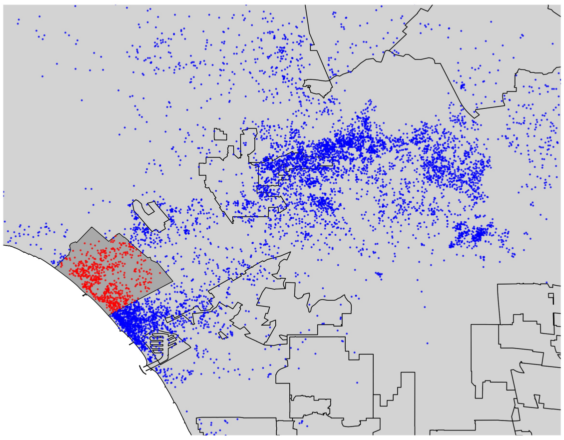
2 The Santa Monica Home-Sharing Ordinance

Santa Monica, a beautiful coastal city in western Los Angeles County, has been a popular tourist destination since the early 20th century. The city's tourist appeal has led to a surge in short-term rental (STR) activity through platforms like Airbnb. In April 2015, there were 695 entire-home listings available on Airbnb in Santa Monica, which amounted to approximately 1.4% of the city's total housing stock. Compared to other cities in the area, Santa Monica ranked second in absolute number of Airbnb listings and fourth in listings per housing unit. Figure 1 illustrates that Santa Monica (indicated by the red dots) has one of the highest concentrations of Airbnb listings in the region surrounding Los Angeles.

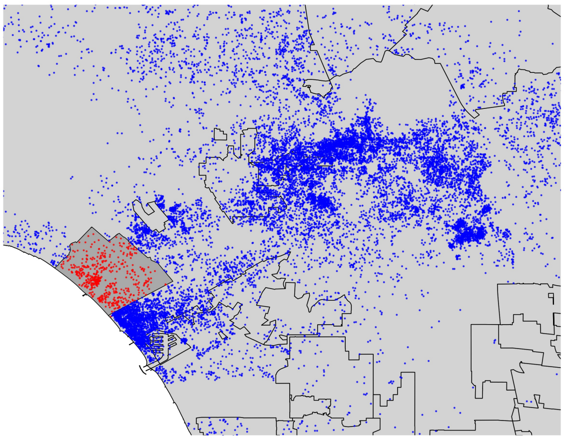
Despite the potential economic benefits of short-term renting activity, the escalating number of vacation rentals has raised concerns regarding their impact on the availability and affordability of housing for permanent residents. To address these concerns, the Santa Monica City Council passed the Home-Sharing Ordinance (HSO) on May 12th, 2015. According to the city's administration, the regulation, which became effective on June 12th, 2015, "was enacted to ensure the availability of residential rental housing for long-term tenants and counteract the detrimental effects of short-term rentals, which threaten the stability and character of the City's neighborhoods, and lead to an increase in rents."

The Home-Sharing Ordinance distinguishes between two types of short-term rentals: "home-sharing" and "vacation rentals." Home-sharing involves renting out space in one's home to short-term guests while at least one primary resident remains on-site. This practice is considered legal under the HSO. To comply with the regulation, hosts must register with the city, obtain a free business license, and pay a 14% transient occupancy tax, identical to the tax levied on hotels. In contrast, vacation rentals refer to housing units exclusively rented out to short-term guests for fewer than 30 days. The guests have sole use of the property and do not share it with the owner or any permanent residents. The Home-Sharing Ordinance prohibits this type of

Figure 1: Airbnb Entire Home Listings in the Area Around Santa Monica



(a) April 2015 (1 month before the HSO)



(b) July 2017 (2 year after HSO)

Notes: HSO stands for Santa Monica's Home-Sharing Ordinance, which took effect in June 2015. Black lines are city boundaries and Santa Monica is highlighted in darker gray. Each dot is an Airbnb entire home listing (i.e. vacation rental). Reds dots are listings inside the boundaries of Santa Monica. Blue dots are listings in other cities. Plot (a): snapshot of Airbnb in April 2015 (last pre-HSO wave). Plot (b): snapshot of Airbnb in July 2017 (last wave of data). *Source:* Author's own work using data available at www.tomslee.net. Additional details on data construction can be found in Section 3.1.

activity. Violators may face administrative fines or criminal prosecution if they refuse to cease operation.[6]

The HSO underwent modifications and amendments over time, with the main aspects of the regulation implemented in the following timeline. The Santa Monica City Council adopted the ordinance on May 12th, 2015; one month later, on June 12th, 2015, it became effective. During the subsequent summer, staff conducted an educational campaign to disseminate information about the new law and issued warning letters to potential violators. Enforcement action was taken only in cases arising from formal complaints during this period.

Simultaneously, the City Council established a "Short-Term Rental Team," exclusively dedicated to enforcing the Home-Sharing Ordinance. While the educational campaign was underway, this team designed its enforcement plan and priorities. By the City Council's goals, professional hosts operating multiple vacation rental units were identified as the highest priority for enforcement. On November 1st, 2015, proactive enforcement began, meaning that instead of relying solely on formal complaints, enforcement officers actively sought out violators. Finally, on January 26th, 2016, the fine for operating a vacation rental unit increased from $75 to $500 per day of illegal activity.

Importantly, evidence suggests that the regulation was actively enforced. According to Koster et al. (2021), the City of Santa Monica has collected more than $4.5 million in taxes from Airbnb and other short-term home rental businesses (remember that shared rooms are allowed as long as they register and pay taxes). Moreover, the enforcement team has levied fines amounting to approximately $80,000 against hosts who have violated the law.

[6]Source: www.smgov.net.

3 Data

3.1 Airbnb Listings

Airbnb is a peer-to-peer online marketplace for short-term rentals and one of the most successful companies in the sharing economy. The platform allows hosts to advertise their housing units to visitors seeking short-term accommodation and generates revenue by charging guests and hosts a percentage of each booking. Since its launch in 2008, Airbnb has facilitated approximately 1.4 billion guest arrivals.[7]

Data on Airbnb comes from Tom Slee, a software engineer and author with expertise in the sharing economy. Slee periodically collects data directly from Airbnb's website using web scraping techniques and makes it publicly available.[8] From this data, I constructed a panel dataset consisting of 29 distinct web scrapes, referred to as "waves." Each wave captures a snapshot of the availability of Airbnb listings in the Los Angeles area on that particular day. The initial wave occurred in September 2014, followed by additional waves in October and November of the same year and then in April and August of 2015. Starting from August 2015, the waves were conducted monthly until July 2017, the date of the last scrape available. This panel provides a two-year post-intervention period to estimate the impact of the HSO on Airbnb activity in Santa Monica.

Before proceeding, a clarification regarding the definition of geographical units is warranted. When analyzing the HSO's effect on Airbnb listings, a geographical unit is defined as a city, a neighborhood within the city of Los Angeles, or an "unincorporated" area (areas without local government and governed by county laws). This definition aligns with the original data scraped by Tom Slee and is helpful because some neighborhoods in Los Angeles have Airbnb markets of comparable size to certain cities in the dataset. When examining the effects on rents, the geographical units of analysis are cities because this definition matches the housing data obtained from Zillow.

3.2 Long-Term Rental Rates

I obtained data on long-term rents from Zillow, the leading real estate online marketplace in the United States. Zillow's database contains information on more than 110 million U.S. homes and indexes that track key housing market variables across a region every month.[9]

I use the Zillow Rent Index (ZRI) to measure rents in the long-term market. The ZRI is a smoothed, seasonally adjusted measure that reflects the median market rent for the entire stock of homes in a given region at a given time. Importantly, since Zillow is a marketplace for landlords and tenants looking for long-term contracts, the ZRI reflects the rental rates faced by residents looking for a home to rent, which is the relevant rental price in terms of policy evaluation (Barron et al., 2021).

[7]Source: www.airbnbcitizen.com.

[8]Source: www.tomslee.net

[9]Source: https://www.zillow.com/research/data.

3.3 U.S. Census Bureau

I supplement the data on Airbnb listings and long-term rents by incorporating city-year-level variables from the U.S. Census Bureau.[10] The baseline control variables, drawn from the American Community Survey (ACS), include a city's population size, average income, the proportion of individuals with a college degree, and the employment rate. Additionally, I include information on the percentage of housing units occupied by renters and the ratio of vacant houses. These variables are employed to investigate the impact of the Home-Sharing Ordinance on housing reallocation within the city.

To proxy for a location's appeal as a tourist destination, I follow Barron et al. (2021) and use the number of establishments in food and accommodation (NAICS code 72) and arts and entertainment (NAICS code 71) gathered from the Business Patterns (BP) dataset. All variables from the ACS vary at the year level. Values are obtained via interpolation whenever they enter as controls in a regression at monthly intervals.

3.4 Summary Statistics

Given that the Home Sharing Ordinance prohibited the operation of vacation apartments but not home-sharing units, the remainder of the paper focuses exclusively on Airbnb's entire home listings. The objective is to assess the impact of the regulation on long-term rents through the reallocation effect, making entire-home listings the most relevant type of short-term rental activity. Shared-home listings, where a resident already lives and shares space with Airbnb travelers in the same property, are less likely to transition to the long-term rental market, even in the event of a complete Airbnb ban.

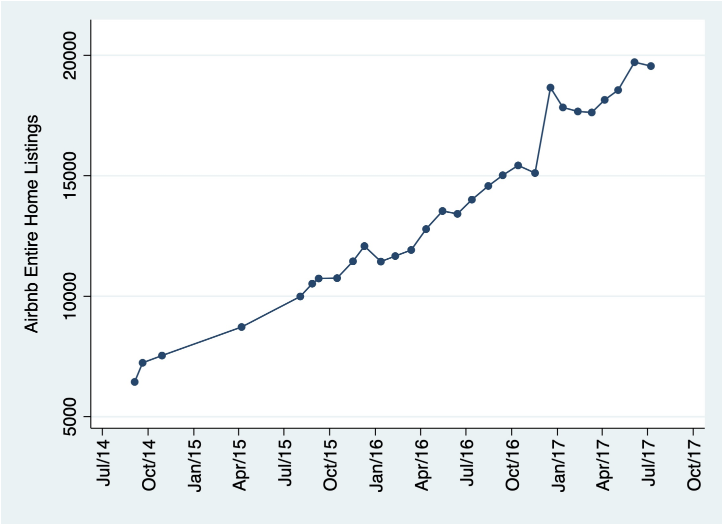
The number of active Airbnb entire home listings in Los Angeles County exhibited consistent growth throughout the study period, as depicted in Figure 2. In September 2014, the date of the first wave of data collection, there were 10,027 Airbnb listings in the area. By July 2017, the last period of the dataset, this number had more than tripled, reaching 32,146.

In contrast to this consistent growth, Airbnb activity in Santa Monica followed a pattern characterized by substantial decreases in listings during the first year following the implementation of the HSO. Figure 3 provides an overview of the total count of entire home listings available on Airbnb in Santa Monica. Each vertical line represents one of the three main developments in implementing the Home-Sharing Ordinance, including its adoption, proactive enforcement, and fine increase. All graphs featuring three vertical lines throughout the paper refer to these events.

The pattern depicted in Figure 3 underscores both the effectiveness of the regulation in curbing Airbnb activity and the presence of imperfect enforcement, with some hosts persisting in operating illegal listings despite the risk of fines. Prior to June 2015, the date of the HSO's implementation, the number of properties listed on the platform rose from 530 in September 2014 to approximately 700 by April 2015, indicating a 31% increase. Following the ordinance's implementation, there was a moderate decrease in listings to around 600 homes. After that, Airbnb listings dropped substantially between the initiation of proactive enforcement and the

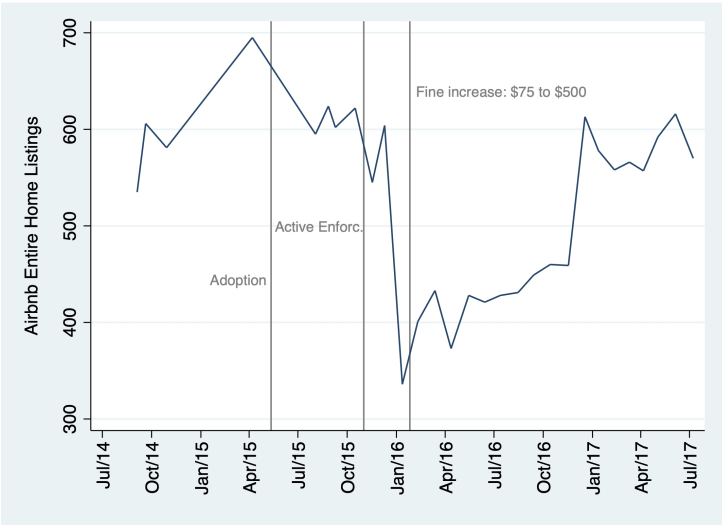
[10] Source: https://data.census.gov/.

Figure 2: Evolution of the Number of Airbnb Entire Home Listings in the Los Angeles County



Notes: Dots indicate the date of each wave of data collection (e.g, web scraping). *Source:* Author's own work using data available at www.tomslee.net. Additional details on data construction can be found in Section 3.1.

Figure 3: Number of Airbnb Entire Home Listings in Santa Monica

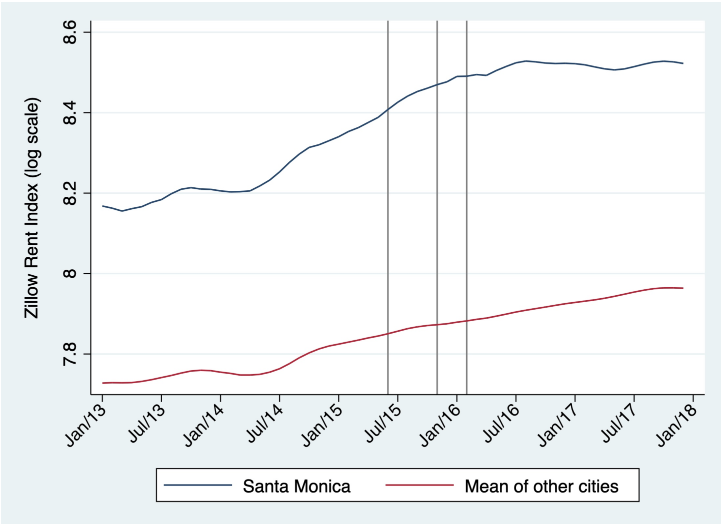


Notes: Each vertical line represents a key development in the implementation of the Home-Sharing Ordinance. *Source:* Author's own work using data available at www.tomslee.net. Additional details on data construction can be found in Section 3.1.

increase in the fine. In January 2016, when Airbnb activity reached its lowest point, the platform only featured 336 properties in Santa Monica. Subsequently, despite the regulation prohibiting vacation apartments in the city, the number of entire home listings on Airbnb in Santa Monica began to rise again.

Turning to data on rents, Figure 4 illustrates the trajectory of the Zillow Rent Index. Two facts emerge from the plot. First, compared to other cities in the county, Santa Monica had higher rent levels and was on a faster-increasing trajectory prior to the regulation. Secondly, while rents in other regions increased on average, Santa Monica's rental prices stabilized in mid-2016. Establishing a causal link between the regulation and this deceleration in rent growth requires determining an appropriate counterfactual for Santa Monica.

Figure 4: Evolution of Rents: Santa Monica vs. Average City in Los Angeles County



Notes: Each vertical line in the graph represents a key development in the implementation of the Home-Sharing Ordinance: adoption, proactive enforcement, and fine increase, respectively. *Source:* Author's own work using data from Zillow, available at www.zillow.com/research/data.

Table 1 outlines key summary statistics of the data, providing a comparative analysis of Santa Monica against other cities in the region. The statistics were computed at four distinct points in time: April 2015 (prior to the regulation's adoption), October 2015 (following the ordinance's implementation but prior to proactive enforcement), February 2016 (three months after proactive enforcement began and when the fine increased from $75 to $500 per day), and July 2017 (the final period of the panel).

When comparing the number of entire homes listed on Airbnb in Santa Monica between April 2015 (695 units) and July 2017 (570 homes), it may initially appear that the regulation had a minimal impact on reducing illegal vacation rental activity, with only an 18% reduction in listings. However, this perspective changes when considering that in other cities, the number of entire home listings increased by about 56% over the sample period. This comparison suggests that the presence of Airbnb in Santa Monica would have been significantly different in the absence of the HSO.

Turning to data on the housing market, the numbers shown in Table 1 imply that the rate of increase in residential rents from the beginning until the end of the sample was similar in Santa

Table 1: Mean Characteristics by Geographical Unit and Period

City	Variable	Apr/2015	Oct/2015	Feb/2016	Jul/2017
Santa Monica	Entire home listings	695	622	401	570
	Price per night ($)	275.86	231.76	282.88	259.57
	Average rating	4.69	4.67	4.67	4.77
	Monthly Rent ($)	4340	4726	4869	4986
	Renter-Occupied Houses	33985	34067	34022	33569
	Vacant Houses	4027	4191	4343	4968
Mean of Other Cities	Entire home listings	128.02	170.20	179.65	201.51
	Price per night ($)	319.14	288.79	273.01	277.81
	Average ratings	4.75	4.75	4.73	4.79
	Monthly Rent ($)	2790	2893	2919	3131
	Renter-Occupied Houses	15200	15310	15375	15541
	Vacant Houses	1872	1845	1828	1807

Source: Author's own work. Data on Airbnb activity (listings, price, rating, and duration) obtained from Tom Slee. Rent data from Zillow. Housing occupancy data from the American Community Survey (ACS). Additional details on data sources and construction can be found in Section 3.

Monica and the average city in the sample, 15%, and 12% respectively. Moreover, between 2015 and 2017, the stock of housing occupied by renters in Santa Monica diminished, in contrast to a slight increase in other cities within the county. Lastly, the count of vacant houses in Santa Monica increased by approximately 25% over the sample period, whereas in other cities, this number reduced by 3.5%.

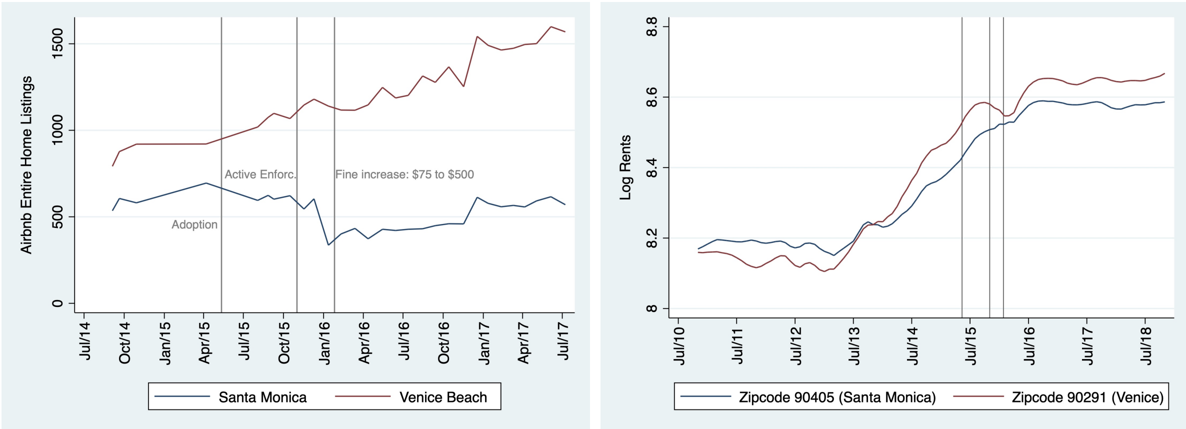
In summary, this initial analysis yields a few insights about average trends. Firstly, it indicates that the HSO significantly impacted Airbnb activity. The evolution in the number of listings in Santa Monica differs substantially from that observed in other cities in the region. Secondly, although there is some evidence of a slowdown in rent increases in Santa Monica around 2016, the difference compared to other cities is less pronounced. Finally, there is no indication that housing allocation shifted from short-term to long-term rentals following the implementation of the HSO.

4 Methodology

4.1 Towards the Right Counterfactual

To determine the causal impact of the Home-Sharing Ordinance, one needs an estimate of what Santa Monica would have been like had the regulation not been imposed. A simple comparison of the quantity of Airbnb listings and residential rents in Santa Monica pre and post-ordinance would not be adequate, as it would involve making arbitrary assumptions about how the trends would evolve. An alternative approach is to use a comparable control city and assume that, absent the regulation, both cities would have followed a similar trend. Along these lines, we can compare Santa Monica to Venice Beach, a neighborhood within the city of Los Angeles that borders Santa Monica to its southeast. Figure 5 illustrates this comparison.[11] [12]

Figure 5: Comparison of Airbnb Listings and Rents in Santa Monica and Venice Beach



(a) Airbnb Activity: Entire Home Listings

(b) Rents: Zillow Rent Index

Notes: Each vertical line represents a key development in the implementation of the Home-Sharing Ordinance: adoption, active enforcement, and fine increase. *Source:* Author's own work using data from Tom Slee for Plot (a) and data from Zillow for Plot (b). Additional details on the data sources and construction can be found in Section 3.

At first glance, Figure 5 indicates that the HSO effectively reduced Airbnb activity but did not significantly impact rents. The slowdown in the increase in rents in Santa Monica around mid-2016 also occurred in Venice, where Airbnb continued to experience constant growth throughout the sample period. However, this empirical strategy faces two challenges. First, the choice of a suitable control city is ambiguous. Second, there is a trade-off between geographical proximity, which ensures some similarity, and the risk of exposure to general equilibrium effects, which may "contaminate" the control city.

4.2 The Synthetic Control Method

An appropriate empirical strategy for estimating the causal impact of the HSO is the Synthetic Control Method (SCM). This method, introduced in a series of papers by Abadie and coauthors (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015), is particularly suitable for evaluating policy interventions that occur at an aggregate level, such as at the city, state, or country level. The idea behind the SCM is that a systematic and data-driven choice of a combination of multiple potential control units better replicates the treated group than any single control unit in isolation.

Formally, let $j = [1, 2, ...J + 1]$ represent each city in Los Angeles County and $t = [1, 2, ...T_0, ...T]$ each period of the dataset.[13] Denoting Santa Monica as city $j = 1$, the SCM estimated effect of

[11]From this point onwards, the term "city" is used loosely to encompass Venice and other administrative units identified separately in the original dataset as distinct Airbnb markets. This definition aligns with the initial data collected by Tom Slee. For further details, see Section 3.

[12]Because Venice Beach is a neighborhood (not a city), and thus, not included as a separate unit is the Zillow data. To create Figure 5b, I selected two adjacent zip codes - one in each city - and plotted the rents for each.

[13]In the analysis of the HSO's effect on Airbnb activity, a period t refers to a wave of web-scraped data collection, whereas in the estimation of the effects on rents, a period is month-year.

the Home-Sharing Ordinance α_{1t}) at each period t after its adoption is given by the difference between the observed outcome of interest Y_{jt} (number of Airbnb listings or residential rents) in Santa Monica and its synthetic counterpart, a weighted average of control cities:

$$\alpha_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{1}$$

where the optimal weight of each control city, $W^* = [w_2^*, ..., w_{J+1}^*]'$, is chosen such that the following expression is minimized:

$$W^* = \arg\min_{W} \sum_{m=1}^{k} v_m (X_{1m} - X_{0m}W)^2 \tag{2}$$

In Equation 2, the vectors X_{jm} contain values of predictor m for the outcome of interest Y_{jt} in city j for periods t preceding the regulation, while v_m represents the weight assigned to each predictor m. Intuitively, the SCM selects a weighted average of cities that most closely resemble Santa Monica prior to the Home-Sharing Ordinance, based on k predictors of Y_{jt}.

4.3 Creating the Synthetic Control for Airbnb Activity

Control Units. The application of the SCM to estimate the effect of the HSO requires the definition of a pool of cities (the ”donor pool”) that are comparable to Santa Monica in terms of Airbnb and housing markets. This step mitigates overfitting and interpolation biases (Abadie and Gardeazabal, 2003).

The definition of the pool of control units begins with the 114 cities (or neighborhoods within Los Angeles) available in Tom Slee’s Airbnb dataset. The first step is to exclude cities with missing information on Airbnb listings during any of the 29 waves of data.[14] Secondly, I eliminated cities that implemented regulations on short-term rentals. Furthermore, locations sharing borders with Santa Monica, such as Venice, were excluded to mitigate potential spillover effects of the regulation. Lastly, to enhance comparability between control cities and Santa Monica, one of the largest Airbnb markets in the region, I refine the pool by focusing on cities that are also prominent on this home-sharing platform. Specifically, cities are ranked based on their mean number of listings pre-HSO, and only those above the median rank are retained in the pool of donors. This process yields the final pool of control units: the 19 cities with the largest Airbnb markets in Los Angeles County.

Baseline Specification. Considering the variation in city sizes, the outcome variable is expressed as a ratio to the housing stock in the city. Specifically, it is the number of entire home units listed on Airbnb per 1,000 housing units in a given city, a metric I refer to as ”normalized listings.” The final step in defining the baseline specification involves selecting a set of predictor variables. As demonstrated by Abadie and Gardeazabal (2003), incorporating linear combinations of the outcome variable can enhance the model fit. However, they also caution against relying solely on the pre-intervention outcome variable as a matching predictor, which might lead to overfitting. In line with this guidance, I include pre-regulation Airbnb

[14]This step ensures a strongly balanced panel, a prerequisite of the Synthetic Control Method (Abadie et al., 2010).

listings alongside a city's average income, population, share of young adults, percentage of owner-occupied housing, and the number of establishments in the food, accommodation, and entertainment sectors.

Note that vectors X in Equation 2 lack a time dimension, and researchers must decide how these predictors enter the analysis. Standard alternatives are, for example, to use their value in a specific wave or average across all or a subset of pre-intervention waves (Abadie et al., 2010). Crucially, given the significant weight assigned to the pre-regulation Airbnb listings (outcome variable) compared to other predictors, it is vital to establish a systematic approach for selecting which linear combination of pre-regulation outcomes to use.

I adopt the methodology outlined by Ferman et al. (2020), which involves testing various linear combinations of pre-treatment outcomes to identify the specification that yields the lowest post-regulation root mean squared prediction error (RMSPE) among control units. For each potential specification, a synthetic control is estimated for each control city as though it were subject to the Home-Sharing Ordinance. The preferred specification is then selected based on its ability to minimize the average out-of-sample prediction error during the post-regulation periods across all control units. As demonstrated in Figure A.2 in the appendix, the implementation of this method identified a baseline specification where the average of normalized Airbnb listings from the last two pre-regulation waves minimized the RMSPE. The default approach—averaging values across all four pre-regulation waves—is utilized for all other predictors.

4.4 Creating the Synthetic Control for Residential Rents

The primary challenge in estimating the causal effect of the HSO on rents is the possibility of violating the parallel pre-trends assumption. As shown in Figure 4, the HSO may be endogenous, as it was implemented when long-term rents in Santa Monica were increasing considerably faster than the average trend. To overcome this challenge, the SCM is my baseline identification strategy.

Sample Period and Control Units. This analysis takes advantage of the fact that data available on housing rents is more comprehensive than for Airbnb, both in terms of the sample period and potential control cities. Regarding the sample period, Zillow provides monthly data on the city-level rent index from November 2010 to November 2018. This range provides enough time to establish the trend before the regulation and to assess its subsequent evolution.

Next, for selecting control cities, I followed a process similar to that described previously. Starting with 114 geographical units with rent data available, I excluded cities that (i) lacked rent data for some period, (ii) implemented some HSO, and (iii) directly bordered Santa Monica. Furthermore, mirroring the methodology of the earlier section, the pool was narrowed to half of the cities most similar to Santa Monica regarding the outcome variable. Ultimately, the donor pool includes the 40 cities with the highest mean pre-HSO rents in the long-term rental market.[15]

[15] For direct comparability with the analysis of Airbnb activity, an alternative approach is to use the same pool of 19 donors employed there. However, this unnecessarily restricts the set of control units. When employing the same pool of donors as in the Airbnb analysis (see Figure B.5 in the Appendix), conclusions remain unaltered, and I find no evidence of a significant effect of the HSO on rents.

Baseline Specification As usual in applications of the synthetic control method, the outcome variable (Zillow rent index) is included as one of the predictors. Additionally, the baseline specification includes other socio-demographic characteristics likely to correlate with housing rents. Specifically, I follow previous studies investigating the effect of Airbnb on housing markets (Barron et al., 2021; Garcia-López et al., 2020) and include the following predictors: log of average income, log of population, proportion with a college degree, employment share, and share of young adults.[16]

Given this choice of variables, the minimization problem described in Equations 1 and 2 is solved for a vector X constituted of the average of each predictor variable over all the pre-HSO periods. The only exception is the rent index, which enters with two terms: the average across all pre-regulation periods and its value on the last pre-HSO period. The latter term aims to enhance the likelihood of the synthetic control reflecting a rent level similar to that of Santa Monica immediately before the regulation.

5 Empirical Results

5.1 The Effect of the HSO on Airbnb Activity

Predictor Balance. Table 2 displays the pre-ordinance characteristics of actual Santa Monica, compared to those of its synthetic control (obtained as specified in Section 4.3). To highlight the importance of using a synthetic control (weighted average), Table 2 also includes the value of the same variables averaged across all 19 control cities in the donor pool. As expected, the synthetic version of Santa Monica closely resembles the actual city. While the mean across the 19 control cities has approximately one-third of the observed Airbnb activity in Santa Monica, the convex combination produced by the SCM closely matches the 12.34 normalized entire home units in the city. Although less pronounced, a similar pattern arises for other predictors.[17]

City Weights. Table 3 illustrates the allocation of weights to each potential control unit. Santa Monica's characteristics are best approximated by a convex combination of just three cities: Marina Del Rey, Los Angeles, and Topanga. In contrast, all other cities in the analysis receive zero weight. This outcome is consistent with the typical findings observed in SCM applications, where only those control units exhibiting similarities to the treated unit in terms of the most pertinent predictor variables are assigned non-zero weights.[18] [19]

[16]To be precise, Barron et al. (2021) use the same set of predictors except for the share of young adults, whereas Garcia-López et al. (2020), in addition to the five predictors I use, also include average household size.

[17]The weight assigned to each predictor in the SCM is proportional to its importance in predicting Airbnb listings. The number of establishments in arts and entertainment receives the lowest weight, resulting in a larger discrepancy between Santa Monica and its synthetic counterpart for this predictor. The weight assigned to each predictor is determined through a data-driven process involving a cross-section regression of normalized listings on all predictors for each wave before the regulation (Abadie et al., 2010; Galiani et al., 2016).

[18]For example, in their study on per capita cigarette consumption trends in California, Abadie et al. (2010) assigned non-negative weights to only five out of the 38 potential control states.

[19]The rationale behind focusing on the 19 largest Airbnb markets was to narrow the pool to cities with Airbnb dynamics more closely related to Santa Monica's. An additional analysis including all cities in the donor pool yielded qualitatively consistent and quantitatively similar results. Notably, when using the extended pool of donors, Marina Del Rey, Los Angeles, and Topanga remained the only cities receiving positive weights in this expanded analysis.

Table 2: Predictor Means for Santa Monica and Control Cities

Variables	Santa Monica		Average of 19 controls cities
	Real	Synthetic	
Normalized Listings (mean across Oct/2014 and Apr/2015)	12.34	12.31	4.33
Ln(Median Income)	11.28	11.27	11.18
Ln(Population)	11.45	11.41	11.02
Share of young adults	25.48	25.46	22.18
Owner-occupancy rate	0.28	0.35	0.47
Ln(Establishments Food & Accommod.)	6.17	5.76	4.98
Ln(Establishments Arts & Entertain.)	6.60	5.86	5.06

Notes: Normalized listings are averaged over the last two pre-regulation waves. The rest of predictors are averaged over all the four pre-regulation waves. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages (Abadie et al., 2011; Galiani et al., 2016).

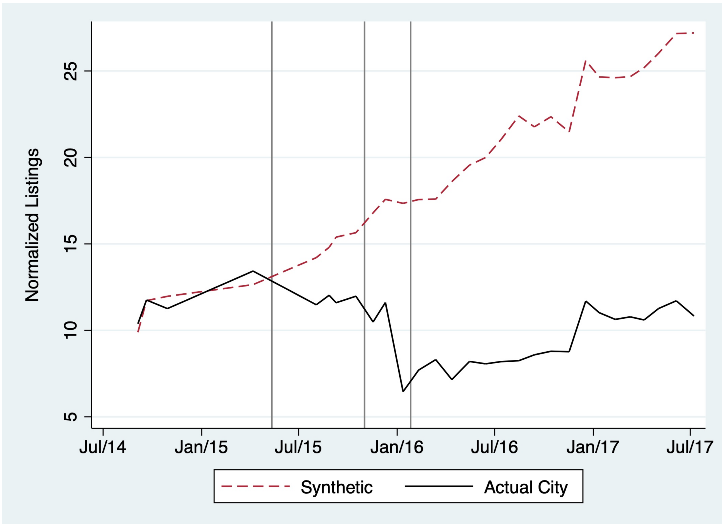
Table 3: Weights of Each Control City in the Synthetic Santa Monica

City	Weight	City	Weight
Altadena	0	Playa Del Rey	0
Burbank	0	San Pedro	0
Culver City	0	Sherman Oaks	0
Encino	0	South Pasadena	0
Glendale	0	Studio City	0
Long Beach	0	Topanga	0.129
Los Angeles	0.351	Valley Village	0
Malibu	0	Van Nuys	0
Marina Del Rey	0.520	Woodland Hills	0
North Hollywood	0	Santa Monica	-

Notes: Table shows the weights assigned to each control city. Predictors included in the model are the the outcome itself (normalized listings) averaged over the two last waves pre-regulation and the supplemental predictors: log income and population, fraction of young adults and owner occupiers, and log establishment counts in food, accommodation, and entertainment, all average over all the four pre-regulation waves. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages (Abadie et al., 2011; Galiani et al., 2016).

Effect Size. Figure 6 depicts the evolution of normalized Airbnb listings in Santa Monica alongside those of its synthetic counterpart. Although the synthetic control does not precisely mirror the pre-regulation trajectory of listings in Santa Monica, it represents the trend more accurately than any individual control city. Post-HSO, a marked divergence between the two trajectories is evident in Figure 6, suggesting that, in the absence of the ordinance, the number of entire home listings in Santa Monica would have likely continued its upward trend. Additionally, note that the synthetic control indicates a marginally lower level of Airbnb activity in the final pre-HSO period compared to actual Santa Monica. This observation suggests that any potential biases from the SCM analysis would tend toward underestimating the HSO's immediate impact.

Figure 6: Trends in Normalized Listings in Santa Monica and its Synthetic Control



Note: Vertical axis measures normalized Airbnb listings (listings per 1000 housing units). Synthetic control computed using the predictors indicated in Table 2. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages (Abadie et al., 2011; Galiani et al., 2016).

The SCM provides a point estimate for the regulatory impact at each post-implementation period. Table 4 details these estimates for three pivotal months: October 2015, which marks three months post-adoption of the regulation but precedes active enforcement and the increase in fines; January 2016, approximately two and a half months following the onset of proactive enforcement but before the increase in the fine; and July 2017, the final sample period, by which time the regulatory framework had been in stable operation for one and a half years. The table displays estimated impacts in terms of normalized listings, accompanied by the corresponding absolute change in the number of listings and the percentage change.

The regulation significantly affected the volume of entire home listings on Airbnb in Santa Monica. Within three months following its enactment, there was a reduction of approximately 190 units, translating to a significant decline of 23.46% in listings. This result suggests that the initial steps of launching an educational campaign about the new law and issuing warning letters to potential violators were effective in starting to curb Airbnb activity. By the end of the sample period, the HSO had led to an 861-unit reduction in Airbnb listings, equating to a

Table 4: Effect of Santa Monica's HSO on Entire Homes Listings on Airbnb

Variable	October 2015	January 2016	July 2017
Listings / 1000 housing units	-3.67	-10.89	-16.36
Number of Listings	-190.66	-566.68	-861.20
In percentage terms (%)	-23.46	-62.78	-60.17

Note: Synthetic control computed using the predictors indicated in Table 2. HSO stands for Home-Sharing Ordinance. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages.

60% decrease. This pronounced decline highlights the regulation's effectiveness in limiting the operation of vacation rentals.

It is noteworthy that in January 2016—eight months after the HSO's passage and two and a half months into the proactive enforcement strategy—Santa Monica saw 567 fewer entire home units on Airbnb than would have been the case without the ordinance, translating to a 62.78% reduction in listings. The significant increase in the ordinance's estimated effect within the three months from October 2015 to January 2016 suggests that proactive enforcement was a very effective measure to limit STRs.[20]

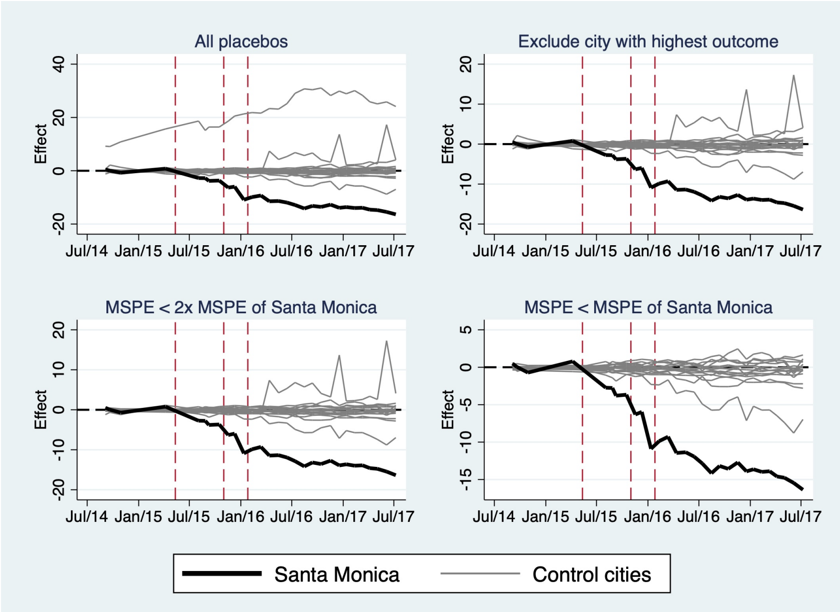
Furthermore, while the decrease in the absolute number of entire home units listed on Airbnb in Santa Monica continued to grow from January 2016 to July 2017, the HSO's effect in percentage terms remained relatively stable. This pattern suggests that during the second half of the sample period, the growth rates of listings in Santa Monica and its synthetic counterpart were similar. Further investigation is required to elucidate the mechanisms underlying the time variation in the regulation's effectiveness in curbing Airbnb activity.

Inference. Following the methodology proposed by Abadie et al. (2010), I employ a placebo-based procedure. This approach involves assigning a "fake" treatment to each control city, creating their respective synthetic controls, and estimating placebo effects. To assess the statistical significance of the actual effects of the Home-Sharing Ordinance, I compare its magnitude to those of the estimated placebo effects.

Figure 7 illustrates the results of this placebo exercise. The top-left graph displays all 20 cities, including Santa Monica and the 19 control units. The placebo effect of one of the control cities stands out, even in the pre-treatment period. This discrepancy arises because, by construction, the city with the largest values of the outcome variable cannot be replicated by a convex combination of the remaining cities. To ensure a meaningful comparison between actual and placebo effects, researchers should remove cities with a substantial difference between actual and synthetic trends even before the treatment. Following this strategy, each additional plot to the right and bottom of Figure 7 excludes cities with a pre-ordinance fit that falls below a specified threshold of pre-regulation goodness of fit. In these plots, we note that the estimated gap for Santa Monica is considerably larger than for any other city.

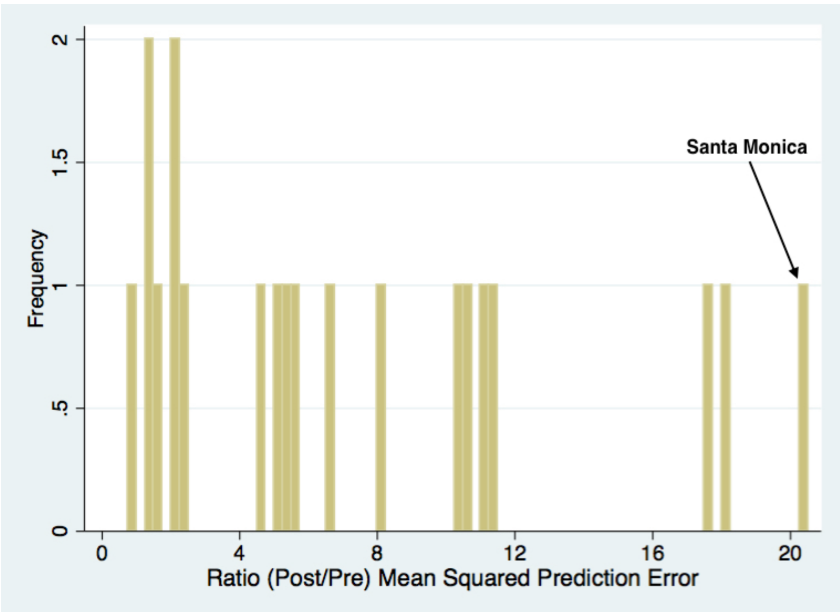
[20] It is possible that an anticipation effect, whereby hosts were aware of the forthcoming increase in the fine for violating the ordinance, may have contributed to the substantial reduction in listings between December 2015 and January 2016. However, this scenario seems improbable. The City Council meeting that announced the fine increase took place on January 26th, 2016, after the wave of data collection on January 12th, 2016.

Figure 7: Gap in Normalized Listings Between the Actual and Synthetic Version of Each City



Note: The vertical axis measures the gap in normalized Airbnb listings between the actual city and its synthetic control. Synthetic controls computed using the predictors indicated in Table 2. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages.

Figure 8: Ratio of Post to Pre-Regulation Root Mean Square Prediction Error



Note: Vertical axis represents the number of cities. Horizontal axis measures the ratio of post to pre-regulation prediction errors, larger values indicate a larger estimated effect using the synthetic control method (SCM). Synthetic controls computed using the preferred specification. Covariates indicated in Table 2. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages.

An alternative approach to inference involves comparing the ratio between post and pre-regulation measures of fit across different cities. Figure 8 displays the ratios of post/pre-ordinance root mean square prediction errors (RMSPE) for all 20 cities included in the study and shows that the highest ratio corresponds to Santa Monica. The probability of estimating a ratio as large as the one for Santa Monica under a random permutation of the regulation in the data is 1/20 = 0.05. Thus, we can say that the impact of the Home-Sharing Ordinance is statistically significant at the 5% level.

Effect of the HSO on Airbnb Prices. The fact that the HSO significantly reduced the number of Airbnb listings operating in Santa Monica suggests that it may also have affected the market for short-term rentals in other ways. Findings from a synthetic control estimation similar to the one described above but focusing on Airbnb prices instead of counts show a positive but not robust effect of the HSO on average Airbnb prices. Figure A.3 in the appendix provides more details on this analysis.

5.2 The Effect of the HSO on Residential Rents

5.2.1 Baseline Results

Figure 9 depicts the evolution in residential rents in Santa Monica compared to its synthetic control. In this baseline specification, the synthetic control method assigns positive weights to three cities: Culver City (0.625), Hawthorne (0.169), and Malibu (0.206). Although the fit was not optimal in the early years of the sample period, the synthetic control tracks rent trends in Santa Monica very well from 2012 onwards. The figure suggests that the Home Sharing Ordinance did not reduce rents in Santa Monica. Two years after the regulation's implementation, rents in the synthetic counterpart of the city were approximately at the same level as those observed in the actual city.

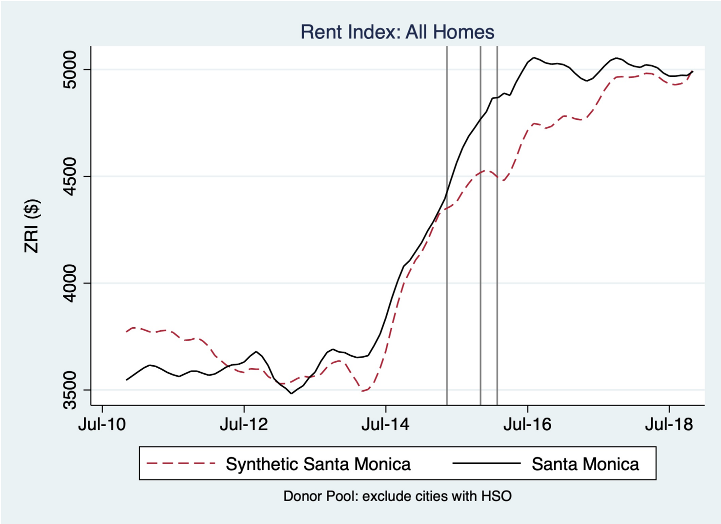
A potential concern is that the synthetic control lags behind Santa Monica in the months immediately after the regulation, making it challenging to visualize the expected effects of the policy on reducing rental prices. However, this is unlikely to be the primary reason for the conclusion that the regulation did not impact rental prices. In one of the robustness exercises described below, I shifted the treatment period forward, ensuring that the synthetic control closely tracked rents in Santa Monica until a period closer to when the decline in rents started (see Figure B.4). Even in this scenario, the synthetic control does not deviate from the observed trend in 2016 and 2017.

5.2.2 Additional Analyses and Robustness

Heterogeneity: Number of Bedrooms. A potential explanation for the finding that HSO did not impact rents could be the varying effects of the ordinance across different housing types. Given that the average number of bedrooms in an Airbnb listing is 1.56, it is plausible that the effects of the HSO are more pronounced in smaller apartments. To investigate this hypothesis, I used Zillow rent indexes computed separately for homes with different numbers of bedrooms.

Results of this analysis are depicted in Figure 10, which shows the results for one and two-bedroom homes. There is no indication of any effect of the regulation on rents of two-

Figure 9: Impact of the Home Sharing Ordinance (HSO) on Rents



Notes: Analysis at the city-month level from November 2010 to November 2018. Outcome variable is the Zillow Rent Index for all homes. The pool of control units comprises the 40 cities in the study area with the highest pre-regulation outcome variable that did not impose home-sharing ordinances during the sample period. Predictors (averaged over the entire pre-regulation period) include the outcome variable, log of average income, log of population, proportion with a college degree, employment share, and the share of young adults (aged 20-34). The outcome variable in the last pre-regulation period (May 2015) is also included as a predictor. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages.

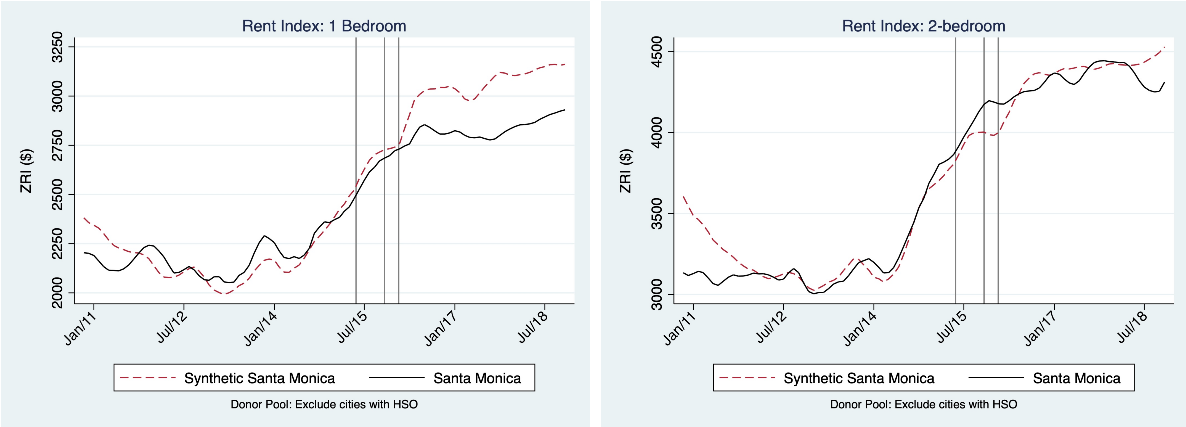
bedroom homes. For one-bedroom houses, however, we observe a difference between actual and synthetic city rents, which may indicate that the regulation lowered rents in this market segment. Nevertheless, placebo-based inference exercises suggest that this apparent effect is not statistically significant. Figure 11 shows the results of the placebo analysis. Santa Monica's effect post-treatment is not significantly different from that in other cities.

Alternative Empirical Strategy: Synthetic Difference in Differences. The synthetic control method (SCM), since it often assigns zero weight to many control units, may be sensitive to the choice of cities to include in the pool of donors. Moreover, it may face challenges when the treated unit has very high levels of the outcome variable, as it will have to assign positive weights to whatever control unit lies above the treated one. With some of the most expensive rents across all cities in the dataset, Santa Monica presents such a challenge.

An alternative approach, the synthetic difference in differences (SDID) method, developed by Arkhangelsky et al. (2021), addresses these issues by combining the benefits of synthetic control and fixed effects estimators. According to Arkhangelsky et al. (2021), SDID "avoids common pitfalls in standard DID and SCM methods - namely an inability to estimate causal relationships if parallel trends are not met in aggregate data (diff-in-diff), and a requirement that the treated unit be housed within a convex hull of control units (SCM)."

The SDID improves upon the standard synthetic control by incorporating time-invariant unit effects, similar to standard fixed-effects models. Like the standard SCM, it features an optimization routine to match pre-treatment trends, allowing it to handle pre-regulation heterogeneity in levels and rent trends simultaneously. Applying this method tends to result in a

Figure 10: The Effect of the HSO on Rents, by Number of Bedrooms



(a) 1 Bedroom Homes

(b) 2 Bedroom Homes

Notes: Analysis conducted at the city-month level from November 2010 to November 2018. Outcome variable is the Zillow Rent Index for 1-bedroom (a) or 2-bedroom (b) homes. The pool of control units consists of the 40 cities in the study area with the highest pre-regulation outcome variable that did not impose home-sharing ordinances during the sample period. Predictors (averaged over the entire pre-regulation period) include the outcome variable, log of average income, log of population, proportion with a college degree, employment share, and the share of young adults (aged 20-34). The outcome variable in the last pre-regulation period (May 2015) is included as a predictor.
Source: Author's own work using Stata's "synth" and "synth_runner" packages.

synthetic control with positive weights on a larger number of units, making it less sensitive to the evolution of rents in one specific city.

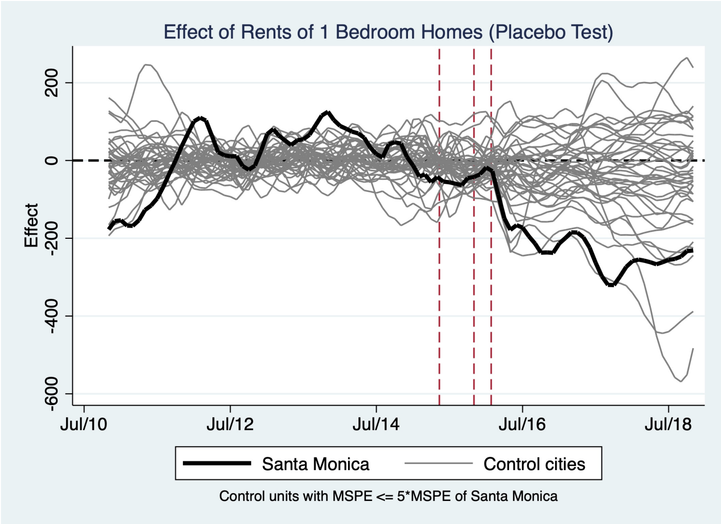
Figure 12 presents the results of applying the SDID method to estimate the effect of the HSO on rents. The left plot shows the weights assigned to each city, and the right plot depicts the evolution of rents for Santa Monica and its synthetic control. Compared to the traditional SCM, more cities receive positive weights (eight instead of three or four). Furthermore, Figure 12 demonstrates that this method constructs synthetic controls with trajectories that run parallel to Santa Monica but allow the two trends to exhibit different levels.

Despite the differences in methodology, the conclusion remains unchanged. There is no evidence that the Home Sharing Ordinance (HSO) in Santa Monica impacted rents in the city.[21] Specifically, the weighted average of these eight cities in L.A. county, none of which imposed HSOs, displays a similar slowdown in rents as the one observed in Santa Monica around mid-2016. This result gives us greater confidence that the observed slowdown in rents around that time is a phenomenon with explanations related to general structural factors rather than something caused explicitly by Santa Monica's HSO.

Robustness Checks. I conducted five additional robustness checks to further assess the regulation's impact. These checks considered houses of different rent tiers, zip codes instead of cities, house prices instead of rents, a shifted treatment period (to account for potential enforcement delays), and a pool of control units analogous to the one used in the analysis examining the effect on Airbnb activity. Please refer to Appendix B for the results generated in

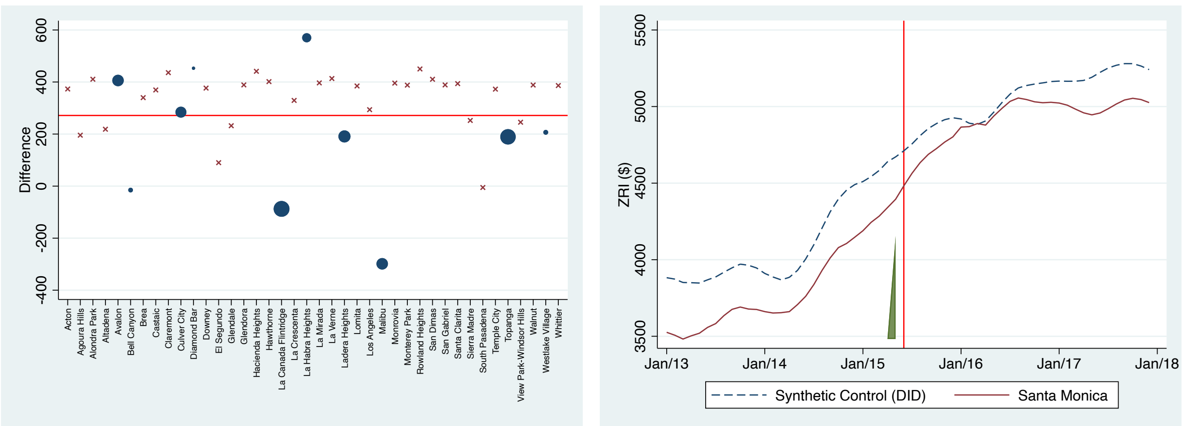
[21]Unlike the SCM, the SDID methodology suggests estimating the effect of the regulation by comparing the average differences in rents between the actual and synthetic control post- and pre-regulation. This procedure results in an estimated zero effect in statistical terms. While not covered in detail here, it is clear from the graph that the difference between treatment and control does not change substantially after the regulation.

Figure 11: Gap in Predicted Rents For All Units: Actual versus Synthetic



Notes: Analysis at the city-month level from November 2010 to November 2018. Outcome variable is the Zillow Rent Index for 1-bedroom homes. The pool of control units comprises the 40 cities in the study area with the highest pre-regulation outcome variable that did not impose home-sharing ordinances during the sample period. Predictors (averaged over the entire pre-regulation period) include the outcome variable, log of average income, log of population, proportion with a college degree, employment share, and the share of young adults (aged 20-34). The outcome variable in the last pre-regulation period (May 2015) is also included as a predictor. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages.

Figure 12: The Effect of the HSO on Rents: Synthetic Difference in Differences.



(a) Control Units' Weights

(b) Synthetic Versus Actual Santa Monica

Notes: Analysis at the city-month level from November 2010 to November 2018. Outcome variable is the Zillow Rent Index for all homes. The pool of control units comprises the 40 cities in the study area with the highest pre-regulation outcome variable that did not impose home-sharing ordinances during the sample period. Predictors (averaged over the entire pre-regulation period) include the outcome variable, log of average income, log of population, proportion with a college degree, employment share, and the share of young adults (aged 20-34). The outcome variable in the last pre-regulation period (May 2015) is also included as a predictor. *Source:* Author's own work using Stata's "sdid" package (Arkhangelsky et al., 2021).

these analyses. In summary, all of these alternative tests led to the same conclusion: there is no evidence that Santa Monica's Home-Sharing Ordinance significantly impacted residential rents in the city.

5.2.3 Examining the Mechanism: Housing Reallocation

Regression Specification. To ensure comparable results, this analysis uses the same set of cities present in the Zillow rent data. As the outcome variables, I focus on the number of houses allocated to different uses, such as those occupied by renters, owners, or vacant. Data for these variables was obtained from the American Community Survey (ACS), which provides data at yearly intervals.[22] Therefore, the dataset used in this section is a city-year panel for cities in L.A. County from 2010 to 2017.

I employed standard two-way fixed effects models to examine the hypothesis that the HSO has affected housing reallocation. Specifically, I estimated regressions of the following form:

$$Ln(Y_{it}) = \alpha + \beta(HSO_{it}) + \delta_i + \gamma_t + \theta' X_{it} + \epsilon_{it} \tag{3}$$

In this equation, Y_{it} represents the number of houses of a given occupancy or vacancy status in city i year t, and HSO_{it} is a binary variable that equals one only for observations referring to Santa Monica from 2015 onwards. Other terms include X_{it}, a vector of city-specific time-varying covariates, including the log of average income, log of population, the proportion with college degree, and share of young adults (aged 20-34); δ_i, which captures city fixed characteristics such as proximity to the beach; γ_t, which captures year-specific shocks affecting all cities, such as economic cycles; and ϵ_{it}, which represents city-specific time-varying unobservable shocks that affect the housing market, such as unobserved shocks to the demand for housing.

The coefficient of interest, β, measures how much the average difference in the log number of housing units of each occupancy/vacancy status between Santa Monica and other cities changes before and after the regulation. It is important to note that, as in the analysis of rents, all cities that have imposed some HSO during the sample period were dropped. Furthermore, it is worth mentioning that the same concerns raised before about the use of fixed effects models for causal interpretation are also present here. Therefore, the results presented here should be interpreted as suggestive.

Occupancy Status. I start by estimating Equation 3 using the log of the number of houses for various occupancy statuses as outcome variables. Table 5 reports the results for the total housing stock (column 1), as well as the number of owner-occupied houses, renter-occupied houses, and vacant houses (columns 2-4). All models include the same set of fixed effects and baseline time-varying demographic controls.

Table 5 presents results that do not support the hypothesis that Santa Monica's HSO reallocated vacation rental units to long-term tenants. The coefficient in column 3 indicates that the HSO did not impact the number of units allocated to long-term renters. Moreover, the coefficients for the first two columns are also not significant, indicating that the HSO did not significantly affect the construction of new housing or the number of houses occupied by owners. On the other hand, column 4 indicates an increase in the number of vacant houses in Santa Monica. The 20% coefficient translates to an impact of approximately 800 units. These results

[22] Ideally, one would utilize higher frequency data on housing allocation changes immediately following the implementation of the Home Sharing Ordinance (HSO). Unfortunately, more granular data (e.g., monthly) on housing occupancy status is unavailable. Nonetheless, the analysis presented in Tables 5 and 6, which includes data from 2016 and 2017, should reflect potential shifts towards long-term tenancy in the two years post-HSO.

Table 5: Santa Monica HSO and House Occupancy Status

	Log of Houses, by Occupancy Status			
	All Houses	Owner Occup.	Renter Occup.	Vacant Houses
Home-Sharing Ordinance	0.010	-0.016	-0.007	0.198***
	(0.006)	(0.013)	(0.022)	(0.035)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	739	739	737	739

Notes: Standard errors clustered at city level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Outcome is the log of the total number of houses, by occupancy status (indicated in the column title). Analysis at the city-year level for the period of 2010 to 2017. Controls are: log of average income, log of population, proportion with college degree, and share of young adults (aged 20-34). *Source:* Author's own work using data from the American Community Survey.

could suggest that landlords prevented from listing their units on Airbnb, did not promptly make them available to residents, and left them vacant.

Type of Vacancy. To shed light on the potential factors underlying the positive impact of the HSO on the number of vacant houses, I exploit data on the underlying reasons for houses to be vacant. Specifically, in the ACS survey, vacant housing units are categorized as for-rent, for-sale, for vacation and seasonal purposes, or other/unknown reasons. This categorization allows us to explore additional hypotheses about the expected effects of a regulation. Firstly, even though the quantity of housing occupied by long-term renters may not have increased due to the regulation, the HSO may have affected the number of houses vacant for rent. Secondly, since the regulation may prevent some landlords from using their housing units for their most profitable use, the HSO may increase the number of houses for sale.

Table 6 presents the results. The first column lists all categories of vacant homes, and subsequent columns highlight specific reasons for vacancy. Firstly, we can see that the impact of the HSO on homes vacant for seasonal purposes is not significant. Nevertheless, Section 5.1 shows that the HSO has had a strong effect in reducing Airbnb activity. Therefore, it seems unlikely that the Census classified properties previously allocated to Airbnb for seasonal use.

Regarding the evidence on the reallocation effect, results in column 3 do not support the hypothesis that the HSO led to an increase in the number of homes offered for permanent renters. In fact, after the ordinance's implementation, the number of vacant homes for rent in Santa Monica has declined faster than in other locations. On the other hand, column 4 supports the hypothesis that absentee landlords may find Santa Monica less attractive as a market to hold their housing assets after the regulation. This conclusion is supported by the positive and significant coefficient in the specification that uses the number of houses vacant for sale as an outcome.

Furthermore, the coefficient for homes vacant for unknown reasons is also positive and significant. However, the ambiguity associated with the "unknown" category complicates drawing precise conclusions. This category includes cases where the reason for a unit's vacancy remained unclear despite the Census surveyor's efforts to contact owners or inquire with neighbors. Despite these uncertainties, one fact remains clear: these units, classified as vacant for

Table 6: Santa Monica HSO and House Vacancy Status

	Log of Vacant Houses, by Type of Vacancy				
	All Vacant	Seasonal	For Rent	For Sale	Unknown
Home-Sharing Ordinance	0.198***	-0.014	-0.264***	0.347***	0.581***
	(0.035)	(0.100)	(0.078)	(0.083)	(0.077)
Controls	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	739	595	682	652	722

Notes: Clustered standard errors in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Outcome is the log of the number of (type-specific) vacant houses. Analysis at the city-year level for the period of 2010 to 2017. Controls: log of average income, log of population, proportion with college degree, and share of young adults (aged 20-34). *Source:* Author's own work using data from the American Community Survey.

unknown reasons, were not being converted into long-term rental properties. This observation indicates a failure of the HSOs to increase the long-term rental housing supply.

In summary, the available evidence suggests that the Home-Sharing Ordinance has led to a decline in the number of Airbnb listings without a corresponding increase in housing allocation to long-term renters. Framing landlords' decisions as a choice between the long and short-term markets, this pattern of findings may be explained by a high value placed on the flexibility offered by short-term rentals.[23] For example, landlords may appreciate the option to occasionally use their housing unit for purposes other than Airbnb, particularly during the summer or holidays.[24]

In this changing regulatory environment, landlords favoring short-term rentals may have adopted a "wait and see" strategy, delaying the transition to long-term rentals.[25] Additionally, absentee landlords affected by the HSO restrictions could choose to sell their properties rather than converting them into long-term rentals. The transition of ownership and subsequent allocation to long-term renters could take time.

6 Discussion and Conclusion

The emergence and expansion of online platforms for short-term rentals (STRs) over the last decade have underscored pressing questions about regulating such activities and evaluating specific regulatory frameworks. As municipalities continue to develop or refine policies to mitigate the effects of short-term rentals, empirical studies emerge as crucial tools for informing these policy decisions. In this context, this paper focuses on Santa Monica, California, a pioneer city in enforcing a comprehensive Home-Sharing Ordinance (HSO) designed to regulate STRs.

[23]Both Garcia-López et al. (2020) and Almagro and Dominguez-Iino (2022) model landlords' decisions as a binary choice between renting in the long-term market to locals or in the short-term market to travelers.

[24]The New York Times article mentioned before provides examples of Airbnb units where owners used the same property to host visiting family members. Source: www.nytimes.com/2023/09/16

[25]Additionally, some landlords who engaged in unlawful short-term renting may have been reluctant to disclose such information to Census surveyors, further contributing to the rise in unknown vacancies.

Using city-level data on Airbnb and residential rents across Los Angeles County, this study innovates using the synthetic control method to assess STR regulations' impacts. The findings are twofold. Firstly, the analysis reveals that the enactment of Santa Monica's Home-Sharing Ordinance led to a significant decrease in the number of Airbnb entire-home listings, with a reduction of roughly 60% (860 units). Secondly, the investigation finds no substantial evidence to suggest that the regulation directly affected residential rents. A potential mechanism behind these results was explored using a two-way fixed-effects model. Results indicate that the ordinance did not lead to a significant shift in housing from short-term to long-term rental markets.

Regarding implications, the findings of this study offer substantial contributions to discussions on housing and urban policy, particularly in the effective regulation of short-term rental platforms like Airbnb. In this context, Cunha and Lobão (2022) suggest supply-side interventions that help to flatten the housing supply curve as a means to counter potential price increases driven by the growth of STRs. Meanwhile, Barron et al. (2021), to address STR-related rising housing costs, suggest measures such as taxing absentee landlords who offer their properties for short-term rent while still allowing owner-occupiers the opportunity to share their homes with visitors through Airbnb.

The lack of a significant impact of STRs on rental prices in my analysis indicates that the effectiveness of STR regulations will depend on the particular characteristics of individual cities. Factors such as a city's status as a major urban center or tourist destination and characteristics of its housing market (e.g., proportions of owner-occupied houses, second homes, and properties owned by investment entities) critically influence the dynamics between short- and long-term rental markets. My findings suggest that a one-size-fits-all approach to STR regulation may not be optimal. Therefore, policymakers should adopt a more granular, context-specific approach in crafting regulations for STR platforms.

Furthermore, this analysis offers significant implications for other stakeholders, particularly platforms like Airbnb. The finding that the Home-Sharing Ordinance in Santa Monica led to a substantial decrease in Airbnb listings without a parallel transition from short- to long-term rentals indicates that, for many property owners, the two forms of rental are not perfect substitutes. This observation highlights the role of platforms like Airbnb in reducing the transaction costs associated with short-term rentals, thereby creating tangible economic advantages. Such platforms can leverage this argument during discussions with city officials to advocate for regulatory measures that address local housing affordability concerns while acknowledging the economic value of short-term rentals.

It is crucial to acknowledge that, beyond its inability to shift housing from Airbnb to the long-term rental market, additional factors might have contributed to the HSO's limited effect on residential rents in Santa Monica. Firstly, challenges in enforcing the regulation led to a significant, yet incomplete, reduction in vacation apartment operations. This partial enforcement may have diluted some of the intended effects on the housing market, underscoring the need for more robust regulatory implementation and compliance mechanisms. Secondly, the decrease in Airbnb activities likely reduced the influx of tourists. Considering that tourists can impose negative externalities on residents (Filippas and Horton, 2023), the HSO's impact on tourism could have enhanced the desirability of specific neighborhoods for locals. This increased appeal may have driven up housing demand and rental prices.

Moreover, the impact of STR platforms on neighborhood dynamics potentially extends beyond housing availability, affecting both the subjective sense of community and the objective quality of neighborhood amenities, such as the variety of local consumption opportunities (Hidalgo et al., 2022; Almagro and Dominguez-Iino, 2022). Additionally, permitting absentee landlords to offer their properties for short-term rentals entails significant distributional consequences (Koster et al., 2021). Given these complexities, future research focusing on the effects of short-term rentals on neighborhood dynamics, coupled with a comprehensive assessment of the welfare implications of various regulatory strategies, represents a valuable direction for exploration. Such studies would support evidence-based policies that equitably accommodate the interests of all stakeholders in the housing market.

References

A. Abadie and J. Gardeazabal. The economic costs of conflict: A case study of the basque country. *American economic review*, 93(1):113–132, 2003.

A. Abadie, A. Diamond, and J. Hainmueller. Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association*, 105(490):493–505, 2010.

A. Abadie, A. Diamond, and J. Hainmueller. Synth: An R package for synthetic control methods in comparative case studies. *Journal of Statistical Software*, 42(13):1–17, 2011. URL https://www.jstatsoft.org/v42/i13/.

A. Abadie, A. Diamond, and J. Hainmueller. Comparative politics and the synthetic control method. *American Journal of Political Science*, 59(2):495–510, 2015.

M. Almagro and T. Dominguez-Iino. Location sorting and endogenous amenities: Evidence from amsterdam. *Available at SSRN 4279562*, 2022.

D. Arkhangelsky, S. Athey, D. A. Hirshberg, G. W. Imbens, and S. Wager. Synthetic difference-in-differences. *American Economic Review*, 111(12):4088–4118, 2021.

K. Barron, E. Kung, and D. Proserpio. The effect of home-sharing on house prices and rents: Evidence from airbnb. *Marketing Science*, 40(1):23–47, 2021.

R. Bekkerman, M. C. Cohen, E. Kung, J. Maiden, and D. Proserpio. The effect of short-term rentals on residential investment. *Marketing Science*, 2022.

A. M. Cunha and J. Lobão. The effects of tourism on housing prices: applying a difference-in-differences methodology to the portuguese market. *International Journal of Housing Markets and Analysis*, 15(4):762–779, 2022.

T. Duso, C. Michelsen, M. Schäfer, and K. D. Tran. Airbnb and rents: Evidence from berlin. 2020.

B. G. Edelman and D. Geradin. Efficiencies and regulatory shortcuts: How should we regulate companies like airbnb and uber. *Stan. Tech. L. Rev.*, 19:293, 2015.

L. Einav, C. Farronato, and J. Levin. Peer-to-peer markets. *Annual Review of Economics*, 8:615–635, 2016.

C. Farronato and A. Fradkin. The welfare effects of peer entry: the case of airbnb and the accommodation industry. *American Economic Review*, 112(6):1782–1817, 2022.

B. Ferman, C. Pinto, and V. Possebom. Cherry picking with synthetic controls. *Journal of Policy Analysis and Management*, 39(2):510–532, 2020.

A. Filippas and J. J. Horton. The tragedy of your upstairs neighbors: The negative externalities of home-sharing platforms. 2023.

A. Filippas, J. J. Horton, and R. J. Zeckhauser. Owning, using, and renting: Some simple economics of the "sharing economy". *Management Science*, 66(9):4152–4172, 2020.

S. Galiani, B. Quistorff, et al. The synth_runner package: Utilities to automate synthetic control estimation using synth. *Unpublished paper, University of Maryland*, 2016.

B. Garcia, K. Miller, and J. Morehouse. In search of peace and quiet: The heterogeneous impacts of short-term rentals on housing prices. *The Center for Growth and Opportunity*, 2024.

M.-À. Garcia-López, J. Jofre-Monseny, R. Martínez-Mazza, and M. Segú. Do short-term rental platforms affect housing markets? evidence from airbnb in barcelona. *Journal of Urban Economics*, 119:103278, 2020.

A. Hidalgo, M. Riccaboni, and F. J. Velázquez. The effect of short-term rentals on local consumption amenities: Evidence from madrid. *Journal of Regional Science*, 2022.

K. Horn and M. Merante. Is home sharing driving up rents? evidence from airbnb in boston. *Journal of Housing Economics*, 38:14–24, 2017.

J. Jiao, K. Hansen, and A. Azimian. Land value impacts of airbnb listings on single-family homes in austin, texas, usa. *International Journal of Housing Markets and Analysis*, 15(2):392–410, 2022.

H. R. Koster, J. Van Ommeren, and N. Volkhausen. Short-term rentals and the housing market: Quasi-experimental evidence from airbnb in los angeles. *Journal of Urban Economics*, 124: 103356, 2021.

R. Lieber. New worry for home buyers: A party house next door. *New York Times*, 10, 2015.

P. Schäfer and N. Braun. Misuse through short-term rentals on the berlin housing market. *International journal of housing markets and analysis*, 9(2):287–311, 2016.

M. J. Seiler, R. B. Siebert, and L. Yang. Airbnb or not airbnb? that is the question: How airbnb bans disrupt rental markets. *Real Estate Economics*, 2023.

G. Zervas, D. Proserpio, and J. W. Byers. The rise of the sharing economy: Estimating the impact of airbnb on the hotel industry. *Journal of Marketing Research*, 54(5):687–705, 2017.

Appendix

A Additional Figures and Analyses

Rents by type of home.

Figure A.1: Evolution of the Zillow Rent Index (ZRI), by Number of Bedrooms.

Notes: Each vertical line in the graph represents a key development in the implementation of the Home-Sharing Ordinance: adoption, proactive enforcement, and fine increase, respectively. *Source:* Author's own work using data from Zillow, available at www.zillow.com/research/data.

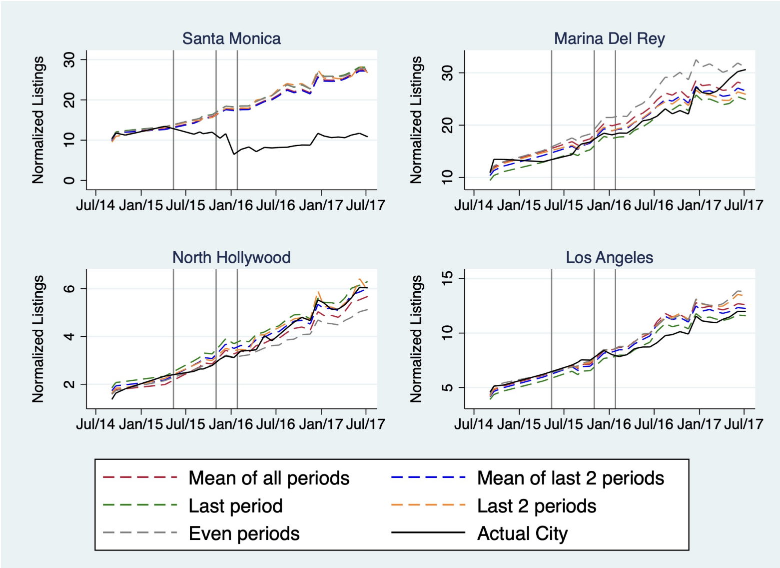
SCM for Airbnb Activity: specifying the functional form. Figure A.2 illustrates the application of Ferman et al. (2020) procedure to choose the SCM specification. It presents the results for three control cities—Marina Del Rey, North Hollywood, and Los Angeles—as well as Santa Monica, based on five distinct specifications, each relying on a different linear combination of pre-regulation listings. Despite having only four pre-regulation waves available, all specifications produce synthetic versions that closely follow post-ordinance trends for control cities. Following the principle of favoring the specification that minimizes post-regulation prediction error among control units, I select the one that employs the mean of the normalized listings over the last two waves before the ordinance was adopted.

Effect of the HSO on Airbnb Prices. I compute the average price of Airbnb listings for each city and period under study. Employing a synthetic control method, this analysis mirrors the approach detailed in Section 4.3, but focuses on the average prices of Airbnb listings as the outcome variable instead of the number of listings.

Figure A.3 displays the main results of this analysis. It reveals substantial fluctuations in Airbnb prices over different periods. These fluctuations may partly reflect the tourism industry's seasonal dynamics, which affect demand and, consequently, pricing. Additionally, the ongoing entry and exit of properties from the Airbnb platform may contribute to these variation in average price.

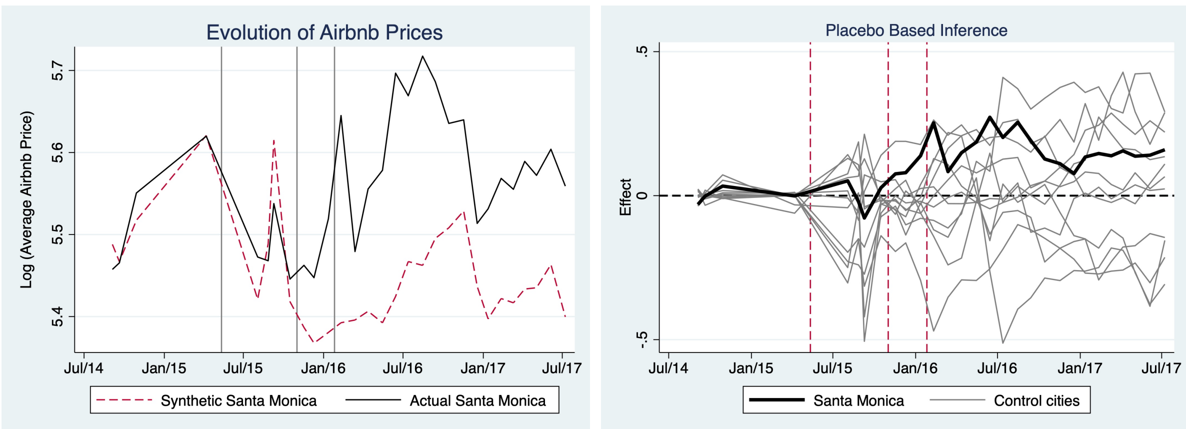
When considering the impact of the HSO on Santa Monica's average Airbnb prices, two primary mechanisms should be considered. Firstly, as argued previously in the paper, the HSO led to a reduction in the availability of vacation apartments within the city, thereby introducing a selection effect. If the ordinance predominantly results in the removal of higher-priced vacation properties, the average market price would be expected to decline. Conversely, if it mainly eliminates the more affordable Airbnb options, the average market price could increase. The

Figure A.2: Effect of Using Different Linear Combinations of Pre-Regulation Airbnb Listings



Note: Vertical axes represent normalized Airbnb listings (listings per 1000 housing units). The legend indicates the way in which the outcome variable enter the computation of the synthetic control. Besides a given linear combination of pre-HSO outcome variable, all models use the same supplemental predictors: log income and population, fraction of young adults and owner occupiers, and log establishment counts in food, accommodation, and entertainment, all averaged over the four pre-Home-Sharing Ordinance (HSO) periods. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages (Abadie et al., 2011; Galiani et al., 2016).

Figure A.3: The Effect of the HSO on Average Airbnb Prices



(a) Santa Monica and its Synthetic Control

(b) Effect in Santa Monica vs Placebo Effects

Notes: Analysis conducted at the city-wave level, covering the period from April 2014 to July 2017. The outcome variable is the logarithm of the average price of all Airbnb listings active within each city-wave. This sample and its specifications mirror those employed in the examination of the Home Sharing Ordinance's effect on the count of Airbnb listings. For detailed information on the data and empirical specification, refer to Sections 3.1 and 4.3. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages.

second mechanism involves a direct price adjustment by hosts, who may raise their rates to compensate for the increased "costs" of operating an Airbnb (e.g., potential fines from the city).

Empirically, I find evidence suggesting that the HSO led to an increase in Airbnb prices in Santa Monica. Notably, Figure A.3a indicates a marked rise in prices within the city around January 2016, a trend not mirrored by Santa Monica's synthetic control. This timing aligns with both the selection effect and price adjustment mechanisms. Remember from Figure 6 that there was a significant drop in the number of Airbnb listings between December 2015 and January 2016. This may be driving the initial divergence between actual city and synthetic control observed in Figure A.3a through the selection effect. Secondly, a key update to the regulatory framework, specifically the increase in fines, took effect on January 26, 2016. This development may explain the pronounced price surge between January and February 2016, as hosts remaining active possibly sought to compensate for the elevated risk of fines by raising their rates. Post-February 2016, although prices in Santa Monica remained above those of the synthetic control, the trends evolved in parallel, suggesting a stabilization of the market in response to the HSO's full implementation.

However, these observed effects not statistically significant at conventional levels. Employing the same placebo-based inference test previously described (Figure A.3b), the analysis reveals that while the estimated effect is positive, it could be attributed to chance. Many placebo effects exhibit magnitudes similar to those observed for Santa Monica. Specifically, during February 2016, when the effect appears most pronounced, the placebo-based p-value stands at 0.11, indicating the effect cannot be deemed significant (p-values for all other examined periods are even higher). Additionally, estimates from standard two-way fixed-effects models, which include time-varying controls such as average income and population at the city-wave level, yield a similar conclusion: the HSO's impact on Airbnb prices is positive but lacks statistical significance.

B Effect of the HSO on Rents: Robustness Checks

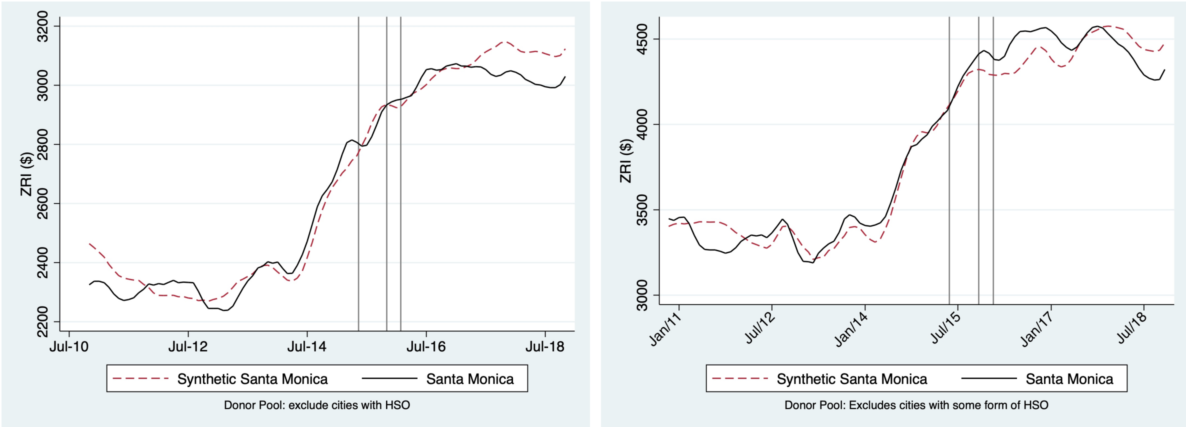
Rent Tier. I examined Zillow's rent indexes by rental price tier (bottom, middle, top) to check for heterogeneity. Results in Figure B.1 show a similar trend between the synthetic control and Santa Monica for both bottom and middle tier homes.

Zip code level. To address concerns regarding the level of aggregation of the rent data, I performed the SCM analysis at the zipcode instead of at the city level. While Santa Monica comprises six zipcodes, for brevity, I present the analysis for two of them. Figure B.2 illustrates that the synthetic control closely follows the post-regulation trends in rents.

House Prices. Previous studies, such as Garcia-López et al. (2020), have shown that short-term rentals have a greater impact on house prices than on rents. To explore whether the HSO had any effect on house prices, I conducted a similar analysis using Zillow's median listed sales price as the outcome variable. Figure B.3 shows the results for a city wide analysis and for one of the zipcodes in Santa Monica, indicating no effect on house prices.

Shifted Treatment. To address concerns about potential underestimation by the synthetic control of Santa Monica's rents immediately after the regulation, I adjusted the SCM treatment period to start in January 2016. This aligns with when the HSO implemented higher fines and Airbnb activity decreased sharply. Figure B.4 confirms earlier findings, with a similar rent slowdown in the synthetic control and Santa Monica.

Figure B.1: The Effect of the HSO on Rents, by Rental Price Tier

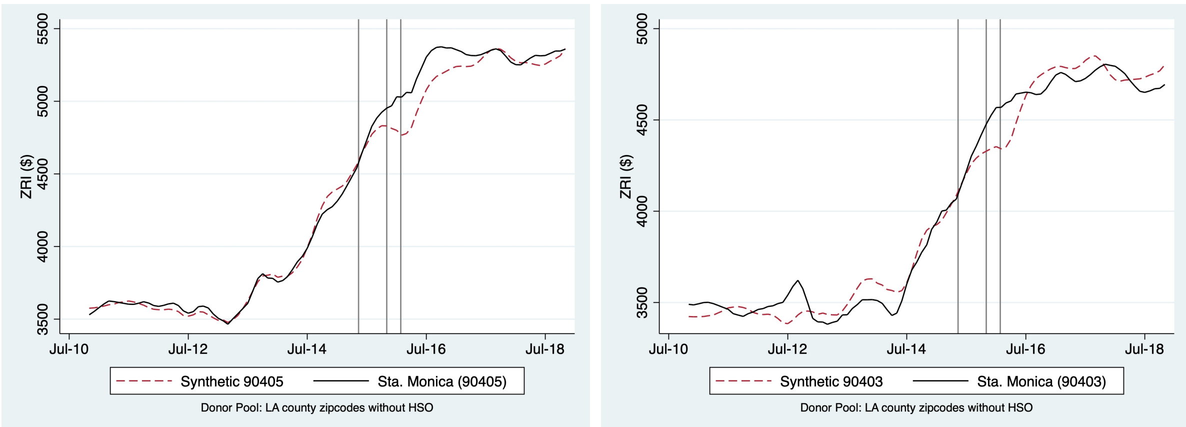


(a) Bottom Tier Rents (Cheap)

(b) Middle Tier Rents (Mid-Range)

Notes: Analysis at the city-month level from November 2010 to November 2018. Outcome variable is the Zillow Rent Index for homes in the bottom tier (a) or medium tier (b) bracket of rents. The pool of control units comprises the 40 cities in the study area with the highest pre-regulation outcome variable that did not impose home-sharing ordinances during the sample period. Predictors (averaged over the entire pre-regulation period) include the outcome variable, log of average income, log of population, proportion with a college degree, employment share, and the share of young adults (aged 20-34). The outcome variable in the last pre-regulation period (May 2015) is also included as a predictor. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages.

Figure B.2: The Effect of the HSO on Rents, for Two of Santa Monica's Zip Codes

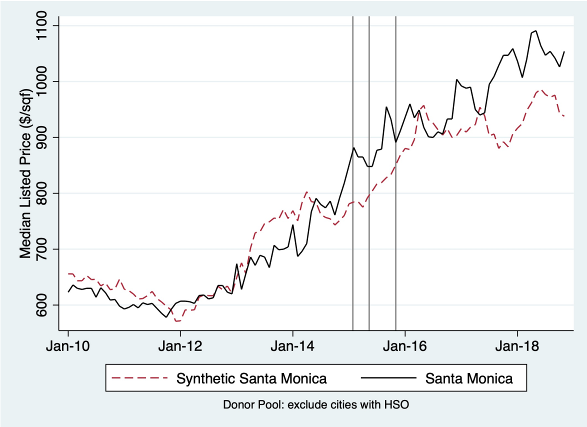


(a) Zip Code 90405

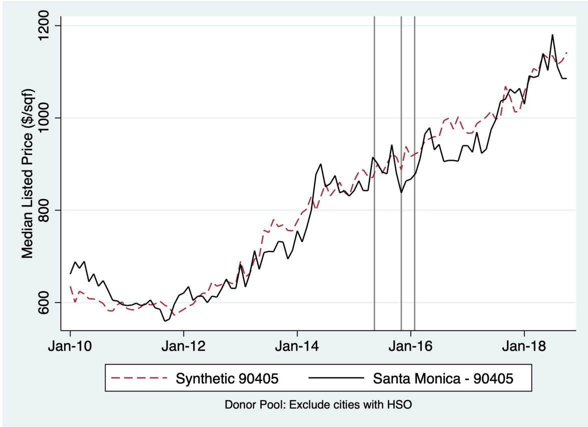
(b) Zip Code 90403

Notes: Analysis at the city-month level from November 2010 to November 2018. Outcome variable is the zipcode level Zillow Rent Index for for all homes. The pool of control units comprises the 40 cities in the study area with the highest pre-regulation outcome variable that did not impose home-sharing ordinances during the sample period. Predictors (averaged over the entire pre-regulation period) include the outcome variable, log of average income, log of population, proportion with a college degree, employment share, and the share of young adults (aged 20-34). The outcome variable in the last pre-regulation period (May 2015) is also included as a predictor. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages.

Figure B.3: The Effect of the HSO on Posted House Prices, City and Zipcode Analysis.



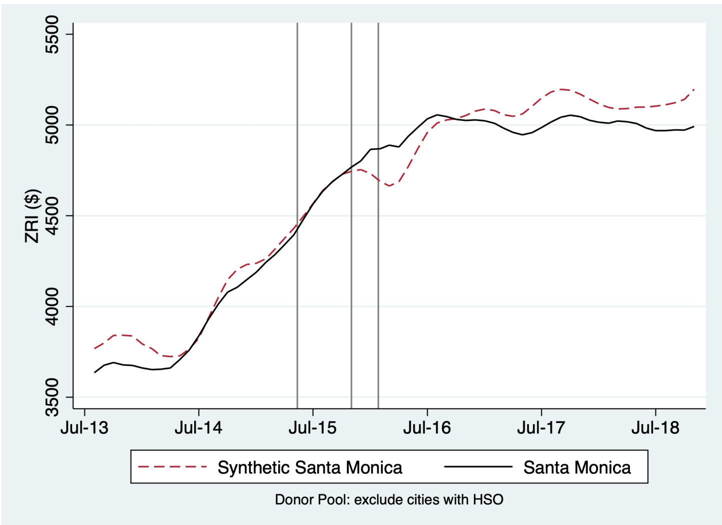
(a) City Level Analysis



(b) Zip Code Level Analysis

Notes: Analysis at the city-month level from November 2010 to November 2018. Outcome variable is the city (a) or zipcode (b) level Zillow median house price. The pool of control units comprises the 40 cities in the study area with the highest pre-regulation outcome variable that did not impose home-sharing ordinances during the sample period. Predictors (averaged over the entire pre-regulation period) include the outcome variable, log of average income, log of population, proportion with a college degree, employment share, and the share of young adults (aged 20-34). The outcome variable in the last pre-regulation period (May 2015) is also included as a predictor. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages.

Figure B.4: The Effect of the HSO on Rents (Shift Treatment Period Forward).

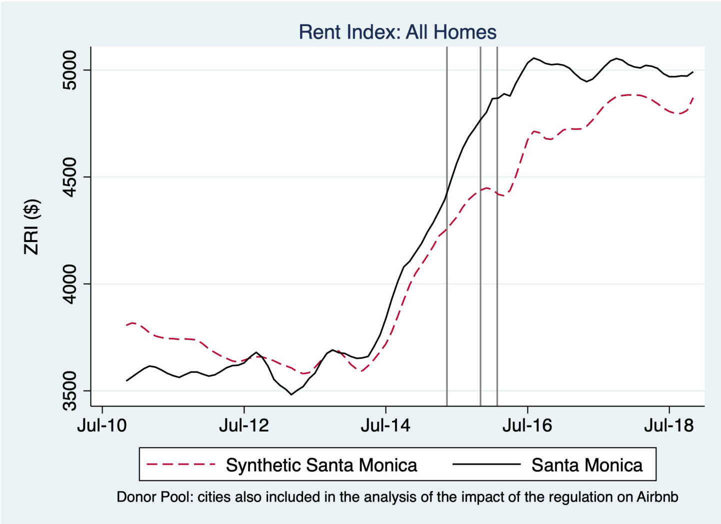


Notes: Analysis at the city-month level from August 2013 to November 2018. Outcome variable is the Zillow Rent Index for all homes. The pool of control units comprises the 40 cities in the study area with the highest pre-regulation outcome variable that did not impose home-sharing ordinances during the sample period. Predictors (averaged over the entire pre-regulation period) include the outcome variable, log of average income, log of population, proportion with a college degree, employment share, and the share of young adults (aged 20-34). The outcome variable in the last pre-regulation period (May 2015) is also included as a predictor. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages.

Alternative pool of control units. Finally, Figure B.5 presents the results of an analysis that is more directly comparable to the assessment of the regulation's impact on Airbnb activity, particularly regarding the pool of control cities. Starting with the same set of cities outlined in Table 3, cities lacking rent data in any of the months during the sample period were excluded, resulting in a final pool of 9 control cities: Altadena, Burbank, Culver City, Glendale, Long

Beach, Los Angeles, Malibu, South Pasadena, and Topanga. Figure B.5 reinforces our earlier findings. The deceleration in rents in Santa Monica aligns with that of its synthetic control, once again suggesting that the regulation itself does not appear to be a causal factor in reducing rents in Santa Monica compared to other cities where Airbnb continued to operate.

Figure B.5: Impact of the Home Sharing Ordinance (HSO) on Rents (Restricted Pool of Cities)



Notes: Analysis conducted at the city-month level from November 2010 to November 2018. Outcome variable is the Zillow Rent Index for all homes. To construct the pool of control units, I started with the same set of 19 cities outlined in Table 3. After dropping cities lacking rent data in one or more months of the sample period, the final pool consists of 9 control cities: Altadena, Burbank, Culver City, Glendale, Long Beach, Los Angeles, Malibu, South Pasadena, and Topanga. Predictors (averaged over the entire pre-regulation period) include the outcome variable, log of average income, log of population, proportion with a college degree, employment share, and the share of young adults (aged 20-34). The outcome variable in the last pre-regulation period (May 2015) is also included as a predictor. *Source:* Author's own work using Stata's "synth" and "synth_runner" packages.