In Search of Peace and Quiet: The Heterogeneous Impacts of Short-Term Rentals on Housing Prices

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Abstract

The supply of short-term rental (STR) housing has grown through platforms such as Airbnb leading to contradictory concerns about increasing housing prices and negative externalities. We provide evidence that in some areas, STRs can decrease housing prices. Using a parsimonious model of housing occupancy with externalities, we show the marginal effect of STRs on housing prices depends on the net impact of STRs on local amenities. Using zip-code-level data from Los Angeles County, California, we show heterogeneity in the marginal effects of Airbnb listings on housing prices across localities. We then examine on a 2015 law restricting STRs in Santa Monica – where we estimate a negative relationship between STRs and housing prices. Using a differences-in-differences approach, we show the law increased housing prices, consistent with our theory. Finally, we provide evidence for our mechanism: "party-related" nuisance calls to Santa Monica police decreased after the policy was enacted.

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1 Introduction

> The Ordinance was passed to ensure that residential rental housing remains available to long-term tenants, and because short-term rentals have undesirable impacts that threaten the stability and character of the City's neighborhoods and result in increased rents.
>
> David Martin (2018), Santa Monica, California
> Director of Planning and Community Development

Driven by online platforms such as Airbnb and VRBO, the short-term housing rental (STR) market has experienced significant global growth over the past decade.[1] By enabling mutually beneficial trades between property owners and transient visitors, these markets increase the utilization of (and surplus created by) housing capacity. By increasing certain amenities (Basuroy et al., 2020) and the option value of owning housing, STRs arguably lead to increases in housing prices (Horn and Merante, 2017; Garcia-López et al., 2020). Criticism of STR platforms has mostly focused on this price effect: increasing prices means that long-term renters may be suddenly priced out of communities in which they have lived for years (Nieuwland and van Melik, 2020).[2] As a consequence, there is an active policy debate focused on regulating these markets with an emphasis on restricting STR activity.

Our contribution to this debate is the simple point implied by the quote from a policy-maker above: the net effect of STRs on housing prices is ambiguous due to the relationship between STRs and local amenities. STRs are an extension of the hospitality industry, and while the presence of hotels in a neighborhood creates positive demand spillovers for other service industries, hotels and other tourism-related firms are also associated with local negative externalities such as public intoxication, petty theft, and other "nuisances" (Brunt and Hambly, 1999; Ho et al., 2009). Insofar that STRs act as substitutes for traditional hospitality firms, as has been argued by Zervas et al. (2017) and Farronato and Fradkin (2018), STRs may generate those negative externalities as well – and Airbnb in particular

[1] A STR is typically defined as the rental of a fully furnished housing unit for a period of between one night and several months. In contrast, long-term rentals are generally characterized by contracts with a term of at least one year.

[2] Furthermore, as homes account for roughly a quarter of aggregate household net wealth, movements in housing prices have first-order consequences for household balance sheets (Stupak, 2019).

has received media attention for "party house" listings (Lieber, 2015).[3] If the cost of those externalities outweighs the benefits of increased revenues for local businesses – in other words, if STRs sufficiently "threaten the stability and character" of neighborhoods (Martin, 2018) – the net effect of STRs on local amenities, and potentially on housing prices, may be negative.

We formalize this idea in Section 3 with a partial equilibrium model of the housing market that builds on the work of Barron et al. (2018). In our model, homeowners may choose between occupying the home and listing it as a short-term rental; this option increases the value of owning housing. However, STRs impose both positive and negative externalities on neighbors. In equilibrium, an increase in the STR rental rate may *reduce* housing prices if the net effect of STRs on amenities for owner-occupiers in the neighborhood is negative and outweighs the effect of the increased revenue earned by absentee landlords. Similarly, an exogenous change in the number of STRs may result in an increase or decrease in housing prices depending on the net impact of STRs on amenities in that neighborhood.

To provide empirical evidence for the implications of the model, we turn to the Los Angeles (LA) metropolitan area which has one of the highest levels of amenities in the United States (Albouy, 2016) but which also features a high degree of income and amenity inequality across communities (Bobo et al., 2000; Wolch et al., 2005; Charles, 2006). We obtain data (described in Section 4) on housing prices from Zillow, data on Airbnb from web scrapes, and crime data from local governments. We begin our analysis in Section 5 by considering the relationship between Airbnb listings and housing prices at the zip code level. As the model makes clear, the number of listings is an equilibrium object so we control for endogeneity with an instrument based on the level of local amenities before the entry of Airbnb. We estimate the relationship for all cities in LA County and find significant heterogeneity. For example, in the City of LA, a 1% increase in the number of Airbnb listings in a zip code is estimated to increase housing prices by 0.25%, but in Burbank, the

[3]By offering "owner-absent" rentals of detached homes, STRs may host activities with negative externalities which would be deterred by, say, the presence of hotel staff. Furthermore, as STRs are generally located in traditionally owner-occupied residential areas, the same activities may generate greater social costs when conducted in an STR as opposed to a hotel.

same increase in listings is estimated to *decrease* housing prices by -0.17%.

We then examine the effects of an STR regulation enacted by the wealthy oceanfront suburb of Santa Monica in Section 6 – a location where we estimate a negative relationship between STRs and housing prices. The law, enacted in 2015 in part due to concerns about increasing housing prices in the city, was arguably the strictest regulation on STR activity in effect in the United States at the time. It is important to note up front that we are not claiming this policy change is exogenous – per contemporaneous press, it was implemented as a response to the simultaneous rise in STR listings and rise in housing prices (Logan, 2015). We first document that the law was (at least temporarily) successful in reducing the number of Airbnb listings most likely to generate negative externalities. Using a differences-in-differences framework with LA as a control, we show that the regulations increased housing prices by 8%. Finally, we provide suggestive evidence for our externality mechanism by examining detailed call data from the Santa Monica Police Department. Using an event study framework, we show that that nuisance calls which we define as "party-related" began decreasing after the law was enacted.[4]

Our work contributes to the recent literature examining the relationship between STR markets and housing prices. Relative to this literature, which we characterize as providing average effects of STRs over large geographies, our work focuses on heterogeneity in the effects of STRs. Within this literature, the closest work to our own is that of Barron et al. (2018) who introduce the instrument described above and use it to estimate the average effect of Airbnb listings on housing prices across the U.S. – their result is similar to our estimate for LA County as a whole. In a working paper, Fonseca (2019) analyzes the immediate effect of Santa Monica's law on listings; using a synthetic control approach, they find little effect of Santa Monica's law on rental prices. In addition to our different focus on the effects of STRs on local amenities, we use data over a longer period to identify effects on housing prices. More

[4]In a conference paper, Han and Wang (2019) study the relationship between STRs and the crime rate in New York City and San Francisco using policy changes that primarily affected commercial listings and find qualitatively similar results.

broadly, we contribute to the growing literature examining the relationship between STRs (largely Airbnb) and other hospitality firms. By arguing that Airbnb listings are associated with negative externalities similar to those created by hotels, our work corresponds with other studies cited above which identify STRs as substitutes for traditional hotels.

Our work also contributes to a broader literature examining the externalities of peer-to-peer markets. Within the transport sector, the rapid expansion of ridesharing apps such as Uber has led to increases in net restaurant creation, providing easier access to previously inaccessible locations (Gorback, 2020). However, there have been added social costs associated with the growth of ridesharing, such as increases in the number of motor vehicle fatalities as well as increases in congestion and road use (Barrios et al., 2020). Understanding the net impact of peer-to-peer markets is essential in determining whether and how to regulate these nascent industries. We conclude in Section 7 with a discussion of these externalities and suggestions for both policymakers and future researchers.

2 Background

Our analyses operate at the intersection of housing and hospitality markets with the long-standing heterogeneity between the various communities of Los Angeles County. In this section, we briefly describe this heterogeneity, provide a short history of STRs and Airbnb, and discuss the specific Santa Monica legislation restricting Airbnb activity.

2.1 Los Angeles County

Los Angeles County, with a population of more than ten million, is the single most populous county in the United States. According to the Bureau of Economic Analysis and the Census Bureau, the county as a whole had a GDP of more than $700 billion and a median household income of $62,978 in 2016. The county is divided into 88 incorporated cities and 76 unincorporated areas with significant and long-documented heterogeneity (Bobo et al., 2000).

Table 1 illustrates some of this heterogeneity by reporting median income, local amenities, and median rents for LA County, the City of LA, and nine other notable cities within the county. Median income in the City of LA is slightly lower than the county as a whole, as communities such as Malibu and Beverly Hills have median incomes more than twice that of the county. Malibu, a western beachside community, features a population density of only 353 residents per square mile, whereas the more centrally located West Hollywood contains 13,359 residents per square mile. Public parks and dining opportunities vary widely as well – while the City of LA features 9.9 park acres per thousand residents, Pasadena offers 2.5 park acres per thousand residents. Pomona, on the far eastern border of the county, offers merely 1.3 restaurants per thousand residents, while Santa Monica offers 4.7.

These differences in observable amenities are likely related to the differences in rental rates for two-bedroom apartments, which in 2016 ranged from $1,187 in Pomona to over $2,500 in Malibu. Los Angeles currently ranks as the least affordable city in America according to the National Association of Home Builders and Wells Fargo Housing Opportunity Index (HOI).[5] The HOI measures the shares of homes sold that would have been affordable to median-income earners. During the fourth quarter of 2019, the HOI revealed only 11.3% of homes sold in Los Angeles were affordable at a median income of $73,100. Population growth, rising income inequality, and supply-side constraints contribute to the Los Angeles metro area having the lowest home-ownership rate out of all major metropolitan areas (Ong et al., 2015).

[5] https://www.nahb.org/News-and-Economics/Housing-Economics/Indices/Housing-Opportunity-Index

Table 1: Neighborhood Amenities for Selected Cities in Los Angeles County

	Income (2016 \$)	Density (res. / mi^2)	Parks (acr. / 1k res.)	Dining & lodg. (# / 1k res.)	Rent (\$ / mnth)
LA (county)	62,978	13,090	3.3	1.9	1,410
LA (city)	58,504	15,637	9.9	2.0	1,473
Beverly Hills	128,985	8,164	1.9	4.7	2,339
Burbank	71,249	8,740	1.1	2.9	1,678
Malibu	125,623	353	9.1	4.0	2,529
Pasadena	79,314	8,549	2.5	3.0	1,604
Pomona	54,328	7,329	1.5	1.3	1,187
San Gabriel	63,644	9,497	0.5	3.1	1,314
Santa Monica	91,098	11,893	1.4	4.7	1,879
Torrance	80,097	9,327	2.4	2.7	1,606
West Hollywood	98,362	13,359	0.6	8.0	2,165

Notes: 'Income' is the 2016 median household income. 'Population' is the number of residents per square mile in 2010. 'Parks' is the number of acres of city parks per 1,000 residents in 2016. 'Dining & lodg.' is the number of establishments in NAICS category 72 in 2010. 'Rent' is the median gross rent in 2016 for renter-occupied housing using with two bedrooms that pay cash. All statistics from the Census Bureau except for parks which is from the 2016 Los Angeles Countywide Comprehensive Park and Recreation Needs Assessment.

2.2 Home sharing and the rise of Airbnb

Home-sharing gained popularity in the US in the 1950s, as vacation rentals – in which visitors have private and exclusive (i.e. without the presence of a long-term resident) use of a housing unit for a while – became a viable alternative to hotels. These rental units were traditionally located in areas that expected and welcomed frequent turnover of travelers as well as the accompanying economic benefits of tourism. Launched in 1995, Vacation Rentals by Owner (VRBO) provided the first online platform for vacation or STR bookings; Booking.com entered a year later. These peer-to-peer markets connected travelers with vacation rental properties that were managed by their owners and allowed the booking of short (i.e. 30 days or fewer) stays. As "the sharing economy" grew, so too did the number and diversity of neighborhoods in which travelers could find these "owner-absent" bookings.

Founded in 2008, Airbnb expanded the STR market by providing hosts a platform through which they could offer single rooms in their occupied homes, which in turn allowed travelers to stay in more residential neighborhoods. While these "owner-present" STRs differ substantially from traditional owner-absent vacation rental offerings (or hotel offerings), they quickly gained in popularity as a cheaper alternative. This in turn exposed a number of new consumers to the possibility of owner-absent rentals. Today, Airbnb's peer-to-peer market offers both owner-absent and owner-present offerings and lists more rooms than the largest six hotel groups combined (Airbnb, 2019), providing travelers a viable alternative to the hotel industry.[6]

2.3 Regulating STRs

Neither the state of California nor the U.S. federal government explicitly regulate STRs – though we discuss the interaction of federal communications laws and local regulations below. Instead, STRs are regulated through local ordinances. In Section 6, we focus on a regulation

[6] `couchsurfing.com` offered owner-present STRs earlier than Airbnb, though their offerings are aimed at lower-income consumers and they do not offer owner-absent STRs.

adopted by Santa Monica on May 12, 2015. According to staff reports and the text of the measure, the city was moved to action because STRs removed "needed permanent housing from the market" and transient visitors could "disrupt the quietude... of the neighborhoods and adversely impact the community" (City of Santa Monica, 2019). The measure nominally banned owner-absent STRs, while allowing owner-present STRs to continue with additional licensing, reporting, and taxation requirements.

While the initial ordinance went into effect in June of 2015, it was immediately legally challenged by Airbnb (among other platforms). While the court case was eventually decided in favor of Santa Monica in 2019, the suit created considerable ambiguity and made enforcement difficult (Dolan, 2019). Landlords, too, worked to circumvent the provisions of the ordinance, finding ways to offer owner-absent STRs that technically complied with the rules. These actions resulted in a number of additional legal challenges, all of which were eventually decided in favor of the city.[7]

These regulatory and enforcement challenges, which have played out in similar ways around the country as local governments attempt to regulate STRs (Martineau, 2019), are often driven by Section 230 of the federal Communications Decency Act (CDA). Broadly construed, CDA 230 protects online platforms from responsibility for content posted by users. STR platforms have successfully used CDA 230 to challenge local regulations which require platforms to participate in filtering illegal listings.[8] These challenges, combined with other perceived abuses of CDA 230 by other platforms, have led to various reform proposals through legislation or regulation (Neuburger, 2020).

[7]See *Diane Hayek v. City of Santa Monica*, Los Angeles Superior Court No. 17STLC02007 (May 30, 2018); *Diane Hayek v. City of Santa Monica*, Los Angeles Superior Court No. BS170950 (August 19, 2019)

[8]Indeed, according to the Ninth Circuit ruling, Santa Monica won largely by constructing its measure in such a way that STR platforms were responsible only for collecting taxes and regulatory information, not removing content. *HomeAway.com, Inc. v. City of Santa Monica*, Ninth Circuit Court of Appeals No. 18-55367 (March 13, 2019)

3 A model of housing with type-of-use externalities

To understand the potentially heterogeneous effects of STRs on housing prices and provide stylized intuition for our empirical work, we introduce a partial equilibrium model of housing choice with type-of-use externalities extending the work of Barron et al. (2018). We aim to demonstrate that the effect of STRs on equilibrium housing prices is ambiguous even in a parsimonious framework and thus we intentionally abstract from several considerations which do not affect the primary mechanism: the interplay between externalities and the option value of offering STRs.

The model environment consists of a finite number of locations J, indexed by j. Each location consists of a fixed quantity of housing H_j. The total number of agents in the housing market is exogenous and given by N. Each agent i jointly decides which location to purchase a home in and their usage of that home: owner-occupier or absentee landlord. We normalize the utility of not entering the market to zero.[9]

The utility individual i receives from location j from being an owner-occupier is

$$u_{i,j,o} = \xi_j(k_j, f(str_j), g(str_j)) - P_j + \epsilon_{i,j,o}.$$

In this equation, $\xi_j : \mathbb{R}^3 \to \mathbb{R}$ is a function that maps three location-specific features into a scalar amenity value. k_j is a fixed, time invariant amenity level that is unrelated to short-term rentals, $f(str_j)$ is an increasing function that maps the level of STRs in location j to the level of *positive* amenities associated with STRs (such as extra restaurants), and $g(str_j)$ is an increasing function that maps the level of STRs to the level of *negative* amenities associated with STRs (such as crime). P_j is the price of housing in location j and $\epsilon_{i,j,o}$ is an idiosyncratic preference shock.

With a slight abuse of notation, we assume that $\frac{\partial \xi_j}{\partial f}$ is positive for all k and g and that

[9]For simplicity, we do not explicitly model long-term renting. The mechanism described here operates similarly in a model with long-term renters as long as those renters are affected by location-specific amenities in a similar way as owner-occupiers.

$\frac{\partial \xi_j}{\partial g}$ is negative for all k and f. We make no explicit assumption about second derivatives – though we note that in general one might expect increases in k to affect $\frac{\partial \xi_j}{\partial f}$ and $\frac{\partial \xi_j}{\partial g}$ differently, i.e. negative externalities may be "worse" if the location is "nicer." As a consequence, the effect of an increase in STRs on local amenity values is ambiguous, as can be seen through the partial derivative

$$\frac{\partial \xi_j}{\partial str_j} = \underbrace{\frac{\partial \xi_j}{\partial f}}_{+} * \underbrace{f'(str_j)}_{+} + \underbrace{\frac{\partial \xi_j}{\partial g}}_{-} * \underbrace{g'(str_j)}_{+}. \tag{1}$$

Locations with different levels of amenities (and therefore different levels of f' and g') and/or different levels of k_j (and therefore different levels of $\frac{\partial \xi_j}{\partial f}$ and $\frac{\partial \xi_j}{\partial g}$) may therefore deliver either greater or lesser utility when the level of STRs changes.

The utility an agent receives from being an absentee landlord is given by

$$u_{i,j,a} = \frac{R_j}{1-\delta} - P_j + \epsilon_{i,j,a}$$

where R_j is the sum of net revenues for STRs in location j net of any rental expenses.[10] We assume R_j is exogenous for simplicity.[11]

Assume for simplicity $\epsilon_{i,j,k}$ (where $k \in \{o, a\}$) is i.i.d. and follows a Type-I extreme value distribution. This implies that the probability (or choice share) $s_{j,k}$ of an individual choosing location j and usage-type k is given by the familiar logit form

$$s_{j,k} = \frac{\exp(\bar{u}_{j,k})}{1 + \sum_{j'} \sum_{k'} \exp(\bar{u}_{j',k'})}.$$

where $\bar{u}_{j,k} = u_{i,j,k} - \epsilon_{i,j,k}$. In equilibrium, these shares must sum to the level of housing available, that is $\sum_{k \in \{o,a\}} s_{j,k} N = H_j$ for all j. Using this market-clearing condition, we can

[10] We assume for simplicity there is no uncertainty in future per-period net revenues.

[11] As STRs compete with other hospitality firms with large numbers of units, the effect of a small change in the number of STR units available in a particular location on R_j is likely to be second-order.

write the equilibrium price for houses in location j:[12]

$$P_j^\star = -\log\left(\frac{(1+\phi_{j'})H_j}{(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j(k_j, f(str_j^\star), g(str_j^\star))))(N-H_j)}\right), \tag{2}$$

where $\phi_{j'} = \sum_{j'\neq j}\left(\exp(-P_{j'} + \frac{R_{j'}}{1-\delta}) + \exp(\xi_j(k_j', f(str_j^{\star\prime}), g(str_j^{\star\prime})))\right)$ and $str_j^\star = s_{j,a} * H_j$ is the equilibrium number of short term rentals in location j. We use the equilibrium housing price expression to derive an expression that guides the interaction between short-term rentals and housing prices. Our analysis focuses on the effects of the *intensive* marginal short term rental on housing prices. This is different than the extensive marginal short term rental because the agent can still chose to be an absentee landlord. With entry or exit of STR, the option to be an absentee landlord for short-term rentals vanishes, and the option value of the home falls. Our key insight comes from the relationship between the equilibrium price, the STR rental rate, and the number of STRs: $\frac{\partial P_j^\star}{\partial R_j}$ and $\frac{\partial P_j^\star}{\partial str_j^\star}$:

$$\frac{\partial P_j^\star}{\partial R_j} = \frac{1}{\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j(\cdot)))}\left(\frac{\exp(\frac{R_j}{1-\delta})}{1-\delta} + \exp(\xi_j(\cdot)) * \frac{\partial \xi_j}{\partial str^\star} * \frac{\partial str_j^\star}{\partial R_j}\right) \tag{3}$$

$$\frac{\partial P_j^\star}{\partial str_j^\star} = \frac{\exp(\xi_j(\cdot))}{(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j(\cdot)))} * \frac{\partial \xi_j}{\partial str_j^\star} \tag{4}$$

Equation (3) illustrates how a change in net discounted STR rental revenues impact equilibrium home prices and Equation (4) provides the direct impact of STR listings on equilibrium housing prices. Note that $\frac{\partial str_j^\star}{\partial R_j} > 0$ – the number of STRs always increases as the present value of revenues increases. However, the sign of Equations (3) and (4) may vary. Equation (4) varies with the sign of $\frac{\partial \xi_j}{\partial str_j^\star}$ – the net effect of STRs on residential amenities. For Equation (3), there are three non-trivial cases to consider. For clarity of exposition, consider the effect of an increase in R_j on the equilibrium price $P_j^\star$.

[12]See Appendix 7.2 for details.

Case 1. $\frac{\partial \xi_j}{\partial str^\star} > 0$: *STRs create net-positive amenities.* In this case, as the number of STRs increases, the value of owner-occupying increases, increasing demand. Thus, equilibrium housing prices increase: $\frac{\partial P_j^\star}{\partial R_j} > 0$.

Case 2. $\frac{\partial \xi_j}{\partial str^\star} < 0$ and $\frac{\exp(\frac{R_j}{1-\delta})}{1-\delta} > \left|\exp(\xi_j(\cdot)) * \frac{\partial \xi_j}{\partial str^\star} * \frac{\partial str_j^\star}{\partial R_j}\right|$: *STRs create net-negative amenities and the change in the marginal benefit to absentee landlords exceeds the magnitude of the change in marginal benefit to owner-occupiers.* In this case, increasing R_j decreases amenities, but that decrease is smaller than the increased value realized by absentee-landlords and thus an increase in R_j leads to a net increase in the demand for houses and the equilibrium housing price increases: $\frac{\partial P_j^\star}{\partial R_j} > 0$.

Case 3. $\frac{\partial \xi_j}{\partial str^\star} < 0$ and $\frac{\exp(\frac{R_j}{1-\delta})}{1-\delta} < \left|\exp(\xi_j(\cdot)) * \frac{\partial \xi_j}{\partial str^\star} * \frac{\partial str_j^\star}{\partial R_j}\right|$: *STRs create net-negative amenities and the change in the marginal benefit to owner-occupiers exceeds the change in the marginal benefit to absentee landlords.* Here, while the increase in R_j increases demand from absentee landlords, the increased number of STRs decreases demand from owner-occupiers by a greater amount. Thus, the net effect on demand for housing is negative and $\frac{\partial P_j^\star}{\partial R_j} < 0$.

These two derivatives can be used to frame the impacts of STR regulations. Some STR regulations (e.g. requiring payment of occupancy or other hospitality business taxes) may be viewed as a change to the present value of being an absentee landlord. Other regulations however may be direct shocks to the number of Airbnb listings allowed — resulting in an exogenous change in $str_j^\star$.

4 Data

To explore the main implication of our model – that the relationship between STRs and housing prices is ambiguous – we collect data on housing prices, Airbnb listings, and crime reports from the Los Angeles metropolitan area. We choose this geography in part due to the long-term presence of Airbnb in the area – meaning any short-term extensive-margin competitive effects of entry likely occurred before the period of our analyses – and due to the policy change in Santa Monica.

Our data on housing prices is the Zillow Home Value Index (ZHVI), which we obtain from `Zillow.com` for 2010-2019. The ZHVI reports the estimated median home value at the month-zipcode level, adjusted for seasonality. To construct the ZHVI, Zillow estimates the potential sale price for all homes in a given area based on recently observed sales in that area (Bruce, 2014). The ZHVI has previously been used to study a variety of issues in housing markets, including land use regulations (Huang and Tang, 2012), strategic responses to mortgage modification programs (Mayer et al., 2014), and credit market shocks (Greenstone et al., 2020).

We obtain Airbnb listing data from `insideairbnb.com` and `tomslee.net`, each of which provides snapshots of consumer-facing listings available on specific days collected from web scrapes. For each listing, we observe a unique host and room identifier, the location of the short-term rental unit, the daily price, and the (mutually exclusive) room type: "Entire unit", "private room", and "shared room". We aggregate these listings to the zip code level and construct measures of STR supply as the total number of listings of each type. These scrapes were collected at irregular intervals (see Appendix Section 7.3 for more details). We obtain all scrapes from 2014 (the earliest available) to 2019. These data have previously been used to understand the relationship between Airbnb listings and housing prices in other geographies (Garcia-López et al., 2020). Finally, to construct the instrument detailed in Section 5, we obtain Google Trends data for "Airbnb" and collect the number of food and accommodation establishments (NAICS 72) in each zip code in 2010 from the ZIP Code Business Patterns data released by the U.S. Census.

Table 2 reports summary statistics for these data. The first set of rows reports the ZHVI for LA county and the cities displayed in Table 1. The last column computes the percentage change from 2014 to 2019. While each city experienced increases in housing prices throughout our data, those increases range from 34% in Torrance to 101% in Beverly Hills. LA city experienced an increase of 46%, while prices in Santa Monica increased by 69%. The second set of rows reports counts of Airbnb listings by type and location. Again, every area experienced considerable growth throughout the period we study. However, Santa Monica experienced the only year-over-year decline of listings in the entire dataset: entire unit listings (which are generally owner-absent) decreased from 606 in 2015 to 450 in 2016 as its regulation was passed, went into effect, and was slowly enforced. However, as STR suppliers in Santa Monica adjusted to the new regulations, the number of listings slowly increased – by 2019, the number of "entire unit" listings exceeded the pre-regulation count.

To provide descriptive evidence of the relationship between STRs and negative externalities, we collect police call data from the Santa Monica Open Data Project from 2013-2019.[13] For each call, we observe the date and time, the location of the caller, and the reason for the call. Importantly, these data encode call reasons at a much finer level of detail than either the Uniform Crime Reporting or National Incident-Based Reporting System standards promulgated by the Federal Bureau of Investigation. Unfortunately, few cities report data at this level of detail and frequency.[14] We focus on calls for which the reason listed included "party complaint", "loud music", or "public intoxication", as those complaints are those frequently referred to in media reports about the nuisance effects of STRs (Lieber, 2015; Griffith, 2020). Table 3 reports summary statistics for these data. The number of each type of call declined over our study period after (generally) initial increases; the total number of calls we consider decreased 33% from 2013 to 2019.

[13] https://data.smgov.net/Public-Safety/Police-Calls-for-Service/ia9m-wspt

[14] For example, Eugene, Oregon, reports call reasons with high granularity, but uses different categories and aggregates to the annual level. Indeed, we are not aware of any cities that report data in a way that can be harmonized with the Santa Monica data for direct comparison.

Table 2: Summary statistics for housing price and Airbnb listing data

Variable	2013	2014	2015	2016	2017	2018	2019	Avg. %Δ
Zillow Home Value Index								
LA (county)	489	541	582	637	693	755	776	8
LA (city)	552	578	625	689	751	821	846	7
Beverly Hills	1,020	1,177	1,352	1,606	1,862	2,176	2,363	15
Burbank	530	581	621	667	713	772	786	6
Malibu	1,139	1,303	1,462	1,680	1,881	2,104	2,204	12
Pasadena	558	605	641	689	744	811	825	7
Pomona	280	322	343	365	394	425	434	8
San Gabriel	589	637	663	689	730	781	779	5
Santa Monica	836	942	1,066	1,209	1,363	1,531	1,595	11
Torrance	600	638	664	703	749	800	805	5
West Hollywood	615	676	712	785	850	920	988	8
Airbnb listing counts								
Entire unit								
LA (county)		6,984	10,491	14,562	18,981	25,320	27,424	32
LA (city)		5,264	7,759	11,053	14,218	18,359	19,393	31
Beverly Hills		137	232	327	436	558	603	36
Burbank		41	80	109	141	192	218	42
Malibu		37	121	194	260	469	399	78
Pasadena		110	178	239	356	402	380	31
Pomona			4	8	17	39	45	92
San Gabriel		2	7	10	34	58	73	152
Santa Monica		559	616	466	583	573	781	9
Torrance		4	15	32	47	76	107	118
West Hollywood		194	292	366	480	534	532	24
Private room								
LA (county)		3,549	5,992	8,421	11,056	14,204	14,342	34
LA (city)		2,581	4,114	5,732	7,132	8,553	8,289	28
Beverly Hills		44	107	115	138	164	151	36
Burbank		30	52	89	116	136	145	40
Malibu		19	43	50	46	81	58	37
Pasadena		69	119	172	247	255	243	32
Pomona			20	30	58	91	96	51
San Gabriel		13	35	50	107	166	185	80
Santa Monica		216	307	367	398	275	290	9
Torrance		20	46	78	97	156	155	58
West Hollywood		62	84	111	142	122	127	17
Shared room								
LA (county)		356	606	1,139	1,524	1,849	1,793	42
LA (city)		285	481	935	1,235	1,505	1,474	43
Beverly Hills		2	11	8	9	8	8	81
Burbank		4	5	7	6	23	24	69
Malibu			1	1	1	1	2	12
Pasadena		7	9	10	9	9	5	-3
Pomona			1	5	11	12	2	76
San Gabriel			2	4	10	37	13	126
Santa Monica		19	21	35	34	15	21	13
Torrance		3	4	8	7	14	13	49
West Hollywood		7	6	6	16	7	3	10

Notes: Entries are averages over monthly observations in the year. Home price index in thousands of units.

Table 3: Summary statistics for Santa Monica police reports

Variable	2013	2014	2015	2016	2017	2018	2019	%Δ14-19
Loud music	121	147	134	139	137	122	113	-23.1
	(26)	(29)	(29)	(26)	(33)	(13)	(28)	-3.4
Party complaint	100	93	86	84	71	58	57	-38.7
	(35)	(24)	(22)	(28)	(17)	(18)	(21)	-12.5
Public intoxication	103	110	91	82	69	62	48	-56.4
	(19)	(23)	(17)	(8)	(14)	(12)	(11)	-52.2
Total	324	351	310	305	277	243	217	-33.0
	(74)	(71)	(56)	(52)	(57)	(29)	(51)	-31.1

Notes: Entries are averages over monthly observations in the year. Standard deviations are reported in parentheses.

5 Evidence of heterogeneous impacts of STRs on housing prices

Equation (4) provides a testable hypothesis: at the margin, the relationship between STRs and housing prices may be positive or negative. In this section, we explore this hypothesis by estimating the effect of Airbnb listings on local housing prices with the aim of demonstrating this ambiguity. Although our data contains the current per-night price of each listing, we focus on Equation (4) as opposed to Equation (3) for two reasons. First, our data represents a noisy estimate of R_j – while the lifetime expected revenue for an STR is correlated with an observed per-night price, reservations and future prices (and therefore the time series of revenues) is unknown. Second, the observed listings represent a selected sample – we do not observe STR pricing for housing units which are not listed. As listings and housing prices are both equilibrium outcomes, we proceed by following an instrumental variable strategy with fixed effects.

Let $ZHVI_{jct}$ be the Zillow Home Value Index for zipcode z in city j at year-month time

t. Equation (4) suggests the following estimating equation:

$$\log(ZHVI_{zjt}) = \beta_{0j} + \beta_{1j} \log(listings_{zjt}) + FX + \epsilon_{zjt} \tag{5}$$

where $listings_{zjt}$ is the number of Airbnb listings, ϵ_{zjt} is an unobservable, and FX is a set of fixed effects.[15] The coefficient of interest is β_{1j}, which varies across neighborhoods. As zip codes are generally collinear with city identifiers within Los Angeles County, we use area code and year fixed effects, which controls for unobserved variation across area codes – such as amenity characteristics that stay constant over time – and across years – such as overall market growth – that is correlated with both Airbnb listings and housing prices.[16]

Despite these fixed effects, there may be some component of ϵ which is correlated with $listings_{zjt}$. We, therefore, employ the instrument of Barron et al. (2018): we interact the Google Trends measure for the search term "airbnb" with the number of establishments in the food services and accommodations industry (NAICS 72) in each zip code in the base year of 2010 – prior to large-scale Airbnb entry in the area. Specifically, if g_t^{air} is the Google Trends measure and b_{zj}^{2010} is the number of establishments in 2010 in zipcode j, our instrument is

$$z_{zjt} = g_t^{air} * b_{zj}^{2010}.$$

Our identifying assumption is that $E[z_{zjt} \cdot \epsilon_{zjt}] = 0$. Intuitively, b_{zj}^{2010} acts as a proxy for the degree to which a given neighborhood attracts tourists over the long term (and therefore may be a more attractive place for entry by an Airbnb host). On its own, however, this variable is likely to also be correlated with housing prices, as food service establishments are likely positive neighborhood amenities. g_t^{air} scales this "touristyness" measure by the overall market size for Airbnb. As the attractiveness of restaurants to long-term residents (or prospective residents) is likely uncorrelated to the nationwide market presence of Airbnb, the

[15]In practice, a small number of observations have zero listings. We therefore use $\log(1 + listings_{zjt})$. Our results are qualitatively robust to dropping these observations.

[16]As the ZHVI is seasonally adjusted, month-of-year fixed effects are not necessary.

interaction of these two variables likely satisfies the exclusion restriction and the instrument is correlated with housing prices in a given period only insofar that it is correlated with the number of Airbnb listings, conditional on the included fixed effects. We report summary information and first-stage estimates for our instrument in Appendix Section 7.2, and discuss the details of our sample selection in Appendix Section 7.3.

Table 4 reports estimates of β_{1j} for the cities of Table 1. In Column (1), we report an estimate for the entire sample: every zip code in LA county. In Column (2), we add fixed effects for the year and area code. While the coefficient decreases relative to Column (1), it is still positive and significantly different from zero: we estimate that a 10% increase in Airbnb listings increases average house prices by 0.93%. These estimates are similar to those reported by Barron et al. (2018), who report that, averaged across the entire United States, a 10% increase in Airbnb listings leads to a 0.76% increase in house prices.[17]

In Columns (3) through (6), we estimate individual coefficients for each city. In Column (3) we include no fixed effects, in Columns (4) and (5) we add year and area code fixed effects, respectively. Column (6) includes both sets of fixed effects and is our preferred specification. Appendix Table 8 reports estimates for this specification for all cities. Across cities, the coefficients vary widely; in West Hollywood, a 10% increase in the number of Airbnb listings increases housing prices by 1.4%, whereas in Santa Monica, a 10% increase in the number of Airbnb listings decreases housing prices by 3.4%.

While we have chosen to report estimates for these particular cities for readers' familiarity, the pattern of heterogeneity in the estimates of β_{1j} is similar in the entire set of estimates. Figure 1 illustrates the distribution of the full set of coefficients estimated in the fully saturated model. Of the 78 cities in our preferred specification,[18] 12 have negative point estimates. We take these results as broadly consistent with the previous literature: for most locations, the estimated relationship between STR listings and housing prices is positive, just as the estimated relationship for the region is positive. However, the average effect for

[17]Indeed, the reported confidence intervals overlap.

[18]We drop 10 cities which are collinear with our fixed effects.

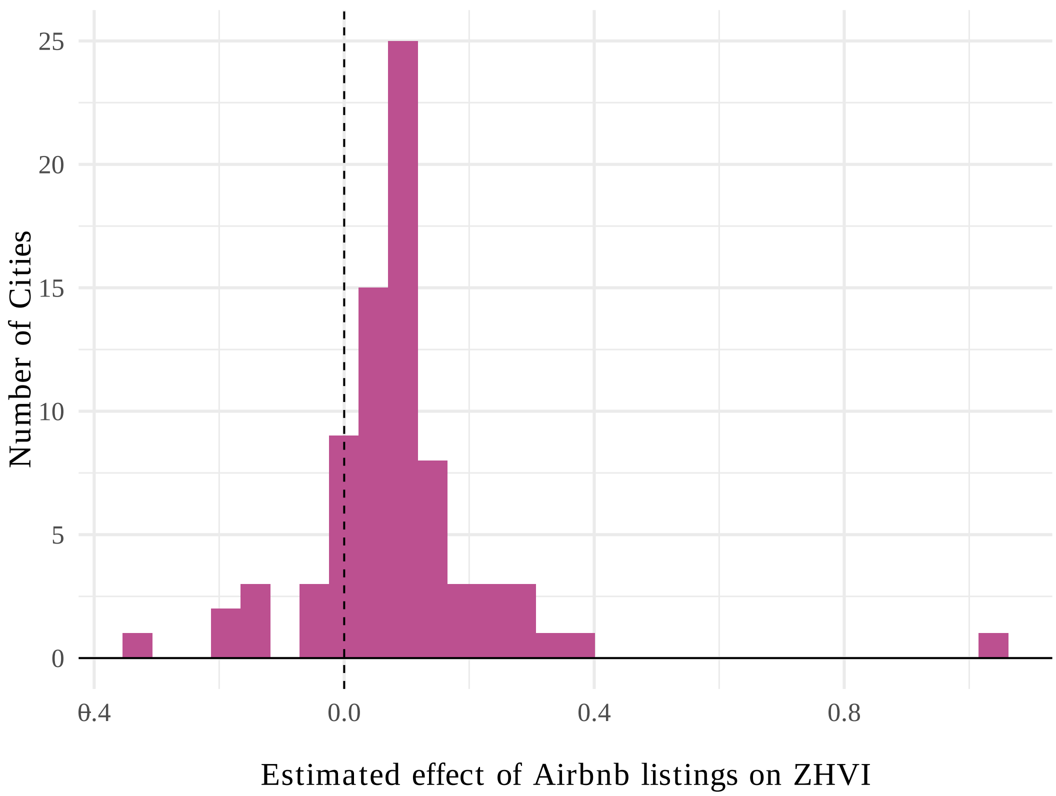
Table 4: The Effect of STRs on Housing Prices for Selected Cities in Los Angeles County

	(1)	(2)	(3)	(4)	(5)	(6)
log(`listings`) for						
LA (entire county)	0.158^{***}	0.093^{***}				
	(0.010)	(0.009)				
LA (city)			0.265^{***}	0.248^{***}	0.270^{***}	0.255^{***}
			(0.017)	(0.017)	(0.017)	(0.018)
Beverly Hills			1.077^{***}	1.022^{***}	1.077^{***}	1.028^{***}
			(0.052)	(0.055)	(0.052)	(0.054)
Burbank			-0.095^{***}	-0.111^{***}	-0.154^{***}	-0.169^{***}
			(0.017)	(0.016)	(0.015)	(0.013)
Malibu			0.305^{***}	0.190^{***}	0.305^{***}	0.203^{***}
			(0.024)	(0.026)	(0.024)	(0.026)
Pasadena			0.161^{***}	0.118^{***}	0.148^{***}	0.109^{***}
			(0.033)	(0.034)	(0.038)	(0.038)
Pomona			0.133^{***}	0.052^{***}	0.133^{***}	0.061^{***}
			(0.012)	(0.015)	(0.012)	(0.016)
San Gabriel			-0.134^{***}	-0.140^{***}	-0.134^{***}	-0.139^{***}
			(0.009)	(0.006)	(0.009)	(0.006)
Santa Monica			-0.329^{***}	-0.342^{***}	-0.329^{***}	-0.341^{***}
			(0.037)	(0.035)	(0.037)	(0.035)
Torrance			0.245^{***}	0.215^{***}	0.245^{***}	0.218^{***}
			(0.018)	(0.019)	(0.018)	(0.019)
West Hollywood			0.252^{***}	0.137^{***}	0.252^{***}	0.149^{***}
			(0.026)	(0.026)	(0.026)	(0.027)
Year FE	No	Yes	No	Yes	No	Yes
Area code FE	No	Yes	No	No	Yes	Yes
R^2	0.061	0.256	0.667	0.670	0.653	0.656
Num. obs.	6800	6800	6800	6800	6125	6125

Notes: This table reports estimates of Equation (5). We estimate coefficients for each city in LA county; full estimates are available in Appendix Table 8. An observation is a zipcode-month. The dependent variable is the log of the Zillow Home Value Index. `listings` is the number of Airbnb listings, which we instrument for with an interaction of Google trends and the number of food establishments. First stage details are reported in Appendix Section 7.2. Heteroskedastic-robust standard errors are in parentheses; we explore alternative clustering techniques in Appendix 7.5. Stars indicate p values: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. In Columns (5) and (6) we drop cities that are collinear with the area fixed effects.

the region aggregates over a substantial degree of heterogeneity at the city level. Our model does not make broad predictions about the characteristics of neighborhoods which are more likely to have a negative relationship between STRs and housing prices – it suggests merely that in these locations, the net external effect of an STR is negative.

Figure 1: The Heterogeneous Effect of Airbnb Listings on Housing Prices



Notes: This figure reports the distribution of β_{1j}s from Equation (5) for all cities. Estimates come from the fully saturated model; Column (6) in Table 4.

6 The effect of Santa Monica's STR regulation

The evidence of the previous section suggests that the marginal impact of additional STRs on housing prices in some areas is negative. Our framework attributes the heterogeneity in the sign of the relationship to the channel of negative amenities (for owner-occupiers) generated by the presence of STRs. This suggests further hypotheses: if an area in which the marginal impact of STRs on housing prices is negative implements a policy which reduces the number of STRs, either through affecting R_j or by decreasing str_j directly, we should expect to see both an increase in housing prices and a decrease in negative amenities.

We test these hypotheses through the lens of Santa Monica's STR restrictions by examining the time series of housing prices and crime reports after the regulation was enacted. Contemporaneous media reports (and the text of the regulation itself) make it clear that the regulation was passed in part as a response to rising housing prices in Santa Monica and thus we do not claim that the policy represents a "clean" natural experiment. However, as the stated goal of the policy was to *decrease* housing prices, any finding to the contrary provides evidence of the heterogeneous impacts of STRs – and our analysis of police report data provides evidence for our proposed mechanism.

We begin by estimating the effect of Santa Monica's STR regulation on housing prices using a differences-in-differences approach at the zip-code level with the city of LA as a control group. First, we document that the reform did in fact change the level of Airbnb listings in Santa Monica. Figure 2 illustrates the effect of Santa Monica's regulation on Airbnb listings. Each point is an individual scrape – while only 4 scrapes were conducted before the policy was enacted, scrapes occurred at roughly monthly intervals for the two years thereafter. While there is an enforcement lag, there is a clear drop in the number of "entire unit" listings after the reform was enacted which does not appear in Los Angeles.

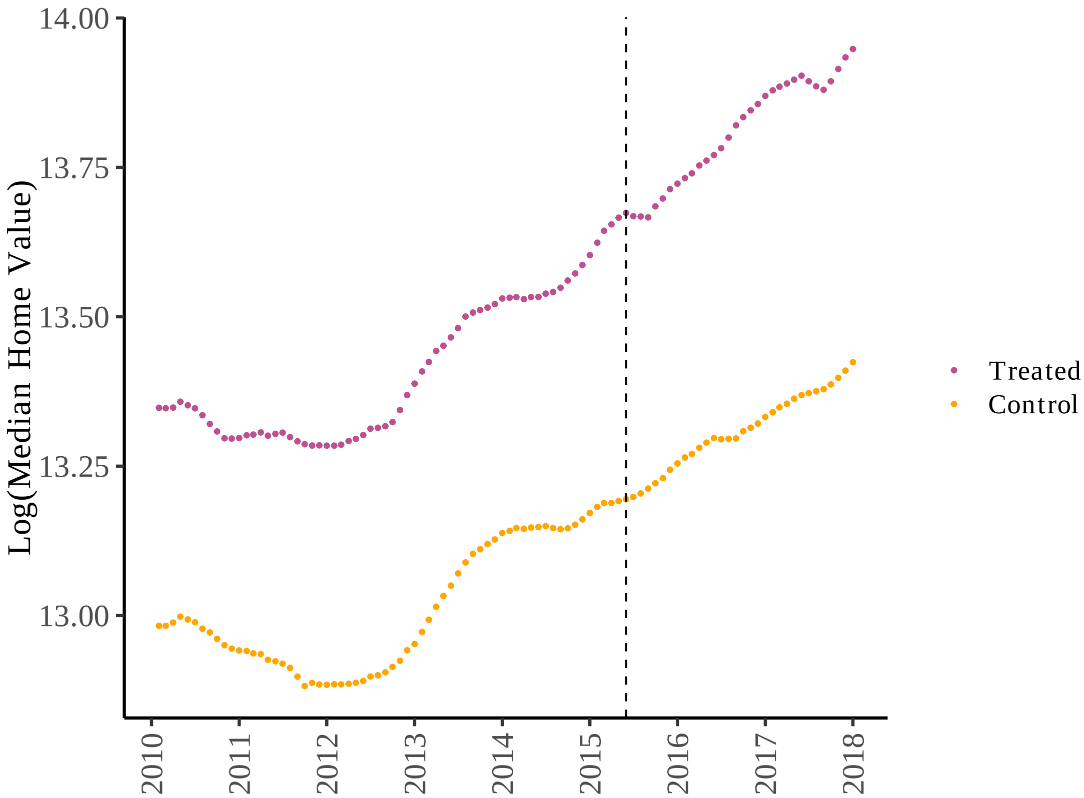
Figure 3 illustrates the time series of housing prices in each city indexed to the date of the reform. Prior to the reform, the index moves roughly similarly in each location. While there appears to be a slight increase in Santa Monica before the reform date, we note that the policy was introduced and discussed prior to enactment and enforcement. In the Appendix, we explore the sensitivity of our results to the reform date.

Let P_{jt} be the housing price (as measured by the ZHVI) for zipcode j at time t. We

Figure 2: Airbnb listings by room type

Notes: Each point on each graph represents an individual observation: a scrape of Airbnb's listings for that city.

Figure 3: Housing prices in Santa Monica and Los Angeles



Notes: Data come from the Zillow House Value Index. Observations are average indexed prices at the monthly level where the average is taken over zipcode-month observations by city. The date of the reform is shown by a vertical dashed line.

estimate the parameters of

$$\log(P_{jt}) = \beta_0 + \beta_1 * trt_j + \beta_2 * post_t + \beta_3 * (trt_j * post_t) + FX + \epsilon_{jt} \tag{6}$$

where we define trt_j as an indicator equal to one if the zip code j falls in Santa Monica and zero otherwise (the city of LA), and $post_t$ as an indicator equal to one if the year-month is later than May of 2015 (when the policy was enacted). The coefficient on the interaction between these two terms (β_3) provides an estimate of the local average treatment effect. As before, FX are fixed effects.

β_3 is identified if the pre-treatment differences in the outcome variable are constant (parallel pre-trends), and if the treatment itself did not generate spill overs into the control groups (see, for example, Hansen et al., 2020). We note that Santa Monica rests at the western edge of Los Angeles, and, per Table 2, the number of Airbnb listings within Santa Monica prior to the reform was approximately 1/16th the number of listings in Los Angeles. We thus conclude that it is unlikely that Santa Monica's reform affected the number of STRs in LA (and thus could have affected LA house prices through the STR channel).[19]

Table 5 reports estimates of Equation 6 when using the bandwidth suggested by the optimal bandwidth technique of Imbens and Kalyanaraman (2011).[20] In Column (1), we do not include fixed effects – in Column (2) we add size fixed effects and in Column (3) we add size and year fixed effects. The point estimates, though noisy, are identical across all three specifications – we estimate that the reform increased housing prices in Santa Monica by 8%. This estimate corresponds with the estimates of the previous section; the reform decreased Airbnb listings in Santa Monica by approximately 13%, which per Table 4 should generate an increase in housing prices of approximately 4.3%.

[19]In Appendix Figure 8 we plot the time series of listings in zip codes immediately bordering Santa Monica. Though the number of observations prior to the reform is limited, we are unable to find evidence of significant spillovers.

[20]In Appendix Figure 9, we explore alternative bandwidth selection techniques.

Table 5: The effect of Santa Monica's STR regulation on housing prices

	(1)	(2)	(3)
`Santa Monica` $\times$ `post reform`	0.083^{**}	0.083^{**}	0.082^{***}
	(0.033)	(0.033)	(0.031)
R^2	0.206	0.305	0.361
Year FEs?	No	No	Yes
R^2	0.177	0.280	0.335
Num. obs.	8862	8862	8862

Notes: This table reports estimates of Equation (6) using the optimal bandwidth technique of Imbens and Kalyanaraman (2011). An observation is a zipcode-month. The dependent variable is the log of the Zillow Home Value Index. Heteroskedastic-robust standard errors are in parentheses. Stars indicate p values: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

We now turn to crime reports in Santa Monica as a potential mechanism for this result. In particular, we use an event study approach to estimate the impact of STR regulations on party-related complaints in Santa Monica. We model the log of the number of calls $calls_t$ at time t (where $t = 0$ at the date when the policy went into effect) as

$$\log(calls_t) = \alpha_0 + \alpha_1 \cdot D + \alpha_2 \cdot t + \alpha_3 \cdot D \cdot t + FX + \varepsilon_t, \tag{7}$$

where D is an indicator equal to one if the observation falls after the normalized policy date. We include month-of-year fixed effects to account for the seasonality of tourism.

Figure 4 illustrates this approach by illustrating the raw data as well as the estimates of Equation (7) when fixed effects are included. Given the delay in enforcement discussed in Section 2, it is perhaps unsurprising that there is no immediate discontinuity in calls at the time the policy is enacted.[21] However, post-reform, calls consistently trend downwards though seasonal variation remains. Table 7 reports the corresponding estimates. Unsurprisingly, the local average treatment effect is effectively zero. However, the slope changes post-reform. This effect is weaker though more precisely estimated when fixed effects are included. In Appendix 7.9 we explore the different call types within our "party-related"

[21] We note that the policy was passed in the spring, just before the summer tourism season.

categorization and find the largest change in slope is for public intoxication calls.

Figure 4: Event study: The effect of Santa Monica's STR regulation on party-related calls to police

Notes: Observations are months. The lines indicate the estimate of Equation (7); the shaded area is the 95% confidence interval of the estimate.

Table 6: Event study evidence of Santa Monica's STR regulation effect on party-related police calls

	(1)	(2)
Post Reform	0.007	-0.044
	(0.082)	(0.050)
Months	-0.001	-0.001
	(0.002)	(0.001)
Post Reform × Months	-0.007^{**}	-0.005^{***}
	(0.003)	(0.002)
Month-of-year FEs?	No	Yes
R^2	0.2558	0.8145
N	89	89

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: This table reports estimates of Equation (7). The bandwidth is chosen per the optimal bandwidth technique of Imbens and Kalyanaraman (2011). An observation is a month-year. The dependent variable is the log of the number of "party-related" police calls reported in Santa Monica. Heteroskedastic robust standard errors are in parentheses. Stars indicate p-values: *** p < 0.01; ** p < 0.05; * p < 0.1.

7 Conclusion

As the STR market has expanded over the past several years, jurisdictions around the world have struggled to respond to its presence. While countless media reports have captured policymakers' concerns about the effect of STRs on long-term housing prices (see, for example, Henley, 2019; Minder and Abdul, 2020), others have focused on the deletrious effects of STRs on neighborhoods, particularly as seen through the eyes of neighboring long-term residents (Griffith, 2020). These different stories are potentially contradictory – if STRs sufficiently reduce local amenities, their presence could be associated with lower housing prices, not higher prices.

In this paper, we present a highly stylized model to demonstrate that the intensive marginal STR listing can reduce housing prices. The model makes a simple point clear: since STRs have both positive and negative impacts on amenities, the impact of STRs on housing prices is an ambiguous function of the *net* effect of STRs on residential amenities. We illustrate this point empirically with both a panel analysis of the relationship between

Airbnb listings and housing prices across jurisdictions within LA county, and a difference-in-differences analysis on Santa Monica's housing prices before and after their 2015 regulation using the city of LA as a control. In both analyses, we found evidence consistent with this story: STRs can lead to lower housing prices, and regulating them can increase housing prices. We provide evidence for our proposed mechanism in the form of an event study of calls to police in Santa Monica – we find that while the policy did not have a measurable immediate effect (likely due to enforcement lags), Santa Monica's policy was associated with a decrease in the number of party-related calls over time.

Our results have broad implications for housing policy. While many policy makers have focused on type-of-use regulations (such as bans or restrictions on STRs) in order to reduce the option value of owning a housing unit and therefore decrease housing prices, we show that such a policy may have the opposite effect. We provide a framework for how to think of why the effect might be positive or negative – but not how to quantify the net effect. We leave it to future work to quantify the aggregate change in residential amenities separately for positive and negative amenities.

These results also point to the need to consider additional effects of peer-to-peer transaction platforms when considering regulation. Across industries, the literature consistently finds that peer-to-peer transactions increase surplus but have increased variance and/or risk relative to more traditional products and services. Examples include Uber (Barrios et al., 2020), Kickstarter (Mollick, 2014), Craigslist (Kroft and Pope, 2014), and Fiverr (Hannák et al., 2017). Furthermore, the provisions of the Communications Decency Act imply that these platforms may engender outcomes which are biased along racial and gendered lines (Doleac and Stein, 2013; Edelman and Luca, 2014; Hannák et al., 2017). At the same time, the potentially positive externalities that these markets generate imply that regulations may have unintended consequences (Cunningham, DeAngelo, and Tripp, Cunningham et al.). In the case of Airbnb and other short-term rental platforms, our results suggest that while federal policy may help ensure uniform treatment, local decision-makers may be best-suited to set local policy.

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Appendix

7.1 Equilibrium Housing Prices

In this section, we derive Equation (2) – the equilibrium housing price equation. To simplify notation, we write $\xi_j = \xi_j(k_j, f(str_j), g(str_j))$. Furthermore, define $\bar{u}_{i,j,k} = u_{i,j,k} - \epsilon_{i,j,k}$ and $\phi_{j'} = \sum_{j' \neq j} \left(\exp(-P_{j'} + \frac{R_{j'}}{1-\delta}) + \exp(\xi_j) \right)$.

Using the market clearing condition we can write:

$$
\begin{aligned}
\left(\frac{\exp(\bar{u}_{j,a})}{1 + \sum_{j'} \sum_{k'} \exp(\bar{u}_{j',k'})} + \frac{\exp(\bar{u}_{j,o})}{1 + \sum_{j'} \sum_{k'} \exp(\bar{u}_{j',k'})} \right) N &= H_j \\
\left(\frac{\exp(-P_j + \frac{R_j}{1-\delta}) + \exp(\xi_j - P_j)}{1 + \sum_{j'} \exp(-P_{j'} + \frac{R_{j'}}{1-\delta}) + \sum_{j'} \exp(\xi_j - P_{j'}))} \right) N &= H_j \\
\left(\frac{\exp(-P_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j))}{1 + \exp(-P_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j)) + \phi_{j'}} \right) N &= H_j \\
\exp(-P_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j))N &= (1 + \exp(-P_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j)) + \phi_{j'})H_j \\
\exp(-P_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j))N - H_j \exp(-P_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j)) &= (1 + \phi_{j'})H_j \\
\exp(-P_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j))(N - H_j) &= (1 + \phi_{j'})H_j \\
\exp(-P_j) &= \frac{(1 + \phi_{j'})H_j}{(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j))(N - H_j)} \\
P_j &= -\log \left(\frac{(1 + \phi_{j'})H_j}{(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j))(N - H_j)} \right)
\end{aligned}
$$

7.2 Instrument Details

When estimating Equation (5), we instrument for the number of Airbnb listings by interacting the Google Trends index for the search term `airbnb` with the number of restaurants in a given zip code in 2010, before the widespread market growth of Airbnb. Figure 5 displays Google Trends data at the monthly level from 2010 through 2019. Figure 6 illustrates the distribution of zip codes in the U.S. according to the log of the per-capita number of food and accommodation establishments (as defined by NAICS 72). On the left graph, dots on the horizontal axis indicate the zip codes that comprise Santa Monica; the right graph illustrates the zip codes in the City of Los Angeles. While the density of restaurants in Santa Monica is clearly above the mean, the distribution of LA zip codes roughly matches the US as a whole. Table 7 reports first-stage estimates. Our instrument enters positively and significantly; the R^2 is 0.129, which we interpret as implying our instrument is not weak.

Figure 5: Google Trends data used in instrument construction

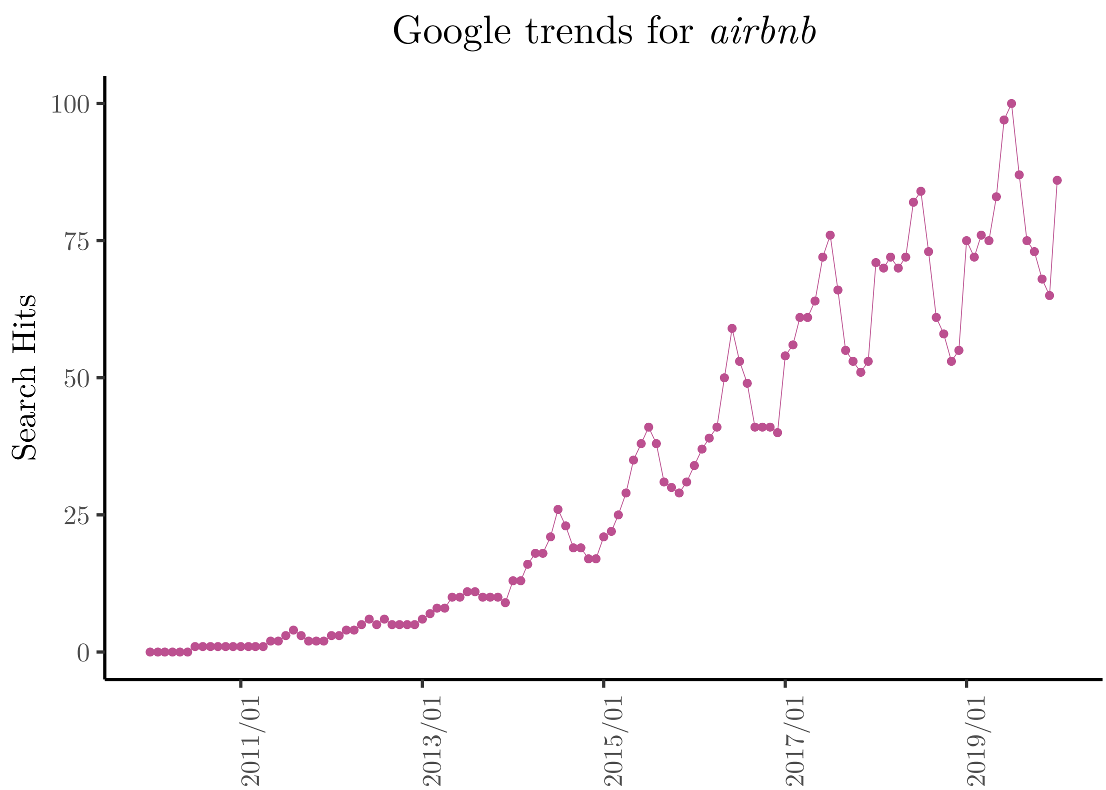


Figure 6: Restaurant data used in instrument construction

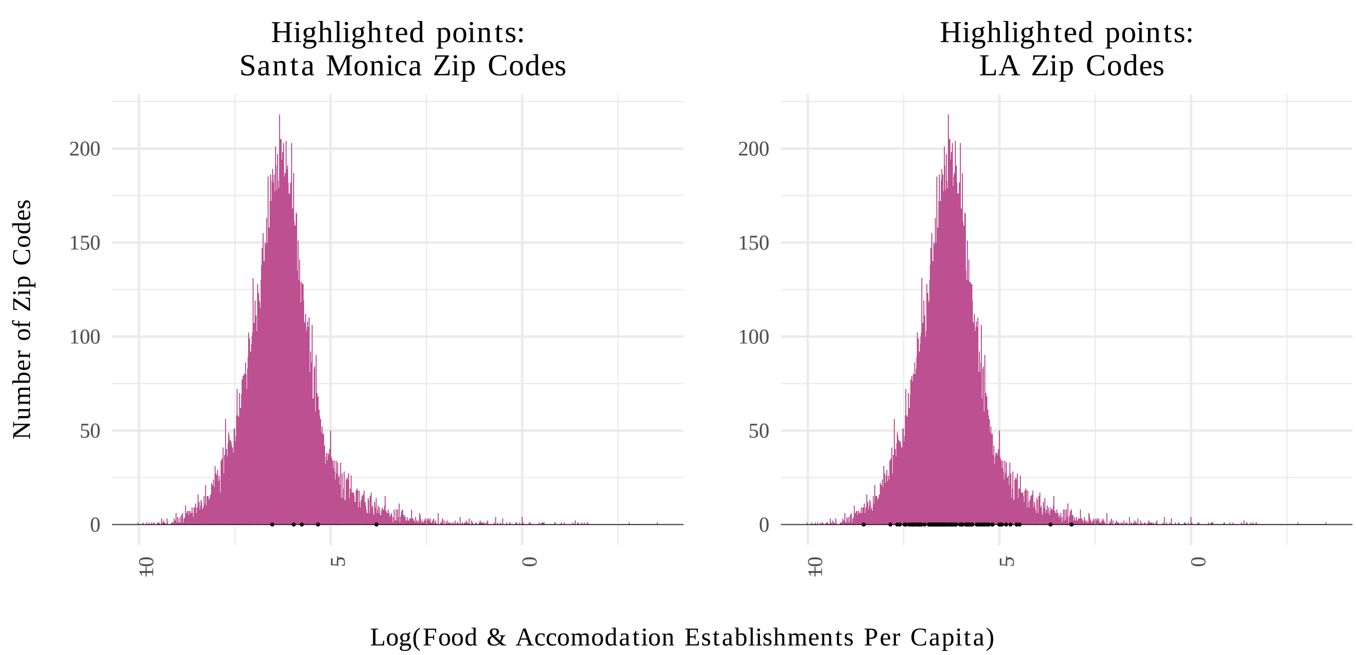


Table 7: First-stage instrument results

	log(`listings`)
(Intercept)	-2.889^{***}
	(0.180)
log(z)	0.770^{***}
	(0.023)
R^2	0.129
Num. obs.	6800

Notes: This table reports first-stage instrumental variables estimates of Equation (5). An observation is a zipcode-month. Heteroskedastic-robust standard errors are in parentheses. Stars indicate p values: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

7.3 Sample Selection Details

In this section, we detail our sample selection. The house price data dates back to 1996 and the calls to police data in Santa Monica dates back to January of 2006. Our Airbnb scrapes (from both sources) are collected at irregular intervals and date back to 2014. For both the differences-in-differences estimation (Equation (6)) and the event study (Equation (7)), we start with the full sample and select the estimation window via (Imbens and Kalyanaraman, 2011).

Since our data on Airbnb scrapes is more limited than the ZHVI data and the incidents call data, we restrict the estimation window for our city-level estimation of Equation (5). We merge the publicly available Tomslee and Inside Airbnb data (using unique listings and time of scrape ids) to assemble the most comprehensive data possible. Both sources contain geo-coordinates of the listings.[22] We intersect the listing locations with US census ZTCA shapefiles and aggregate within zip codes and year-month to obtain total listings by zip-code-year-month. As demonstrated in Figure 2, before the policy, the scrapes are somewhat irregular. We thus restrict our estimation window from July 2015 to July 2017 as in this window, we have scrapes for each year-month. We then merge this data to the Zillow ZHVI data along with the instrument (which is constructed at the zip-code year-month level) to obtain our panel used to estimate Equation (5).

[22]Note that these coordinates are often listed with noise to maintain landlord privacy. We likely measure some listings in zip-codes adjacent to their true zip code. We interpret this as adding classical measurement error to our sample.

7.4 IV results for all cities

Table 8: The relationship between Airbnb listings and housing prices for all cities in Los Angeles County

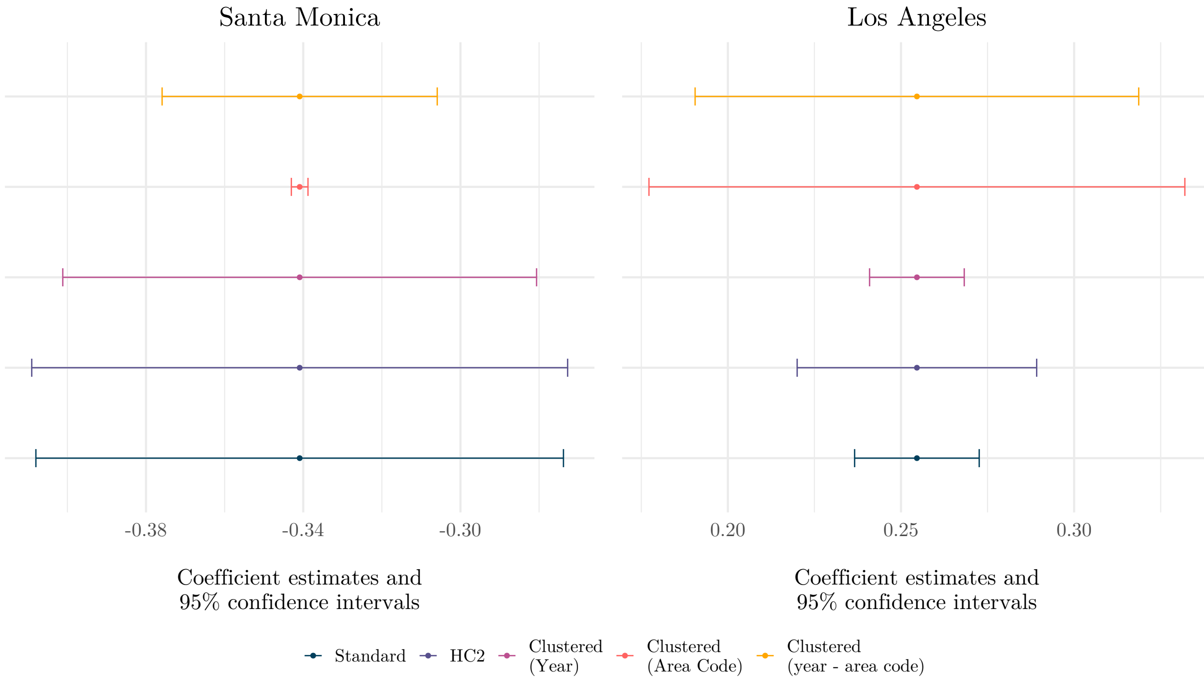
City	Estimate	City	Estimate	City	Estimate	City	Estimate
Agoura Hills	0.0199 (0.0207)	**Duarte**	0.0564*** (0.0199)	**Lawndale**	0.1272*** (0.0233)	**San Fernando**	0.0946*** (0.022)
Alhambra	-2e-04 (0.0085)	**East Los Angeles**	0.041*** (0.0084)	**Lomita**	0.0688*** (0.0206)	**San Gabriel**	-0.1391*** (0.006)
Altadena	0.0912*** (0.0216)	**El Monte**	0.0761*** (0.022)	**Long Beach**	0.1284*** (0.0308)	**San Marino**	0.3556*** (0.0381)
Arcadia	0.1296*** (0.0293)	**El Segundo**	0.184*** (0.0263)	**Los Angeles**	0.2546*** (0.0176)	**Santa Fe Springs**	0.0601*** (0.0208)
Artesia	0.0888*** (0.021)	**Florence-Graham**	0.1633*** (0.0243)	**Lynwood**	0.1159*** (0.0226)	**Santa Monica**	-0.3409*** (0.0348)
Avalon	-0.0332* (0.0198)	**Gardena**	-0.0476*** (0.0178)	**Malibu**	0.2026*** (0.0264)	**Sierra Madre**	0.0477** (0.0208)
Azusa	0.0755*** (0.0201)	**Glendale**	-0.1523*** (0.0079)	**Manhattan Beach**	0.3076*** (0.036)	**Signal Hill**	0.0362* (0.0216)
Baldwin Park	0.086*** (0.0221)	**Glendora**	-0.2002*** (0.0115)	**Maywood**	0.104*** (0.0236)	**South El Monte**	0.0695*** (0.0213)
Bell	0.0991*** (0.0233)	**Hacienda Heights**	0.0204 (0.0205)	**Monrovia**	0.0357* (0.0207)	**South Gate**	0.1075*** (0.0223)
Bellflower	0.092*** (0.022)	**Hawaiian Gardens**	0.1652*** (0.0298)	**Montebello**	0.076*** (0.0205)	**South Pasadena**	0.2717*** (0.0346)
Beverly Hills	1.028*** (0.0543)	**Hawthorne**	0.1218*** (0.0231)	**Norwalk**	0.0821*** (0.0215)	**Temple City**	0.0327 (0.0199)
Burbank	-0.1693*** (0.0131)	**Hermosa Beach**	0.2518*** (0.034)	**Palos Verdes Estates**	0.1261*** (0.0236)	**Topanga**	0.0861*** (0.0205)
Calabasas	0.0104 (0.021)	**Huntington Park**	0.1139*** (0.0218)	**Paramount**	0.114*** (0.0249)	**Torrance**	0.2183*** (0.019)
Carson	-0.0013 (0.0373)	**Inglewood**	-0.0358*** (0.0107)	**Pasadena**	0.1093*** (0.0384)	**West Carson**	0.1172*** (0.0231)
Cerritos	0.0069 (0.0195)	**La Canada Flintridge**	0.2678*** (0.0315)	**Pico Rivera**	0.0908*** (0.0212)	**West Covina**	0.0393 (0.0305)
Commerce	0.0922*** (0.0215)	**La Crescenta-Montrose**	0.0827*** (0.0219)	**Pomona**	0.061*** (0.0155)	**West Hollywood**	0.1495*** (0.0266)
Compton	0.0437*** (0.0049)	**La Puente**	0.0729*** (0.0218)	**Rancho Palos Verdes**	0.0398** (0.0195)	**West Puente Valley**	0.076*** (0.021)
Covina	-0.1491*** (0.0212)	**La Verne**	0.0126 (0.0195)	**Redondo Beach**	0.285*** (0.017)	**Whittier**	-0.0107 (0.0167)
Culver City	0.1726** (0.0823)	**Ladera Heights**	0.1159*** (0.0258)	**Rosemead**	0.0663*** (0.0204)		
Downey	0.0449 (0.0308)	**Lakewood**	0.0841*** (0.0095)	**Rowland Heights**	0.0094 (0.0208)		
Year FE				Yes			
Area code FE				Yes			
R^2				0.656			
Num. Obs				6125			

Notes: This table reports the full set of relevant coefficients for Column (6) of Table 4. An observation is a zipcode-month. Cities include both incorporated sub-county jurisdictions and unincorporated areas as defined by the U.S. Census. The dependent variable is the log of the Zillow Home Value Index. Heteroskedastic-robust standard errors are in parentheses. Stars indicate p values: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

7.5 IV Results: Alternative Standard Error Clustering

In this section, we present our primary IV estimates with alternative standard error clustering. Our estimates are remarkably robust to different standard error types. As a visual tool, we provide a coefficient plot for Santa Monica and La, in which we vary the standard error type. We use our most saturated specification (with year and area code fixed effects) for each specification presented.

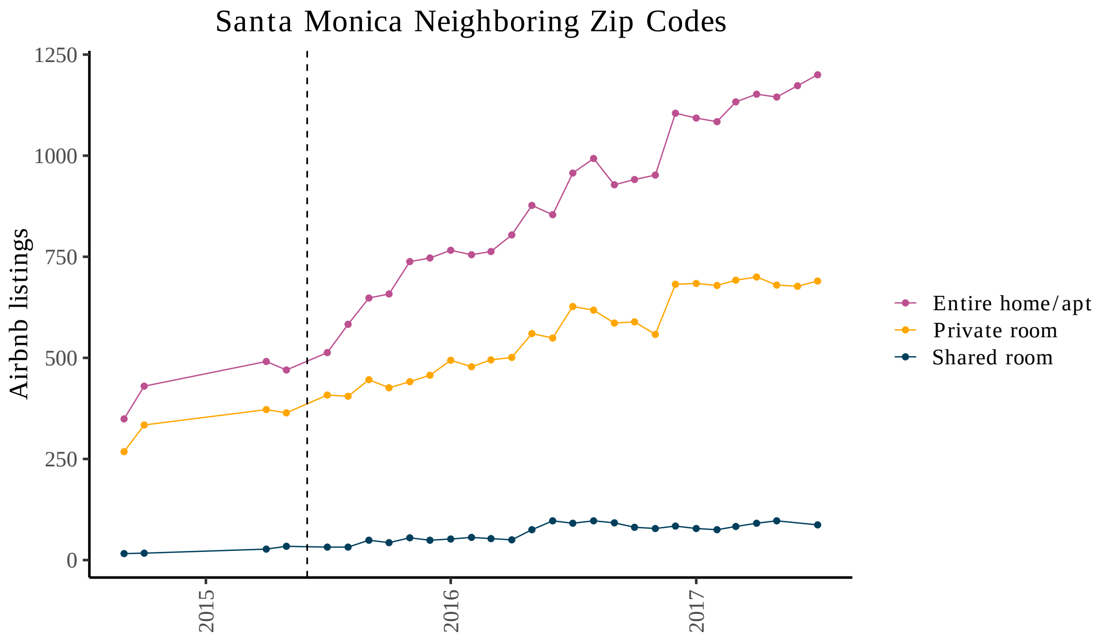
Figure 7: Comparing standard errors under alternative clustering methodologies



7.6 Airbnb Listings in Neighboring Zips

To check for policy spillovers, in this section we document airbnb listings in zip codes directly adjacent to Santa Monica.

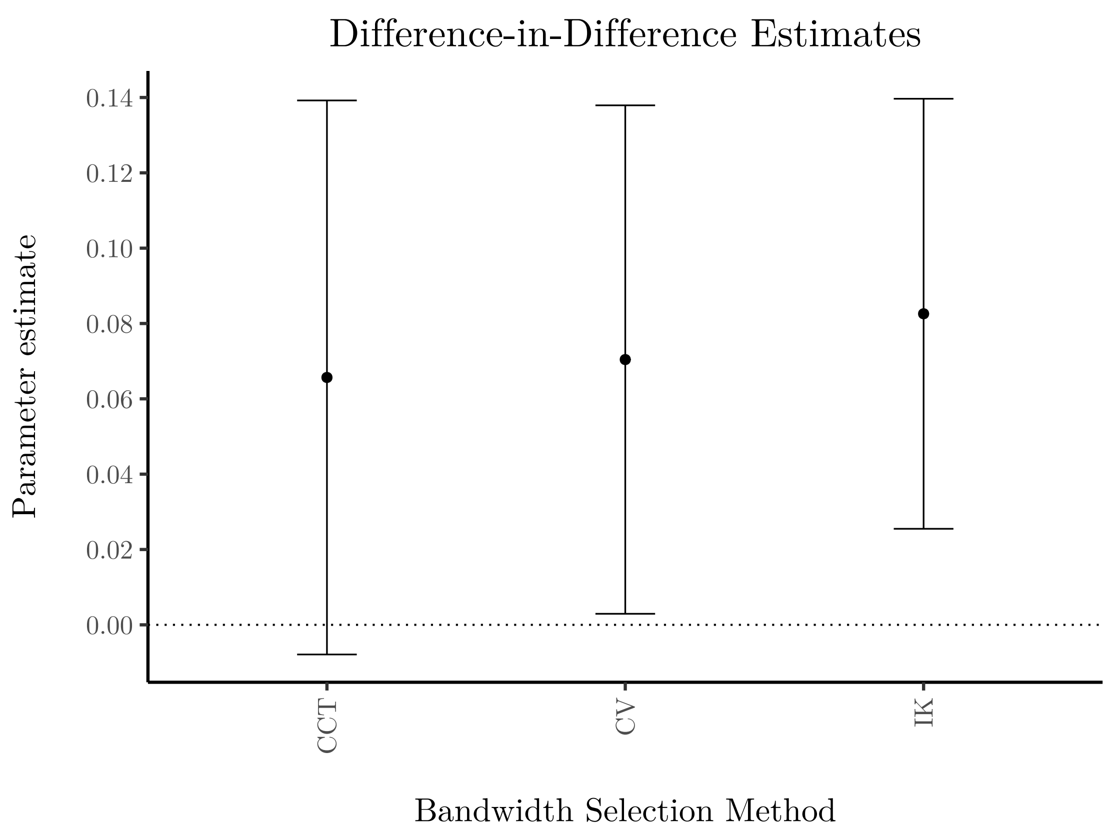
Figure 8: Airbnb Listings in zip codes adjacent to Santa Monica



7.7 Santa Monica's STR Regulation: Other Optimal Bandwidth Techniques

In this section, we re-estimate our difference-in-differences specification that examines the effect of Santa Monica's STR regulation on housing prices. In the main paper, we used the specification of Imbens and Kalyanaraman (2011). Here, we explore using the methods of Calonico et al. (2014) and Ludwig and Miller (2007). The coefficient estimates are presented below. Note that using the selection method of CCT, we cannot reject the null hypothesis that the effect of the policy was different than zero. Hence, we view our results as providing evidence that the policy *may* have increased housing prices – but more conservatively – could have also done nothing. In no specification do we find a reduction in housing prices from the policy.

Figure 9: Alternative bandwidth techniques



7.8 Santa Monica's STR Regulation: Placebo Tests

In this section, we explore the sensitivity of our Difference in Differences results to altering the timing of the STR regulation as a falsification test. We vary the policy date to 24 months after the official policy date and re-estimate Equation 6 and report the results in Table 9. Note that we do not find evidence that the placebo date policy had any impact on housing prices.

Table 9: The effect of Santa Monica's placebo STR regulation on housing prices

	(1)	(2)	(3)
`Santa Monica` × `post reform`	0.039	0.039	0.039
	(0.047)	(0.047)	(0.046)
Area FEs?	No	Yes	Yes
Year FEs?	No	No	Yes
R^2	0.130	0.249	0.259
N	5029	5029	5029

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: This table reports a placebo test and estimates of Equation (6) using the optimal bandwidth technique of Imbens and Kalyanaraman (2011) and setting the placebo policy date to 24 months after the official policy date. An observation is a zipcode-month. The dependent variable is the log of the Zillow Home Value Index. Heteroskedastic-robust standard errors are in parentheses. Stars indicate p values: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 10: Placebo test event student evidence of Santa Monica's STR regulation effect on party-related police calls

	Total	Party	Noise	Intox
Post Reform	-0.122^{*}	-0.038	-0.122	-0.217^{***}
	(0.060)	(0.105)	(0.091)	(0.071)
Months	0.003	-0.002	-0.000	0.015^{***}
	(0.003)	(0.005)	(0.005)	(0.005)
Post Reform × Months	0.001	-0.004	0.011	-0.009
	(0.004)	(0.007)	(0.007)	(0.006)
Month FEs?	Yes	Yes	Yes	Yes
R^2	0.8649	0.8166	0.6819	0.7303
N	48	48	48	48

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: This table reports placebo test estimates of Equation (7), where the placebo policy date is 24 months after the official policy date. An observation is a month. The dependent variable is the log of the number of "party-related" police calls reported in Santa Monica. Heteroskedastic robust standard errors are in parentheses. Stars indicate p-values: *** p < 0.01; ** p < 0.05; * p < 0.1.

7.9 Heterogeneity in Party Results

In this section we explore underlying heterogeneity that drives our fall in party related differences in discontinuities. We look at three specific complaints: party complaints, noise complaints, and public intoxication complatints. We estimate the same RDD specification as in the main body of the paper but for each of these separately. The figures and estimates can be found below.

Table 11: Event study evidence of heterogeneity of Santa Monica's STR regulation effect on party-related policy calls

	Party	Party	Noise	Noise	Intox	Intox
Post Reform	0.093	0.016	0.071	0.023	-0.151^{**}	-0.183^{***}
	(0.127)	(0.082)	(0.094)	(0.072)	(0.074)	(0.066)
Months	-0.005	-0.006^{***}	0.002	0.001	0.001	0.000
	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Post Reform × Months	-0.006	-0.004	-0.005^{*}	-0.004	-0.012^{***}	-0.011^{***}
	(0.005)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Month-of-year FEs?	No	Yes	No	Yes	No	Yes
R^2		0.282	0.761	0.040	0.610	0.572
0.738						
N	87	87	87	87	87	87

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Notes: This table reports estimates of Equation (7). The bandwidth is chosen per the optimal bandwidth technique of Imbens and Kalyanaraman (2011). An observation is a month-year. The dependent variable is the log of the number of "party-related" police calls reported in Santa Monica: party complaints, noise complaints, public intoxication complaints.. Heteroskedastic robust standard errors are in parentheses. Stars indicate p-values: *** p < 0.01; ** p < 0.05; * p < 0.1.

Figure 10: Event study for party complaint incidents in Santa Monica

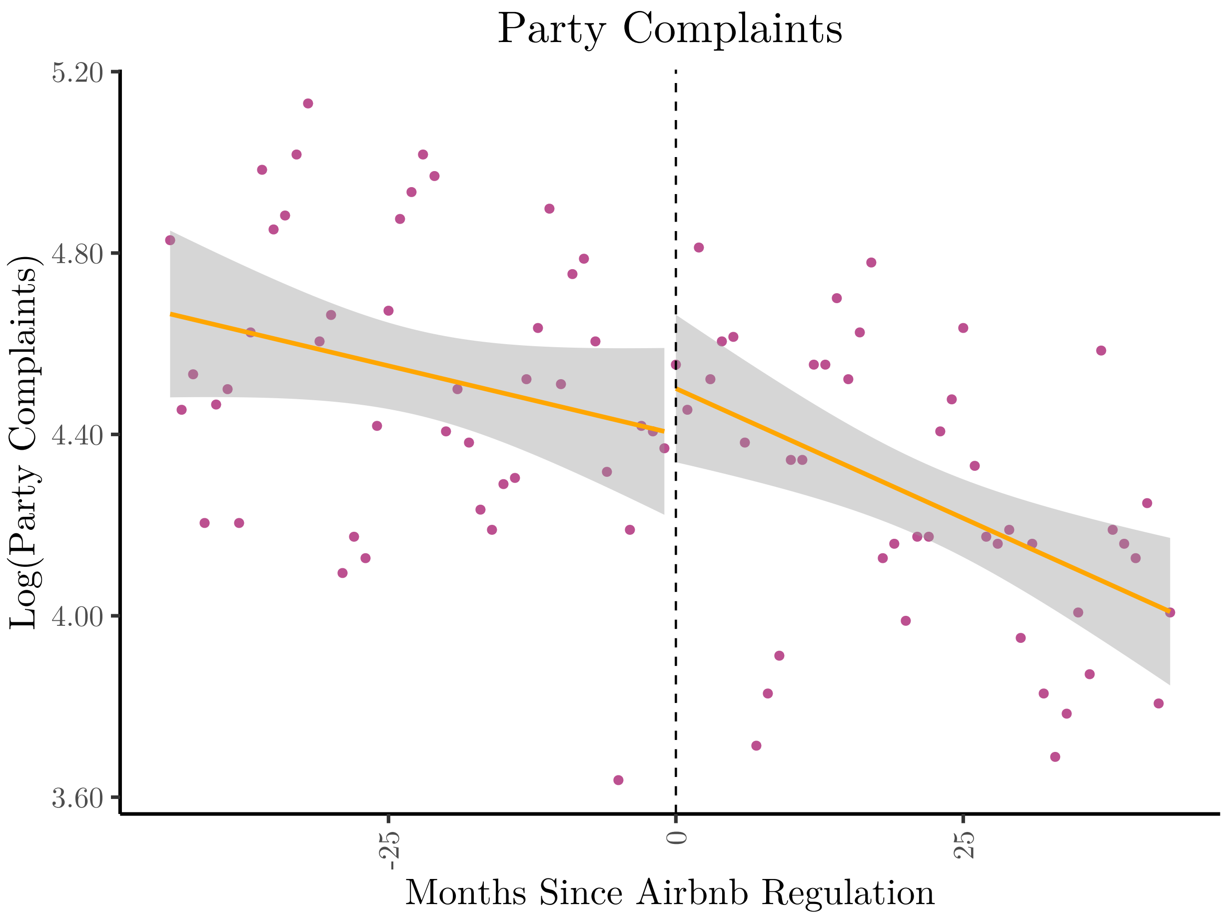


Figure 11: Event study for loud music incidents in Santa Monica

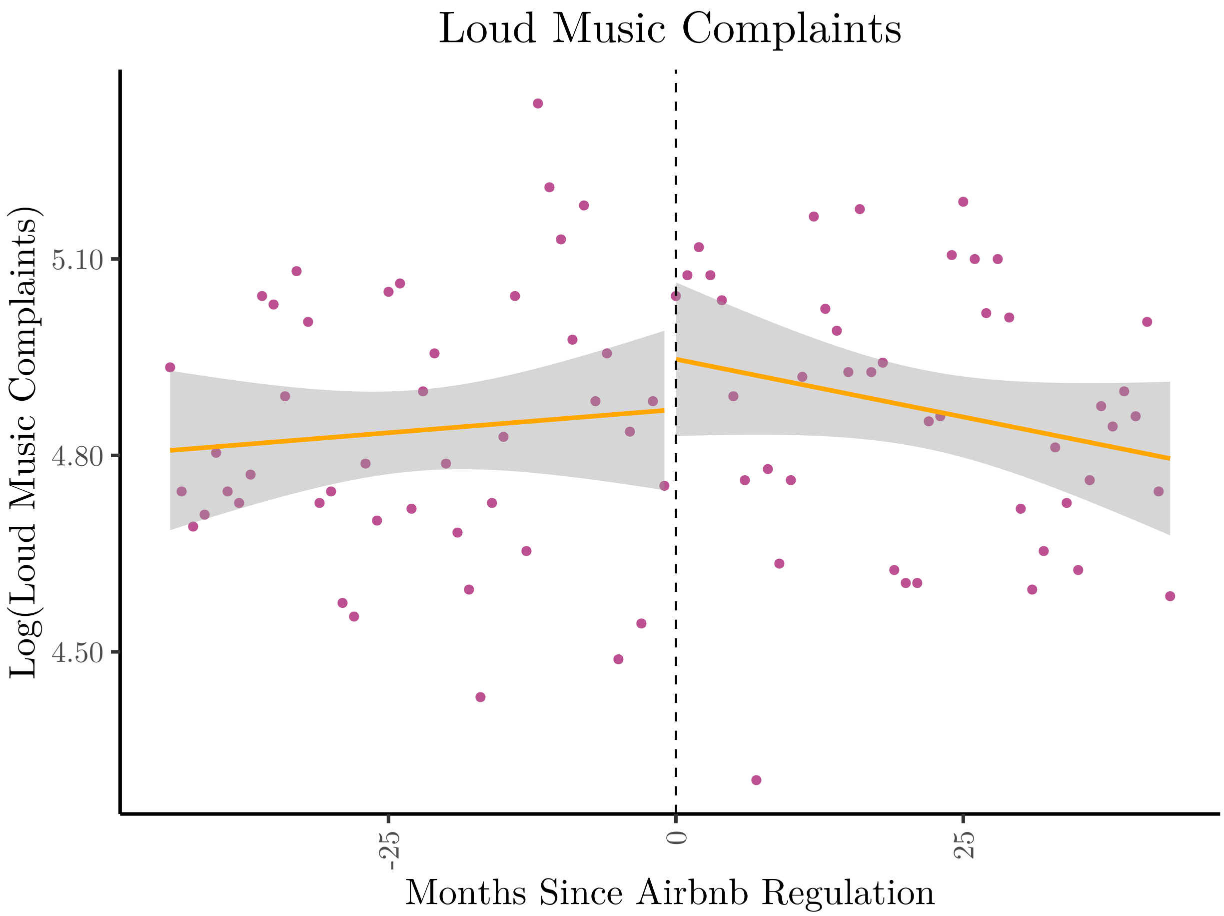


Figure 12: Event study for public intoxication incidents in Santa Monica.