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

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Abstract

The supply of housing for short-term rental (STR) has grown dramatically with the emergence of platforms such as Airbnb. This trend has led 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 the consequences of a 2015 law restricting STRs within the City of Santa Monica in the coastal region of Los Angeles County. In that City, we estimate a negative relationship between the prevalence of STRs and housing prices. Using a differences-in-differences approach, we show that the 2015 law increased housing prices – which can be rationalized by our theory. Finally, we provide evidence for a potential mechanism: "party-related" nuisance calls to the Santa Monica Police Department decreased after the policy was enacted.

JEL codes: R31, R5, L5, H7, Z38, K42
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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 the emergence of online platforms such as Airbnb and VRBO, short-term rentals (STRs) in the housing market have experienced significant global growth over the past decade.[1] By enabling mutually beneficial transactions between property owners and transient visitors with reduced information costs, these markets increase the utilization of (and economic surplus created by) housing capacity. Given that they increase certain amenities (Basuroy et al., 2020) and the option value of home-ownership, STRs have the potential to increase housing prices (Horn and Merante, 2017; Garcia-López et al., 2020). Criticism of STR platforms has focused mostly on this price effect: higher housing prices means that long-term renters may be increasingly priced out of communities where they have lived for years (Nieuwland and van Melik, 2020).[2] As a consequence, there is an active policy debate surrounding STR regulation with an emphasis on restricting STRs on both the extensive and intensive margins.

Our contribution to this debate is an assessment of the simple point implied by the quote from a policymaker featured above: the net effect of STRs on housing prices is ambiguous due to the relationship between STRs and local amenities. STRs represent an extension of the capital stock available to the hospitality industry. However, 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

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

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

as public intoxication, petty theft, and other "nuisances" (Brunt and Hambly, 1999; Ho et al., 2009). Insofar as STRs offer services that can substitute for the services of traditional hospitality firms—as has been proposed by Zervas et al. (2017) and Farronato and Fradkin (2018)—STRs may generate similar negative externalities. Airbnb, in particular, has received negative media attention for its "party house" listings (Lieber, 2015).[3] If the cost of such externalities outweighs the benefits from increased demand for local businesses—in other words, if STRs sufficiently "threaten the stability and character" of neighborhoods (Martin, 2018)—the net effect of STRs on the overall level of local amenities, and potentially on housing prices, may be negative. In this paper, we demonstrate this both theoretically and empirically.

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. (2020). In our model, homeowners choose between occupying their home themselves and listing it as a short-term rental. Having this option increases the value of owning housing. However, STRs also impose both positive and negative externalities on their 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 sufficiently negative to outweigh the effect of the increased surplus earned by absentee landlords. Similarly, an exogenous change in the number of STRs in a given neighborhood may result in an increase or a decrease in housing prices, depending on the net impact of STRs on aggregate amenities and disamenities in that neighborhood.

To provide empirical evidence for the implications of our model, we turn to Los Angeles (LA) County, California. This area has one of the highest levels of amenities in the United States (Albouy, 2016) but also features a high degree of income and amenity inequality across its various communities (Bobo et al., 2000; Wolch et al., 2005; Charles, 2006). As we describe in Section 4, we employ data on individual housing prices from Zillow, data on

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

Airbnb participation for individual dwellings 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 our model makes clear, the number of Airbnb listings is endogenous so we employ an instrument based on the level of local amenities in each zip code prior to the entry of Airbnb into the regional housing market. We estimate the relationship for all cities in LA County and find significant heterogeneity. For example, in the City of Los Angeles, a 1% increase in the number of Airbnb listings in a zip code is estimated to increase housing prices by 0.23%, but in Burbank, a higher-income, lower-density community, the same increase in listings is estimated to *decrease* housing prices by 0.11%.

We examine the effects of an STR regulation enacted by the wealthy oceanfront suburb of Santa Monica in Section 6 – a jurisdiction for which we estimate a negative relationship between STRs and housing prices. The 2015 law, enacted 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 (Sanders, 2015). It is important to note, upfront, that we are not claiming this policy change is exogenous to housing prices—per the contemporaneous press, it was implemented in response to a simultaneous increase in STR listings and housing prices (Logan, 2015). We first document that the law was (at least temporarily) successful in reducing the number of Airbnb listings that would be most likely to generate negative externalities. Using a differences-in-differences framework with the rest of LA County as a control, we show that these regulations increased housing prices by about 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 that could be defined as "party-related" decreased after the law was enacted.[4]

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[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.

Our work contributes to the recent literature examining the relationship between STR markets and housing prices. Relative to this literature, which we broadly characterize as providing average effects of STRs, 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. (2020) 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 contrast, we extend their model and focus our empirical work on a particular geography to demonstrate significant heterogeneity. In a recent working paper, Fonseca (2019) analyzes the immediate impact of Santa Monica's law on long-term rental prices using a synthetic control approach, and finds little effect. In addition to our different focus on the effects of STRs on local amenities, we use data on home-ownership prices over a longer period to identify the effects of the law. We also contribute to the growing literature examining the relationship between STRs and other hospitality firms, such as hotels and motels. By arguing that Airbnb listings are associated with negative externalities similar to those created by hotels, our work is complementary to other studies cited above which identify STRs as substitutes for traditional hotels.

Our work further 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, by providing restaurant patrons with 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 private housing and hospitality markets, taking advantage of 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 ordinance restricting STRs.

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, LA 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 sustained heterogeneity (Bobo et al., 2000).

Table 1 illustrates some of this heterogeneity in terms of median income, local amenities, and median rents for LA County overall and for the City of LA and nine other notable cities within the county. See Appendix Figure A.1 for a map of these cities within LA County. Median income in the City of LA is slightly lower than the county as a whole, given that communities such as Malibu and Beverly Hills have median incomes more than twice that for the county as a whole. Malibu, a western beachside community, has a population density of only 353 residents per square mile, whereas the more centrally located West Hollywood has 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 only 2.5 park acres per thousand residents. Santa Monica offers 4.7 restaurants per thousand residents, while Pomona, on the far eastern border of the county, offers merely 1.3.

These differences in observable amenities are likely related to the differences in average 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 Housing Opportunity Index (HOI) sponsored by the National Association of Home Builders and Wells Fargo.[5] The HOI for a community measures the share of homes sold that would have been affordable to median-income earners. During the fourth quarter of 2019, the HOI indicated that 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).

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 some period – 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 stays (i.e. 30 days or fewer). 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 gave travelers more options for lodging in residential neighborhoods. While these "owner-present" STRs differ substantially from traditional owner-absent vacation rental offerings (or hotel offerings), they quickly grew in popularity as a cheaper alternative. This in turn exposed several new consumers to the possibility of owner-absent rentals. Today, Airbnb's peer-to-

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[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 $)	Density (res. / mi²)	Parks (ac. / 1k res.)	Dining & lodg. (# / 1k res.)	Rent ($ / mth)
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 with two bedrooms. All statistics from the Census Bureau except for parks which is from the 2016 Los Angeles Countywide Comprehensive Park and Recreation Needs Assessment.

peer market offers both owner-absent and owner-present options and lists more rooms than the largest six hotel groups combined (Airbnb, 2019).[6]

2.3 Regulating STRs

Neither California nor the U.S. federal government explicitly regulates 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 Santa Monica's Ordinance 2484CCS, which was adopted by its City Council on May 12, 2015. According to staff reports and the text of the measure, the city was roused 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.

The ordinance was debated in the months before passage and was an outgrowth of a longer-term process by the City Council to update Santa Monica's land-use and transportation plan that began in December 2013 and continued for several months beyond the adoption of the short-term rental regulation (Martin, 2015). This "spin-off" ordinance was not unique—the City Council of Santa Monica passed many other spin-off ordinances as a result of this process, including ordinances related to housing discrimination, water conservation, and commercial fitness instruction. Crucially, the major components of the ongoing planning effort primarily concerned requirements for commercial buildings and multi-family dwellings and thus it is unlikely that this process alone would have created significant changes in housing prices until its provisions went into affect and future construction projects were designed in compliance with those provisions.

When the ordinance went into effect in June of 2015, Airbnb (among other platforms) quickly launched a legal challenge which made enforcement difficult (Dolan, 2019). The

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[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.

city had no ability to prevent landlords from honoring reservations made before the ordinance went into effect. Landlords worked to circumvent the provisions of the ordinance, finding ways to offer owner-absent STRs that complied with the rules. These circumventions included modifications to listings that likely decreased the probability that renters would generate externalities. For example, the owner may be present for a short period at the beginning and end of the rental period, or be occupying an adjacent dwelling. These actions resulted in several additional legal challenges.[7] Ultimately, the city prevailed in all cases. We return to these issue when we analyze police calls in Section 6.

Such regulatory and enforcement challenges have played out in similar ways around the country as local governments attempt to regulate STRs (Martineau, 2019). These challenges 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 the filtering of illegal listings.[8] These challenges, combined with other perceived abuses of CDA 230 by other platforms, have led to various proposals for reform through legislation or regulation (Neuburger, 2020).

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, thereby extending the work of Barron et al. (2020). Our goal is not to generate "sharp" falsifiable predictions—rather in the context of a literature which has estimated that STRs generate increases in housing prices we show

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[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)

that the effect of STRs on equilibrium housing prices is ambiguous even in a parsimonious framework. Thus we abstract from several considerations which do not affect the primary mechanism: the interplay between externalities and the option value (to home-owners) of offering STRs.

The model environment consists of a finite number of jurisdictions J, indexed by j. Each jurisdiction offers 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 in which jurisdiction to purchase a home and their usage of that home, i.e. whether to be an owner-occupier or an absentee landlord. We normalize to zero the utility of not entering the market.[9]

The utility derived by individual i from owning and occupying housing in jurisdiction j 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 jurisdiction-specific features into a scalar amenity value. The feature 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 jurisdiction 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 jurisdiction 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, g and f and that $\frac{\partial \xi_j}{\partial g}$ is negative for all k g, 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 jurisdiction is "nicer." As a consequence, the effect of an increase in STRs on jurisdictional amenity values is

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

ambiguous, as can be seen through the partial derivative

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

Jurisdictions 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 confer either greater or lesser utility when the level of STRs increases.

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 STR revenues in jurisdiction j net of any rental expenses.[10] We assume for simplicity R_j is exogenous.[11]

Also for simplicity, assume $\epsilon_{i,j,k}$ (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 jurisdiction 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, markets must clear: $\sum_{k \in \{o,a\}} s_{j,k} N = H_j$ for all j. Using this market-clearing condition, we can write the equilibrium price for houses in location j (see Appendix 7.1 for details):

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

where $\phi_{j'}^\star = \sum_{j' \neq j} \left(\exp(-P_{j'} + \frac{R_{j'}}{1-\delta}) + \exp(\xi_j(k_j', f(str_j^{\star'}), g(str_j^{\star'})))\right)$ and $str_j^\star = s_{j,a} \times H_j$

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[10]We assume for simplicity there is no uncertainty in future per-period net revenues.
[11]As STRs compete with other hospitality firms having large numbers of units, the effect of a small change in the number of STR units available in a particular jurisdiction on R_j is likely to be second-order.

is the equilibrium number of short-term rentals in jurisdiction j. We use the equilibrium housing price expression to derive an expression that guides the interaction between short-term rentals and housing prices. 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 $\frac{\partial P_j^\star}{\partial str_j^\star}$:

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

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

Equation (3) illustrates how a change in net discounted STR rental revenues impacts equilibrium home prices. 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 STR revenue increases. However, the sign of $\frac{\partial P_j^\star}{\partial R_j}$ and $\frac{\partial P_j^\star}{\partial str_j^\star}$ may vary. $\frac{\partial P_j^\star}{\partial str_j^\star}$ varies with the sign of $\frac{\partial \xi_j}{\partial str_j^\star}$ – the net effect of STRs on residential amenities. For $\frac{\partial P_j^\star}{\partial R_j}$, 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 $P_j^\star$.

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-occupied homes will increase, 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 $\frac{\exp(\frac{R_j}{1-\delta})}{1-\delta} > \left| \exp(\xi_j(\cdot)) \times \frac{\partial \xi_j}{\partial str^\star} \times \frac{\partial str_j^\star}{\partial R_j} \right|$: *STRs create net-negative amenities and the magnitude of 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 not fully offset by 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 $\frac{\exp(\frac{R_j}{1-\delta})}{1-\delta} < \left| \exp(\xi_j(\cdot)) \times \frac{\partial \xi_j}{\partial str^\star} \times \frac{\partial str_j^\star}{\partial R_j} \right|$: *STRs create net-negative amenities and the decrease in the marginal benefit to owner-occupiers exceeds the decrease in the marginal benefit to absentee landlords.* Here, while the increase in R_j increases demand by absentee landlords, the increased number of STRs decreases demand by owner-occupiers by a greater amount. Thus, the net effect on demand for housing is negative and $\frac{\partial P_j^\star}{\partial R_j} < 0$.

Equations (3) and (4) can be used to frame the expected impacts of STR regulations. Some STR regulations (e.g. occupancy taxes 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—*e.g* limits on individual choices to be absentee landlords — resulting in a direct 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 LA County. We choose this geography in part due to the long-term presence of Airbnb in the area. Any short-term extensive-margin competitive effects of entry are thus likely to have occurred before the period of our analyses. LA County also offers a distinct policy change in Santa Monica, but not elsewhere in the county.

Our data on housing prices is the Zillow Home Value Index (ZHVI), which we obtain from `Zillow.com` for the interval 1996-2019. The ZHVI reports the estimated median home value at the zip-code-month level, adjusted for seasonality. To construct the ZHVI, Zillow estimates the sale price for all homes in each zip code based on recent 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`, where each of these sources provides snapshots of consumer-facing listings available on specific days, collected by web-scraping. For each listing, we observe a unique host and room identifier, the jurisdiction for 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 based on the total number of listings of each type. These data were scraped at irregular intervals (see Appendix Section 7.3 for more details). We obtain all scrape dates 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 instrumental variable described in Section 5, we obtain Google Trends data for "Airbnb", and also 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 as used in our analyses. We discuss the details of our sample construction procedure in Appendix Section 7.3. The first set of rows reports the ZHVI for LA County as a whole and for the set of its constituent cities displayed in Table 1. The last column computes the average annual percentage change in each ZHVI between 2014 and 2019. Each city experienced increases in housing prices throughout our data. However, these increases range from 5% in Torrance to 15% in Beverly Hills. LA city experienced an increase of 7%, while prices in Santa Monica increased by 11%. The second set of rows reports counts of Airbnb listings by type and jurisdiction. 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 dataset: entire unit listings (which are generally owner-absent) decreased from 606 in 2015 to 450 in 2016 as the Santa Monica STR regulation was passed, went into effect, and was increasingly 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

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count, though per our discussion in Section 2, the efforts of listers to comply with Santa Monica's regulations means these listings likely generated externalities at lower rates.

To provide descriptive evidence of the relationship between STRs and negative externalities, we collect data on police calls from the Santa Monica Open Data Project for 2013–2019.[12] For each call, we observe the date and time, the location of the caller, and the reason for the call. Importantly, these data encode the reason for the call at a much finer level of detail than is used for either the Uniform Crime Reporting data or National Incident-Based Reporting System data compiled by the Federal Bureau of Investigation. Unfortunately, few cities in the U.S. report data at this level of detail and none that do at the same frequency.[13] We focus on calls for which the reason listed includes "party complaint", "loud music", or "public intoxication", because these particular types of complaints are those referenced most frequently in media reports about the nuisance effects of STRs (Lieber, 2015; Griffith, 2020). Table 3 reports summary statistics for these complaint data. After (generally) initial increases, the number of each type of call declined over our study period. The total number of calls we consider decreased 33% from 2013 to 2019.

5 Evidence of heterogeneous impacts of STRs on housing prices

Equation (4) suggests a testable hypothesis: at the margin, the relationship between STRs and housing prices may be positive *or negative*.[14] In this section, we test this hypothesis by estimating the effects of Airbnb listings on local housing prices. 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 represent a noisy estimate of R_j – while

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

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

[14]The null hypothesis is that the relationship between STRs and housing prices is weakly positive.

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

Variable	2014	2015	2016	2017	2018	2019	Avg. %Δ
Zillow Home Value Index							
LA (county)	541	582	637	693	755	776	8
LA (city)	578	625	689	751	821	846	7
Beverly Hills	1,177	1,352	1,606	1,862	2,176	2,363	15
Burbank	581	621	667	713	772	786	6
Malibu	1,303	1,462	1,680	1,881	2,104	2,204	12
Pasadena	605	641	689	744	811	825	7
Pomona	322	343	365	394	425	434	8
San Gabriel	637	663	689	730	781	779	5
Santa Monica	942	1,066	1,209	1,363	1,531	1,595	11
Torrance	638	664	703	749	800	805	5
West Hollywood	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 across monthly observations during each year. The Zillow Home Value Index is measured in thousands of dollars and reflects the median home value in the given jurisdiction in each year as estimated by Zillow.

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 across monthly observations over each year. Standard deviations are reported in parentheses.

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 that are not listed. As listings and housing prices are both equilibrium outcomes, we proceed by following an instrumental variable strategy in conjunction with fixed effects.

Let $ZHVI_{jct}$ be the Zillow Home Value Index for zip code z in jurisdiction j at year-month time t. Equation (4) suggests the following estimating equation:

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

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. To control for jurisdiction-level characteristics that stay constant over time and are correlated with both Airbnb listings and housing prices, we include geography-based fixed effects. While zip code fixed effects are an obvious option, zip codes in LA county are generally coterminal with city boundaries, and therefore zip code fixed effects would preclude identification of β_{1j}.

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[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.

We cannot use city fixed effects for the same reason. Therefore, we turn to area code fixed effects. There are 11 area codes in LA County, each covering a geographically contiguous area with boundaries that (generally) do not overlap with city boundaries. Appendix Figure A.2 illustrates these area code boundaries along with city boundaries. While these areas were not designed to be completely homogeneous, their geographic continuity ensures at least some correlation between the jurisdictions within their scope. For example, area code 310 includes the entire coastline of LA County across several cities. We also include year fixed effects to account for time-varying characteristics that are correlated with both Airbnb listings and housing prices, such as population growth and macroeconomic conditions.[16]

Despite these fixed effects, there may be some component of ϵ which is correlated with $listings_{zjt}$. Therefore, we employ the instrument proposed by Barron et al. (2020). 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 NAICS 72 establishments in 2010 in zip code j, our instrument is

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

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 a potential Airbnb host). On its own, however, this variable is likely also to be correlated with housing prices, because food service establishments are probably positive neighborhood amenities. The g_t^{air} variable scales this "touristy-ness" measure by the overall market size for Airbnb. Given that the attractiveness of restaurants to long-term residents (or prospective residents) is likely not correlated with the nationwide market presence of Airbnb (as measured by Google Trends), the interaction

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

between these two variables will likely satisfy the exclusion restriction. Furthermore, this instrument is correlated with housing prices in a given period only insofar as it is correlated with the number of Airbnb listings, conditional on the included fixed effects.[17] We report summary information and first-stage estimates for our instrument in Appendix Section 7.4.

Table 4 reports our estimates of β_{1j} for the cities listed in Table 1. In Column (1), we report an estimate for the entire sample which includes every zip code in LA county with no fixed effects. In Column (2), we add fixed effects for the year and area code. While the key β_{1j} 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 in LA County by 0.93%. These estimates are similar in magnitude to those reported by Barron et al. (2020), who report that a 10% increase in Airbnb listings leads to a 0.76% increase in house prices averaged across the entire United States.[18]

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 first year and then area code fixed effects. Column (6) includes both sets of fixed effects and is our preferred specification. Appendix Table A.2 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 1.55%, whereas in Santa Monica, a 10% increase in the number of Airbnb listings *decreases* housing prices by 2.66%.

We have chosen to report estimates for these particular cities because they are more likely to be familiar to many readers. However, the estimated heterogeneity in the estimates of β_{1j} is similar across the entire set of estimates. Figure 1 depicts the distribution of the full set of β_{1j} coefficients for each jurisdiction using our fully saturated model. Of the 78 cities in our preferred specification, 7 have negative point estimates — 5 of which are distinguishable from zero in the statistically significant sense.[19] We take these results as broadly consistent

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[17]One may be concerned that spillovers are not contained to the area-code level. To the extent that STRs are substitutes for hotels, public intoxication incidents will likely occur near the location of the STR.

[18]Indeed, the reported confidence intervals overlap.

[19]We drop 10 cities which are collinear with our fixed effects: Acton, Castaic, Claremont, Diamond Bar,

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

	(1)	(2)	(3)	(4)	(5)	(6)
log(`listings`) for						
LA (entire county)	0.158***	0.129***				
	(0.010)	(0.013)				
LA (city)			0.255***	0.252***	0.236***	0.226***
			(0.016)	(0.018)	(0.015)	(0.016)
Beverly Hills			0.660***	0.653***	0.976***	0.691***
			(0.064)	(0.065)	(0.047)	(0.054)
Burbank			−0.056***	−0.059***	−0.142***	−0.110***
			(0.017)	(0.018)	(0.015)	(0.017)
Malibu			0.204***	0.196***	0.276***	0.189***
			(0.014)	(0.021)	(0.022)	(0.021)
Pasadena			0.255***	0.246***	0.339***	0.239***
			(0.017)	(0.024)	(0.031)	(0.024)
Pomona			0.110***	0.103***	0.121***	0.091***
			(0.007)	(0.016)	(0.011)	(0.015)
San Gabriel			−0.133***	−0.135***	−0.122***	−0.123***
			(0.012)	(0.012)	(0.008)	(0.009)
Santa Monica			−0.265***	−0.267***	−0.298***	−0.266***
			(0.043)	(0.043)	(0.033)	(0.037)
Torrance			0.202***	0.197***	0.222***	0.188***
			(0.021)	(0.023)	(0.017)	(0.019)
West Hollywood			0.172***	0.163***	0.228***	0.155***
			(0.012)	(0.020)	(0.024)	(0.020)
Year FE	No	Yes	No	Yes	No	Yes
Area code FE	No	Yes	No	No	Yes	Yes
R^2	0.061	0.256	0.659	0.659	0.654	0.648
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 A.2. 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 7.4. Heteroskedastic-robust standard errors are in parentheses; we explore alternative clustering techniques in Appendix 7.6. 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.

with the previous literature: for most jurisdictions, the estimated relationship between STR listings and housing prices is positive, just as the estimated relationship for the region as a whole is positive. However, the average effect for the region aggregates over a substantial degree of heterogeneity at the city level.

Our model does not make sharp predictions about the characteristics of neighborhoods that 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. Equation (1) implies that the relevant jurisidiction-level characteristics are the rates at which STRs change both positive and negative local amenities, and the rate at which those amenities translate into the utility of owner-occupation in the jurisdiction. This provides a scaffolding with which to frame a discussion of the different jurisdictions listed in Table 4.

The three cities with negative estimated coefficients are Burbank, San Gabriel, and Santa Monica. For simplicity, suppose that the rate at which amenities translate into utility is constant across jurisdictions. Burbank is adjacent (but not home) to Universal Studios Hollywood, a popular tourist attraction for adults aged 18 to 34 which sells alcohol (Glueck, 2016). If short-term renters are spending tourist dollars outside of Burbank and returning to their rental after an evening of alcohol consumption, $f'(str_j)$ may be low and $g'(str_j)$ may be high. San Gabriel is adjacent to Pasadena, which hosts a number of notable events throughout the year, including the Rose Bowl Parade and Rose Bowl Game, both events associated with high alcohol consumption (Rose Bowl Community Prevention Council, 2013). Similarly to Burbank, if short-term renters of properties in San Gabriel spend their tourism dollars elsewhere, $f'(str_j)$ may be low and $g'(str_j)$ may be high. We note that Pasadena itself has a positive estimated coefficient. Even if $g'(str_j)$ is the same for both San Gabriel and Pasadena, if short-term renters of properties in Pasadena tend to spend their tourism dollars *in Pasadena*, $f'(str_j)$ for Pasadena will be higher than for San Gabriel, thus offsetting $g'(str_j)$. Indeed, the estimated coefficient for Pasadena is significantly lower than the coeffi-

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La Mirada, Lake Hughes, Lancaster, Littlerock, Monterey Park, Palmdale, San Dimas, Santa Clarita, Valyermo, and Walnut.

cient for Malibu and Beverly Hills, which do not have similar events. Finally, Santa Monica is the closest beach access for students of both the University of California, Los Angeles, and the University of Southern California. If local STRs allow students (and their guests) to imbibe more heavily, confident in the presence of local (private) lodgings, $g'(str_j)$ may be high while $f'(str_j)$ may be low. We investigate this externality channel for Santa Monica in Section 6.1.

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

Estimated effect of Airbnb listings on ZHVI
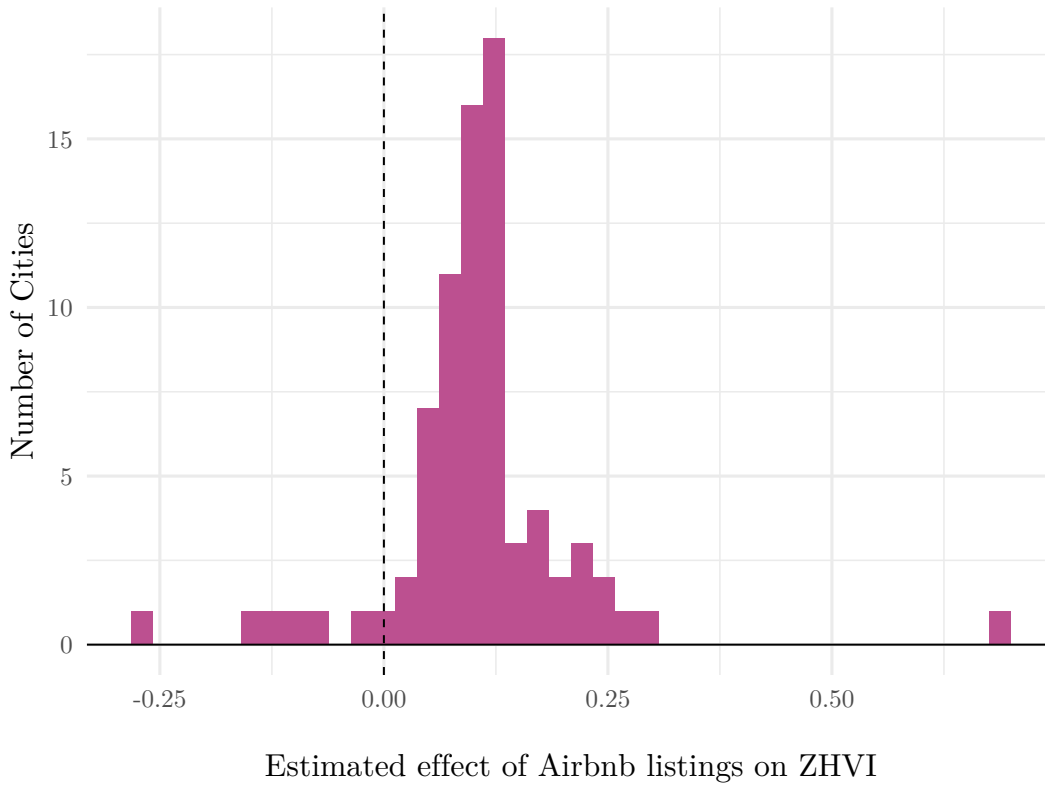
Notes: This figure depicts a histogram of the estimated β_{1j}s from Equation (5) for all cities. Estimates come from the fully saturated model; Column (6) in Table 4.

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 can be 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 some further hypotheses. Suppose an area in which the marginal impact of STRs on housing prices is negative implements a policy that reduces the number of STRs, either through affecting R_j or by decreasing str_j directly. Then we should expect to see both an increase in housing prices and a decrease in negative amenities.

We test these hypotheses by exploring the effects of Santa Monica's STR restrictions by estimating the effect of the regulation on housing prices using a difference-in-differences approach at the zip code level using the City of LA as a control. Contemporaneous media reports (and the text of the regulation itself) make it clear that the regulation was passed in part as a response to rapidly rising housing prices in Santa Monica. Thus we cannot claim that the policy represents a "clean" natural experiment. However, given that the stated goal of the policy was to *decrease* housing prices, any finding to the contrary provides evidence of the heterogeneous impacts of STRs. Our analysis of police report data then provides evidence for our proposed mechanism.

First, we document that the reform did in fact reduce the level of Airbnb listings in Santa Monica. Figure 2 illustrates the effect of Santa Monica's STR regulation on Airbnb listings. Each point requires a separate web scrape. Only 4 scrapes were conducted before the policy was enacted, but subsequent scrapes occurred at roughly monthly intervals for the two years following the implementation of the regulation. While there is an enforcement lag, there is a clear drop in the number of "entire unit" listings after the reform, and no similar drop appears for the City of LA. The number of entire-home listings eventually rebounded to the pre-regulation level. As discussed in Section 2, this was in part due to ongoing changes in behavior and legal challenges by landlords, Airbnb itself, and the City of Santa Monica. Conversations with city officials indicate that the policy effectively changed the nature of entire-home listings to reduce those which may generate negative externalities, though verifying those claims is difficult due to the nature of the Airbnb data.

Figure 2: Airbnb listings by room type
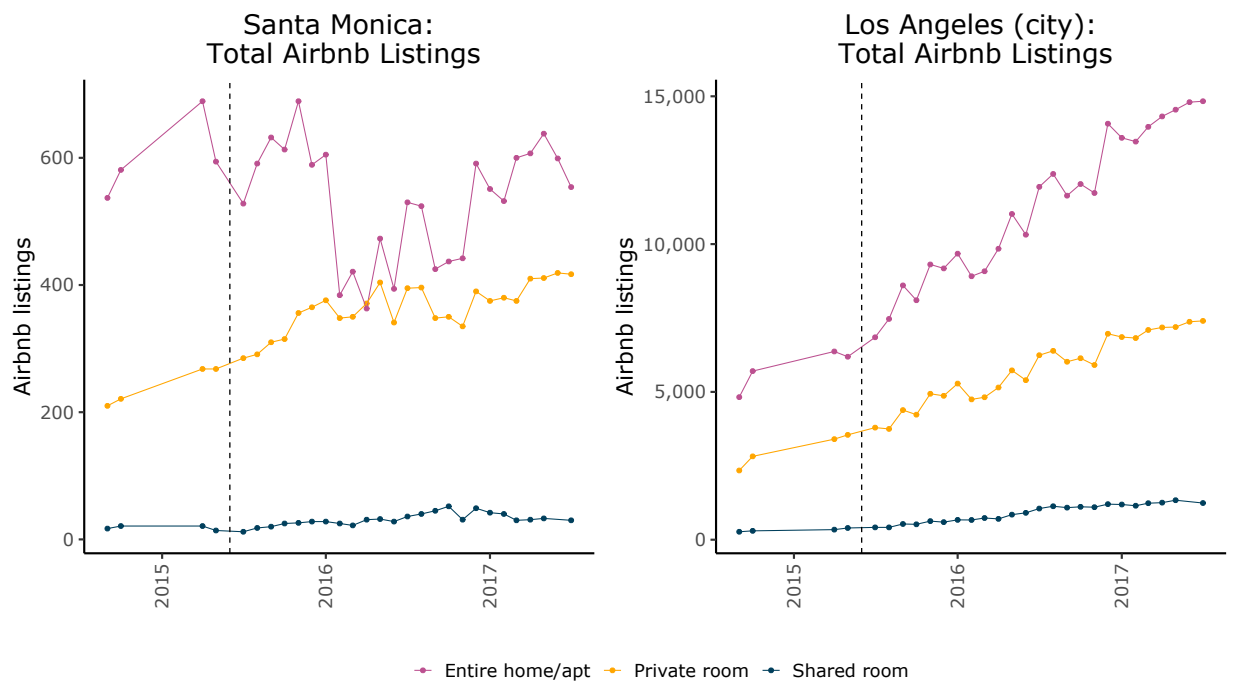
Notes: Each point on each graph represents a separate web scrape of Airbnb's listings for that city. Web scrape data was obtained from insideairbnb.com and tomslee.net and harmonized. See Section 4 for details.

Let P_{jt} be the housing price (as measured by the ZHVI) for zip code j at time t. We estimate the parameters of

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

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 for area code and year.

The parameter β_3 is identified if the pre-treatment differences in the outcome variable are the same (parallel pre-trends), and if the treatment itself did not generate spillovers the affect the control groups (see, for example, Hansen et al., 2020). We note that Santa Monica rests at the western edge of LA County, and, per Table 2, the number of Airbnb listings within Santa Monica before the reform numbered approximately 1/16th of those in the City of Los Angeles. We thus conclude that it is unlikely that Santa Monica's reform affected the number of STRs in the City of Los Angeles (and thus could have affected LA house prices through the STR channel).[20]

To evaluate the parallel pre-trend assumption, we plot the difference between Santa Monica and Los Angeles in the average of the log of housing prices over time, where the average is taken over the zip codes that comprise each city, in Figure 3. We begin our analysis in 2012, the "trough" of housing prices in the region in the wake of the Great Recession. The difference is relatively constant for several years prior to the reform, but increases starting in mid-2014 (in levels, both cities were experiencing increases in housing prices at this time). As the reform was discussed for some time before enactment, we interpret much of this movement as a potential anticipation effect. In Appendix 7.8, we perform a

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[20]In Appendix Figure A.3 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, significant spillovers are not apparent.

placebo analysis as a falsification test.

Figure 3: Housing prices in Santa Monica and Los Angeles
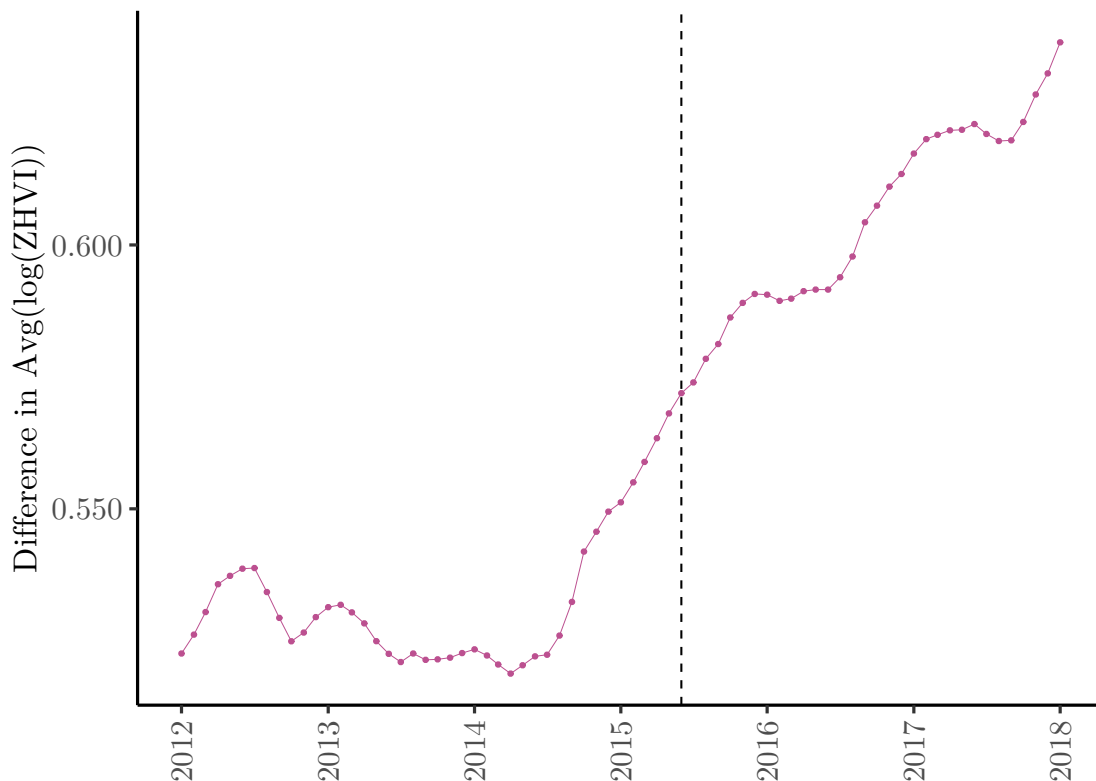
Notes: Data come from the Zillow House Value Index. Observations are the difference in the average log of housing prices between Santa Monica and Los Angeles, where the average is taken over the zip-code-month observations for each city. The date of the reform is shown by a vertical dashed line.

Table 5 reports estimates of Equation (6) using a bandwidth of 36 months to avoid the effects of the Great Recession.[21] In Column (1), we do not include fixed effects – in Column (2) we add area code fixed effects, and in Column (3) we add year fixed effects. The point estimates are statistically identical across all three specifications – we estimate that the reform increased housing prices in Santa Monica by 7.7% relative to a counterfactual of no reform. This estimate conforms to the estimates in the previous section; the reform decreased Airbnb listings in Santa Monica by approximately 15% which per Table 4 should generate an increase in housing prices of approximately 4%. In Appendix Figure A.7, we show our results

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[21]In an earlier draft of this paper, we used the optimal bandwidth technique of Imbens and Kalyanaraman (2011) to perform this analysis, which suggested a longer bandwidth overlapping the Great Recession.

are largely robust to alternative bandwidth selection techniques in the literature. Though power is reduced, we can still conclude that the policy did not likely *reduce* housing prices.

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

	(1)	(2)	(3)
Santa Monica × post reform	0.077**	0.077**	0.077**
	(0.035)	(0.035)	(0.033)
R^2	0.179	0.283	0.328
Area FEs?	No	Yes	Yes
Year FEs?	No	No	Yes
Num. obs.	7690	7690	7690

Notes: This table reports estimates of Equation (6) using a bandwidth of 36 months (see text for details). An observation is a zip-code-month. The dependent variable is the log of the Zillow Home Value Index. Heteroskedastic-robust standard errors are in parentheses. Stars indicate p values: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

6.1 Exploring negative externalities in the form of police calls

Our framework suggests that the results in the previous sector are driven by negative externalities generated by STRs. To evaluate this mechanism, 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 police calls $calls_t$ at time t (where $t = 0$ for the month 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 using the raw data as well as the estimates for Equation (7) when fixed effects are included. Table 7 reports the corresponding parameter estimates. Given the delay in enforcement mentioned in Section 2 and the fact that existing

reservations were largely honored, it is perhaps unsurprising that there is no immediate discontinuity in police calls at the time the policy is enacted. However, post-reform, calls trend consistently downwards. This effect is weaker, although more precisely estimated, when fixed effects are included. In Appendix 7.9 we explore the different types of police calls comprising our "party-related" categorization and find the largest change in slope is for police calls about public intoxication. This trend persists for more than two years after the policy was enacted, despite the eventual increase in listings seen in Figure 2. As discussed in Section 2, negotiations and legal maneuvers between Airbnb listers and the City of Santa Monica resulted in post-reform listings that were qualitatively different and may have been less likely to generate party-related police calls.

Figure 4: Event study of the effect of Santa Monica's STR regulation on party-related police calls
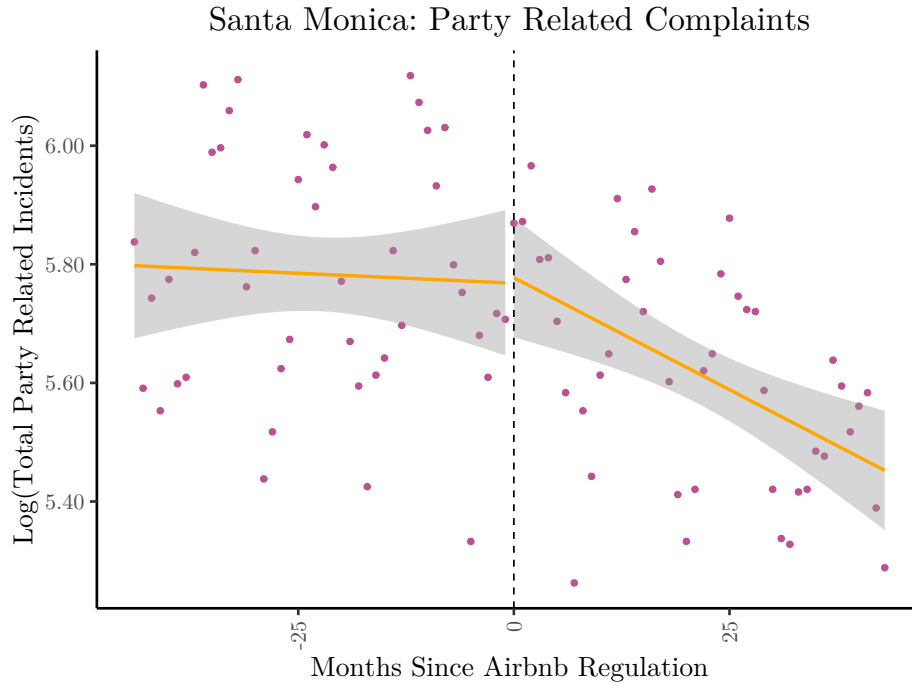
Notes: Observations are monthly totals. The lines indicate the estimate of Equation (7); the shaded area is the 95% confidence interval of the estimate.

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 short-term rental (STR) housing market has expanded over the past several years, jurisdictions around the world have struggled to respond to its presence. Several media reports have captured policymakers' concerns about the effect of STRs on long-term housing prices (e.g. Henley, 2019; Minder and Abdul, 2020). Other reports have focused on the deleterious effects of STRs on neighborhoods, particularly from the perspective 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 STR listings at the intensive margin can reduce housing prices. Our model makes a simple point: since STRs can have both positive and negative impacts on local amenities, the impact of STRs on housing prices is an ambiguous function of the *net* effect of STRs on amenities and therefore the effect of policies designed to curb STRs on housing prices is ambiguous as well. 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 of 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 the hypotheses stemming from our model: 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 policy calls over time.

Our results have broad implications for housing policy. Many policy makers have focused on type-of-use regulations on housing units to restrict or ban STRs. These restrictions are expected to reduce the option value of owning a housing unit and therefore to decrease housing prices. However, we show that such a policy may have the opposite effect. We provide a framework for thinking about why the effect might be positive or negative by separately considering the effect of STRs on positive and negative local amenities. In particular, the pattern of negative relationships between STR listings and housing prices may suggest that local policymakers may wish to focus their attention on STRs when short-term visitors are likely to spend their tourism dollars in other jurisdictions—bringing any negative externalities back to their temporary "home." This conclusion, however, is based on *ad hoc* examinations of tourism in the particular jurisdictions within LA County—an qualitative exercise which would be challenging to translate to a quantifiable form that is broadly applicable across geographies. We leave it to future work to systematically and separately quantify the effects that STRs have on positive and negative amenities across jurisidictions.

These results also point to the importance of taking into account possible 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 tend to increase 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,

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2014), and Fiverr (Hannák et al., 2017). Furthermore, the provisions of the Communications Decency Act imply that these platforms have the potential to 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 may generate imply that regulations may have unintended consequences (Cunningham et al., 2019). In the case of Airbnb and other short-term housing rental platforms, our results suggest that while federal policy may help ensure more uniform treatment for consumers, local decision-makers may be best-suited to set local policy for residents.

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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 $\phi_{j'} = \sum_{j' \neq j} \left(\exp(-P^{\star}_{j'} + \frac{R_{j'}}{1-\delta}) + \exp(\xi_j) \right)$. Using the market clearing condition we can write:

$$\left(\frac{\exp(\bar{u}_{j,a})}{1 + \sum_{j'} \sum_{k'} \exp(\bar{u}_{j',k'})} + \frac{\exp(\bar{u}_{j,o})}{1 + \sum_{j'} \sum_{k'} \exp(\bar{u}_{j',k'})} \right) N = H_j$$

$$\left(\frac{\exp(-P^{\star}_j + \frac{R_j}{1-\delta}) + \exp(\xi_j - P^{\star}_j)}{1 + \sum_{j'} \exp(-P^{\star}_{j'} + \frac{R_{j'}}{1-\delta}) + \sum_{j'} \exp(\xi_j - P^{\star}_{j'}))} \right) N = H_j$$

$$\left(\frac{\exp(-P^{\star}_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j))}{1 + \exp(-P^{\star}_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j)) + \phi_{j'}} \right) N = H_j$$

$$\exp(-P^{\star}_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j)) N = (1 + \exp(-P^{\star}_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j)) + \phi_{j'}) H_j$$

$$\exp(-P^{\star}_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j)) N - H_j \exp(-P^{\star}_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j)) = (1 + \phi_{j'}) H_j$$

$$\exp(-P^{\star}_j)(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j))(N - H_j) = (1 + \phi_{j'}) H_j$$

$$\exp(-P^{\star}_j) = \frac{(1 + \phi_{j'}) H_j}{(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j))(N - H_j)}$$

$$P^{\star}_j = -\log \left(\frac{(1 + \phi_{j'}) H_j}{(\exp(\frac{R_j}{1-\delta}) + \exp(\xi_j))(N - H_j)} \right)$$

7.2 Maps

In this section, we provide two maps to assist readers who may not be familiar with LA County. Figure A.1 illustrates the 88 incorporated cities in Los Angeles County. We highlight those which are displayed in Tables 1 and 4. Figure A.1 provides an overview of the area codes used as fixed effects and their intersection with cities in Los Angeles County.

Figure A.1: The cities of LA County
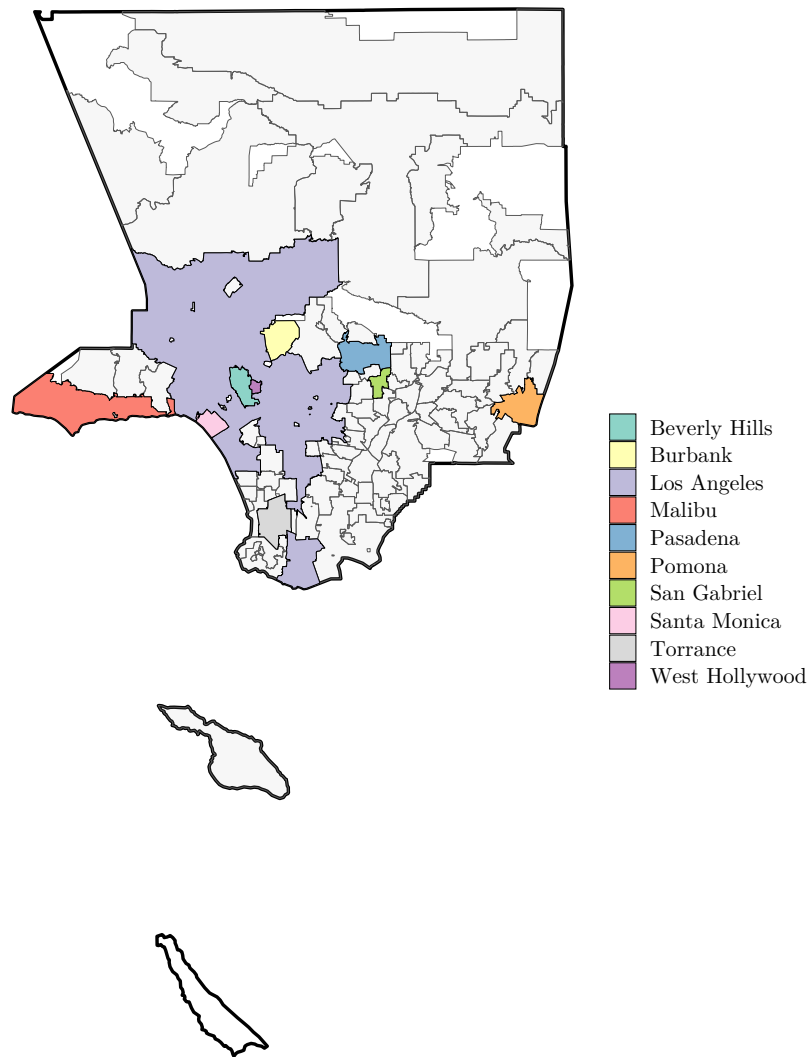
This figure depicts incorporated city boundaries in LA County. The highlighted cities are those displayed in Table 4. White areas within the county borders are unincorporated.

Figure A.2: The area codes of LA County

Area Codes   Cities   County
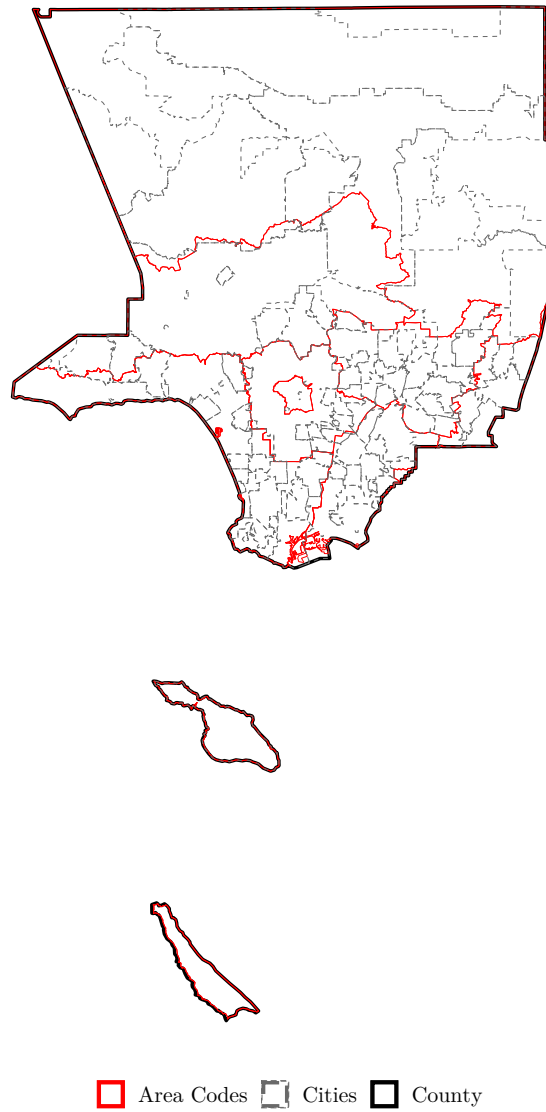
This figure overlays area codes on the city boundaries of LA county.

7.3   Sample Construction Details

In this section, we detail our sample construction procedure. Observations of house prices begin in 1196 and observations of police calls begin in 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 the optimal bandwidth technique of (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 to assemble the most comprehensive data possible. Each dataset contains a `room id` and `scrape date` variables. The room id variable is specific to an individually listed *room*.[22] After merging the Tomslee and Inside Airbnb data, we keep observations based on a unique `room id` and `year-month` pairing; which drops duplicate observations from both repeated scrapes within a month and observations that are shared by Tomslee and Inside Airbnb.

Both of our sources contain geo-coordinates of the listings. 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).

These coordinates are often listed with noise to maintain landlord privacy. Inside Airbnb notes that the noise-induced in these coordinates keeps the true coordinates within a 150m radius. Thus likely measure some listings in zip-codes adjacent to their true zip code. We

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[22]The Inside Airbnb data contains a few year-months with multiple scrapes – such as November of 2019. Since we ultimately care about the number of listings at the zip-code year month level, we keep one `room id` per `year month`.

interpret this as adding classical measurement error to our sample, thus attenuating our estimates towards zero. However, for this reason (as well as the policy change in Santa Monica), it is possible that we may observe some spillovers between adjacent zip codes. In Figure A.3, we plot the number of Airbnb listings each month for zip codes immediately adjacent to Santa Monica. This graph follows the pattern displayed by the City of Los Angeles closely—and does not follow the pattern observed in Santa Monica—indicating that policy- or measurement-error-based spillovers are unlikely.

Figure A.3: Airbnb Listings in zip codes adjacent to Santa Monica
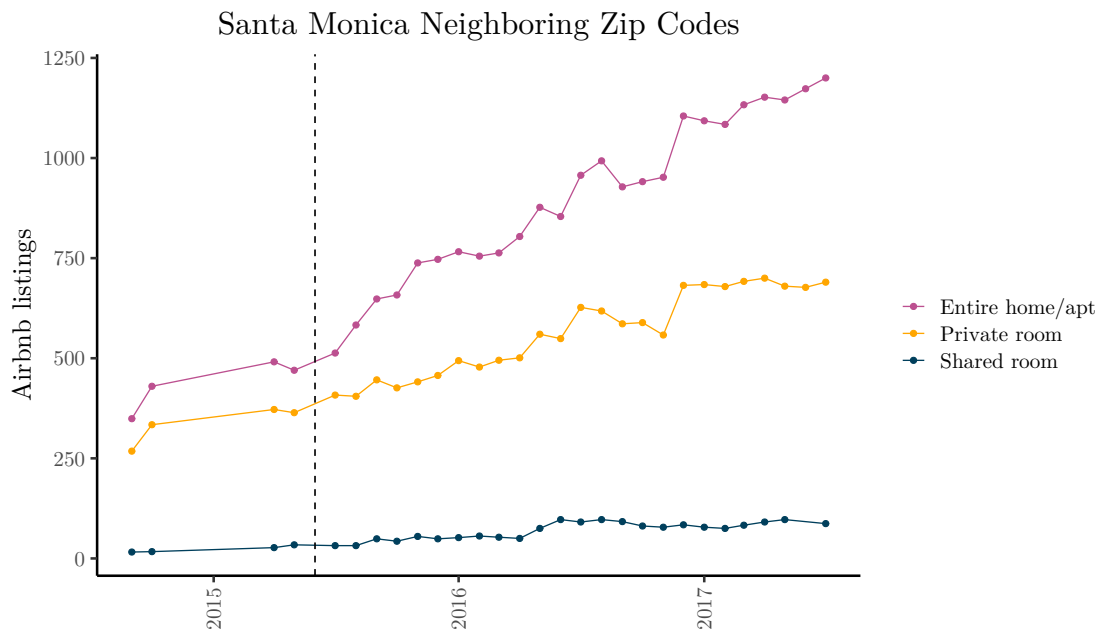
Notes: Each point on each graph represents a separate web scrape of Airbnb's listings for that city. Web scrape data was obtained from insideairbnb.com and tomslee.net and harmonized.

7.4 Instrument Details

When estimating Equation (5), we instrument for the number of Airbnb listings by inter-acting 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 A.4

displays Google Trends data at the monthly level from 2010 through 2019. Figure A.5 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 A.1 reports first-stage estimates. Our instrument enters positively and significantly.

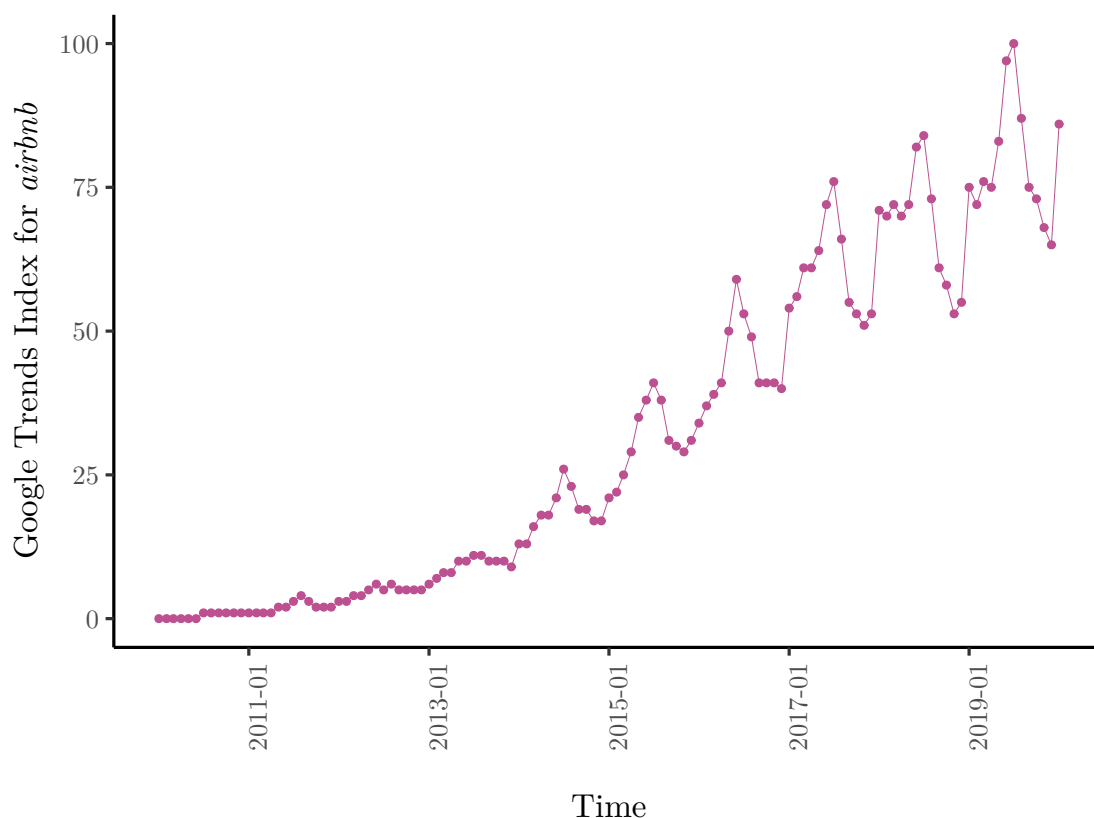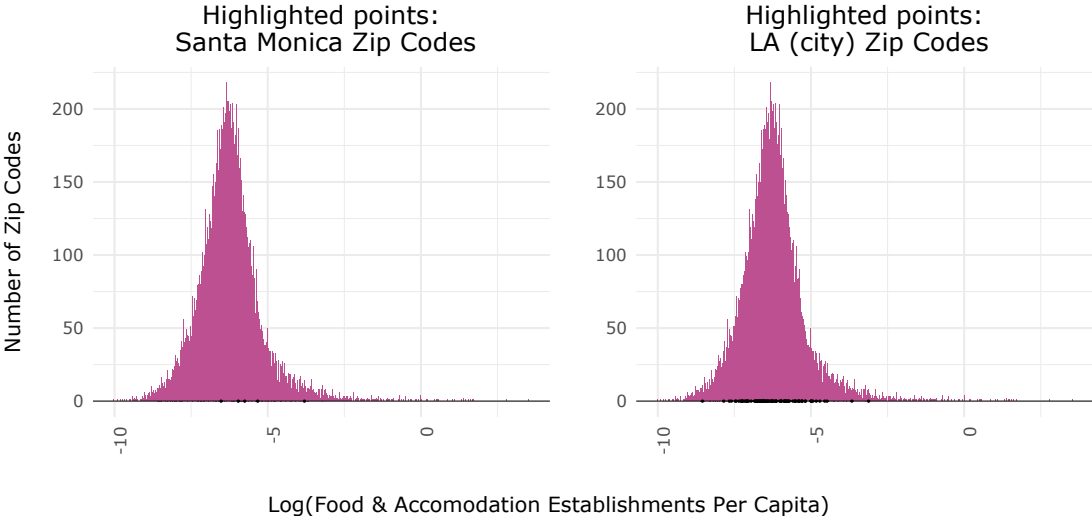**Figure A.4: Google Trends data used in instrument construction**

Figure A.5: Restaurant data used in instrument construction

Notes: These figures illustrate the distribution of zip codes in the U.S. according to the log of the per-capita number of food and accomodation establishments in 2010 (as defined by NAICS 72). Dots on the horizontal axis indicate zip codes for the cities in question.

Table A.1: First-stage instrument results

	log(listings)
log(z)	0.770***
	(0.029)
R²	0.648
Num. obs.	6125

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. Additional parameters of Equation (5) are included, but not reported for space. Stars indicate p values: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

7.5 IV results for all cities

**Table A.2: 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	0.0633*** (0.0165)	Duarte	0.0893*** (0.0165)	Lawndale	0.1376*** (0.0182)	San Fernando	0.1161*** (0.0178)
Alhambra	0.037*** (0.0102)	East Los Angeles	0.0614*** (0.0088)	Lomita	0.0979*** (0.0171)	San Gabriel	-0.1228*** (0.0093)
Altadena	0.1122*** (0.0176)	El Monte	0.0988*** (0.0175)	Long Beach	0.1278*** (0.0274)	San Marino	0.2957*** (0.0259)
Arcadia	0.1331*** (0.0217)	El Segundo	0.176*** (0.0207)	Los Angeles	0.2261*** (0.0156)	Santa Fe Springs	0.0921*** (0.0169)
Artesia	0.1112*** (0.0176)	Florence-Graham	0.1619*** (0.0186)	Lynwood	0.1298*** (0.0179)	Santa Monica	-0.2661*** (0.0369)
Avalon	0.0271* (0.0156)	Gardena	0.0332* (0.0187)	Malibu	0.1885*** (0.0205)	Sierra Madre	0.0834*** (0.0168)
Azusa	0.1014*** (0.0164)	Glendale	-0.0736*** (0.0087)	Manhattan Beach	0.2647*** (0.0261)	Signal Hill	0.0751*** (0.0171)
Baldwin Park	0.1099*** (0.0176)	Glendora	-0.1538*** (0.014)	Maywood	0.1206*** (0.0179)	South El Monte	0.0986*** (0.0172)
Bell	0.118*** (0.0179)	Hacienda Heights	0.0639*** (0.0165)	Monrovia	0.0747*** (0.0168)	South Gate	0.1241*** (0.0178)
Bellflower	0.1132*** (0.0172)	Hawaiian Gardens	0.1629*** (0.0203)	Montebello	0.1032*** (0.0171)	South Pasadena	0.2391*** (0.0236)
Beverly Hills	0.6913*** (0.0543)	Hawthorne	0.1334*** (0.0181)	Norwalk	0.1072*** (0.0172)	Temple City	0.0723*** (0.0164)
Burbank	-0.1103*** (0.0168)	Hermosa Beach	0.2269*** (0.0243)	Palos Verdes Estates	0.137*** (0.018)	Topanga	0.1057*** (0.0167)
Calabasas	0.0571*** (0.0168)	Huntington Park	0.1286*** (0.0179)	Paramount	0.1294*** (0.0185)	Torrance	0.1881*** (0.0192)
Carson	0.0684** (0.0284)	Inglewood	-0.009 (0.0117)	Pasadena	0.1108*** (0.0322)	West Carson	0.1313*** (0.018)
Cerritos	0.0552*** (0.0161)	La Canada Flintridge	0.2357*** (0.0229)	Pico Rivera	0.1131*** (0.0172)	West Covina	0.071*** (0.0252)
Commerce	0.113*** (0.0172)	La Crescenta-Montrose	0.1082*** (0.0175)	Pomona	0.0914*** (0.0148)	West Hollywood	0.1549*** (0.0198)
Compton	0.054*** (0.0058)	La Puente	0.1009*** (0.0173)	Rancho Palos Verdes	0.0781*** (0.0165)	West Puente Valley	0.1031*** (0.0172)
Covina	-0.0314 (0.0224)	La Verne	0.0589*** (0.0161)	Redondo Beach	0.2175*** (0.0187)	Whittier	0.0421*** (0.0163)
Culver City	0.1761*** (0.0535)	Ladera Heights	0.1292*** (0.0195)	Rosemead	0.0957*** (0.0167)		
Downey	0.0818*** (0.0252)	Lakewood	0.0919*** (0.0101)	Rowland Heights	0.0563*** (0.0165)		

Year FE	Yes
Area code FE	Yes
R²	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: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

7.6 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 A.6: Comparing standard errors under alternative clustering
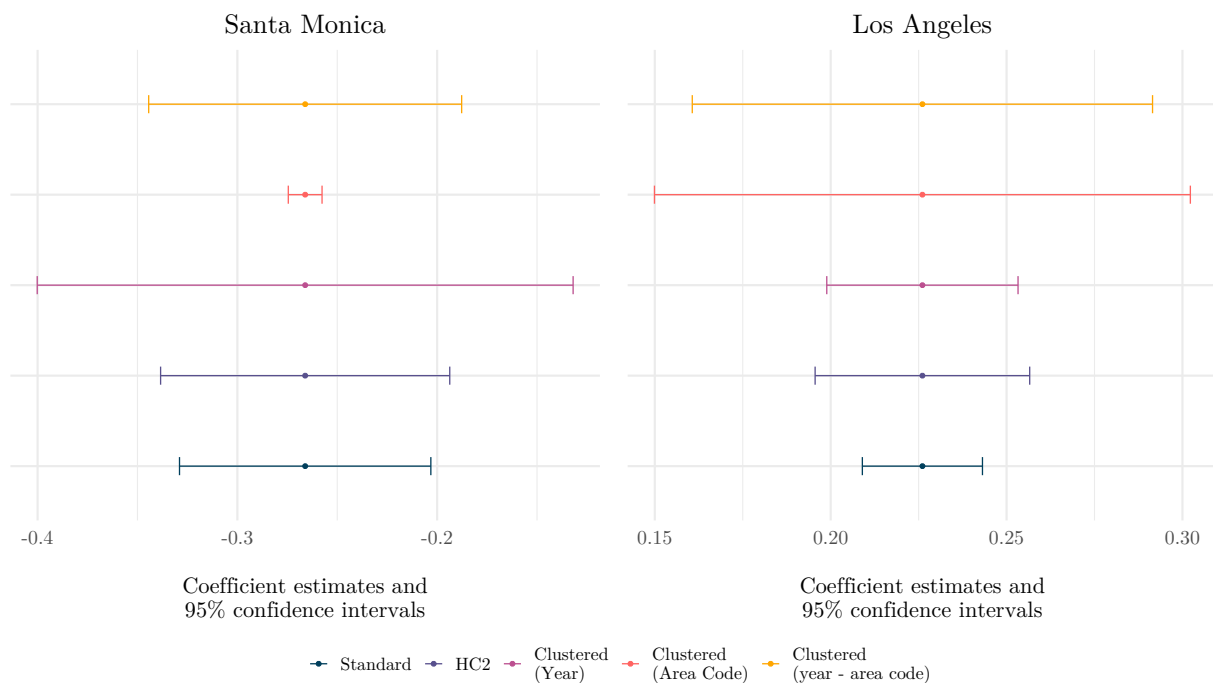
7.7 Santa Monica's STR Regulation: Other Optimal Bandwidth Techniques

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 a window of 36 months to avoid the influence of the Great Recession on housing prices. Here, we explore using the methods of Calonico et al. (2014), Ludwig and Miller (2007), and Imbens and Kalyanaraman (2011). The coefficient estimates are presented in Figure A.7 along with 95% confidence intervals. Note that using the selection method of CCT and CV, 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 A.7: Alternative bandwidth techniques

Difference-in-Difference Estimates
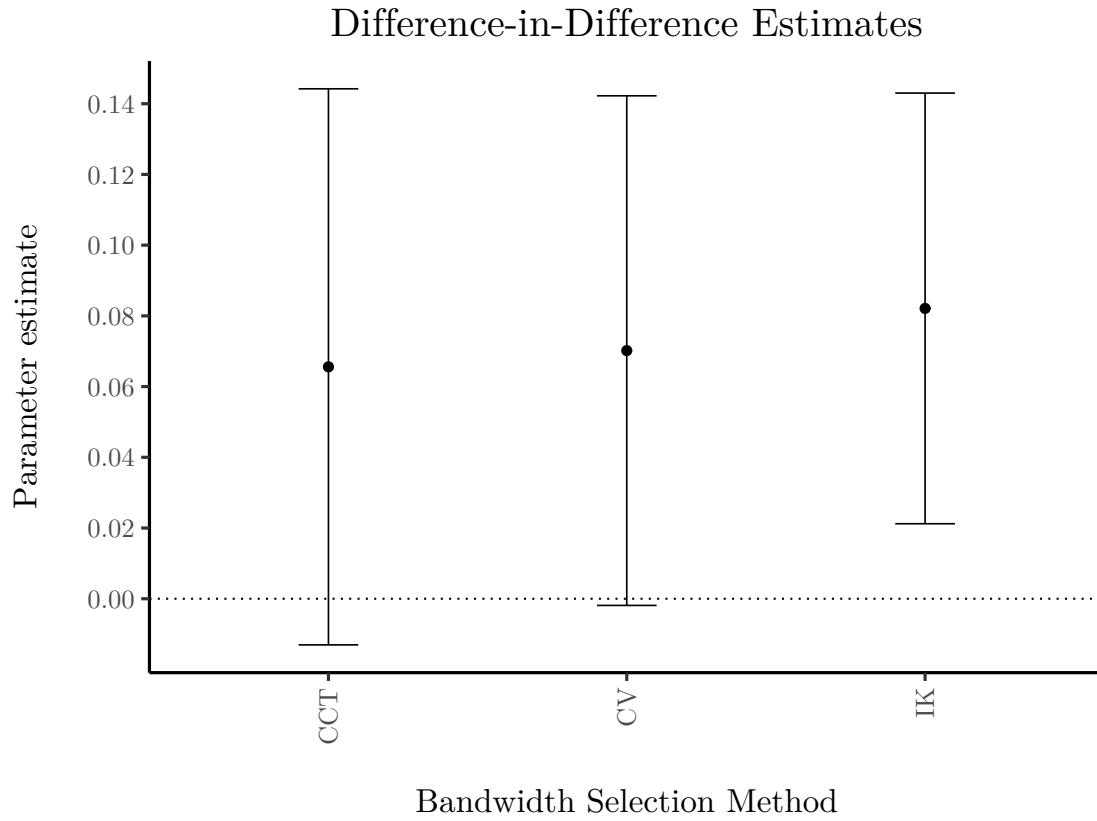
Notes: This figure illustrates point estimates and 95% confidence intervals for estimates of the effect of Santa Monica's STR regulation on housing prices per Equation (6) using different bandwidth selection techniques. CCT refers to Calonico et al. (2014), CV refers to Ludwig and Miller (2007), and IK refers to Imbens and Kalyanaraman (2011).

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 A.3. We do not find evidence that the placebo date policy had any impact on housing prices. We report the exercise for estimates of Equation (7) and report the results in Table A.4. Again, we do not find any evidence that the placebo policy had any effect on police calls in Santa Monica.

Table A.3: Placebo test for 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 A.4: Placebo test for 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 $\times$ 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 Police Call Results

In this section we explore underlying heterogeneity that drives the fall in police calls for party-related complaints that we estimate in Section 6. We examine three specific complaints: party complaints, noise complaints, and public intoxication complatints. We estimate the same RDD specifications as in Table 6 for each call type separately. The results are reported in Table A.5. We illustrate these estimates with the raw data in Figures A.8, A.9, and A.10, analogously to Figure 4.

Table A.5: 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.

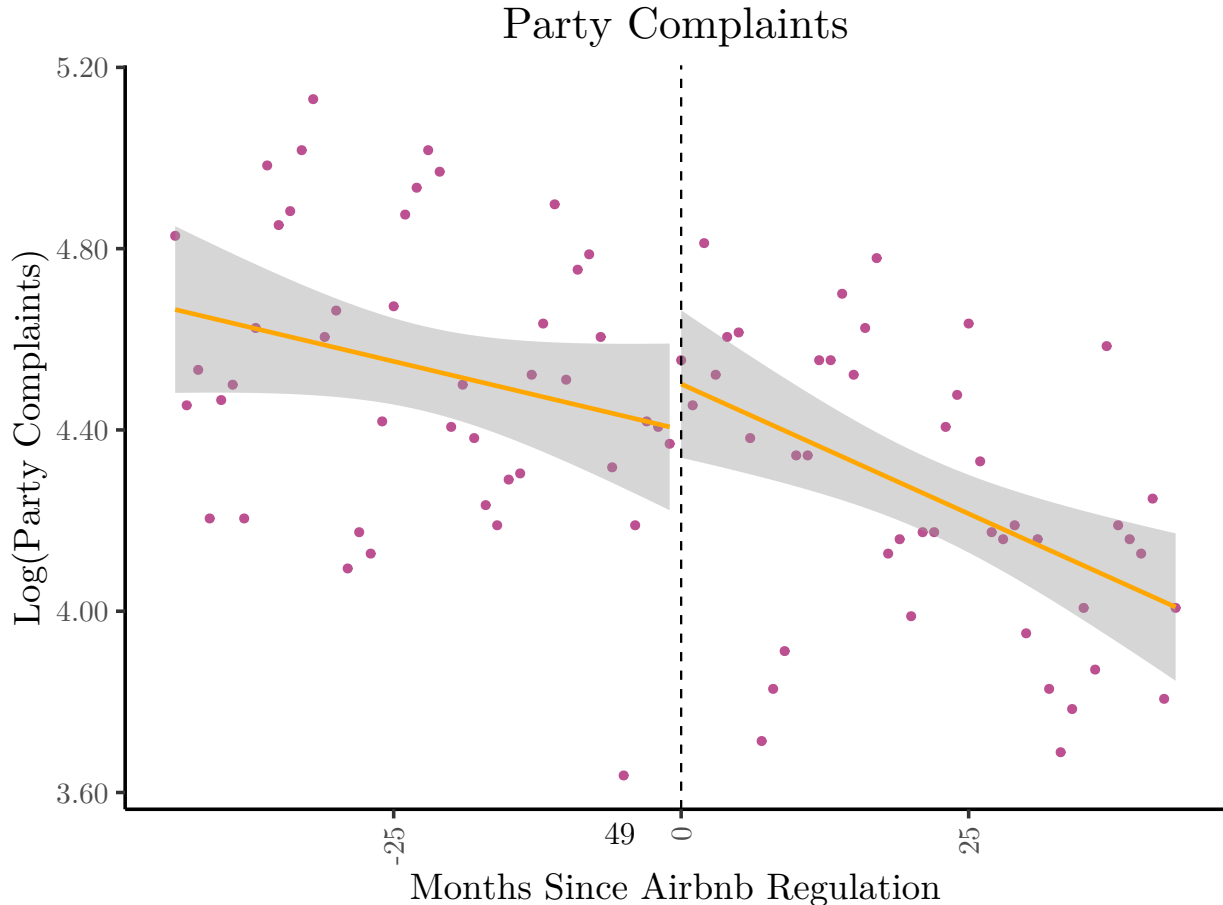**Figure A.8: Event study for party complaint incidents in Santa Monica**

Party Complaints

Figure A.9: Event study for loud music incidents in Santa Monica
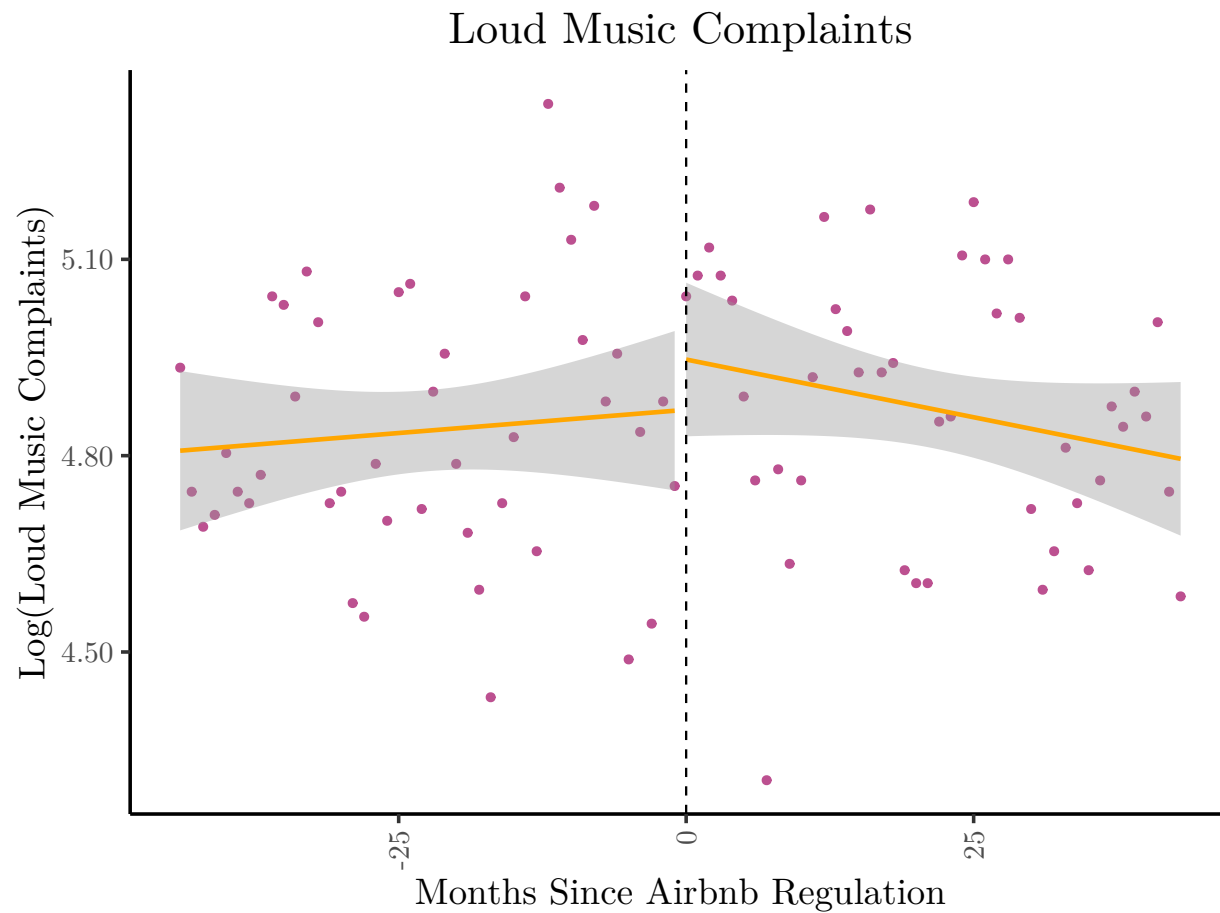
Loud Music Complaints

Figure A.10: Event study for public intoxication incidents in Santa Monica.

Public Intoxication
Incidents