What is the Cost of Homeless Encampments to a City's Residents? Evidence from Los Angeles

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Abstract

This paper studies the impact of homeless encampments on residential property values with a novel procedure that infers the presence of encampments using citizen-made complaints about them. I find that 58% of residential properties transacted in Los Angeles between March 2016 and August 2022 had homeless encampments within 0.3 miles and sold on average for 3.14% less than they otherwise would have, a total realized loss of over $2.5 billion across more than 70,000 properties. I use the realized losses on property transactions to price the citywide externalities associated with homeless encampments at $32.4 billion, more than double the projected cost of housing all 31,000 people living on the streets of Los Angeles. Pricing the externalities from homeless encampments leads to a more thorough accounting of the costs associated with homelessness, not just for those experiencing it, but for all residents of cities that struggle to contain it.

1 Introduction

Homelessness imposes substantial costs both on those experiencing it and on governments providing supportive social services for it. The latter is tracked closely by cities and states and the former has been well-documented in sociological studies (Meanwell (2012), Kushel and Moore (2023), Mabhala et al. (2017)). Yet there is another cost, overlooked and understudied, that arises when homelessness leads to the proliferation of encampments: collections of tents and other makeshift shelters like cardboard boxes and tarps in public spaces not meant for permanent dwelling. The negative externalities from homeless encampments—increases in trash, debris and human waste; visible drug use (Smith (2023)) and mental breakdowns (Dembosky et al. (2023)); antisocial and criminal behavior including harassment, theft, vandalism, sexual assault and murder (Grover (2023), Manthey (2020), Mutasa (2022))—are substantial, but have never been priced due to data limitations. This paper makes the first such attempt using unique data from Los Angeles that tracks homeless encampments. I observe how their presence gets capitalized into the sale price of nearby residential properties and use that information to extrapolate the citywide cost of the externalities from homeless encampments.

Despite the homelessness crisis in Los Angeles and many otherwise economically prosperous American cities, good measurements on this subpopulation are lacking. The American Housing Survey (AHS) only yields responses from housing units, completely missing the unhoused. The American Community Survey (ACS) and Current Population Survey (CPS) do collect information from the unhoused but only from the sheltered homeless population (Meyer et al. (2022)): those residing in temporary supportive housing in homeless shelters or hotel/motel rooms. The ACS and CPS do not survey the unsheltered homeless population—those in the tents and makeshift shelters that form homeless encampments as well as those sleeping in their car, van, or camper. The only consistent data on the unsheltered population comes from the Department of Housing and Urban Development's

Point-in-Time (PIT) Count, an annual tally of the number of sheltered and unsheltered homeless done by thousands of individuals canvassing cities all over America.[1] The PIT Count provides the best available data on the unsheltered homeless population,[2] but there are two inhibiting factors that preclude its use in measuring how the presence of homeless encampments gets capitalized into property values. The first is that the enumeration of the homeless population happens over just one night in January each year.[3] Since would-be buyers of a property are continuously updating their information sets of neighborhood characteristics that influence property values (Bayer et al. (2021)) and since the location and number of homeless encampments is not fixed, it would be difficult, ex ante, to justify using data collected in January to assess the impact on properties sold in the Fall. The second concern is that census tracts are the most granular geographic level at which the PIT Count is publicly available, obscuring the distance from any one property to the nearest homeless encampment.[4]

I correct for the temporal and spatial gaps in the PIT Count with a unique set of data: geotagged, time-stamped citizen-made complaints about homeless encampments in Los Angeles. I compare the number of complaints to the enumerated homeless population in the PIT Count and show that complaints broadly track the presence of the tents and makeshift shelters that comprise homeless encampments. Cardinally, I show that one additional complaint approximately corresponds to two additional tents and/or makeshift shelters.

I then use a spatial hedonic property price model to assess how complaints of homeless

[1] The decennial Census also counts the unsheltered homeless population but only every ten years.

[2] I should note that 75% of homelessness scholars raised concerns about the accuracy of the PIT in a survey from the Government Accountability Office (GAO (2020)). The doubts stem from studies like Hopper et al. (2008) where researchers placed individuals dressed as homeless persons around New York City on the night of the PIT Count and 29% of them reported not being counted. Despite these issues though, the PIT Count is still the most widely used data set for scholars studying the unsheltered homeless population.

[3] For large cities/counties like Los Angeles, it can take two or three nights to complete the count.

[4] The Los Angeles Homeless Services Authority has the latitude and longitude for each homeless individual counted in the LA PIT in the year 2022, but in no years prior to that.

encampments affect sale prices. Although the capitalization of homeless encampments into residential properties has not been studied before, this empirical approach fits squarely within the large literature examining the effects of local (dis)amenities on property prices. On crime, Bayer et al. (2021), Boggess et al. (2013), Cigdem-Bayram and Prentice (2018), Tita et al. (2006), and Ihlanfeldt and Mayock (2010) use spatial hedonic property price models to show that violent crime, but not property crime, is capitalized into sale price. On the perceived threat of future criminal malfeasance, Linden and Rockoff (2008), Pope (2008), and Caudill et al. (2015) show that the presence of a sex offender in the neighborhood causes losses of up to 2-4% for properties up to one mile away. On pollution, Chay and Greenstone (2005) and Currie et al. (2015) find that declines in air quality are negatively capitalized into property values. And on the positive side of the ledger, Figlio and Lucas (2004) and Black (1999) use border discontinuity models to show that neighborhood school quality is positively capitalized into one's property value.

The disamenity I study in this paper, the presence of a homeless encampment, causes a 3.14% loss in value for the average treated property—those with at least one complaint within 0.3 miles. The marginal effect on property values per complaint is non-linear: -2.28% within 0.1 miles and -1.57% within 0.1-0.3 miles for the first complaint, -0.28% (-0.11%) for each of the next 24 complaints within 0.1 (0.1-0.3) miles, and insignificant beyond that. 58% of residential properties that transacted between March 2016 and August 2022 were treated and endured a collective $2.52 billion in realized losses. Extrapolating that 58% of the roughly 1.5 million residential properties citywide were treated between March 2016 and August 2022, I price the total cost of the externalities associated with homeless encampments at over $32 billion, more than double the city's annual budget and the projected cost to construct enough shelter beds to house all of the city's 31,000 unsheltered homeless individuals. That widespread homeless encampments are a problem is undisputed among elected leaders and residents of Los Angeles, but this paper affirms that the costs are quite large and elucidates the exigency of policy intervention to mitigate this harm.

2 Background and Setting

Los Angeles is an ideal setting to assess the externalities of homeless encampments for two reasons. First, it has the largest population of unsheltered homeless individuals nationwide—one that has more than doubled between 2013 and 2023. Preferably, the city would find temporary supportive housing for its unhoused residents, but the *entire county* of Los Angeles has only around 26,000 emergency shelter beds for its 75,000 unhoused persons. The inadequate supply of shelter beds has led to a proliferation of homeless encampments across sidewalks, underpasses, and public parks all over the city.[5] And much to the chagrin of residents unlucky enough to be near an encampment, there is Supreme Court precedent precluding city officials from forcibly removing unsheltered populations from their place of temporary residence in public spaces without providing temporary supportive housing. This legal precedent creates the second reason Los Angeles is a good setting for my research question: homeless encampments persist in the same place for long periods of time, increasing the likelihood that their presence will be capitalized into a nearby property's value.[6] To successfully remove an encampment, law enforcement must coordinate with non-profits to secure available shelter beds, offer those beds to members of an encampment, and then conduct the removal of the encampment's members who refuse them, a process that can take months.[7] The relative persistence of homeless

[5] The problem is bad enough that homelessness was the number one issue on voters' minds during the citywide elections in 2022 (Littlejohn (2022) & Baldassare et al. (2023)).

[6] This fact may partially mitigate the concern about using the PIT Count taken in January to assess impacts on price for properties transacting in the Fall, but only partially since homeless encampments do occasionally get removed by law enforcement and move for other idiosyncratic reasons throughout the year.

[7] KCRW, a NPR-affiliated radio station in Los Angeles, has a podcast called *City of Tents: Veteran's Row* that details the lengthy, logistically challenging process of removing one large homeless encamp-

encampments in one place is confirmed by Ward et al. (2023), who, between October 2021 and 2022, conducted a semi-monthly PIT-style count at three hot-spots for homeless encampments in Los Angeles. They find that the population of unsheltered individuals never substantially decreased at any location, but rather continued to grow concurrently with the problem of homelessness citywide.

Residents frustrated or worried about the presence of homeless encampments nearby can complain to the city about their existence. They can call City Hall, their local councilmember, the Bureau of Sanitation, or submit a request through the My311 app or website to notify the city of a homeless encampment.[8] Given its convenience, 82% of complaints about homeless encampments in Los Angeles are made through My311. All complaints made to the city are pinpointed with an address and latitude and longitude coordinates, and also include a time and date marker. Between 2016 and 2022, Los Angeles residents made 294,932 complaints about homeless encampments at 83,243 unique locations. Figure 1 shows the spatial distribution of these complaints: the darker the color, the higher the number of complaints. With the vast majority of non-mountainous land covered, complaints are not a problem for a select few "bad" areas in the city. Thousands of complaints were in close proximity to multi-million dollar homes and reported in wealthy neighborhoods like Brentwood, Woodland Hills, Granada Hills, West L.A. and Venice.

3 Data

It would be sublime if I could examine the total number of complaints made on the day of the PIT count to assess how well complaints predict the presence of homelessness in

ment in the upscale Brentwood neighborhood of Los Angeles. Seeing this encampment in November 2020 in a place I, a native Angeleno, never once thought I would see a homeless encampment gave me the idea for this paper.

8 My311 is an app available in most large cities across the country that residents can use to request a variety of city services such as street cleaning, pothole repairs, and new garbage bins. Some cities allow residents to use My311 to alert the them of the presence of a homeless encampment.

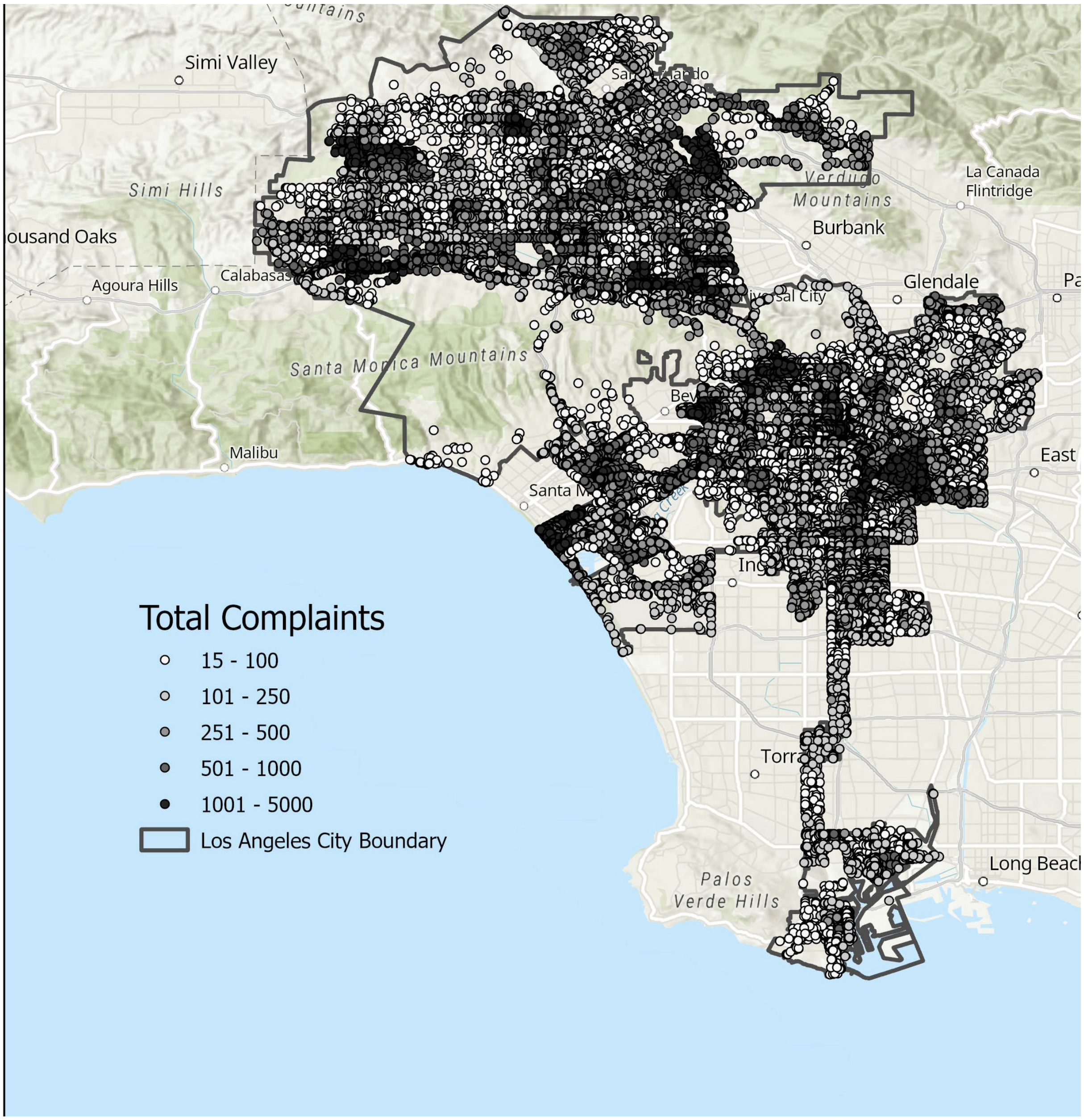

Figure 1: Each point on the map is one of over 80,000 unique locations with reports of homeless encampments. Total complaints is the number of complaints made between 2016 and 2022 in a given census tract.

a census tract. Unfortunately, the frequency of complaints is too low to use one day's worth to infer a relationship between complaints and the presence of homelessness. The highest number of complaints observed in any year is 60,247 in 2022, an average of 0.17 per census tract per day. Therefore, I count the total complaints in a census tract over a window of time t centered around the day of the PIT Count ($d = 0$) in year y:

$$Complaints_{cty} = \sum_{d=-t/2}^{t/2} Complaints_{dcy} \tag{1}$$

where $Complaints_{cty}$ is number of complaints in census tract c over time frame t in year y. I set $t = 60$ so $Complaints_{cty}$ is counting the number of complaints thirty days before and after the PIT Count in year y.[9]

Ex ante, the number of complaints in a census tract should primarily be driven by the number of unsheltered homeless individuals. Sheltered individuals, out of sight for most residents, should have a negligible impact on the number of complaints. The following equation tests this hypothesis:

$$Complaints_{cty} = \beta_0 + \omega_c + \delta_y + \beta_1 Sheltered_{cy} + \beta_2 Unsheltered_{cy} + \epsilon_c. \tag{2}$$

where ω_c is a census tract fixed effect, δ_y is a year fixed effect, $Sheltered_{cy}$ ($Unsheltered_{cy}$) is the total number of sheltered (unsheltered) persons in census tract c counted in the PIT in year y. Standard errors are clustered at the census tract level. The census tracts that comprise Skid Row and its immediate surroundings are excluded from the analysis.[10] Table 1 shows the results from Equation 2. Columns 1 and 3 in Table 1 show that the

[9] As Table 8 in Appendix A.1 shows, the relationship between complaints and the PIT count is not sensitive to the choice of t.

[10] Skid Row is a permanent encampment in Downtown Los Angeles that has thousands of people living on the streets at all times. Including these census tracts could distort the relationship between complaints and homelessness because relatively few people (other than the unhoused) live in that area.

Table 1: The Components of the PIT Driving Complaints

	Dependent Variable: Complaints				
	(1)	(2)	(3)	(4)	(5)
Sheltered	-0.004	-	-0.005	-	-
	(0.003)		(0.003)		
Unsheltered	-	0.065**	0.065**	-	-
		(0.01)	(0.01)		
Tents	-	-	-	0.44**	-
				(0.11)	
Makeshift Shelters	-	-	-	0.15*	-
				(0.07)	
Tents & MS	-	-	-	-	**0.29****
					(0.06)
Cars	-	-	-	-0.13	-0.13
				(0.08)	(0.08)
Vans	-	-	-	0.06	0.06
				(0.09)	(0.09)
Campers	-	-	-	0.06	0.05
				(0.05)	(0.05)
Observations	5,964	5,964	5,964	5,964	5,964

Notes: Complaints counted 30 days before and after the PIT count in late January. Data comes from 994 census tracts in the city of L.A. No PIT count in 2021. 2022 PIT count took place in late February 2022 instead of January due to concerns over the omicron variant. Standard errors are clustered the census tract level.
* Significance at 5% level
** Significance at 1% level

sheltered population, unconditional or conditional on the unsheltered population, has no effect on complaints. Columns 2 and 3 show that within a census tract, an additional unsheltered individual is associated with an additional 0.065 complaints, conditional or unconditional on the sheltered population. The point estimates for the unsheltered population in Columns 2 and 3 though are masking substantial heterogeneity. Data from the PIT Count of the unsheltered population includes subcategories for the number of enumerated tents, makeshift shelters, campers (RVs), vans, and cars.[11] I separate out the subcategories of the unsheltered population and run the following regression:

$$\begin{aligned} Complaints_{cty} = \beta_0 + \omega_c + \delta_y + \beta_1 Tents_{cy} + \beta_2 MakeshiftShelters_{cy} \\ + \beta_3 Cars_{cy} + \beta_4 Vans_{cy} + \beta_5 Campers_{cy} + \epsilon_c \end{aligned} \tag{3}$$

Ex ante, those sleeping in cars and vans are unlikely to generate substantial complaints since they are not easily visible for residents. Campers can be eyesores and may engender complaints, but it is not always obvious that an RV parked on the street has someone living in it full-time. The primary catalysts of complaints should be the two subcategories that measure the components of homeless encampments: tents and makeshift shelters. Column 4 of Table 1 confirms thus supposition: each tent (makeshift shelter) is associated with an additional 0.44 (0.15) complaints while cars, vans and campers have no significant effect on complaints.

With Column 4 of Table 1 affirming that tents and makeshift shelters are the primary drivers of complaints, I combine them into one variable, $Tents$ & MS, and re-run Equation 3. The coefficient on $Tents$ & MS in Column 5 then allows for a rough cardinal relationship between complaints and tents/makeshift shelters. One additional tent and/or makeshift shelter is associated with 0.29 more complaints, which means one additional complaint is associated with $\approx$ 3 tents/makeshift shelters. But census tract-years with large observed numbers of tents and makeshift shelters in the PIT may be attenuating the coefficient on $Tents$ & MS if there is a threshold at which the marginal tent or makeshift shelter no longer generates more complaints. Figure 2 compares the enumerated tents and

[11] The category for the "completely unsheltered" (those with no kind of physical barrier between themselves and the elements) is not explicitly delineated in the breakdown of the unsheltered population in the PIT Count, but it is a very small group of people. A regression of the total unsheltered population on its five components shows that 95% of the variation in the total unsheltered population is explained by the five observable categories of the unsheltered population. When testing a model that uses the residuals from that regression as an estimate of the completely unsheltered, results in Table 1 do not change at all.

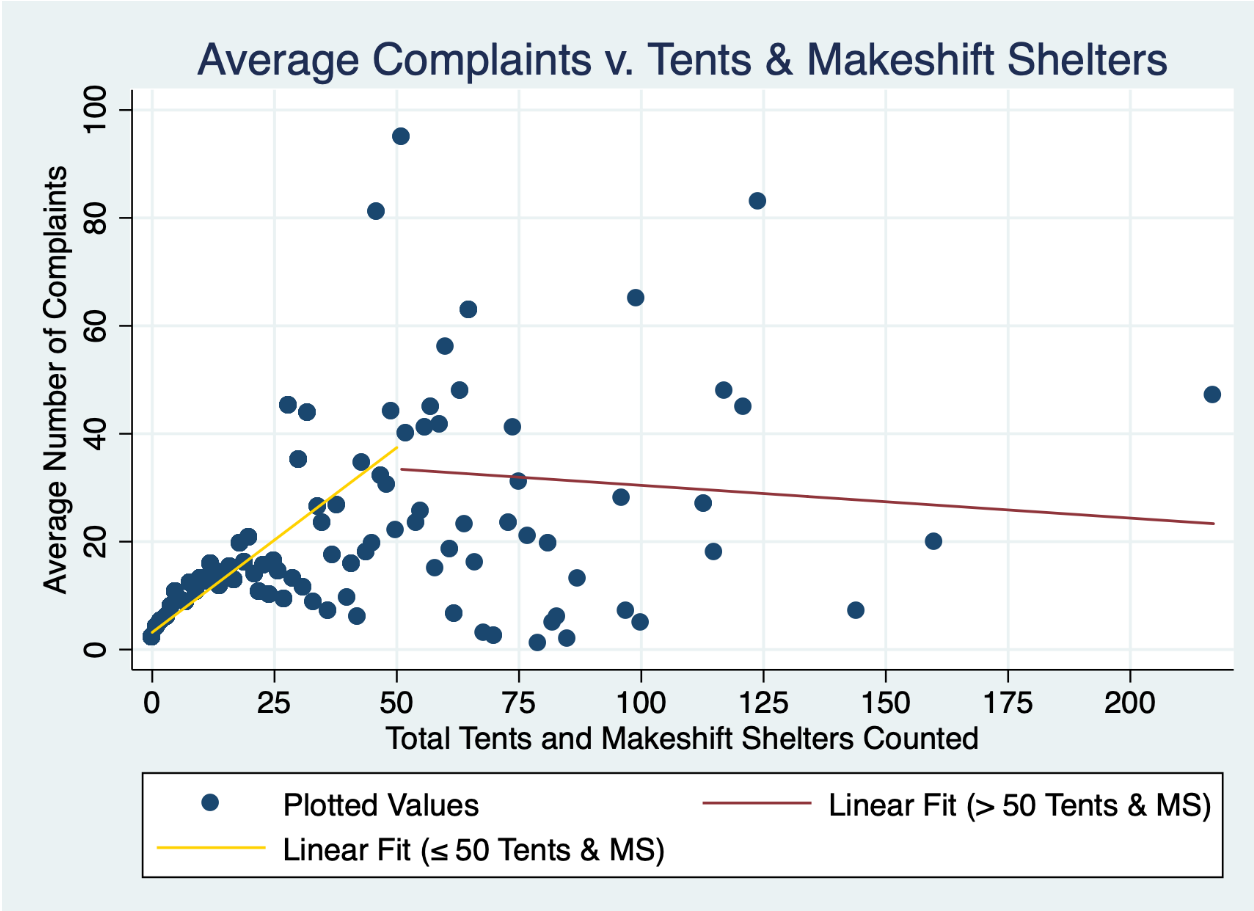

Figure 2: No relationship between the average number of complaints and $Tents\ \&\ MS$ beyond 50 tents and makeshift shelters

makeshift shelters in a census tract-year and the corresponding average number of complaints[12] in those census tract-years. The figure linearly fits the relationship between the the two variables using the top 1% of census tract-years by number of tents and makeshift shelters (50) as a point of delineation. While there is a clear positive relationship between complaints and $Tents\ \&\ MS$ when $Tents\ \&\ MS \leq 50$, there is no relationship when $Tents\ \&\ MS > 50$. Given the evidence shown in Figure 2, I run a spline regression with one knot ($K_1 = 50$) to tease out the differences in the marginal effect of an additional

[12] Again counted 30 days before and after the day of the PIT count

tent/makeshift shelter on complaints:

$$
\begin{aligned}
Complaints_{cty} = \beta_0 + \omega_c + \delta_y + \beta_1 \min[\, Tents\&MS_{cy},\ 50\,] \\
+\beta_2(Tents\&MS_{cy} - K_1)_+ + \beta_3 Cars_{cy} + \beta_4 Vans_{cy} + \beta_5 Campers_{cy} + \epsilon_c
\end{aligned} \tag{4}
$$

Table 2 presents the estimates for β_1 and β_2 and the results show that one additional tent/makeshift shelter is associated with an additional 0.48 complaints when $Tents$ & $MS \leq$ 50, but there is no significant relationship when $Tents$ & $MS > 50$. Therefore, the correct cardinal relationship between tents/makeshift shelters and complaints is one complaint-per-two tents/makeshift shelters up until the latter reaches fifty, beyond which the cardinal relationship disappears.[13]

Table 2: Marginal Effect of Tents/Makeshift Shelters on Complaints

	Dependent Variable: Complaints
	(1)
$Tents\&MS \leq 50$	**0.48****
	(0.08)
$Tents\&MS > 50$	-0.02
	(0.07)
Observations	5,964

Notes: Complaints counted 30 days before and after the PIT count in late January. Data comes from 994 census tracts in the city of L.A. No PIT count in 2021 due to the pandemic. Standard errors clustered at the census tract level.
* Significance at 5% level
** Significance at 1% level

3.1 Property Price Data

The data on property sales was purchased from the LA County Assessor's office. With complaints data only being publicly available starting in 2016, I restrict the sample to

[13] Appendix A.1 shows that the one-to-two relationship below fifty tents and makeshift shelters is robust when adding additional knots to Equation 4.

sales of residential properties in the city of Los Angeles starting in March 2016 and ending in August 2022.[14] Properties that sold in Skid Row are excluded for consistency. The data shows the sale price and all relevant physical characteristics of the property: number of bedrooms, bathrooms, square footage, age of the property, amenities (pool, tennis court, accessory dwelling unit, manicured lawn), structure type (single-family home, duplex, apartment building, etc.), quality of the structure (determined by the Los Angeles County Assessor's Office), and the presence of property tax delinquencies or exemptions. Any property missing any information on the aforementioned characteristics is excluded from the sample. In addition, only the most recent sale price for a given property is observable in this data set, so properties that transacted more than once between March 2016 and August 2022 are missing their price for all but the most recent sale. Overall, just over 30% of residential property transactions are excluded from this analysis because they do not have a corresponding sale price or are missing basic characteristic information, but the sample still contains 121,581 residential property sales. One final noteworthy aspect of this data is that I observe the day the property transfers ownership, which is not the same as the sale date. Properties enter into escrow upon sale and the typical length of time in escrow is around thirty days, but it can last up to sixty days. For all cash offers (16% of transactions in the LA metro area according to Katz (2021)), escrow can last as little as a week.[15]

Table 3 contains summary statistics on the observable characteristics for the properties, broken up by single-family homes and multi-unit properties (which includes everything from duplexes to high rise apartment buildings). 80% of multi-unit properties sold were

[14] Property sales start in March 2016 because the method to assess the presence of homeless encampments aggregates the number of complaints in the sixty days prior to when the property transfers ownership. Thus, properties sold in February 2016 can not be "fully" treated and they are excluded from the sample. The data was purchased in September 2022 which is why August 2022 is the end date.

[15] 16% is actually on the lower side compared to the whole country where 30% of all property sales were transacted in cash (Katz (2021)).

Table 3: Summary Statistics: Residential Properties

	(1)	(2)	(3)
Sale Price	\$1.19M	\$1.30M	\$1.02M
	(\$1.10M)	(\$1.11M)	(\$1.06M)
Bedrooms	3.36	3.25	3.53
	(3.06)	(1.02)	(4.78)
Bathrooms	2.80	2.47	3.33
	(3.02)	(1.28)	(4.54)
Square Feet	2,035	1,975	2,132
	(1,976)	(1,097)	(2,867)
Units	1.40	-	2.04
	(2.36)		(3.72)
Age (Years)	57.6	65.2	45.4
	(29.2)	(26.4)	(29.4)
Building Quality	7.03	6.90	7.23
	(1.58)	(1.56)	(1.57)
Complaints (≤ 0.1 *miles*)	0.74	0.38	1.31
	(4.11)	(2.63)	(5.69)
Complaints $(0.1 - 0.2$ *miles*$]$	2.56	1.57	4.15
	(9.85)	(7.82)	(12.3)
Complaints $(0.2 - 0.3$ *miles*$]$	4.66	3.12	7.15
	(14.4)	(12.8)	(16.5)
Complaints $(0.3 - 0.4$ *miles*$]$	6.52	4.70	9.44
	(16.7)	(14.2)	(19.7)
All Properties	✓	-	-
Single Family Homes	-	✓	-
Multi Unit Properties	-	-	✓
Observations	121,581	75,011	46,570

Notes: Multi-unit properties includes apartments/townhouses as well entire multi-unit complexes. Building Quality is on a scale from 1 to 14. Numbers presented for each variable are the mean with the standard deviation in parenthesis.

individual condos or apartment units and 20% were sales of an entire building of apartments or condos. The latter explains the larger average number of bedrooms, bathrooms, and square footage for multi-unit properties. Still, the average single-family home sold for nearly $300,000 more than the average apartment/multi-unit property. Complaints are measured up to 0.4 miles away from a residential property and counted in four 0.1 miles rings. Complaints are higher at every distance threshold for apartments and multi-unit buildings compared to single-family homes, a result of multi-unit housing being closer to arterial streets with more urban amenities (proximity to bars, restaurants, shops) and disamenities (crime, traffic, pollution and, of course, homeless encampments).[16]

3.2 The Superiority of the Complaints Data

To illustrate the superiority of the complaints data, consider how the impact of homeless encampments on properties would have to be estimated using the PIT data. Without geographically precise identifying information about the location of unsheltered individuals, the best one could do is compare property sales within a census tract to the enumerated unsheltered population in the census tract in a given year:

$$ln(Price)_{imcy} = \lambda_0 + \nu_m + \rho_c + \zeta_y + \lambda_1 Unsheltered_{cy} + \delta P_i + \epsilon_c \tag{5}$$

where $ln(Price)_{imcy}$ is the log price of property i sold in month m in census tract c in year y, ν_m is a month fixed effect to control for seasonality in property price, ρ_c is a census tract fixed effect, ζ_y is a year fixed effect, P_i is the vector of all observable characteristics for property i, and standard errors are clustered at the census tract level. Column 1 of Table 4 shows that changes in the unsheltered population have no significant effect on property prices.[17] Perhaps using intuition, one could guess that tents and makeshift shelters should be the primary components of the PIT impacting property values. Column 2 shows the

[16] Appendix A.3 shows differential effects of complaints on residential property values, depending on whether it is a single-family home or multi-unit property.

[17] Note that the coefficients have been multiplied by 100 to show percentage changes.

Table 4: Assessing Property Losses Using the PIT Data

	Dependent Variable: Log Sale Price			
	(1)	(2)	(3)	(4)
Unsheltered	0.008	-	-	-
	(0.014)			
Tents & MS	-	0.006	-	-
		(0.05)		
Tents	-	-	-0.19**	-0.15
			(0.06)	(0.14)
Makeshift Shelters	-	-	0.19	0.32*
			(0.10)	(0.15)
Cars	-	-	0.12	-0.09
			(0.12)	(0.13)
Vans	-	-	0.13	0.13
			(0.11)	(0.12)
Campers	-	-	-0.02	-0.02
			(0.06)	(0.07)
Top 1% Tents Excl	-	-	-	✓
Observations	92,316	92,316	92,316	91,430

Notes: PIT data comes from 994 census tracts in the city of L.A. No PIT count in 2021 due to the pandemic. Coefficients are presented in percentage terms. Standard errors clustered at the census tract level.
* Significance at 5% level
** Significance at 1% level

results of Equation 5, substituting in $Tents\ \&\ MS_{cy}$ for $Unsheltered_{cy}$ and again there is no significant effect. Column 3 shows the results of Equation 5 with all components of the unsheltered population separated out. At first blush, it appears that this approach shows that an additional tent decreases residential property values by 0.19%, but Column 4 pushes on this finding to see if it holds when excluding the top 1% of census tract-years by number of tents ($\geq$ 23 tents). Column 4 shows the effect disappears and also illogically suggests that one additional makeshift shelter *increases* property values by 0.32%. Table 4 confirms that any attempt to quantify the impact of homeless encampments on property values would have been a fruitless endeavor with the PIT data.

4 Empirical Approach

Using the complaints data to measure how the presence of homeless encampments (tents and makeshift shelters) impacts property values, I start with a simple spatial hedonic property price model:

$$ln(Price)_{inmy} = \lambda_0 + \nu_m + \chi_{ny} + \lambda_1 Complaints_{inmy} + \delta P_i + \epsilon_n \tag{6}$$

where $ln(Price)_{inmy}$ is the log price of property i sold in census block n in month m in year y and $Complaints_{inmy}$ is the total number of complaints about homeless encampments counted within 0.4 miles of property i over the 60 days prior to when property i transfers ownership in census block n in month m in year y.[18] χ_{ny} is a census block-by-year fixed effect and standard errors are clustered at the census block level.[19] The median (average) census block has eleven (sixteen) property sales in each year. λ_1 shows the marginal effect of each complaint on a property's value.

To test for variation in the marginal effect of a complaint based on distance, I divide complaints into four 0.1 mile rings:

$$\begin{aligned} ln(Price)_{inmy} = \gamma_0 + \nu_m + \chi_{ny} + \gamma_1 D_1 Complaints_{inmy} + \gamma_2 D_2 Complaints_{inmy} + \\ \gamma_3 D_3 Complaints_{inmy} + \gamma_4 D_4 Complaints_{inmy} + \delta P_i + \epsilon_n \end{aligned} \tag{7}$$

where $D_1Complaints_{inmy}$ is the the number of complaints of homeless encampments $\leq$ 0.1 miles away from property i, $D_2Complaints_{inmy}$ is complaints within (0.1,0.2] miles, $D_3Complaints_{inmy}$ is complaints within (0.2-0.3] miles, and $D_4Complaints_{inmy}$ is com-

[18] Considering the typical length of escrow, counting complaints sixty days prior to the date of ownership transfers ensures that I am observing the presence of homeless encampments right around the time of sale.

[19] Census block level groupings are the smallest geographical cluster put out by the US Census Bureau and they ensure that unobservable heterogeneity among properties is minimized to the largest extent possible.

plaints within (0.3,0.4] miles. The effect should be the strongest in D_1 and subsequently decrease in each successive ring, but it is possible that the marginal effect of a complaint is similar between two successive distance rings. Distance rings will be grouped together if the difference in magnitudes between any two γ's is not statistically significant at the 5% level.

Regardless of how the distance thresholds are grouped together though, I anticipate, a priori, that the marginal effect of a complaint is nonlinear: going from zero complaints to one complaint should have a larger effect on property values than going from nine to ten complaints, and so on. Consider that the zero-one complaint margin is the difference between having no problem with homeless encampments around one's property to having *some* problem with homeless encampments. Each additional complaint beyond the first should have a lower marginal effect on property value up to the point where the complaints no longer reliably signal an increase in the presence of homeless encampments. To account for the potential non-linear marginal effects, I use a spline regression with two knots. The first knot is placed at one complaint to isolate the difference between a property being treated and untreated. The ideal placement of the second knot would be at the point where an additional complaint has zero marginal effect on the property's value. The precise point is unobservable ex ante, but the results from Table 2 suggest that beyond 25 complaints, the marginal complaint may not be signaling an increase in tents and makeshift shelters; if an increase of two tents/makeshift shelters corresponds to approximately one additional complaint and the 51$^{\text{st}}$ tent/makeshift shelter does not generate an increase in complaints, then the 26$^{\text{th}}$ complaint and beyond does not correlate with an increase in tents and makeshift shelters. Therefore, the second knot is placed at 25 complaints. With two knots, the three set spaces $S \in \mathbb{R}$ over which the marginal effect of a complaint will be teased out are: S_1: $Complaints_{inmy} \in [0, K_1]$, $S_2 : Complaints_{inmy} \in (K_1, K_2]$, and $S_3 : Complaints_{inmy} \in (K_2, \infty)$ where $K_1 = 1$ and $K_2 = 25$. The general form for this linear spline regression with two knots (using one distance threshold as in Equation 6) is:

$$\begin{aligned} ln(Price)_{inmy} = \sigma_0 + \nu_m + \chi_{ny} + \sigma_1 I_{C\geq 1} + \sigma_2 \min[(Complaints_{inmy} - K_1)_+ \ , 24\ ] \\ + \sigma_3 (Complaints_{inmy} - K_2)_+ \ + \ \delta P_i + \epsilon_n \end{aligned} \tag{8}$$

where $I_{C\geq 1}$ is an indicator function equal to one when $Complaints_{inmy} \geq 1$. σ_1 shows the marginal effect of a complaint in S_1, σ_2 shows the marginal effect per complaint in S_2, and σ_3 shows the marginal effect of a complaint in S_3.

4.1 Threats to Identification

Homeless encampments, in any city, tend to cluster on arterial streets with more foot traffic and larger sidewalks, near urban green spaces, near highway and bridge underpasses to get shade, and near homeless shelters that can provide food, clothing, and a potential place to sleep indoors if a bed is available. For each property then, I calculate its distance to the nearest major arterial street, the nearest highway[20], the nearest public park or green space, and the nearest homeless shelter. If complaints about homeless encampments are partially capturing distance to a busy street, highway, green space or shelter, (all of which should affect the price one's property sells for) then the inclusion of these controls should reduce the magnitude of λ, γ, and σ.

Another possible threat to the validity of this model is the presence of criminal activity that could be associated with complaints of homeless encampments. Neighborhoods on the decline would likely see both an increase in crime and homeless encampments and a large body of research shows that violent crimes get capitalized into proximate property

[20] Highways in Los Angeles are nearly all elevated structures that run above streets and have underpasses in which homeless people often set up tents and makeshift shelters. There are hardly any elevated rail lines in the city and there are no upper and lower levels to major streets, which means distance to a highway is the best barometer of distance to an underpass where homeless individuals are more likely to set up their temporary living arrangement.

values.[21] To address this possible bias, I control for the presence of nearby violent crime as classified by the Los Angeles Police Department.[22]

5 Results

Table 5 shows the results of Equations 6 and 7. Column 1 excludes the controls for violent crime and distance to the nearest park/green space, arterial street, highway, and homeless shelter (henceforth referred to as PAHH). Column 2 adds distance to PAHH and Column 3 adds controls for violent crime. Row 1 of Table 5 shows the marginal effect on property values for any complaint within 0.4 miles (λ_1 in Equation 6). Column 1 shows that each additional complaint anywhere within 0.4 miles of a property decreases value by 0.029%.[23] When controlling for distance to PAHH, the coefficient in Column 2 decreases to -0.023% per complaint. Controls for violent crime further decrease the coefficient to -0.019% per complaint. The attenuation of the coefficient is consistent with complaints partially reflecting the presence of violent crime and close proximity to urban disamenities that attract homelessness. But any concern ex ante that the *majority* of the effect of complaints is coming from either criminal behavior or proxy to a city space that attracts homelessness is relieved by the results in Column 3. Rows 2-5 in Table 5 show the results of Equation 7 and, as expected, the marginal effect of a complaint differs by distance. Controlling for violent crime and distance to PAHH, Column 3 shows that one complaint within 0.1 miles (D_1) reduces property values by 0.22%. Within 0.1-0.2 miles (D_2), one complaint reduces property values by 0.039%. Beyond 0.2 miles, the marginal effect of an additional complaint on property values is insignificant.

[21] See Bayer et al. (2021), Boggess et al. (2013), Ihlanfeldt and Mayock (2010), Tita et al. (2006), Cigdem-Bayram and Prentice (2018)

[22] Crime data is publicly available from the city of Los Angeles and I employ a similar methodology: counting all the violent crimes within 0.4 miles of a property up to sixty days prior to ownership transfer. I do not control for violent crimes where the suspect is a homeless person.

[23] Note that the coefficients have been multiplied by 100 to show percentage changes.

Table 5: The Impact of Homelessness on Property Values

	Dependent Variable: Log Sale Price			
	(1)	(2)	(3)	(4)
Complaints	-0.029**	-0.023**	-0.019*	-0.036**
	(0.009)	(0.008)	(0.008)	(0.009)
$D_1 Complaints$	-0.25**	-0.22**	-0.22**	-0.38**
	(0.07)	(0.07)	(0.06)	(0.09)
$D_2 Complaints$	-0.055**	-0.043*	-0.039*	-0.10**
	(0.02)	(0.02)	(0.02)	(0.03)
$D_3 Complaints$	-0.023	-0.018	-0.015	-0.04*
	(0.015)	(0.015)	(0.014)	(0.02)
$D_4 Complaints$	0.004	0.007	0.011	0.028
	(0.012)	(0.011)	(0.012)	(0.016)
Distance to PAHH	-	✓	✓	✓
Crime Controls	-	-	✓	✓
Top 1% Excluded	-	-	-	✓
Observations	121,581	121,581	121,581	120,739

Notes: Column 2 adds distance to parks, arterial streets, highways, and homeless shelters. Column 3 adds the total number of violent crimes within 0.4 miles of a home over the past sixty days. Column 4 excludes the top 1% of treated properties based on total complaints within 0.4 miles, the threshold for which is 182. Coefficients displayed have been multiplied by 100 to show percentage changes. Standard errors clustered at census block level.
* Significance at 5% level
** Significance at 1% level

Ex ante, there was reason to suspect that the marginal effect of a complaint would be non-linear. Column 4 of Table 5 shows one plausible way to test this suspicion: excluding, by number of complaints within 0.4 miles, the top 1% of treated properties. The threshold is 182 complaints and properties above it have an average of 267 complaints compared to 13 for those below it. The coefficient in Row 1 nearly doubles to -0.036% per complaint between Column 3 and Column 4, showing that the marginal effect of a complaint within 0.4 miles is non-linear. For D_1 (D_2), the marginal effect roughly doubles in value to -0.38% (-0.10%) per complaint and the marginal effect of a complaint is now statistically significant and negative in D_3: each additional complaint reduces property values by 0.04%. For D_4, there is no significant marginal effect with or without the top 1% of properties by complaints excluded from the sample. Additionally, a t-test of $\gamma_2 = \gamma_3$ cannot be rejected with 95% confidence in either Column 3 or Column 4 whereas every other test of equality between coefficients in Rows 2-5 can. Moving forward then, I combine $D_2 Complaints$ and $D_3 Complaints$ into one distance threshold capturing all complaints 0.1-0.3 miles away from a property: $D_{23} Complaints$.

My preferred specification—given the evidence of non-linear marginal effects, combined distance parameter for D_2 and D_3, and insignificance of complaints in D_4—is:

$$\begin{aligned} ln(Price)_{inmy} = \sigma_0 + \nu_m + \chi_{ny} + \sigma_1 I_{D_1C \geq 1} + \sigma_2 \min[\,(D_1Complaints_{inmy} - K_1)_+ \,, 24\,] \\ +\sigma_3(D_1Complaints_{inmy} - K_2)_+ \; + \sigma_4 I_{D_{23}C \geq 1} \; + \sigma_5 \min[(D_{23}Complaints_{inmy} - K_1)_+ \,, 24\,] \\ +\sigma_6(D_{23}Complaints_{inmy} - K_2)_+ + \sigma_7 D_4Complaints_{inmy} + \delta P_i + \epsilon_n \end{aligned} \tag{9}$$

where D_1C is an abbreviation for $D_1Complaints_{inmy}$ and $D_{23}C$ is an abbreviation for $D_{23}Complaints_{inmy}$ in the indicator functions I. σ_1 (σ_4) shows the marginal effect of going from zero to one complaint in D_1 (D_{23}). σ_2 (σ_5) shows the marginal effect per complaint between 2 and 25 complaints in D_1 (D_{23}), and σ_3 (σ_6) shows the marginal effect of the 26^{th} complaint and beyond in D_1 (D_{23}). Table 6 shows the results of Equation 9. Going from zero to one complaint decreases property values by 2.28% (1.57%) in D_1 (D_{23}). Between 2 and 25 complaints, the marginal complaint reduce property values by 0.28% (0.11%) in D_1 (D_{23}). Beyond 25 complaints though, there is no clear marginal effect of an additional complaint.[24] Taken together, the results conform with the expectation that the largest impact occurs on the extensive margin: a single complaint indicates treatment status and the presence of the negative externalities associated with a homeless

[24] I do check the results of Equation 9 when separating out complaints in D_4 across S_1, S_2, and S_3 and there is no significant effect in any of the set spaces for complaints 0.3-0.4 miles away from a property.

Table 6: Differing Marginal Effects By Number of Complaints

	Dependent Variable: Log Sale Price
1 *Complaint in* D_1	**-2.28****
	(0.41)
$1 < Complaints \leq 25$ *in* D_1	**-0.28***
	(0.12)
$Complaints > 25$ *in* D_1	-0.05
	(0.05)
1 *Complaint in* D_{23}	**-1.57****
	(0.38)
$1 < Complaints \leq 25$ *in* D_{23}	**-0.11****
	(0.04)
$Complaints > 25$ *in* D_{23}	0.003
	(0.010)
Controls for Crime and Distance to PAHH	✓
Observations	121,581

Notes: Coefficient shows the marginal effect of an additional complaint within the specified distance parameter and complaint threshold. Coefficients displayed have been multiplied by 100 to show percentage changes. Standard errors clustered at the census block level.
* Significance at 5% level
** Significance at 1% level

encampment. As the number of complaints increases and the number of tents/makeshift shelters continues to grow near one's property, the cost of the externalities associated with homeless encampments increases. Beyond 25 complaints, which roughly corresponds to fifty tents/makeshift shelters, additional complaints no longer signal an increase in the size of the homeless encampment and are no longer negatively capitalized into property values.[25]

[25] Appendix A.2 tests different placements of the second knot and adds a third knot to ensure that the results are robust across multiple specifications.

5.1 Calculating the Total Realized Losses and Externalities from Homeless Encampments

The results in Table 6 are used to calculate the total realized losses in property values. For each property i:

$$\begin{aligned} PL_{inmy} = 2.28 * I_{D_1C\geq 1} + 0.28 * \min[\ (D_1Complaints_{inmy} - K_1)_+\ , 24\ ] \\ + 1.57 * I_{D_{23}C\geq 1} + 0.11 * \min[(D_{23}Complaints_{inmy} - K_1)_+\ , 24\ ] \end{aligned} \tag{10}$$

where PL_{inmy} is the percentage loss for property i.[26] To calculate a range of percentage losses for property i, I replace the estimate for PL_{inmy} with the upper and lower bound on its 95% CI.[27] The percentage losses per property are used to calculate the ATT (3.14%) and the ATE (1.82%) along with their upper and lower bounds: $ATT \in [1.90\%, 4.38\%]$ & $ATE \in [1.10\%, 2.54\%]$.[28] An astounding 58% of all properties transacted between March 2016 and August 2022 were treated and sold for 3.14% less than they otherwise would have due to nearby homeless encampments. The percentage losses are used to calculate the dollar losses per property and in aggregate:

$$DL_{inmy} = SalePrice_{inmy} - \frac{SalePrice_{inmy}}{1 - PL_{inmy}} \tag{11}$$

$$Total\ Dollar\ Losses = \sum_{i=1}^{121581} (DL_{inmy}) \tag{12}$$

[26] Because there is no significant marginal effect beyond 25 complaints, I treat complaints beyond 25 as having zero marginal effect on the total percentage loss.

[27] I use the delta method to calculate the correct standard error when a property has complaints across multiple set spaces and/or distance parameters.

[28] Specifically, the average of all 121,581 properties' lower and upper bound on PL_{inmy} is used to calculate the lower and upper bounds, respectively, for the ATE. The upper and lower bounds for the ATT are derived from average of the 70,394 treated properties' upper and lower bounds, respectively.

where DL_{inmy} is the dollar loss for property i caused by the nearby presence of homeless encampments. Table 7 shows the total dollar losses in residential property wealth along with the upper and lower bound estimates on total losses, which are calculated by replacing PL_{inmy} in Equation 11 with the upper and lower bound on the percentage loss for property i. The estimates in lost wealth are \$2.52 billion with an upper bound of \$3.59 billion and a lower bound of \$1.50 billion. Those losses are spread over 70,394 properties that transacted between March 2016 and August 2022 with complaints in D_1, D_{23}, or both. Table 7 also estimates the total cost of the externalities of homeless encampments citywide. By multiplying the average treatment effect (1.82%) times the average sale price (\$1.19 million) times the total stock of housing units (1.5 million), I estimate the average total cost of the externalities of homeless encampments between March 2016 and August 2022 to be \$32.4 billion. Replacing the average treatment effect with its upper (2.54%) and lower (1.10%) bound yields the upper and lower bounds on the size of the externalities: \$45.2 billion and \$19.6 billion, respectively.

The key assumption underpinning the price of the externalities is that at any given time in Los Angeles between March 2016 and August 2022, the ATE for the 1.5 million residential properties in the city was 1.82%, the same ATE for all of the transacted properties in the sample. This presumes that the presence of homeless encampments is uncorrelated with the likelihood of selling. If properties with encampments in close proximity are more likely to transact (perhaps homeowners want to get away from the encampments as fast as possible), then sales would be disproportionately occurring in areas of the city with more homeless encampments, and the 1.82% effect would overstate the true average treatment effect across the city. On the other hand, properties with homeless encampments nearby may be less likely to transact if potential sellers suspect the encampments harm their property's value and choose to keep their properties off of the market until the encampment is removed. If so, the ATE of 1.82% would underestimate the citywide effect from homeless encampments. I test for possible selection into property sales by aggregating property transactions and complaints in each month at the block group level and observing how the frequency of sales changes when complaints of homeless encampments change. Appendix A.4 shows the results from this analysis and the takeaway is that increases in complaints have a negative effect on the number of property sales. I estimate that citywide, nearly 5% fewer properties transact on an annual basis due to the presence of homeless encampments. This suggests that 1.82% is **underestimating** the average treatment effect for properties citywide. By extension, the externalities from homeless encampments calculated in Table 7 are slight underestimates as well.

One last noteworthy aspect of the externalities from homeless encampments is that they are disproportionately concentrated in wealthier areas of the city. Appendix A.3 shows that the marginal effect per complaint and the ATT are substantially larger in census tracts with higher median incomes. This is intuitively consistent with the notion that residents in wealthier census tracts with low amounts of crime, clean air, and few urban disamenities are going to suffer larger dollar losses from the presence of a homeless encampment than residents in lower-income census tracts with higher crime, poor air quality, and other urban disamenities. Essentially, the marginal effect of a disamenity like a homeless encampment is lower in poorer areas that already have a relatively large number of disamenities compared to richer areas with relatively few disamenities.

Table 7: Aggregate Costs of Homeless Encampments

	(Point Est.)	(LB Est.)	(UB Est.)	(*Treated Properties*)
Realized Losses:	**$2.52B**	$1.50B	$3.59B	70,394
Total Cost of Externalities:	**$32.4B**	$19.6B	$45.2B	868,500

Notes: Table shows the total realized dollar losses for residential property values as well as estimates of externalities imposed on all residents of Los Angeles from encampments. Treated properties is the estimated number of properties affected by homeless encampments, both among those that sold and citywide.

6 Discussion and Concluding Thoughts

Homeless encampments impose significant costs on Los Angeles residents, a fact residents acknowledge[29] and the catalyst for why the problem has been at the forefront of policy debates in the city over the last decade. At its root, homelessness is driven by a lack of affordable and available housing[30] and as such, the city put Proposition HHH to its voters in 2016: a proposal that passed overwhelmingly and enabled the city to issue up to $1.2 billion in bonds for the construction of 10,000 permanent supportive housing units over ten years.[31] After a slow start (the first permanent supportive housing unit did not open until three years after Prop HHH passed), the city had constructed 2,300 permanent supportive housing units by the end of 2022 and claims to be on track to complete 10,000 by 2026 (Scott (2023)). But with an average cost of half a million dollars for each of the units already built, total costs will well exceed the $1.2 billion allocated in Prop HHH (Galperin (2022)). Moreover, there are 31,000 unsheltered persons sleeping on the streets of Los Angeles so 10,000 permanent supportive housing units will not fix the problem.

6.1 Constructing More Permanent Supportive Housing

The results from this paper suggest that residents of Los Angeles would be willing to pay far more than $1.2 billion to remove homeless encampments. Even with the high cost of $500,000 per permanent supportive housing unit (construction cost of the average **single-family home** nationwide was just under $300,000 in 2022 according to HomeAdvisor),

[29] Again, it was the number one issue for voters in the 2022 election according to Littlejohn (2022) and Baldassare et al. (2023).

[30] Cities with high housing costs and low vacancy rates present challenges to all residents but those challenges are particularly acute for individuals with the highest likelihood of becoming homeless: people struggling with addiction, mental health challenges, or poverty. On the margin then, expensive cities tend to push more vulnerable people into homelessness. This is a finding that has been repeatedly confirmed in the literature on the root causes of homelessness (Colburn and Aldern (2022), O'Flaherty (2004), Glynn and Fox (2019), Quigley and Raphael (2001), Corinth (2015), Byrne et al. (2012)).

[31] Note this is a relatively unambitious target given that the unsheltered population in 2016 was well above 10,000.

building 31,000 permanent supportive housing units would cost \$15.5 billion, less than half of the estimated size of the externalities associated with homeless encampments: \$32.4 billion.

However, there are numerous political and logistical barriers the city must overcome to construct these units. First, nearly three quarters of the residential-designated land in the city is zoned for detached single-family homes ((Menendian et al. (2022)) and any permanent supportive housing for the homeless will have to be in dense multi-unit properties. The land is zoned for single-family homes because property-owning residents perceive negative externalities from an increase in the construction of any kind of new multi-unit housing in their neighborhood: losses to their own property's value, more traffic, fewer parking spots, and an aesthetic distaste for how multi-unit properties fit in neighborhoods zoned for detached single-family homes (Saadi (2017)). When proposing to construct permanent supportive housing for unsheltered persons, there is also an added safety concern because a disproportionate share of unhoused individuals are mentally ill and/or drug-addicted. Therefore, even the parts of the city with land zoned for multi-unit development will resist the construction of permanent supportive housing for the unhoused. At its core, the problem is everyone believes the housing for the homeless should be built somewhere besides their own neighborhood, the cumulative impact of which is a paralyzing effect on the construction of new housing citywide as proposed projects get tied down in legal processes initiated by homeowners associations trying to prevent their construction.[32] And yet, to fix the problem of widespread homeless encampments, the permanent supportive housing has to be built *somewhere* in Los Angeles lest its residents wish to continue to absorb its immense costs.

[32] Legal actions from homeowners associations and other interest groups trying to block construction is a large reason why the city has spent over \$500,000 per permanent supportive housing unit so far.

6.2 Condensing the Distribution of Homeless Encampments

In September 2023, California Governor Gavin Newsom and other politicians in cities and states struggling to control the proliferation of homeless encampments petitioned the Supreme Court to overturn the precedent forbidding the removal of encampments without presenting alternative shelter. If the Supreme Court obliges, law enforcement would be free to remove homeless encampments from certain public spaces, creating a new spatial equilibrium throughout the city. Politicians could formally designate select parts of a city where homeless people can camp in public spaces and rigorously enforce their prohibition in all other areas. For the majority of residents, this will limit exposure to encampments and vastly reduce the total costs of the externalities. Given the logistical barriers to the construction of more temporary supportive housing, such a solution will likely be more politically palatable as well. However, it relies on a gamble that the current conservative majority on the Supreme Court will overturn the precedent on this matter even though a previous conservative majority declined to do so in 2019. It also discounts the preferences of the unhoused people themselves who may not want to move their tent or makeshift shelter from its current location. Yet, politicians like Governor Newsom and Los Angeles Mayor Karen Bass must balance the interests of all of their constituents and it is clear that the current spatial equilibrium of encampments in Los Angeles is politically untenable given the extraordinarily large cost it imposes on the city's residents.

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Appendix

A.1: Supplemental Material on Complaints Data

Choosing t

To verify that the relationship between complaints and homelessness is not sensitive to the choice of t, I run the following model:

$$Complaints30_{ct} = \beta_0 + \beta_1(Complaints60_{ct}) + \epsilon_{ct} \tag{13}$$

where $Complaints30_{ct}$ is the number of complaints per day when $t = 30$ and $Complaints60_{ct}$ is the number of complaints per day when $t = 60$. I also check $Complaints90_{ct}$ and $Complaints120_{ct}$ against $Complaints30_{ct}$. If the number of complaints per day does not change with t, then β_1 should be very close to one in each specification.[33] The results in Table 8 confirm that the size of t is not biasing the coefficients in Table 1.

Table 8: Complaints and Homelessness not sensitive to t

	Dependent Variable: Complaints30		
	(X=60)	(X=90)	(X=120)
$ComplaintsX$	1.026**	1.042**	1.003**
	(0.0047)	(0.0063)	(0.0076)
Observations	5,964	5,964	5,964

Notes: Complaints counted 30 days before and after the PIT count in late January. Data comes from 994 census tracts in the city of L.A. No PIT count in 2021 due to the pandemic.
* Significance at 5% level
** Significance at 1% level

[33] It will not be exactly one though because the rate of complaints per day will not be exactly the same as t increases.

Adding Knots to Equation 4

While there is a clear delineation in the relationship between tents/makeshift shelters and complaints when the former is above and below fifty, it is also possible there are additional knots that change the cardinal relationship between complaints and tents/makeshift shelters. Table 9 shows the results of Equation 4 when adding a knot at 100 tents/makeshift shelters and 25 tents/makeshift shelters. With the additional knot at 25 tents/makeshift

Table 9: Marginal Effect of Tents/Makeshift Shelters on Complaints With 3 Knots

	Dependent Variable: Complaints
	(1)
$Tents\&MS < 25$	**0.49****
	(0.09)
$25 < Tents\&MS \leq 50$	**0.51***
	(0.23)
$50 < Tents\&MS \leq 100$	-0.17
	(0.18)
$Tents\&MS > 100$	0.17
	(0.09)
Observations	5,964

Notes: Complaints counted 30 days before and after the PIT count in late January. Data comes from 994 census tracts in the city of L.A. No PIT count in 2021 due to the pandemic. Standard errors clustered at the census tract level.
* Significance at 5% level
** Significance at 1% level

shelters, the relationship is still two tents/makeshift shelters per one complaint when $Tents\&MS \leq 50$.

Adding a knot at 100 tents/makeshift shelters does not show that additional tents/makeshift shelters correspond with more complaints when $50 < Tents\&MS \leq 100$. Beyond 100 tents and makeshift shelters though, the coefficient is significant at the 10% level, suggesting it is possible that the positive relationship with complaints reappears. Table 10 investigates this possibility by adding another knot at 150 tents/makeshift shelters while also checking to see if adding a knot at five tents/makeshift shelters changes the cardinal relationship. The results from Table 10 confirm there is no positive relationship with

Table 10: Marginal Effect of Tents/Makeshift Shelters on Complaints With 5 Knots

	Dependent Variable: Complaints
	(1)
$Tents\&MS \leq 5$	**0.83****
	(0.17)
$5 < Tents\&MS \leq 25$	**0.35***
	(0.15)
$25 < Tents\&MS \leq 50$	**0.59***
	(0.24)
$50 < Tents\&MS \leq 100$	-0.18
	(0.20)
$100 < Tents\&MS \leq 150$	-0.16
	(0.32)
$Tents\&MS > 150$	0.19
	(0.22)
Observations	5,964

Notes: Complaints counted 30 days before and after the PIT count in late January. Data comes from 994 census tracts in the city of L.A. No PIT count in 2021 due to the pandemic. Standard errors clustered at the census tract level.
* Significance at 5% level
** Significance at 1% level

complaints when tents and makeshift shelters extend beyond 100. The knot at five tents and makeshift shelters suggests the first five tents/makeshift shelters might have a relationship with complaints that is closer to one-to-one, but a test of equality between the marginal effects for $Tents\&MS \leq 5$ and $5 < Tents\&MS \leq 25$ cannot be rejected with 95% confidence.

Tables 9 and 10 show that the cardinal relationship of two-to-one tents/makeshift shelters to complaints if $Tents\&MS \leq 50$ is robust to the inclusion of more knots.

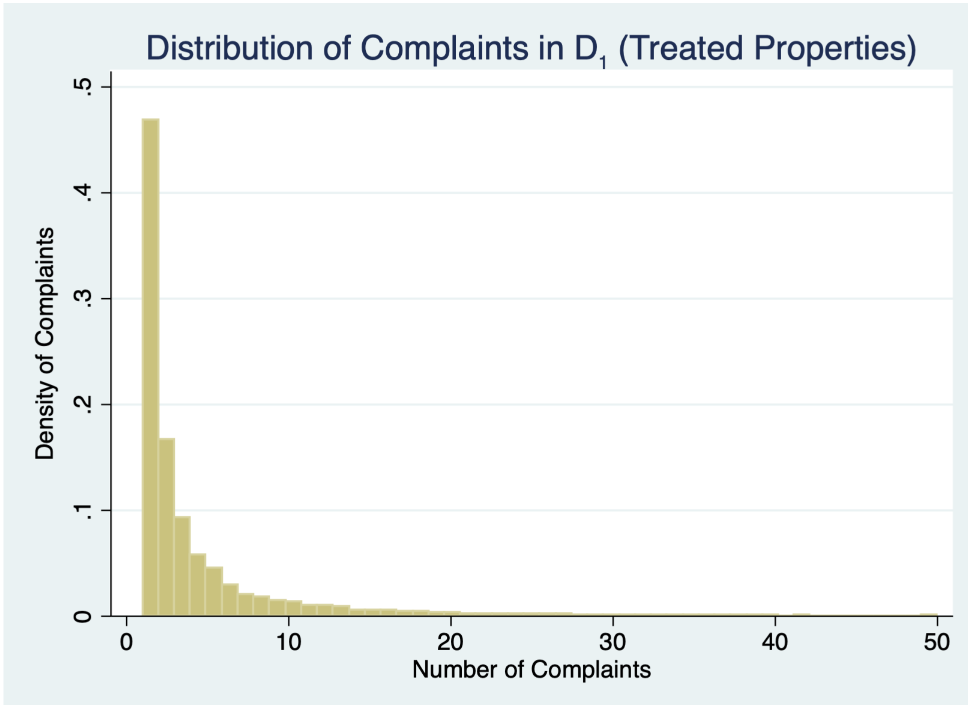

Figure 3: Complaints Heavily Left-Skewed in D_1

A.2: Additional Spline Regressions

Power Concerns on the Zero-One Margin

A natural concern about placing the first knot at $K_1 = 1$ is whether there is enough power to tease out a marginal effect. But because the distribution of complaints is highly left-skewed in D_1 and D_{23}, there are thousands of properties with just one complaint in either or both distance thresholds. Figures 3 and 4 show the distribution of complaints for treated properties in D_1 and D_{23}, respectively.

Testing Different Knots

Table 11 shows the results with Knot 2 chosen at the cutoff for the 99$^{\text{th}}$ percentile of complaints for treated properties in D_1 and D_{23}, respectively. Knot 1 (K_1) is at 1, Knot

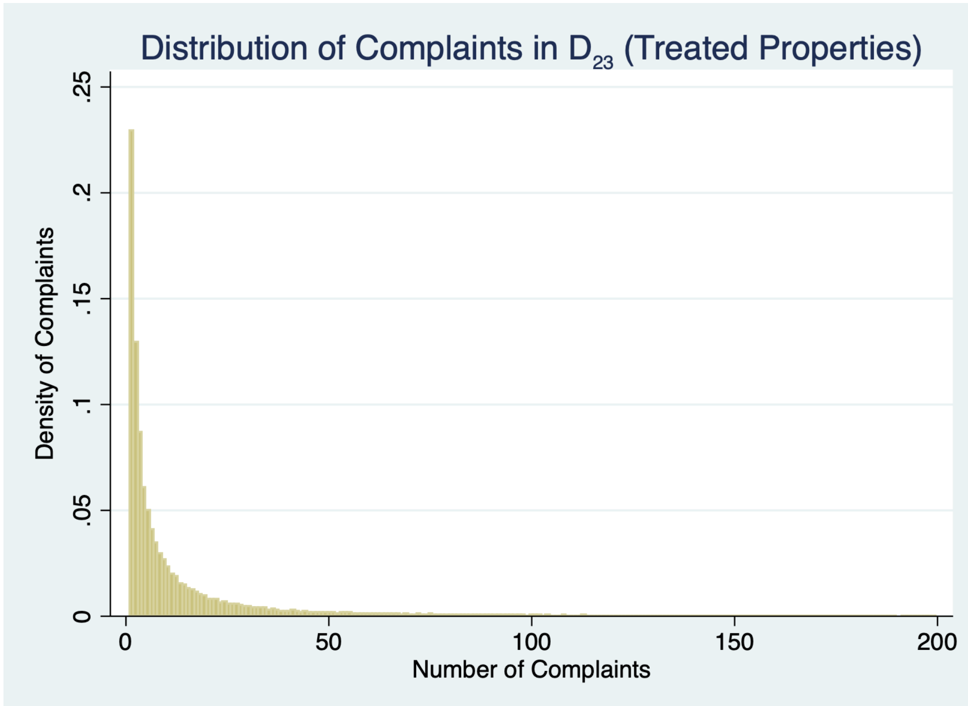

Figure 4: Complaints Slightly Less Left-Skewed in D_{23}

2 in D_1 (K_{21}) is at 43, and Knot 2 in D_{23} (K_{22}) is at 122.[34] In D_1, the results in Table 11 look very similar to those in Table 6. In D_{23}, the marginal effect per complaint between 2 and 122 is less than half of what is shown in Table 6, but this is driven by the larger set space over which the marginal effect is being teased out. Beyond 122 complaints in D_{23}, there is a slight positive significant effect (one additional complaint **increases** property values by 0.018%.) This suggests that properties with over 353 complaints experience positive effects on their property values from homeless encampments. There are only twelve properties in the entire sample with more than 353 complaints in D_{23} and the positive effect disappears with the addition of another knot (shown in Table 12), suggesting that the positive marginal effect of complaints beyond 122 is not robust across different specifications.

The additional knot in Table 12 is placed between 1 and 43 (122) in D_1 (D_{23}). This

[34] The maximum number of complaints in D_1 is 229 and the maximum number of complaints in D_{23} is 1,531.

Table 11: Marginal Effect with Different 2[nd] Knot

	Dependent Variable: Log Sale Price
	(1)
1 *Complaint in* D_1	-2.34**
	(0.42)
$1 < Complaints \leq 43$ *in* D_1	-0.26*
	(0.11)
$Complaints > 43$ *in* D_1	0.04
	(0.15)
1 *Complaint in* D_{23}	-1.76**
	(0.40)
$1 < Complaints \leq 122$ *in* D_{23}	-0.038**
	(0.015)
$Complaints > 122$ *in* D_{23}	0.018*
	(0.009)
Distance to PAHH	✓
Crime Controls	✓
Observations	121,779

Notes: Coefficients displayed have been multiplied by 100 to show percentage changes. Knot 1 (K_1) is at 1, Knot 2 in D_1 (K_{21}) is at 43, and Knot 2 in D_{23} (K_{22}) is at 122.
* Significance at 5% level
** Significance at 1% level

knot is placed at the 90$^{\text{th}}$ percentile of complaints for treated properties in D_1 (D_{23}) which is equivalent to 10 (31) complaints. Table 12 shows that in D_{23}, there does not appear to be a negative significant marginal effect in complaints beyond 31. Table 12 also shows that in D_1, there is no statistically significant effect between two and ten complaints. However, the point estimate (-0.19) is within one standard deviation of the point estimate for the marginal effect of complaints between 2 and 43 shown in Table 11, suggesting that there is still likely a negative effect between two and ten complaints.

Table 12: Marginal Effect in a Spline Regressions with 3 Knots

	Dependent Variable: Log Sale Price (1)
1 *Complaint in* D_1	-2.37**
	(0.43)
$1 < Complaints \leq 10$ *in* D_1	-0.19
	(0.17)
$10 < Complaints \leq 43$ *in* D_1	-0.31*
	(0.15)
$Complaints > 43$ *in* D_1	0.05
	(0.07)
1 *Complaint in* D_{23}	-1.62**
	(0.38)
$1 < Complaints \leq 31$ *in* D_{23}	-0.09**
	(0.033)
$31 < Complaints \leq 122$ *in* D_{23}	-0.006
	(0.009)
$Complaints > 122$ *in* D_{23}	0.013
	(0.007)
Distance to PAHH	✓
Crime Controls	✓
Observations	121,779

Notes: Coefficients displayed have been multiplied by 100 to show percentage changes. Knot 1 (K_1) is at 1, Knot 2 in D_1 (K_{21}) is at 10, and Knot 2 in D_{23} is at 31. Knot 3 in D_1 (K_{31}) is 43 complaints and Knot 3 in D_{23} (K_{32}) is 122.
* Significance at 5% level
** Significance at 1% level

A.3: Losses by Neighborhood and Property Type

While there are large negative effects from homeless encampments citywide, there may be heterogeneous effects for different types of properties or neighborhoods. Wealthier census tracts are generally better able to shield themselves from citywide disamenities like bad air quality and crime. If this is the expectation for the presence of homeless encampments too, properties in census tracts with above the citywide median income are likely to endure larger losses than those in census tracts below the citywide median income. Similarly, single-family homes should be affected more by homeless encampments than multi-unit properties since the areas zoned for single-family homes are done so specifically to avoid the disamenities of denser urban spaces. Using Equation 9, Table 13 tests if complaints affect properties differently based on census tract median household income[35] and property type (single family vs. multi-unit).

Columns 1 and 2 in Table 13 show that the effect on the zero-one margin in D_1 is more than twice as large in the above median income census tracts compared to the below median income census tracts. The magnitude of the marginal effect between 2 and 25 complaints in D_1 is relatively similar between the above and below-median income census tracts but there is no significance for the coefficient in above median income census tracts. This is an unexpected finding so I calculate the ATT for properties with between 2 and 25 complaints in D_1 in Table 14.[36] In above median income census tracts, the average property with between 2 and 25 complaints lost 3.98% compared to 3.49% for the average property with one complaint and the average property with more than 25 complaints in D_1 lost a whopping 18.84% in value. It is clear then that more complaints lead to larger

[35] With my sample spread over 7 years, I take the average of all the reported median incomes within a census tract, and then split the census tracts above and below the median of the average census tract median income.

[36] $D_1S_1 = 1$ when a property has one complaint in D_1, $D_1S_2 = 1$ when a property has between 2 and 25 complaints in D_1, and $D_1S_3 = 1$ when a property has more than 25 complaints in D_1. $D_{23}S_1$, $D_{23}S_2$, and $D_{23}S_3$ follow the same pattern for D_{23}.

losses in D_1 for properties in wealthier census tracts. In below median income census tracts, the results from Table 13 suggest significant effects on the zero-one margin for both D_1 and D_{23}. In Table 14 though, there is no significant ATT for properties with just one complaint in either D_1 or D_{23} in below median income census tracts, but the point estimates are within one standard deviation of the estimates in Table 13.

Table 13: Marginal Effect Per Complaint By Income and Property Type

	Dependent Variable: Log Sale Price			
	(1)	(2)	(3)	(4)
1 *Complaint in* D_1	-3.14**	-1.34**	-1.54**	-1.72**
	(0.69)	(0.48)	(0.37)	(0.69)
$1 < Complaints \leq 25$ *in* D_1	-0.32	-0.23*	-0.37**	-0.15
	(0.21)	(0.10)	(0.09)	(0.11)
Complaints > 25 *in* D_1	-0.009	0.011	0.017	-0.04
	(0.06)	(0.09)	(0.07)	(0.06)
1 *Complaint in* D_{23}	-1.43**	-1.12**	-0.77**	-0.90
	(0.52)	(0.44)	(0.25)	(0.90)
$1 < Complaints \leq 25$ *in* D_{23}	-0.11*	-0.07	-0.07**	-0.025
	(0.04)	(0.04)	(0.025)	(0.06)
Complaints > 25 *in* D_{23}	0.012	-0.012	0.013*	0.004
	(0.009)	(0.018)	(0.005)	(0.02)
Above Median	✓	-	-	-
Below Median	-	✓	-	-
Single-Family Props	-	-	✓	-
Multi-Unit Props	-	-	-	✓
Observations	60,991	60,590	75,011	46,570

Notes: Columns 1 & 2 separate the sample based on whether the block group-year is in a census tract in above or below the median census tract income. Columns 3 & 4 separate properties by whether they are single-unit or multi-unit. Coefficients are displayed in percentage terms. Standard errors clustered the census block level.
* Significance at 5% level
** Significance at 1% level

When comparing single family homes to multi-unit properties, the key distinctions is that there is no detectable treatment effect beyond 0.1 miles for multi-unit properties while there are effects up to 0.3 miles away for single-family properties. Given the proximity to arterial streets[37] and urban amenities **and** disamenities, the results in Columns 3 and 4 of Tables 13 and 14 suggest prospective buyers do not penalize multi-unit properties for the presence of homeless encampments as long as it is greater than 0.1 miles away.

Overall, Tables 13 and 14 suggest that the costs of the externalities of homeless encampments are disproportionately born out in wealthier and single-family only areas.

Table 14: Average Effects By Income and Property Type

	Dependent Variable: Log Sale Price			
	(1)	(2)	(3)	(4)
D_1S_1	-3.49**	-0.90	-1.26**	-1.73*
	(0.71)	(0.57)	(0.43)	(0.79)
D_1S_2	-3.98**	-2.85**	-3.44**	-2.34*
	(1.51)	(0.68)	(0.51)	(1.07)
D_1S_3	-18.84**	-5.71	-10.11**	-6.80*
	(6.83)	(2.97)	(2.44)	(3.44)
$D_{23}S_1$	-1.07*	-0.74	-0.38	-0.99
	(0.49)	(0.48)	(0.29)	(0.86)
$D_{23}S_2$	-2.20**	-1.70**	-1.35**	-1.00
	(0.68)	(0.55)	(0.29)	(1.14)
$D_{23}S_3$	-3.71**	-3.00*	-1.60*	-2.54
	(1.08)	(1.43)	(0.70)	(1.88)
Above Median	✓	-	-	-
Below Median	-	✓	-	-
Single-Family Props	-	-	✓	-
Multi-Unit Props	-	-	-	✓
Observations	60,991	60,590	75,011	46,570

Notes: Columns 1 & 2 separate the sample based on whether the block group-year is in a census tract in above or below the median census tract income. Columns 3 & 4 separate properties by whether they are single-unit or multi-unit. Coefficients are displayed in percentage terms. ATT in D_4 is insignificant and omitted from the table. Standard errors clustered at the census block level.
* Significance at 5% level
** Significance at 1% level

[37] The average multi-unit property is 126 meters away from an arterial street compared to 192 meters for the typical single-family home

A.4 Complaints and the Likelihood of Selling

To model how the number of complaints in a census block affects the number of properties that sell in a census block, I use the following equation:

$$Num\_Sales_{nmy} = \Delta_0 + \Theta_m + \Gamma_{ny} + \sum_{z=1}^{12} \Delta_{m-z} Total\_Complaints_{n,m-z} + \epsilon_n \tag{14}$$

where Num_Sales_{nmy} is the total number of properties sold in census block n in month m in year y. Θ_m is a month fixed effect, Γ_{ny} is a census block-by-year fixed effect, and $\sum_{z=1}^{12} Total\_Complaints_{n,m-z}$ is the total number of complaints observed in census block n in each of the twelve months prior to month m. If Δ_{m-z} is negative, then increases in complaints correlate with fewer properties sold in month m and this would suggest that the ATE is underestimated. If Δ_{m-z} is positive, then this would suggest that the ATE is overestimated.

Table 15 shows that up to eleven months prior to m, one additional complaint correlates with 0.005-0.008 fewer properties sold. The effects are almost all statistically significant at the 1% level. Beyond eleven months into the past though, there is no detectable significant effect from complaints. To properly interpret the effects shown in Table 15, consider that the average marginal effect across all months $m-1$ to $m-11$ ≈ -0.006, the average number of complaints per block-group-month is 0.5, and there are 2,498 block groups in the city. Therefore, (11*0.006*0.5*2,498) 82.5 fewer properties are selling each month due to the presence of homeless encampments than would otherwise be expected, or just under 1000 on a yearly basis. Given that roughly 20,500 properties transacted in my sample each year, 4.8% fewer properties sold than otherwise would have due to the presence of homeless encampments. This suggests that the 1.82% average treatment effect is a slight underestimate because there are more than 58% of properties with a homeless encampment within 0.3 miles at any given time in the city.

Table 15: Complaints and Likelihood of Selling

	Dependent Variable: Number of Sales in Month m
Total Complaints 1 Month Prior	-0.006*
	(0.0025)
Total Complaints 2 Months Prior	-0.006**
	(0.0012)
Total Complaints 3 Months Prior	-0.007**
	(0.0013)
Total Complaints 4 Months Prior	-0.008**
	(0.0013)
Total Complaints 5 Months Prior	-0.008**
	(0.0014)
Total Complaints 6 Months Prior	-0.006**
	(0.0016)
Total Complaints 7 Month Prior	-0.005*
	(0.002)
Total Complaints 8 Months Prior	-0.005**
	(0.0015)
Total Complaints 9 Months Prior	-0.007**
	(0.0016)
Total Complaints 10 Months Prior	-0.006**
	(0.0016)
Total Complaints 11 Months Prior	-0.005**
	(0.0014)
Total Complaints 12 Months Prior	-0.0009
	(0.0015)
Observations	164,868

Notes: Standard errors clustered at the census block level.
* Significance at 5% level
** Significance at 1% level