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Abstract

A topic of intense and heated discussion in urban America is the impact of homelessness. While there is an immense rhetoric surrounding this subject, quantitative analysis is scarce. This study attempts to provide some precise insight into the economic costs of homelessness. Specifically, we estimate the impact that proximity to a homeless encampment has on the prices of nearby residences. Using hedonic models, based on data from Seattle from 2017 to 2020, we show that proximity to a homeless encampment has generally an insignificant effect on house prices; however once we use a quantile regression approach we find that homeless encampments have a detrimental effect on prices of houses in higher-price segments: houses in the highest price segments (75% and 95% quantiles) are priced 2.2% and 3.9% lower than an otherwise identical residence, if they are within 0.75 miles of a nearby homeless encampment. For the average sale in our sample, this figure represents an approximate loss in value of $21,340 and $66,822, respectively. We obtain slightly weaker, but similar results once we adjust for spatial autocorrelation.

Keywords: Hedonic models, homelessness, housing prices, quantile regression, spatial autocorrelation

Document de travail

1 Introduction

Since 2018, when the US Court of Appeals for the Ninth Circuit ruled that cities couldn't limit public camping if they didn't have alternative shelter spaces to offer, pretty much every city in the Western states has been inundated with large-scale homeless encampments. It is creating a public health nightmare—in Los Angeles County, roughly 2,000 homeless individuals died in 2021; in San Diego, nearly 600 homeless people died on the streets in 2022. They die of overdoses, heat exposure, cold exposure, and infectious diseases that spread in the camps; they are crushed when trees fall on tents during storms. Many are murdered; others commit suicide. It's also a public safety nightmare that is causing a growing political backlash.

You Can't Solve the Homelessness Crisis Without Housing.

https://www.thenation.com/article/economy/encampments-shelters/March 24, 2023

T*hat had seemed to them like an open question each morning for the last three years, as an epidemic of unsheltered homelessness began to overwhelm Phoenix and many other major American downtowns. Cities across the West had been transformed by a housing crisis, a mental health crisis and an opioid epidemic, all of which landed at the doorsteps of small businesses already reaching a breaking point because of the pandemic. In Seattle, more than 2,300 businesses had left downtown since the beginning of 2020.*

NY Times, March 19, 2023, A Sandwich Shop, a Tent City and an American Crisis

The homelessness crisis has been a prominent feature in the US media for the last four decades. Homelessness began to be a major public issue following the recession of 1981-1982. In 1987 President Reagan signed the Stewart B. McKinney Homeless Assistance Act (later renamed the McKinney-Vento Homeless Assistance Act), which provided funds for homeless assistance, such as shelters. But the problems became greater after the The United States Court of Appeals for the Ninth Circuit in 2018 ruled that individuals with no other place to go could not be punished for sleeping outside. The Covid crisis, the flaws in the shelter system and the lack of affordable housing exacerbated the situation. As of the end of 2023, the total US homeless population is estimated to be $653,104$; this is the highest figure since HUD began reporting these data in 2007.[1]

While politicians and others continue to struggle with solutions, very little progress is evident. Part of the problem has been the noticeable lack of precise data on the economic impact of homelessness, despite the enormous costs expended in efforts to address the crisis. For example, estimates of the annual cost to taxpayers of one chronically homeless person are between \$30,000 and \$50,000.[2] However, the existing literature on homelessness focuses mainly on survey data.

Homeless encampments are a negative externality, creating substantial financial and social costs for the associated cities. Because of its data availability, our analysis focuses on the City of Seattle. Analyzing the most recent data for Seattle, there are an average of 33 medical emergencies per day; 4.5 fire emergencies per day; an average of 2 shootings per week. In January 2023, the King County Regional Homelessness Authority (KCRHA) released a draft plan that calls for \$25.5 billion over five years to end homelessness in King County.[3] Added to this are the linkages with crime and drug usage (particularly opiods and phentanyl, which led to nearly one death per day).[4]

It is thus reasonable to expect that consumers would view proximity to homeless encampments as a significant negative factor in their housing decisions: buyers should be willing to pay more for a residence located far away from these encampments, all else equal. In addition, fear of crime has been showed to depress housing prices.[5]

[1] HUD (2023).

[2] https://www.usich.gov/resources/uploads/asset_library/Ending_Chronic_Homelessness_in_2017.pdf.

[3] https://kcrha.org/. King County represents Seattle and its immediate vicinity.

[4] Seattle Moving on Homelessness as Encampments Drop. *The Seattle Medium.* February 3, 2023.

[5] A relevant analysis is found in Linden and Rockoff (2008).

We make no attempt to pass judgment on the "morality" of encampments or to offer solutions to this critical problem. Our goal is merely to clarify the economic impact of proximity to an encampment using a single metric: its incremental impact on residential housing prices. Based on these general issues and the related references reviewed in the following section, we have the following null hypothesis:

H_0: Proximity to a homeless encampment does not influence residential property prices.

Our empirical analysis is based on Seattle data from 2017 to 2020.[6] We estimate hedonic models with and without adjustments for spatial autocorrelation. We believe our study can provide new insight into this important topic for a number of reasons. Our data are recent and unique, covering a relatively long time period with a large number of observations. Our econometric techniques and unique data (in particular, quantile regression, our treatment of spatial autocorrelation and our use of homeless encampment closure data) hopefully can offer a new perspective. To the best of our knowledge, ours is the first study to analyze the relation between homeless encampments and the prices of residential housing.

The data on homeless encampments are imprecise, making quantitative analysis challenging. It is impossible to determine exactly when an encampment starts, so we use the only officially documented data available: the closure date, i.e, the date when the City of Seattle determines that all of the residents of an encampment have been "relocated." We construct a variable that measures the sold residence's proximity to a homeless encampment, assuming that the encampment existed there 3 months and 6 months prior to the sale date In many cases the encampment has been in place much longer.

This study provides an estimate of the economic costs of homelessness by measuring the impact that proximity to a homeless encampment has on the prices of nearby residences. Using hedonic models, we show that proximity to a homeless encampment generally has an insignificant effect on house prices; however once we use a quantile regression approach we find that proximity to a homeless encampment depresses prices of houses in higher-price

[6] Data on homeless encampment closures are not available before or after this period. This topic is discussed further in Section 3.

segments. Houses in the highest price segments (75% and 95% quantiles) are priced 2.2% and 3.9% lower than an otherwise identical residence, if they are within 0.75 miles of a homeless encampment. For the average sale in our sample, this figure represents an approximate loss in value of $\$21,340$ and $\$66,822$, respectively.[7] The corresponding figures for residences that are within 1.0 miles of a homeless encampment are 1.0% and 4.0%, respectively. We obtain slightly weaker, but similar results once we adjust for spatial autocorrelation. These results highlight the very significant negative impact of proximity to a homeless encampment.

The remainder of this paper is organized as follows. Section 2 presents a very brief review of the literature most relevant to our topic, focusing on the econometric issues. Section 3 describes our data set and methodology. Section 4 summarizes our empirical results and Section 5 presents our conclusions.

2 Literature Review

2.1 Homelessness in Seattle

According to the HUD: ... *homelessness includes both sheltered and unsheltered people. Sheltered people are living in domestic violence shelters, transitional shelters, safe havens that serve homeless individuals with severe mental illness, or hotels/motels. Unsheltered people live outdoors, in cars, in abandoned buildings, or in other places not meant for human habitation.* Homelessness in Seattle is hardly a recent phenomenon. In 1854 Seattle had its "Skid Road" and, near Pioneer Square, its first documented homeless tent.[8] Like many other cities during the Great Depression Seattle had its Hoovervilles; the largest lasting from 1931 to 1941 and housing about 11,000.[9]

Since HUD began collecting these data in 2007, despite a long period of relative prosperity,

[7] In our sample, the average sale price in the 75 (95) percentile is $970,000 ($1,713,400).
[8] Ensign (2021).
[9] https://depts.washington.edu/depress/hooverville.shtml.

the Washington State homeless population has grown by 57.3%.[10] A contributing factor to this increase is the rise in housing prices and rental rates; since 2007, the average annual rate of rent increase in Seattle is 3.5%.[11] An earlier analysis of Seattle's homeless situation is City of Seattle (2017), which, i.a., documents mean (median) encampment durations of about 107 (70) days in the 6 permitted Seattle encampments.

Quigley, Raphael and Smolensky (2001) shows that small increases in housing vacancy rates or mild decreases in market rents can generate substantial declines in homelessness. Homeless encampments are generally associated with higher crime rates;[12] this can lead to increased housing turnover.[13]

Based on survey data, Allgood and Warren (2003) estimates a mean (median) duration of a homeless period of 761 (270) days. Mogk, Shmigol, Futrell, Stover and Hagopian (2020) provides more recent survey data from Seattle and estimate mean and median durations of 41.2 and 25.5 months. Sparks (2017) presents a unique perspective on Seattle homeless encampments based on his experience of spending 6 months as a resident in a tent city. The impact of encampments close to major throughfares is discussed in Ricord (2020).

HUD estimates from December 2023 document that Washington State's homeless population was estimated to be 4.3% of the total, making it the 3^{rd} largest concentration of homeless in the US. By comparison, Washington's total population is 2.4% of the US total, based on the most recent census data. An overview of homeless encampments and community responses can be found in HUD (2019) and references therein.

2.1.1 Homeless encampments

Homeless encampments range from a loose organization of a few individuals to much larger, and often more formal arrangments with established rules and norms of behavior. The encampments range from those that are officially sanctioned to much more loosely structured

[10] HUD (2023).
[11] FRED.
[12] E.g., Russell (2020).
[13] Braakmann (2023).

camps. Seattle's homeless live on the streets, under highway overpasses, in tent cities and in RV camps, i.a. According to data from December 2023, there were 523 tents and 227 RVs documented in Seattle homeless encampments.[14] The City has made extensive efforts to clean up (sweep) these encampments, but often the occupants return soon after being ousted, even though the City often erects barriers or increases regulation to try to prevent this, so that sweeps can present, at best, a temporary solution.[15] The potential negative impact of sweeps is discussed in National Health Care for the Homeless Council. (2022). Residents of homeless encampments typically cite freedom of movement, "safety in numbers" and greater protection from police harassment as motivation for electing an encampment versus the alternatives.[16]

2.2 Econometric Issues

A potential problem with hedonic models for housing prices is spatial correlation: because of similarities in omitted variables or unobservable characteristics, it is likely that model errors for nearby residences are positively correlated. Pace and LeSage (2009) provides a comprehensive overview. In our context, related work includes Zietz, Zietz and Sirmans (2008) and Zhang (2016). Our methodology essentially follows Zhang (2016) and is described in more detail in Kallberg and Shimizu (2023). We provide a more succinct overview in the following section.

[14] https://harrell.seattle.gov/2024/02/17/one-seattle-homelessness-action-plan-posts-q4-and-year-end-2023-data/

[15] E.g., https://komonews.com/news/local/its-a-revolving-door-rvs-tents-return-to-sodo-neighborhood-months-after-city-cleanup-encampment-homeless-treatement-housing-drug-use-theft-vandalism-unsanitary-inspection

[16] See Burness and Brown (2016) and HUD (2019).

3 Data and Methodology

3.1 Data

The data analyzed in this study come from several sources. We obtain data on property transactions from the King County Assessor's website. This website provides transaction data for residential and commercial properties, as well as for lands, easements etc. The property transactions data available for downloads date back to the 1950s; our data cover single-family houses in the City of Seattle from 2017 through 2020 to match the availability of our homeless encampment data. We use the property transactions data to build a dataset for our hedonic variables: sale prices, square footage (of living area, basement etc.), number of bedrooms and bathrooms, year of construction and indicators for natural views (Lake Washington, Mt Rainier, Puget Sound etc.).

We apply a number of selection filters to remove: (i) non-arm's length transactions, (ii) transactions where multiple residential properties are sold, (iii) transactions with sale prices below $10,000 and (iv) other filtering criteria commonly used in the real estate literature. In addition, we remove transactions made in "thin-cells," defined as zip codes with relatively few home sales. In total, we have $28,778$ single-family residential property sales in the City of Seattle over the January 1, 2017 - December 31, 2020 period. Demographic data are collected from the Washington State Office of Financial Management. The data are available on an annual basis and provide the following demographic data: population, age, gender and race (all at the census tract level).

Homeless encampment sweeps refer to attempts by local authorities to forcibly close the encampment, often with some attempt to provide alternative housing options. The data on these sweeps are hand collected from the City of Seattle's website. During $2017 - 2020$, the website periodically uploaded a report that summarizes: 1) location of an encampment site, 2) characteristics of the encampment, including the number of tents/vehicles/structures identified, 3) photos of the encampment and most importantly, 4) first and last (completion) dates of the removal. Table 1 reports the characteristics of the homeless encampments used in our study. There are 260 homeless encampments that have been identified and eventually removed by the City of Seattle during 2017 – 2020. Out of 260 encampments, many consisted of only a handful of tents or other structures; we removed encampments with fewer than 10 obstacles from the sample. This reduces the number of encampments analyzed in our analysis to 47 sites. On average, there are 21 tents or a total of 27 obstacles (including bedrolls, vehicles and other structures) per encampment site. Where homeless people reside varies from one site to another – the majority are located in heavy traffic zones and within 50 ft of a guardrail (83 percent and 72 percent of the sample, respectively). These encampments are shown in Figure 1, which clearly depicts their concentrations around I5, the main Seattle highway running north and south.

The data on homeless encampments are imprecise. It is impossible to determine precisely when an encampment starts, so we are forced to use the data available on closures. When an investigator from the City of Seattle visits an encampment, she records the date when: the encampment is identified/inspected, a warning is issued (for removal), start of the removal and end (completion) of removal. The mean (median) number of days took to complete the removal (from the first day when the encampment was identified) is 46 (18) days. Our approach is to construct a variable that measures a sold house's proximity to a homeless encampment, assuming that the encampment existed there 3 months and 6 months prior to the sale date (more details are discussed in Section 3.2 and precise definitions of our proximity variables are provided in the Appendix).

3.1.1 Property and demographic data

Table 2 provides summary statistics for our key explanatory variables based on our sample of $28,778$ sales from January, 2017 to December, 2020. The mean (median) sale price is $\$876,203$ ($\$760,000$). The property-level statistics show a mean (median) living area of $1,853$ ($1,680$) sq. ft.; lot area of $4,688$ ($4,700$) sq. ft.; number of bedrooms 3.2 (3.0).

Residences with a view (principally of the Olympic or Cascade Mountains) represent 11.8% of the total.

Panel C presents the correlations between our key variables. The generally small, negative correlations between sale price and measures of proximity to a homeless encampment suggest that our statistical analysis is unlikely to produce strong results on average, but by applying quantile regression we can potentially tease out different results across the distribution of sale prices.

3.2 Methodology

3.2.1 Hedonic models using quantile regression

Our empirical analysis of prices uses a spatial hedonic model weighting the physical characteristics of the property and its neighborhood. This approach is described in several surveys, i.a., Herath and Maier (2010). Our approach is to add proximity to a homeless encampment to the hedonic models to test for the implicit (hedonic) price of the attribute, thus incorporating tangible and intangible costs.

Incorporating quantile regression within the hedonic model approach allows the conditional distribution of the dependent variable to be determined as a function of the independent variables. An example of its application is Zietz, Zietz and Sirmans (2008), which uses quantile regression to show that different property characteristics are not priced identically across the entire distribution of house prices. We also adopt this approach, which allows us to determine if the price relation between the proximity to homeless encampments varies with the residence's price.

3.2.2 Spatial autocorrelation

A further extension of the hedonic model methodology incorporates spatial autocorrelation, which attempts to account for the (assumedly positive) correlation between residuals from the hedonic model for neighboring residences.[17] Our approach to capture the relation between neighboring observations follows that described in Getis (2010: p. 256). Here $[Wy]_{it}$ is a spatial weight matrix, defined as $[Wy]_{it} = \sum_{j=1}^{n} w_{ij} y_j$ where y_j is the sales price for a "nearby recently sold" house j; w_{ij} is the weight (or spatial lag) assigned to y_j based on the inverse distance d between house i and house j. Here we determine the inverse distance calculation by $\left(\frac{1}{d^2}\right)$, which is the most frequent choice in the related literature.

To calculate Wy for home i's sale, we first identify sales of its neighbor homes ($j = 1, 2, ...$) that occurred within $2,000$ feet, within the past 24 months. For each neighbor home sale j, we measure the distance from home sale i and use the sale price y_j for neighbor home j to calculate $w_{ij} y_j$. Finally, we calculate the spatial weight matrix for the sale of house j, $[Wy]_{it}$, using the above equation.

3.2.3 Empirical modeling

We perform our main analysis in two steps: (i) traditional ordinary least squares (OLS) and quantile hedonic models, and (ii) two-stage least squares (2SLS) hedonic models and instrumental variable quantile hedonic regressions (IQHR) to account for spatial autocorrelation.

For the first approach, we include demographic and proximity variables in a traditional hedonic model to examine their marginal impact on house prices. We estimate our first model using OLS as:

$$\log(\textit{sale price}) = \beta_0 + \beta X + \phi \textit{demographic variables} + \gamma \textit{proximity}$$
$$\textit{variables} + \textit{dummies} + \epsilon \qquad (1)$$

where the dependent variable is the log of house sale price; X is a vector of property and neighborhood characteristics; *demographic variables* is a vector capturing demographic characteristics; *proximity variables* is a vector characterizing proximity to homeless encampments and distance to CBD (central business district); dummies are dummies for month

[17] Zhang (2016) and Waltl (2019).

and year. Precise definitions of the dependent and explanatory variables are provided in the Appendix. For each property, we measure the distance to nearby encampments and to the CBD using the straight (Euclidean) distance in our main analysis.

Next, we use quantile regression to examine whether our key explanatory variables have a different impact across the distribution of the dependent variable. Specifically, we estimate the following quantile regressions:

$$\log(sale\ price) = \beta_0 + \beta_\tau X + \phi(\tau) demographic\ variables + \gamma(\tau) proximity\ variables + dummies + \epsilon \qquad (2)$$

where the dependent and explanatory variables remain the same as in Eq.1. We run Eq. 2 for various quantiles (τ) of house prices: .05 (lowest-end), .25, .50 (median), .75 and .95 (highest-end).

Next, we extend the models in Eqs. 1 and 2 by incorporating the spatial autocorrelation between a house's sale price and the sale prices of its neighboring houses. We follow Zhang (2016) to estimate the following two-stage least squares (2SLS) model that accounts for the correlation between residuals from the hedonic models and the prices of neighboring houses. In the first stage, we regress Wy (as defined in Section 3.2.2.) against the spatially lagged, exogenous instruments X (hedonic variables from Eq. 1). We then use the coefficient estimates from the first stage to compute the predicted value for $\widehat{Wy}$. In the second stage, we add $\widehat{Wy}$ to Eq. 1 and Eq. 2. The 2SLS hedonic model can be written as:

$$\log(sale\ price) = \beta_0 + \widehat{\rho W y} + \beta X + \phi demographic\ variables + \gamma proximity\ variables + dummies + \epsilon \qquad (3)$$

We also estimate a quantile regression model with the instrumental variable approach, namely the instrumental quantile hedonic regression (IQHR) model as:

$$\log(Sale\ price) = \beta_0 + \widehat{\rho W y} + \beta_\tau X + \phi(\tau) demographic\ variables + \gamma(\tau) proximity\ variables + dummies + \epsilon \qquad (4)$$

Equations 3 and 4 are analogous to Equations 1 and 2, except that we add an instrumental variable approach to account for spatial autocorrelation (Wy).

4 Empirical Results

4.1 Results without spatial autocorrelation adjustments

Table 3 presents the results of running OLS and quantile regressions without incorporating adjustments for spatial autocorrelation. To measure the impact of proximity to a homeless encampment on house prices, we use *Within6mo_075* (a dummy variable that is equal to 1 if a house is sold within 0.75 miles of a homeless encampment, assuming that the encampment existed for 6 months prior to the sale date) in Panel A.

Model 1 reports our OLS regression results (as estimated in equation 1). We obtain results that parallel those found in related hedonic models; sale price increases for a house with a larger living or lot size; younger age; multi-stories; a fireplace or natural view. The number of bedrooms exhibits a negative impact, since the living area size is already factored into the model. In terms of demographics (which are measured at the census tract level), higher total population as well as white and Asian population lead to higher house prices; higher male population has a negative relation and old population has an insignificant relation. Proximity to the city's central business district (CBD) has a significant negative sign, suggesting that buyers are willing to pay more to live closer to the CBD for shorter commuting time, better access to amenities, etc.

Our focus is on the impact of homeless encampments and we see an insignificant relation between proximity to a homeless encampment and housing prices from the OLS results (model 1). The OLS model does not consider the potentially different impact of homeless encampments across the dependent variable's distribution; for example, home buyers in the higher-end price segments may be more sensitive to their proximity to a homeless encampment than those in the lower-end price segments. To address this issue, we perform quantile regressions (as estimated in equation 2) and report the results in models 2 – 6. Similar to the OLS results, we find that the impact of proximity to a homeless encampment is insignificant for houses in the lowest two quantiles (5% and 25%) and in the median quantile (50%). When we focus on the results for the highest two quantiles (75% and 95%), we find that the impact of homeless encampments is significantly negative: for example, in the 95% quantile estimates, houses within 0.75 miles of a homeless encampment sell for 3.9% lower than an otherwise identical residence.

We also note that some hedonic variables show a different impact across different quantiles: the number of bathrooms has an insignificant relation with house prices in the OLS, 5% and 25% quantiles but its effect turns significant and positive in the 50%, 75% and 95% quantiles. Whether a house has been renovated has no effect on house prices for OLS, but it has a significant and negative (positive) effect in the 5% and 25% (75% and 95%) quantiles.

In Panel B, we substitute *Within6mo_100 (1 mile)* for *Within6mo_075 (0.75 miles)* and re-run the OLS and quantile regressions. We obtain qualitatively similar results to those reported in Panel A, except that the impact of homeless encampments becomes insignificant in the 75% quantile. It is only in the highest quantile (95%) that proximity to a homeless encampment depresses house prices.

4.2 Results with spatial autocorrelation adjustments

The results presented in the previous subsection do not account for spatial autocorrelation (i.e., possibly positive correlation between residuals from the hedonic model for neighboring residences). In Table 4 we incorporate adjustments for spatial autocorrelation and re-run our analysis in a 2SLS framework. Model 1 reports the results of 2SLS regressions estimated in equation 3: for each house sale y_i, we construct a spatial weight matrix Wy, the weighted average price of "nearby recently sold" houses j (for $j = 1, 2, \ldots$), as described in Section 3.2.2. In the first stage, we regress Wy against the spatially lagged, exogenous instruments X (hedonic variables from equation 1). Using the coefficient estimates from the first stage, we compute the predicted value for the spatial autocorrelation term, Wy, to be added as a regressor in the second stage of the 2SLS model. In addition, we run instrumental variable quantile hedonic regressions (IQHR, as estimated in equation 4) for 5%, 25%, 50%, 75% and 95% quantiles.

We use the same explanatory variables (hedonic, demographic and proximity variables) as in the OLS and quantile regressions. One significant change from the previous OLS and quantile regressions is that now we run the 2SLS (model 1) and IQHR (models 2 – 6) models to incorporate spatial autocorrelation. For brevity we only discuss results that differ significantly from those in Table 3.

First, we find that the spatial lag coefficient, ρ on Wy, is positive and significant in the 2SLS result and in each of the price quantiles, indicating that there exist similarities in omitted variables or unobservable characteristics shared among nearby residencies. The coefficients ρ on Wy range from 0.335 to 0.359 with an average value of 0.352. With the adjustment for spatial autocorrelation, property age (*Age*) retains the significant negative sign across all the models, suggesting that younger houses sell for higher prices. Old population (*%Old*) now has a significant negative in all the models, indicating that in neighborhoods with higher old population have lower house prices.

Focusing on the effect of homeless encampments, we find that its coefficients are significantly negative for the 2SLS (model 1) and 75% and 95% quantiles (models 5 and 6) with the coefficients of -0.014, -0.015 and -0.026, respectively.

Compared to the results from Table 3, these estimates seem to be smaller; however in a spatial lag model one needs to account not only for these direct impacts (e.g., -0.014 for 2SLS), but also for the total impact by incorporating the coefficient ρ. For a row-standardized spatial-lag matrix (Wy), its row elements sum to one. Thus, the total impact of homeless encampment while accounting for spatial autocorrelation is (for 2SLS): $\frac{-.014}{1-\rho} = \frac{-.014}{1-.359} = 0.022$. For the quantile regression results, the total impact of proximity to a homeless encampment is 2.2% and 2.0% in the 75% and 95% quantiles, respectively.

In Panel B, we substitute *Within6mo_100 (1 mile)* for *Within6mo_075 (0.75 miles)* and re-run the 2SLS and IQHR regressions. As expected, the coefficients on *Within6mo_100* are smaller than those on *Within6mo_075* from Panel A. The coefficients on the other explanatory variables generally mirror those from Panel A. Overall, the results from Tables 3 and 4 indicate that the effect of homeless encampments is significant and negative only for houses in the highest price quantiles (75% and 95%); generally the same results hold for models that incorporate adjustments for spatial autocorrelations.

4.3 Robustness

In our baseline models (Tables 3 and 4), we assumed that a homeless encampment existed 6 months prior to the sale date, and then constructed *Within6mo_075 (Within6mo_100)* to examine the effect of proximity to a homeless encampment on house prices for houses within 0.75 miles (1.00 mile) distance to an encampment. In our data (as described in Section 3.1) we do not have a precise initiation date for a homeless encampment. As encampment inspections and removals are performed in response to complaints made by residents, some encampments may be removed in a short period of time and hence do not remain for 6 months.

As a robustness check, we substitute *Within3mo_075* (*Within3mo_100*) for *Within6mo_075* (*Within6mo_100*) to allow for the possibility that some encampments are removed more quickly than our initial assumption of 6 months. Table 5 displays the results for 2SLS and IQHR with adjustments for spatial autocorrelations. Panel A (B) uses *Within3mo_075* (*Within3mo_100*) as a proximity to a homeless encampment variable. Other explanatory variables remain the same as those used in the baseline regressions. The coefficients on spatial autocorrelation, hedonic and sociodemographic variables are qualitatively unchanged from the baseline results (Table 4). In Panel A, the negative effect of homeless encampments is significant only for the 2SLS (model 1) and 75% quantile (model 5); in Panel B, the effect is only significant for the 2SLS (model 1) and 95% quantile.

We can conclude that our basic results - a significant negative impact for more expensive residences - is reasonably robust to assumptions about encampment longevity.

5 Conclusions

This study explores the link between proximity to a homeless encampment and the pricing of residential housing using a unique data set for the City of Seattle from 2017 to 2020. We correct for spatial autocorrelation to account for the positive correlations between hedonic model pricing errors for nearby houses. We then use quantile regression to evaluate how these model factor estimates vary across different price strata.

The lack of empirical research in this area is partially due to the difficulty in obtaining quantitative data on homeless encampments. The City of Seattle's documentation of its encampment closures offers us an, albeit imprecise, method to locate encampments and thus, using sales of nearby residence, estimate their impact on housing prices, correcting for other quantifiable characteristics.

Our analysis shows that proximity to a homeless encampment has a significant and negative impact only on more expensive residences: houses in the highest price segments (75% and 95% quantiles) that are within 0.75 miles of a homeless encampment are priced 2.2% and 3.9% lower than an otherwise identical residence. For the average sale in our sample, this figure represents an approximate loss in value of $\$21,340$ and $\$66,822$, respectively. These figures suggest that proximity to a homeless encampment has a significant negative economic impact, but that this impact is concentrated in the highest value residences. When we adjust for spatial autocorrelation, we find slightly weaker, but similar results.

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Figure 1: Locations of homeless encampments and home sales

This figure reports locations of homeless encampments and single-family home sales in Seattle from 2017 to 2020. Each marker icon (in red) represents the location of an encampment with at least 10 obstacles (tents, structures, bed rolls and/or vehicles). Each dot (in blue) represents the location of a house sale. The target circle icon (in black) represents the location of Seattle's central business district (CBD).

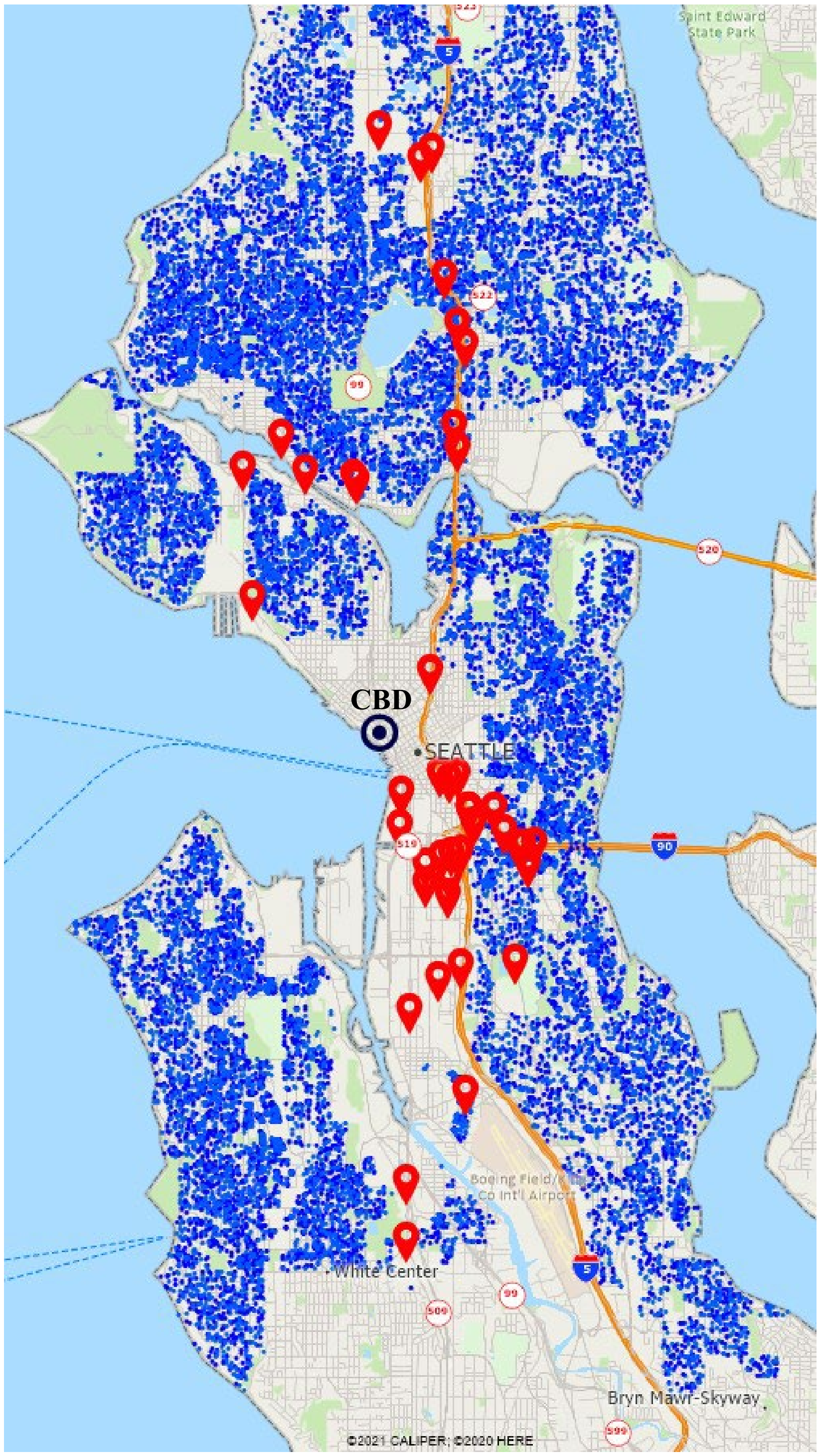

Table 1: Homeless encampment characteristics

This table reports the characteristics of the homeless encampment sites used in our study. There are 260 homeless encampment sites found and reported to the City of Seattle from 2017 to 2020. An encampment is defined as "*one or more tent, structure, or assembly of camping equipment or personal property located in an identifiable area within the City of Seattle, which appears to a reasonable person as being used for camping* (FAS Encampment Rule 17-01)." We remove encampment sites with fewer than 10 obstacles (including *Tents*, *Structures*, *Bed Rolls* and *Vehicles*, as defined by the City of Seattle). This filtering reduces the number of encampment sites in our analysis to 47 sites. For each encampment, the date of first inspection of the site, the date of clean-up and the end date of clean-up (removal date) are reported. *# of days until removal* is defined as (end date of clean-up – date of first inspection).

Total # of encampments	47
Avg. # of obstacles per camp	
Tents	21.17
Structures	4.28
Bed rolls	0.21
Vehicles	1.70
Total # of obstacles	27.21
Locations/characteristics of encampments	
Park	4.26%
Sidewalk	25.53%
Roadway	29.79%
Within 50ft of Water	6.38%
Within 50ft of a Guardrail	72.34%
Heavy Traffic	82.98%
Near Industrial Zone	21.28%
Forested Area	48.94%
Play Area	2.13%
Average # of days until removal	
Mean	46.30
Median	18.00

Table 2: Summary statistics

The sample consists of 28,787 single-family home sales in Seattle from 2017 to 2020. Panel A reports the summary statistics for the hedonic variables (property characteristics, distance to the city central and proximity to homeless encampments). Panel B reports the summary statistics for sociodemographic variables. Panel C reports the correlations. Definitions of the variables are provided in the Appendix.

Panel A: Hedonic variables and distance measures

	N	Mean	Median	Std Dev	Min	Max
Property-level characteristics						
Sale Price	28,787	876,203	760,000	497,852	10,000	14,275,000
WY	28,787	814,456	750,627	339,097	9,321	6,257,625
Living Area (in 000s)	28,787	1.853	1.680	0.779	0.350	4.440
Lot Area (in 000s)	28,786	4.688	4.700	2.876	0.375	15.695
Bedrooms	28,787	3.165	3.000	0.936	0.000	11.000
Bathrooms (full size)	28,787	1.448	1.000	0.689	0.000	7.000
Age	28,787	55.283	67.000	39.513	0.000	120.000
One Story	28,787	0.397	0.000	0.489	0.000	1.000
Renovated	28,787	0.038	0.000	0.192	0.000	1.000
Fireplace	28,787	0.666	1.000	0.472	0.000	1.000
Environmental - natural views						
Lake/Mountain View	28,787	0.118	0.000	0.323	0.000	1.000
Proximity measures						
Distance to CBD (straight miles)	28,787	4.749	4.828	1.758	1.123	8.992
Proximity to homeless encampments						
Within3Mo_025 (within 0.25 miles)	28,787	0.002	0.000	0.042	0.000	1.000
Within3Mo_050 (within 0.50 miles)	28,787	0.007	0.000	0.085	0.000	1.000
Within3Mo_075 (within 0.75 miles)	28,787	0.014	0.000	0.116	0.000	1.000
Within3Mo_100 (within 1.00 mile)	28,787	0.022	0.000	0.146	0.000	1.000
Within6Mo_025 (within 0.25 miles)	28,787	0.003	0.000	0.058	0.000	1.000
Within6Mo_050 (within 0.50 miles)	28,787	0.014	0.000	0.116	0.000	1.000
Within6Mo_075 (within 0.75 miles)	28,787	0.027	0.000	0.161	0.000	1.000
Within6Mo_100 (within 1.00 mile)	28,787	0.040	0.000	0.196	0.000	1.000

Panel B: Sociodemographic variables (475 tract-year observations)

	Mean	Median	Std Dev	Min	Max
Population	5,443	5,139	1,920	1,433	11,930
%Male	0.495	0.491	0.023	0.446	0.592
%Female	0.505	0.509	0.023	0.408	0.554
%White	0.676	0.755	0.198	0.090	0.902
%Asian	0.163	0.119	0.124	0.040	0.639
%Black	0.087	0.040	0.095	0.007	0.426
%Old	0.122	0.117	0.046	0.027	0.273

Panel C: Correlations

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
(1) Log(Sale Price)	1.000									
(2) Log(WY)	0.741*	1.000								
(3) Living Area	0.721*	0.463*	1.000							
(4) Lot Area	0.191*	0.095*	0.372*	1.000						
(5) Bedrooms	0.412*	0.204*	0.671*	0.290*	1.000					
(6) Bathrooms	0.337*	0.148*	0.493*	0.072*	0.426*	1.000				
(7) Age	0.009	0.153*	0.001	0.432*	0.072*	-0.160*	1.000			
(8) One Story	-0.278*	-0.165*	-0.236*	0.401*	-0.157*	-0.229*	0.389*	1.000		
(9) Renovated	0.035*	0.001	0.087*	0.062*	0.098*	0.090*	0.150*	0.052*	1.000	
(10) Fireplace	0.267*	0.211*	0.337*	0.303*	0.273*	0.148*	0.140*	0.092*	-0.007	1.000
(11) Lake/Mountain View	0.334*	0.302*	0.333*	0.250*	0.136*	0.117*	0.063*	-0.005	0.021*	0.154*
(12) Distance to CBD	-0.315*	-0.408*	-0.070*	0.407*	0.036*	-0.049*	0.066*	0.309*	-0.002	0.119*
(13) Within3mo_025	-0.010	-0.004	-0.019*	-0.038*	-0.023*	-0.009	-0.026*	-0.026*	-0.008	-0.019*
(14) Within3mo_050	-0.014*	0.001	-0.029*	-0.038*	-0.030*	-0.015*	-0.009	-0.013*	-0.011	-0.026*
(15) Within3mo_075	-0.004	0.018*	-0.018*	-0.038*	-0.019*	-0.012*	-0.005	-0.016*	-0.010	-0.022*
(16) Within3mo_100	-0.005	0.017*	-0.017*	-0.031*	-0.013*	-0.010	-0.007	-0.011	-0.004	-0.015*
(17) Within6mo_025	-0.008	-0.003	-0.024*	-0.046*	-0.026*	-0.002	-0.031*	-0.029*	-0.005	-0.024*
(18) Within6mo_050	-0.013*	0.004	-0.034*	-0.050*	-0.023*	-0.008	-0.010	-0.016*	-0.011	-0.023*
(19) Within6mo_075	-0.007	0.015*	-0.026*	-0.052*	-0.014*	-0.008	-0.004	-0.017*	-0.011	-0.017*
(20) Within6mo_100	-0.005	0.018*	-0.022*	-0.043*	-0.004	-0.004	-0.004	-0.013*	0.000	-0.010

	(11)	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*	*(17)*	*(18)*	*(19)*	*(20)*
(11) Lake/Mountain View	1.000									
(12) Distance to CBD	-0.025*	1.000								
(13) Within3mo_025	-0.005	-0.034*	1.000							
(14) Within3mo_050	-0.015*	-0.048*	0.493*	1.000						
(15) Within3mo_075	-0.014*	-0.054*	0.357*	0.725*	1.000					
(16) Within3mo_100	-0.016*	-0.049*	0.282*	0.573*	0.790*	1.000				
(17) Within6mo_025	-0.012*	-0.045*	0.721*	0.353*	0.255*	0.200*	1.000			
(18) Within6mo_050	-0.015*	-0.063*	0.357*	0.724*	0.522*	0.409*	0.495*	1.000		
(19) Within6mo_075	-0.018*	-0.072*	0.254*	0.517*	0.712*	0.559*	0.353*	0.713*	1.000	
(20) Within6mo_100	-0.019*	-0.067*	0.207*	0.419*	0.578*	0.732*	0.287*	0.579*	0.812*	1.000

* shows significance at the 0.05 level

Table 3: Quantile regressions – results without spatial autocorrelation adjustments

This table reports the results of OLS regression (model 1, as estimated in Eq. 1) and quantile regressions (models 2 – 6, as estimated in Eq. 2) for 5, 25, 50, 75 and 95 percent quantiles, respectively. Definitions of the variables are provided in the Appendix. Standard errors are reported in parentheses: for OLS regression, standard errors are clustered by year and month. For quantile regressions, standard errors are obtained through bootstrap replications. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.

Panel A: The effect of proximity to a nearby homeless encampment (within 0.75 miles)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Log (Sale Price)	OLS	Q: 0.05	Q: 0.25	Q: 0.50	Q: 0.75	Q: 0.95
Living Area	0.325***	0.303***	0.311***	0.322***	0.340***	0.356***
	(0.006)	(0.007)	(0.004)	(0.003)	(0.004)	(0.007)
Lot Area	0.016***	0.003	0.009***	0.015***	0.019***	0.033***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Bedrooms	-0.017**	-0.015***	-0.007***	-0.007***	-0.009***	-0.014***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)
Bathrooms	0.005	-0.007	0.002	0.005**	0.005***	0.013***
	(0.004)	(0.006)	(0.003)	(0.002)	(0.002)	(0.004)
Age	-0.000*	-0.001***	-0.000***	-0.000***	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
One Story	-0.072***	-0.049***	-0.059***	-0.065***	-0.064***	-0.081***
	(0.008)	(0.011)	(0.005)	(0.004)	(0.004)	(0.006)
Renovated	-0.010	-0.204***	-0.056***	0.008	0.041***	0.072***
	(0.030)	(0.030)	(0.017)	(0.011)	(0.008)	(0.016)
Fireplace	0.034***	0.040***	0.036***	0.024***	0.021***	0.006
	(0.005)	(0.009)	(0.003)	(0.003)	(0.004)	(0.005)
Lake/Mountain View	0.097***	0.062***	0.057***	0.077***	0.105***	0.183***
	(0.013)	(0.011)	(0.006)	(0.005)	(0.008)	(0.015)
Population	0.015*	-0.046***	0.014***	0.025***	0.022***	0.033***
	(0.005)	(0.013)	(0.005)	(0.004)	(0.005)	(0.007)
%Male	-0.178**	-0.551***	-0.036	0.038	-0.103	0.067
	(0.044)	(0.203)	(0.085)	(0.081)	(0.109)	(0.158)
%White	0.721***	0.876***	0.703***	0.700***	0.687***	0.736***
	(0.033)	(0.061)	(0.019)	(0.014)	(0.017)	(0.025)
%Asian	0.201***	0.399***	0.182***	0.180***	0.197***	0.352***
	(0.030)	(0.093)	(0.033)	(0.023)	(0.028)	(0.046)
%Old	0.090	0.032	0.012	-0.013	0.033	0.109*
	(0.049)	(0.100)	(0.043)	(0.042)	(0.042)	(0.061)
Distance to CBD	-0.065***	-0.066***	-0.061***	-0.062***	-0.066***	-0.079***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Within6mo_075	-0.016	-0.003	-0.001	-0.002	-0.022**	-0.039***
	(0.011)	(0.025)	(0.009)	(0.008)	(0.009)	(0.011)
Constant	12.697***	12.970***	12.462***	12.428***	12.617***	12.532***
	(0.016)	(0.190)	(0.075)	(0.060)	(0.067)	(0.094)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	28,778	28,778	28,778	28,778	28,778	28,778

Table 3: (cont'd)
Panel B: The effect of proximity to a nearby homeless encampment (within 1 mile)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Log (Sale Price)	OLS	Q: 0.05	Q: 0.25	Q: 0.50	Q: 0.75	Q: 0.95
Living Area	0.325***	0.303***	0.311***	0.322***	0.341***	0.357***
	(0.006)	(0.007)	(0.003)	(0.003)	(0.004)	(0.006)
Lot Area	0.016***	0.003	0.009***	0.015***	0.019***	0.033***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Bedrooms	-0.017**	-0.014***	-0.007***	-0.007**	-0.009***	-0.014***
	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)
Bathrooms	0.005	-0.008	0.002	0.005**	0.005**	0.013***
	(0.004)	(0.006)	(0.003)	(0.002)	(0.002)	(0.004)
Age	-0.000*	-0.001***	-0.000***	-0.000***	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
One Story	-0.072***	-0.053***	-0.059***	-0.065***	-0.065***	-0.081***
	(0.008)	(0.010)	(0.005)	(0.004)	(0.004)	(0.007)
Renovated	-0.010	-0.206***	-0.056***	0.008	0.042***	0.070***
	(0.030)	(0.029)	(0.016)	(0.012)	(0.010)	(0.015)
Fireplace	0.034***	0.042***	0.035***	0.024***	0.021***	0.006
	(0.005)	(0.008)	(0.004)	(0.002)	(0.003)	(0.004)
Lake/Mountain View	0.097***	0.063***	0.057***	0.077***	0.106***	0.180***
	(0.013)	(0.012)	(0.007)	(0.006)	(0.008)	(0.013)
Population	0.015*	-0.044***	0.014***	0.025***	0.021***	0.032***
	(0.005)	(0.014)	(0.005)	(0.004)	(0.004)	(0.006)
%Male	-0.179**	-0.491***	-0.045	0.030	-0.114	0.038
	(0.044)	(0.189)	(0.077)	(0.082)	(0.105)	(0.157)
%White	0.721***	0.881***	0.706***	0.702***	0.684***	0.742***
	(0.033)	(0.063)	(0.018)	(0.015)	(0.016)	(0.024)
%Asian	0.200***	0.400***	0.188***	0.183***	0.192***	0.366***
	(0.031)	(0.099)	(0.031)	(0.025)	(0.026)	(0.043)
%Old	0.090	0.023	0.017	-0.011	0.032	0.092
	(0.050)	(0.089)	(0.041)	(0.040)	(0.045)	(0.063)
Distance to CBD	-0.065***	-0.066***	-0.061***	-0.062***	-0.066***	-0.079***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Within6mo_100	-0.011	-0.022	0.008	0.001	-0.010	-0.040***
	(0.013)	(0.018)	(0.007)	(0.005)	(0.007)	(0.009)
Constant	12.698***	12.918***	12.464***	12.427***	12.626***	12.545***
	(0.017)	(0.195)	(0.065)	(0.058)	(0.064)	(0.093)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	28,778	28,778	28,778	28,778	28,778	28,778

Table 4: IV quantile regressions – results with spatial autocorrelation adjustments
This table reports the results of 2SLS regression (model 1, as estimated in Eq. 3) and instrumental-variable (IV) quantile regressions (models 2 – 6, as estimated in Eq. 4) for 5, 25, 50, 75 and 95 percent quantiles, respectively. Definitions of the variables are provided in the Appendix. Standard errors are reported in parentheses: for 2SLS regression, standard errors are clustered by year and month. For IV quantile regressions, standard errors are obtained through bootstrap replications. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.

Panel A: The effect of proximity to a nearby homeless encampment (within 0.75 miles)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Log (Sale Price)	2SLS	Q: 0.05	Q: 0.25	Q: 0.50	Q: 0.75	Q: 0.95
Log (WY)	0.359***	0.359***	0.335***	0.339***	0.343***	0.375***
	(0.019)	(0.017)	(0.008)	(0.008)	(0.010)	(0.016)
Living Area	0.269***	0.255***	0.257***	0.268***	0.288***	0.304***
	(0.009)	(0.006)	(0.004)	(0.003)	(0.003)	(0.007)
Lot Area	0.014***	0.002	0.010***	0.014***	0.018***	0.029***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Bedrooms	-0.009***	-0.007*	0.001	0.001	-0.002	-0.007**
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Bathrooms	0.009***	-0.005	0.006**	0.008***	0.010***	0.016***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
Age	-0.001***	-0.002***	-0.001***	-0.001***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
One Story	-0.063***	-0.046***	-0.054***	-0.055***	-0.057***	-0.065***
	(0.003)	(0.007)	(0.003)	(0.002)	(0.003)	(0.007)
Renovated	0.008	-0.216***	-0.027	0.038***	0.062***	0.084***
	(0.024)	(0.019)	(0.020)	(0.009)	(0.008)	(0.009)
Fireplace	0.019***	0.029***	0.017***	0.012***	0.011***	0.003
	(0.005)	(0.007)	(0.003)	(0.003)	(0.003)	(0.004)
Lake/Mountain View	0.054***	0.028**	0.029***	0.042***	0.058***	0.099***
	(0.002)	(0.012)	(0.005)	(0.005)	(0.006)	(0.013)
Population	0.013***	-0.007	0.018***	0.019***	0.011***	0.018***
	(0.003)	(0.010)	(0.003)	(0.004)	(0.004)	(0.007)
%Male	-0.143***	-0.372**	-0.070	0.020	-0.001	0.207
	(0.018)	(0.159)	(0.057)	(0.055)	(0.063)	(0.126)
%White	0.446***	0.534***	0.465***	0.431***	0.412***	0.410***
	(0.025)	(0.043)	(0.016)	(0.012)	(0.015)	(0.024)
%Asian	0.137***	0.190***	0.141***	0.121***	0.142***	0.200***
	(0.025)	(0.066)	(0.023)	(0.020)	(0.018)	(0.041)
%Old	-0.224***	-0.215***	-0.222***	-0.229***	-0.259***	-0.206***
	(0.023)	(0.069)	(0.032)	(0.029)	(0.033)	(0.052)
Distance to CBD	-0.038***	-0.035***	-0.038***	-0.038***	-0.040***	-0.045***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Within6mo_075	-0.014***	-0.002	-0.002	-0.004	-0.015**	-0.026**
	(0.003)	(0.015)	(0.007)	(0.005)	(0.007)	(0.011)
Constant	8.003***	8.036***	8.155***	8.133***	8.237***	7.720***
	(0.247)	(0.309)	(0.102)	(0.109)	(0.142)	(0.228)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	28,778	28,778	28,778	28,778	28,778	28,778

Table 4: (cont'd)
Panel B: The effect of proximity to a nearby homeless encampment (within 1 mile)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Log (Sale Price)	2SLS	Q: 0.05	Q: 0.25	Q: 0.50	Q: 0.75	Q: 0.95
Log (WY)	0.359***	0.359***	0.335***	0.339***	0.343***	0.375***
	(0.019)	(0.018)	(0.008)	(0.009)	(0.010)	(0.017)
Living Area	0.269***	0.255***	0.257***	0.268***	0.288***	0.304***
	(0.009)	(0.005)	(0.004)	(0.003)	(0.003)	(0.007)
Lot Area	0.014***	0.002	0.010***	0.014***	0.018***	0.029***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Bedrooms	-0.009***	-0.007*	0.001	0.001	-0.002	-0.007*
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)
Bathrooms	0.009***	-0.005	0.006**	0.008***	0.010***	0.016***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
Age	-0.001***	-0.002***	-0.001***	-0.001***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
One Story	-0.063***	-0.046***	-0.054***	-0.055***	-0.057***	-0.065***
	(0.003)	(0.007)	(0.003)	(0.003)	(0.003)	(0.006)
Renovated	0.008	-0.216***	-0.027	0.038***	0.062***	0.083***
	(0.024)	(0.019)	(0.020)	(0.009)	(0.008)	(0.009)
Fireplace	0.019***	0.029***	0.017***	0.012***	0.011***	0.003
	(0.005)	(0.007)	(0.003)	(0.003)	(0.003)	(0.004)
Lake/Mountain View	0.054***	0.028**	0.029***	0.042***	0.058***	0.099***
	(0.002)	(0.012)	(0.005)	(0.005)	(0.006)	(0.013)
Population	0.013***	-0.007	0.019***	0.019***	0.011***	0.018***
	(0.003)	(0.009)	(0.003)	(0.004)	(0.004)	(0.007)
%Male	-0.144***	-0.370**	-0.069	0.019	-0.005	0.189
	(0.018)	(0.158)	(0.056)	(0.056)	(0.064)	(0.133)
%White	0.446***	0.534***	0.465***	0.430***	0.412***	0.412***
	(0.025)	(0.043)	(0.016)	(0.012)	(0.015)	(0.023)
%Asian	0.137***	0.191***	0.141***	0.120***	0.142***	0.204***
	(0.026)	(0.065)	(0.024)	(0.021)	(0.018)	(0.039)
%Old	-0.224***	-0.215***	-0.222***	-0.228***	-0.259***	-0.214***
	(0.023)	(0.065)	(0.031)	(0.030)	(0.032)	(0.049)
Distance to CBD	-0.038***	-0.035***	-0.038***	-0.038***	-0.040***	-0.045***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Within6mo_100	-0.009***	-0.005	-0.001	0.001	-0.008*	-0.019*
	(0.003)	(0.013)	(0.006)	(0.004)	(0.004)	(0.010)
Constant	8.003***	8.039***	8.155***	8.135***	8.242***	7.726***
	(0.247)	(0.300)	(0.102)	(0.111)	(0.139)	(0.228)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	28,778	28,778	28,778	28,778	28,778	28,778

Table 5: Robustness checks

This table reports the results of 2SLS and IV quantile regressions, as estimated in Eq. 3 and 4, substituting *Within3mo_075* for *Within6mo_075* in Panel A and *Within3mo_100* for *Within6mo_100* in Panel B. In all models, adjustments for spatial autocorrelation (*WY*) are included. Definitions of the variables are provided in the Appendix. Standard errors are reported in parentheses: for 2SLS regression, standard errors are clustered by year and month. For IV quantile regressions, standard errors are obtained through bootstrap replications. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.

Panel A: The effect of proximity to a nearby homeless encampment (within 0.75 miles)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Log (Sale Price)	2SLS	Q: 0.05	Q: 0.25	Q: 0.50	Q: 0.75	Q: 0.95
Log (WY)	0.359***	0.359***	0.335***	0.339***	0.343***	0.376***
	(0.019)	(0.019)	(0.008)	(0.008)	(0.010)	(0.017)
Living Area	0.270***	0.255***	0.257***	0.268***	0.288***	0.304***
	(0.009)	(0.005)	(0.004)	(0.003)	(0.003)	(0.007)
Lot Area	0.014***	0.002	0.010***	0.014***	0.018***	0.029***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Bedrooms	-0.009***	-0.007*	0.001	0.001	-0.002	-0.007**
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Bathrooms	0.009***	-0.005	0.006**	0.008***	0.010***	0.016***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
Age	-0.001***	-0.002***	-0.001***	-0.001***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
One Story	-0.063***	-0.046***	-0.054***	-0.055***	-0.057***	-0.065***
	(0.003)	(0.007)	(0.003)	(0.002)	(0.003)	(0.006)
Renovated	0.008	-0.217***	-0.027	0.038***	0.062***	0.083***
	(0.024)	(0.019)	(0.020)	(0.009)	(0.008)	(0.009)
Fireplace	0.019***	0.029***	0.017***	0.012***	0.011***	0.003
	(0.005)	(0.007)	(0.003)	(0.003)	(0.003)	(0.004)
Lake/Mountain View	0.054***	0.028**	0.029***	0.042***	0.057***	0.099***
	(0.002)	(0.012)	(0.005)	(0.005)	(0.006)	(0.012)
Population	0.013***	-0.006	0.018***	0.019***	0.011***	0.019***
	(0.003)	(0.010)	(0.003)	(0.004)	(0.004)	(0.007)
%Male	-0.144***	-0.376**	-0.070	0.021	0.000	0.201
	(0.018)	(0.161)	(0.057)	(0.054)	(0.063)	(0.137)
%White	0.446***	0.534***	0.465***	0.431***	0.412***	0.411***
	(0.025)	(0.044)	(0.016)	(0.012)	(0.014)	(0.024)
%Asian	0.137***	0.189***	0.141***	0.122***	0.142***	0.203***
	(0.026)	(0.066)	(0.023)	(0.021)	(0.018)	(0.041)
%Old	-0.223***	-0.216***	-0.222***	-0.230***	-0.259***	-0.215***
	(0.023)	(0.068)	(0.030)	(0.030)	(0.033)	(0.048)
Distance to CBD	-0.038***	-0.035***	-0.038***	-0.038***	-0.040***	-0.045***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Within3mo_075	-0.016**	0.007	-0.004	-0.008	-0.020*	-0.023
	(0.006)	(0.019)	(0.010)	(0.006)	(0.010)	(0.015)
Constant	8.003***	8.035***	8.156***	8.133***	8.238***	7.713***
	(0.247)	(0.308)	(0.101)	(0.110)	(0.140)	(0.235)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	28,778	28,778	28,778	28,778	28,778	28,778

Table 5: (cont'd)
Panel B: The effect of proximity to a nearby homeless encampment (within 1 mile)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Log (Sale Price)	2SLS	Q: 0.05	Q: 0.25	Q: 0.50	Q: 0.75	Q: 0.95
Log (WY)	0.359***	0.359***	0.335***	0.339***	0.343***	0.376***
	(0.019)	(0.019)	(0.008)	(0.009)	(0.010)	(0.017)
Living Area	0.270***	0.255***	0.257***	0.268***	0.288***	0.304***
	(0.009)	(0.006)	(0.004)	(0.003)	(0.003)	(0.007)
Lot Area	0.014***	0.002	0.010***	0.014***	0.018***	0.029***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Bedrooms	-0.009***	-0.007*	0.001	0.001	-0.002	-0.007**
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)
Bathrooms	0.009***	-0.005	0.006**	0.008***	0.010***	0.016***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
Age	-0.001***	-0.002***	-0.001***	-0.001***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
One Story	-0.063***	-0.046***	-0.054***	-0.055***	-0.057***	-0.065***
	(0.003)	(0.006)	(0.003)	(0.002)	(0.003)	(0.006)
Renovated	0.008	-0.216***	-0.027	0.038***	0.063***	0.083***
	(0.024)	(0.019)	(0.020)	(0.009)	(0.008)	(0.009)
Fireplace	0.019***	0.029***	0.017***	0.012***	0.011***	0.003
	(0.005)	(0.007)	(0.003)	(0.003)	(0.003)	(0.004)
Lake/Mountain View	0.054***	0.028**	0.029***	0.042***	0.057***	0.099***
	(0.002)	(0.012)	(0.005)	(0.005)	(0.006)	(0.012)
Population	0.013***	-0.006	0.019***	0.019***	0.011***	0.018***
	(0.003)	(0.010)	(0.003)	(0.004)	(0.003)	(0.007)
%Male	-0.145***	-0.375**	-0.069	0.020	-0.005	0.190
	(0.019)	(0.160)	(0.057)	(0.055)	(0.064)	(0.135)
%White	0.445***	0.535***	0.465***	0.430***	0.412***	0.412***
	(0.025)	(0.044)	(0.016)	(0.012)	(0.015)	(0.024)
%Asian	0.136***	0.190***	0.141***	0.121***	0.141***	0.204***
	(0.026)	(0.063)	(0.023)	(0.021)	(0.018)	(0.041)
%Old	-0.223***	-0.216***	-0.221***	-0.229***	-0.259***	-0.220***
	(0.023)	(0.068)	(0.031)	(0.030)	(0.033)	(0.048)
Distance to CBD	-0.038***	-0.035***	-0.038***	-0.038***	-0.040***	-0.045***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Within3mo_100	-0.010*	0.008	0.001	-0.001	-0.010	-0.023**
	(0.006)	(0.018)	(0.009)	(0.006)	(0.006)	(0.010)
Constant	8.004***	8.033***	8.156***	8.134***	8.244***	7.721***
	(0.247)	(0.308)	(0.099)	(0.112)	(0.142)	(0.236)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	28,778	28,778	28,778	28,778	28,778	28,778

Appendix: Variable definitions

Variable	**Definition**
Transaction prices	
Sale Price	Sale price of property ($)
Log (Sale Price)	Log of sale price
WY	The weighted average sale price ($) of neighbor properties within 2000 feet
Log (WY)	Log of WY
Property-level characteristics	
Living Area	Total living area in ft^2
Lot Area	Total lot area in ft^2
Bedrooms	# of bedrooms
Bathrooms	# of full-size bathrooms
One Story	A dummy variable equal to 1 for one-story property; zero otherwise
Renovated	A dummy variable equal to 1 if renovated (within the past 10 years) ; zero otherwise
Age	Year of sale - year built
Fireplace	A dummy variable equal to 1 for property with fireplace; zero otherwise
Environmental - natural views	
Lake/Mountain view	A dummy variable equal to 1 for property with natural view (*Mt Rainier, Cascades, Puget Sound, Lake Washington, Olympics, Others*); zero otherwise
Proximity measures	
Distance to CBD	Straight distance (in miles) to Seattle's central business district (CBD)
Within3Mo_025 *Within3Mo_050* *Within3Mo_075* *Within3Mo_100*	*Within3Mo_025, Within3Mo_050, Within3Mo_075* and *Within3Mo_100* are dummy variables equal to 1 for a home sale made within 0.25, 0.50, 0.75 and 1 mile-distance, respectively, to a nearby homeless encampment (assuming that the encampment existed for 3 months prior to the closure); zero otherwise
Within6Mo_025 *Within6Mo_050* *Within6Mo_075* *Within6Mo_100*	*Within3Mo_025, Within3Mo_050, Within3Mo_075 and Within3Mo_100* are dummy variables equal to 1 for a home sale made within 0.25, 0.50, 0.75 and 100 mile-distance, respectively, to a nearby homeless encampment (assuming that the encampment existed for 6 months prior to the closure); zero otherwise

Appendix: (cont'd)

Variable	Definition
Sociodemographic variables	
Population	Log of population per census tract
% Male	Percent of male population per census tract
% Female	Percent of female population per census tract
% White	Percent of white population per census tract
% Asian	Percent of Asian population per census tract
% Black	Percent of black population per census tract
% Old	Percent of population over age 65 per census tract