NBER WORKING PAPER SERIES

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Working Paper 25427
http://www.nber.org/papers/w25427

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2019

We thank Metin Cakir, Bern Dealy, Monica Deza, Daniel Grossman, Michael Grossman, Jason Kerwin, Joseph Ritter, Jane Ruseski and seminar participants at City University of New York-Graduate Center, University of Minnesota, and West Virginia University for comments and suggestions. We also thank Cathie Alderks, Jessica Blose, and Felix Rodriguez for excellent data assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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JEL No. H0,I1,R3

ABSTRACT

Substance use disorders (SUDs) are a major social concern in the United States and other developed countries. There is an extensive economic literature estimating the social costs associated with SUDs in terms of healthcare, labor market outcomes, crime, traffic accidents, and so forth. However, beyond anecdotal claims that SUD treatment centers (SUDTCs), settings in which patients receive care for their SUDs, have a negative effect on property values, there is scant empirical work on this question. In this paper, we investigate the effect of SUDTCs on residential property values using data from Seattle, Washington, and SUDTC location, entry, and exit information. To mitigate bias from the potential endogeneity of SUDTC location choices, we apply a spatial differences-in-differences (SDD) model, which uses property and SUDTC location to construct treatment and comparison groups. Our findings suggest that SUDTCs endogenously locate in lower value areas, and naïve models imply that the entry of an SUDTC leads to a 3.4% to 4.6% reduction in property values. When an SDD model is applied, we find no evidence that SUDTCs affect property values. Overall, our findings suggest anecdotal claims that SUDTCs reduce property values are potentially overstated.

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1. Introduction

Substance use disorders (SUDs) are chronic health conditions that impose substantial costs, both costs fully internalized by the affected individual and costs externalized to society. For the affected individual, SUDs hinder overall health, employment, financial stability, and relationships, and can lead to incarceration and other legal consequences, and for some, death. In terms of negative externalities, SUDs are incredibly costly to society in terms of direct addiction treatment costs which have historically been financed by public payers within the U.S., increased costs of general healthcare, increased reliance on social services, traffic accidents, and crime and violence (Carpenter 2005; Balsa et al. 2009; French, Fang, and Balsa 2011; Jayakody, Danziger, and Pollack 2000; Anderson, Hansen, and Rees 2013; Markowitz and Grossman 2000; Popovici, Maclean, and French 2017; Terza 2002).

Overall, the annual costs of SUDs to the U.S. are estimated to be very high: $544B (Caulkins, Kasunic, and Lee 2014).[1] For comparison, government estimates suggest that heart disease and stroke, which are leading causes of mortality and morbidity, are associated with $359B each year in terms of healthcare costs and lost productivity in the U.S. (Department of Health and Human Services 2018).[2] Given these high costs, both private and public agents allocate substantial financial resources to curtail SUDs. For instance, the U.S. spends approximately $28B annually on direct SUD treatment, with 71% of this treatment financed by public payers (Substance Abuse and Mental Health Services Administration 2014).[3] While treatment programs are obviously heterogeneous, there is compelling evidence that numerous treatment modalities are clinically effective and cost-effective in reducing SUDs and associated

[1] This estimate is inflated by the authors from the original estimate of $481B (with $255B attributable to alcohol and $226B attributable to psychoactive drugs) in 2011 dollars to 2018 dollars using the Consumer Price Index (CPI).
[2] Inflated from the original estimate ($317B in 2011 dollars) to 2018 dollars using the CPI.
[3] Inflated by the authors from the original estimate of $23.4B in 2009 dollars to 2018 dollars using the CPI.

social costs (Collins et al. 2010; Doran 2008; French and Drummond 2005; Holder 1998; McCollister and French 2003; Murphy and Polsky 2016). Moreover, receiving SUD treatment is not uncommon. For instance, in 2016, 3.8M Americans 12 years and older received SUD treatment (Center for Behavioral Health Statistics and Quality 2017).

SUD treatment is generally regarded as valuable to society. However, situating an SUDTC, a setting in which many patients receive care for their SUDs, is often an unpopular and contentious decision. In particular, there is a 'not in my back yard' (NIMBY) sentiment, where local residents boycott SUDTC openings as they are concerned that the introduction of an SUDTC may increase noise, traffic, crime, nuisance behavior, and generally unpleasant activities in the neighborhood (Keiger 2016).[4] These perceived negative attributes of SUDTCs could plausibly translate into reductions in residential property values. As residential properties reflect the most substantial investment that most Americans undertake in their lives (Kraft and Munk 2011), this potential external cost of SUDTCs may result in a considerable reduction in wealth for many individuals and families. In 2016, there were 18,087 licensed SUDTCs in the U.S. (Substance Abuse and Mental Health Services Administration 2017). Thus, if NIMBY concerns are valid, then many individuals and families are exposed to centers that may substantially reduce the worth of their most valuable investment.

While there is a large literature evaluating the extent to which a wide range of both amenities and dis-amenities affect residential property values (Chay and Greenstone 2005; Gawande and Jenkins-Smith 2001; Gibbons 2004; Muehlenbachs, Spiller, and Timmins 2015;

[4] For instance, recent articles by media outlets in both Massachusetts and New York document the negative sentiment towards SUDTC openings by local residents. We refer an interested reader to the following websites: https://www.urbancny.com/urban-colonialism-and-how-a-neighborhood-fought-a-development-and-won/, https://theswellesleyreport.com/2018/10/wellesley-residents-urge-opioid-treatment-center-reps-to-reconsider-location/ (accessed December 20, 2018).

Pope and Pope 2012; Thaler 1978; Li et al. 2015; Davidoff and Leigh 2008), there is surprisingly little empirical work investigating the effect of SUDTCs. To the best of our knowledge, only one study explores this question. In a real estate study, La Roche, Waller, and Wentland (2014) apply three-stage-least squares to property sales data from Central Virginia over the period 2001 to 2011 to test for SUDTC effects. The authors document that SUDTCs are associated with an 8% reduction in residential property values. The results of La Roche, Waller, and Wentland (2014) suggest a substantial negative effect of SUDTCs on property values and provide *prime facie* support for NIMBY concerns. However, given the identification strategy employed by La Roche, Waller, and Wentland (2014), how best to interpret these findings is unclear. In particular, the three stage least squares approach used by LaRoche and colleagues is identified off non-linearities in the model. Such identification departs from approaches based on quasi-experimental variation that are used in many recent empirical economic studies studying factors that influence property values (outlined in Section 2.1).

Moreover, the net effect of SUDTCs on property value is *ex ante* ambiguous. In addition to the potentially negative aspects of SUDTCs articulated in NIMBY concerns, there are factors associated with SUDTCs that may in fact increase property values. First, if SUDTCs offer effective treatment to neighborhood residents, these facilities can reduce SUD prevalence and associated harms. Swensen (2015) shows that SUDTC entry reduces the level of SUDs, proxied by overdose deaths, within the local area. In terms of reducing costs associated with SUDs, recent economic work by Bondurant, Lindo, and Swensen (2018), and Wen, Hockenberry, and Cummings (2017) shows that SUDTCs reduce crime within the local area. Clinical evidence provides further support for the inverse treatment-crime relationship (Doran 2008; Ettner et al. 2006; McCollister et al. 2003; Rajkumar and French 1997; Westerberg et al. 2016).

Furthermore, Freeborn Fand McManus (2010) document that additional SUDTCs in a county decrease alcohol-related fatal traffic fatalities in that locality. A second pathway through which SUDTCs could raise property values is increased employment opportunities (e.g., hiring SUDTC employees) and economic activity (e.g., demand for SUDTC-related goods and services) within a local area. For instance, in 2016, the average SUDTC employed 22 workers and the economic opportunities for local residents are often touted when a center opens.[5]

Finally, an empirical reason for an observed association between SUDTC entry and property values is the potential endogeneity of SUDTC location choices. If SUDTCs strategically locate in areas with lower (or higher) property values, such sorting could lead to biased estimates of property value effects. This final pathway suggests that any observed correlation between SUDTC entry and property values could be spurious and not causal.

To empirically address endogenous location choices in estimation of amenities and dis-amenities, several recent studies apply a spatial differences-in-differences (SDD) estimator (Congdon-Hohman 2013; Dealy, Horn, and Berrens 2017; Linden and Rockoff 2008). The SDD model is comparable in many ways to canonical differences-in-differences (DD) methods, which estimate average changes in outcomes in treatment and comparison groups, pre- and post-treatment (Angrist and Pischke 2008). In the SDD model, spatial location information (as opposed to legislatively defined geographic areas or groups defined by their demographics, e.g., age and/or gender) is used to construct the treatment and comparison groups in close proximity to the (dis)amenity. No study has applied an SDD to estimate the effects of SUDTCs.

[5] Authors' calculation of the 2016 U.S. Census Bureau Community Business Patterns data base for the following industry codes: 621420 (outpatient treatment facilities) and 623220 (residential inpatient treatment facilities) (Swensen 2015; Bondurant, Lindo, and Swensen 2018). More details available on request. Please see the following news article: https://www.bizjournals.com/dayton/news/2018/12/14/addiction-treatment-center-invests-1m-in-dayton.html (accessed December 20, 2018).

In this paper, we follow the recent hedonic pricing model literature and estimate the effect of SUDTCs on residential property values using an SDD model. We use granular residential property value and administrative SUDTC data from Seattle, Washington. Specifically, we link property values data over the period 2003 to 2016 with geocoded government administrative data on the exact locations of all licensed SUDTCs in Seattle.

Several findings emerge from our analysis. First, we document that SUDTCs endogenously locate in lower property values areas, which implies that estimates generated in models which do not address such sorting are vulnerable to bias. Second, naïve (non-SDD) models that do not account for endogenous location choices produce estimates that imply a modest, but statistically significant, negative effect of SUDTC entry on property values of 3.4% to 4.6%. Third, when an SDD estimator is used, we find no statistically significant evidence that SUDTC entrance into a local area leads to changes property values. Indeed, in our preferred specifications we can rule out all but modest decreases in property values. Our findings are stable across numerous robustness checks, including alternative distance band specifications and time dynamics. Our findings suggest that anecdotal NIMBY concerns regarding the stigma associated with being located in close proximity to an SUDTC, and related reductions in residential property values, may not be fully warranted.

The paper proceeds as follows. Section 2 provides background on the related residential property value literature, SUDs, and SUDTCs. Our conceptual framework and empirical model are presented in Section 3. Data are reported in Section 4. Section 5 presents our main results and robustness checking. Section 6 concludes.

2. Background

2.1 Background on amenities and dis-amenities, stigma, and residential property values

There is a large and historic hedonic pricing model literature evaluating the effect of various amenities and dis-amenities on residential property values. Comprehensively reviewing this vast literature is beyond the scope of this study. Instead, we attempt to briefly summarize studies most relevant for our research question.

In terms of amenities, access to high quality schools (Davidoff and Leigh 2008), ‘walkability’ (Rauterkus and Miller 2011), diversity (Koster and Rouwendal 2012), and proximity to parks and green spaces (Anderson and West 2006; Voicu and Been 2008) increase residential property values. On the other hand, dis-amenities such as airport noise (Espey and Lopez 2000; Pope 2008), forest infestations (Price, McCollum, and Berrens 2010), nuclear waste sites (Gawande and Jenkins-Smith 2001; McCluskey and Rausser 2003a), rail stations (Bowes and Ihlanfeldt 2001), and wildfires (Kalhor et al. 2018) reduce residential property values.

Similarly, undesirable and socially repugnant behaviors by neighborhood residents, which can be viewed as dis-amenities, within the local area have been linked with lower residential property values. In particular, several studies show that increased crime reduces property values (Gibbons 2004; Thaler 1978; Pope and Pope 2012). For instance, Pope and Pope (2012) find a substantial increase in residential property values following the large decline in U.S. crime rates that occurred in the 1990s. Studies also evaluate the effect of convicted sex offenders migrating into a neighborhood on local residential property values. Federal legislation passed in 1996, known as ‘Megan’s Law’, requires that all states create a sex offender registry and make information regarding sex offender residential addresses publicly available. Evaluating this law, Larsen, Lowrey, and Coleman (2003) find a reduction in value of 17% for residential properties in close proximity to sex offenders in Montgomery County, Ohio.

In sum, the hedonic pricing literature documents that many forms of dis-amenities reduce residential property values. In addition to an initial decline in residential property values, several studies provide convincing evidence that this reduction in value persists over time. For instance, several environmental risks leave a permanent, or highly persistent, ‘scar’ on property values (McCluskey and Rausser 2003b). Put differently, even after the dis-amenity is removed from the local area, residential property values persistently remain at a lower level. The particular mechanisms behind a scaring effect are not entirely clear and are likely heterogeneous across dis-amenities, but this phenomena suggests that affected property owners may persistently own a less valuable asset. Given the importance of residential properties for overall wealth and financial well-being, permanent reductions in property values are concerning.

A key empirical challenge in estimating the effect of any local (dis)amenity on property values is the potential endogeneity of (dis)amenity location. Put differently, amenities and dis-amenities, including SUDTCs, are not likely to be randomly assigned across neighborhoods and instead are plausibly located based on the (presumably) rational decisions of economic agents; in our context SUDTC owners and operators. Taking such systematic location selection into account, Linden and Rockoff (2008) reevaluate the effect of sex offenders on property values using an SDD estimator, which creates treatment and comparison groups based on geographic distance to the sex offender location. Applying this model to data from Mecklenburg County, North Carolina, the authors document that, on average sex, offenders locate in lower property value areas, and failure to account for these endogenous location choices can lead to a substantial overestimate of the effect of a sex offender on property values. After accounting for the endongeous location of offenders, Linden and Rockoff find that the arrival of sex offender within a neighborhood reduces the average residential property values by 4%. This estimate is less than one quarter of the Larsen et al (2003) non-SDD estimate of a 17% reduction in property values.

The SDD approach has also recently been used to study the effect of several other dis-amenities on residential property values. Congdon-Hohman (2013) and Dealy, Horn, and Berrens (2017) use this technique to study the effect of clandestine methamphetamine laboratories ('meth labs') on property values. The production of meth involves the combination of explosive and deadly chemicals; this process is harmful to health. Both studies show that meth labs endogenously locate in lower value areas and a significant decrease in property values associated with lab discovery. Dealy, Horn, and Berrens (2017) also identify a stigma effect: property values of residences sourrounding the meth lab remain persistently lower even after the lab is fully decomtaiminated following a state-mandated environmental clean-up process. Stigma effects suggest that the dis-amenity permanently, or at least persistently, alters neighborhood characteristics (real or perceived) in a way that reduces the value of nearby properties. For instance, clandestine meth labs may result in lingering environmental toxins in the neighborhood that persistently harm (or are perceived to harm) residents' health.

Brooks, Humphreys, and Nowak (2016) study the effect of strip clubs on residential property values in Seattle, Washington – the same location that we examine – using an SDD model. The authors find that club openings and closing have no statistically significant effect on the value of nearby residences. This study is important for our work as it focuses a dis-amenity that may plausibly impose similar costs and benefits on the neighborhood as an SUDTC.

Our contribution to this literature is twofold. First, we examine the effects of SUDTCs on property values using an SDD estimator which will allow us to account for endogenous location choices and hence recover causal estimates of SUDTC effects on residential property values. Second, we test for potential stigma effects associated with SUDTCs.

2.2 Background on SUDs and SUDTCs

In 2016, 20 million U.S. residents 12 years and older, or 7.5% of the population, met diagnostic criteria for an SUD (Center for Behavioral Health Statistics and Quality 2017). According to the American Psychiatric Association (2013) SUDs 'occur when the recurrent use of alcohol and/or drugs causes clinically and functionally significant impairment, such as health problems, disability, and failure to meet major responsibilities at work, school, or home.' Afflicted individuals may act out in violent and reckless ways, and turn to illegal activities to procure funds to purchase substances. Many individuals with an SUD have co-occurring mental illness (Grant, Stinson, Dawson, Chou, Dufour, et al. 2004; Grant, Stinson, Dawson, Chou, Ruan, et al. 2004), which plausibly exacerbates substance-related problems.

In addition to individuals meeting the clinical definition of an SUD, millions of Americans engage in risky substance misuse such as binge drinking, heavy drinking, and nonmedical use of prescription drugs, and are thus at risk of developing an SUD.[6] For instance, in 2016, 24.5% and 6.0% of U.S. residents 12 year and older were classified as binge and heavy drinkers respectively, while 10.6% of adults used illicit drugs in the past 30 days (Center for Behavioral Health Statistics and Quality 2017).

Given the high levels of substance misuse, unintentional fatal alcohol poisonings and (overall) psychoactive drug overdoses are the leading causes of injury death in the U.S. with over

[6] According to the Centers for Disease Control and Prevention (CDC), binge drinking is defined as consuming five (four) or more drinks in one drinking session for men (women) while heaving drinking is defined as drinking two (one) or more drinks per day for men (women). Non-medical use of prescription medications is defined as the use of medications without a prescription from a healthcare provider, use of the medication in a manner other than as directed (e.g., taking a higher dosage than prescribed), and/or use only for the medication's psychotropic experience.

58,000 deaths in 2016, which exceeds the deaths attributable to suicides, traffic accidents, and firearm-related accidents (Centers for Disease Control and Prevention 2018a). Further, the U.S. is currently experiencing an unprecedented rise in SUD-related mortality, largely due to OUD overdoses (Rudd et al. 2016). For instance, each day there are 115 OUD-related overdose deaths and this rate has more than quadrupled since 1999 (Centers for Disease Control and Prevention 2018b). The rise in OUD and associated harms has prompted the federal government to declare that the country is experiencing an 'opioid epidemic' (Centers for Disease Control and Prevention 2018b) and allocate billons of dollars in financing to support OUD prevention, treatment, and harm reduction (114th U.S. Congress 2015).

Although SUDs are incredibly harmful, numerous treatment modalities have been shown to be effective in treating these conditions (Collins et al. 2010; Doran 2008; French and Drummond 2005; Holder 1998; McCollister and French 2003; Murphy and Polsky 2016; Schori 2011). In 2016, 3.8M Americans ages 12 years and older received some form of SUD treatment (Center for Behavioral Health Statistics and Quality 2017). However, addiction specialists contend that treatment is substantially underused: only 10% of individuals who meet diagnostic criteria for an SUD receive treatment in any given year (Center for Behavioral Health Statistics and Quality 2017). While there are myriad reasons for not seeking treatment, including not wanting to stop using substances, inability to locate a provider is a commonly stated barrier. Taking this reason for not receiving treatment at face value, expanding the number of providers (including the specialized SUDTCs that we examine in our study) could increase treatment uptake and, in turn, reduce SUD prevalence and associated harms. Further, allowing providers to locate in areas that are convenient to patients may enhance treatment uptake and outcomes.

SUD treatment often begins with detoxification, a process that many times involves the use of medications to ease withdrawal symptoms (e.g., tremors, pain, and nausea) and allows the body to rid itself of substances. After detoxification is complete, there are a wide range of effective treatment options available to patients. For example, counselling services, outpatient care, residential treatment, and inpatient hospital care are all widely used, and in many cases, highly effective treatment modalities. In our analysis we focus on care that is offered in specialized outpatient and inpatient treatment centers (residential facilities and psychiatric hospitals). This modality of care represents the majority of care received within the U.S. Further, specialty care involves patients residing in the center and/or regularly visiting the center for an extended period of time (e.g., a common treatment duration is 30 days), and SUDTCs are large in size with approximately 88 patients on any given day receiving treatment.[7] Thus, if NIMBY concerns exist, we contend that they are most likely to be observed in this the type of care we consider in this study. We do not consider office-based care or treatment received in non-psychiatric hospitals. We refer interested readers to an excellent review of treatment modalities available to patients provided by the National Institute on Drug Abuse (2018).

3. Conceptual framework and empirical approach

3.1 Hedonic pricing model

Our empirical analysis, outlined below, is grounded in hedonic pricing theory. Within this framework residential properties are viewed as assets that provide owners with a bundle of characteristics that, in turn, affects utility. The characteristics that define the residential property as an asset include structural attributes (e.g., property size and quality; S_i) and neighborhood

[7] Authors' calculation based on the National Survey of Substance Abuse Treatment Services (N-SSATS).

attributes (e.g., schools and parks; N_i). We augment the standard hedonic pricing framework to incorporate proximity to an SUDTC (Q_i) as a residential property attribute that affects utility.

Rational consumers are assumed to choose the residential property that maximizes their utility function subject to a standard budget constraint. At market equilibrium, residential property *i* will sell at price P_i according the following pricing equation:

$$P_i = f(S_i, N_i, Q_i) \tag{1}$$

The effect of each attribute on price is simply the partial derivate of that attribute with respect to price in Equation (1): ${\partial P_i}/{\partial X_i}$ where $X_i \in \{S_i, N_i, Q_i\}$. All else equal, we expect amenities (e.g., larger properties and good schools) to increase values and dis-amenities (e.g., poor quality properties and limited access to parks) to reduce values.

As noted in Section 1, the relationship between proximity of a residential property *i* to an SUDTC (Q_i) has an ambiguous effect the price (P_i). SUDTCs are associated with numerous factors in the local area that could have both positive (e.g., reduced SUD prevalence, and increased employment opportunities and demand for local goods and services) and negative (e.g., crime, violence, traffic, noise pollution, and nuisance behaviors) effects on property values, leaving the net effect unclear. While we are not able to separately estimate each of the possible pathways through which SUDTCs could influence residential property values, our objective is to provide an estimate of the overall average SUDTC effect, which is a first order question.

3.2 SDD model

We apply an SDD model to test for the causal effect of SUDTCs on proximal property values. The treatment and comparison groups are constructed using geographic distance bands, or 'rings', surrounding each SUDTC. Residential properties located within a ring with radius *r* around the SUDTC form the treatment group. Residential properties located in a second concentric ring, with radius $k= r+\varepsilon$ with $\varepsilon>0$, form the comparison group. This identification strategy compares properties adjacent to an SUDTC with a comparison group of properties in very close proximity to, but just far enough away, so as to be unaffected by the SUDTC.

Figure 1 displays an example of a location-defined treatment group and comparison group. In our main specifications, we define the treatment group as those properties within 0.2 miles of a SUDTC as the treatment group and define those properties 0.2 to 0.4 miles from an SUDTC as the comparison group. Clearly the true geographic definitions of the treatment and comparison group are *a priori* unknown, and any selected definition is to some extent arbitrary. Moreover, it is plausible that the true definition varies across (dis)amenties (e.g., clandestine methamphetamine labs, parks, schools, and sex offenders) and, indeed, different studies use different distances (see studies applying an SDD cited in Section 2.1). Thus, in robustness checks, and following Dealy, Horn, and Berrens (2017), we re-estimate our SDD regressions using alternate distance-ring specifications. Results (reported later in the manuscript) are highly robust across these alternative specifications, which supports the hypothesis that our findings are not driven by selection of a specific treatment and comparison group combination.

Specifically, we apply the following SDD model:

$$\ln\left(P_{i,j,t}\right) = X_{i,j,t}\beta + \left(\theta_1 D_{i,j,t}^{0.2} + \theta_2 D_{i,j,t}^{0.4}\right) + \left(\theta_3 D_{i,jt,}^{0.2} + \theta_4 D_{i,jt,}^{0.4}\right)\tau_{i,t}^{entry} + \alpha_{j,t} + \varepsilon_{i,j,t} \quad (2)$$

In this equation, $P_{i,j,t}$ is the inflation adjusted sales price, where *i* indicates an individual property, *j* indicates the location of the property (i.e., zip code) and *t* indicates the time period (i.e., year) in which the property is sold. We take the logarithm to account for skewness in sales prices. In terms of explanatory variables, $X_{i,j,t}$ is vector of property characteristics, $a_{j,t}$ is a vector of year-by-area fixed effects, and $\varepsilon_{i,j,t}$ is the error term.

We cluster standard errors at the zip code level. We have 34 zip codes in our sample, which implies that we may have too few clusters in our data to generate consistent estimates of our standard errors. However, in robustness checking reported later in the manuscript, we show that our results are not appreciably different if we instead apply a wild-cluster bootstrap approach to inference that has been shown to produce consistent standard error estimates when the number of clusters is small (Cameron and Miller 2015).

We also estimate a variant of Equation (2) in a 'limited sales sample' which includes only property sales that occur within 0.4 miles of an SUDTC. Thus, sales that occur outside the treatment and comparison groups are excluded from this analysis sample. In this specification we include year-by-SUDTC fixed effects, and cluster standard errors at the SUDTC level. We have 114 clusters in this specification. While the full sample is more common in the extant hedonic pricing model literature, the limited sales sample is more analogous to the canonical DD model in which all localities are either in the treatment or comparison group. For these reasons, we present results based on both samples and specifications. Our results are not appreciably different across these two specifications, however.

The treatment group is indicated by $D_{i,j,t}^{0.2}$, which represents properties within 0.2 miles of where an SUDTC is located and the comparison group is indicated by $D_{i,j,t}^{0.4}$, which represents properties within 0.4 miles of where an SUDTC is located. Due to the overlapping structure of the distance variables, θ_2 captures preexisting level differences in properties within 0.4 of an SUDTC compared with properties more than 0.4 miles away from an SUDTC. Analogously, θ_1 will capture preexisting level differences in property values for residences located within 0.2 miles of an SUDTC and properties located within 0.2 to 0.4 miles of an SUDTC. These variables are akin to the 'treatment' indicator in a canonical DD model. The timing of SUDTC opening is captured by $\tau_{i,t}^{entry}$, which indicates the time period after the SUDTC enters a local area and parallels the 'treatment*post' interaction in the canonical DD model. The parameter of interest (θ_3) estimates the change in property values for properties within 0.2 miles of an SUDTC relative to properties 0.2 to 0.4 miles and θ_4 will capture any time trends associated with properties in the general vicinity of where an SUDTC locates.

As noted in Section 2.1, another important consideration when estimating the effect of SUDTCs on property values is stigma, or a potential lasting effect of an SUDTC on proximal residential property values after the SUDTC has exited the local area. To test for stigma effects, we estimate an augmented version of Equation (2) that incorporates SUDTC exits:

$$\ln\left(P_{i,j,t}\right) = X_{i,j,t}\beta + \left(\theta_1 D_{i,j,t}^{0.2} + \theta_2 D_{i,j,t}^{0.4}\right) + \left(\theta_3 D_{i,j,t}^{0.2} + \theta_4 D_{i,j,t}^{0.4}\right)\tau_{i,t}^{entry} + \left(\theta_5 D_{i,j,t}^{0.2} + \theta_6 D_{i,j,t}^{0.4}\right)\tau_{i,t}^{exit} + \alpha_{j,t} + \varepsilon_{i,j,t} \quad (3)$$

In this specification $\tau_{i,t}^{exit}$ is an indicator variable for the time period after an SUDTC exits, and θ_5 will capture any rebound effect on property values of the SUDTC exiting. Thus, θ_3 + θ_5 will represent any lasting stigma effect of an SUDTC on property values. Stigma effects may occur if, for instance, SUDTCs permanently reduce SUD prevalence within the neighborhood, then this change could reduce SUD-related behaviors (crime, violence, etc.). On the other hand, if an SUDTC permanently draws individuals with SUDs and who engage in crime, violence, nuisance behaviors, and so froth into the neighborhood, then we may observe persistently lower residential property values. We test for such effects through Equation (3). We investigate joint significance of these terms with an *F*-test.

4. Data

4.1 Residential property sales data

We use all residential property transactions in Seattle, Washington between January 1st, 2003 and December 31st, 2016 in our analysis. In 2016 Seattle was the 18th largest city in the U.S., with 704,352 residents, and was the largest city in Washington State. Thus, our effects are representative of a large, Pacific coast U.S. city. We obtained residential property sales data from the King County Department of Assessments (Seattle is located in King County). This agency provides detailed property sales through its online platform.[8] These data include all legal sales that occurred in the county, and contain the exact location and sales price. In particular, in Seattle all residential property sales are required to be registered with the Department of Assessments. We convert all sales prices to 2016 dollars using the Consumer Price Index.

The King County Department of Assessments data also contain a wide range of property characteristics including: the number of living units, number of stories, number of bedrooms, number of bathrooms, total living space, percentage of the property constructed with brick stone, whether the property had been renovated prior to its sale, and the age of the property. Also, the data contain square footage information for the basement, garage, porch, and deck. For all properties, the King County Department of Assessment provides a variable that captures building quality. This variable ranges from 1 to 20, where higher values indicate greater property quality.

We exclude some observations from the analysis sample to minimize outliers and remove other observations unlikely to be actual residential properties. Observations with sale price less than $50,000 (*n*=1,157) and above $2 million (*n*=926) are excluded. Likewise, observations with no bathrooms (*n*=1,043), no bedrooms (*n*=80), and living space less than 100 square feet (*n*=7), and observations sold pre-construction (*n*=4,248) are excluded. After exclusions, the final analysis dataset contains 131,862 residential property sale transactions.

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[8] These data are publicly available: http://info.kingcounty.gov/assessor/DataDownload/default.aspx (last accessed, December 20, 2018).

4.2 SUD treatment centers (SUDTCs)

We obtain SUDTC information from the Substance Abuse and Mental health Services Administration's (SAMHSA) National Directory of Drug and Alcohol Abuse Treatment Programs (NDDAATP).[9] This directory includes all licensed specialty SUDTCs that are known to SAMHSA and complete the National Substance Abuse Treatment Services Survey (N-SSATS). The N-SSATS is used by SAMHSA to monitor SUD treatment service provision within the U.S.; we do not use the N-SSATS information directly in our study.

The NDDAATP is the premier resource available to prospective patients and providers seeking a center that can provide specialized SUD treatment for themselves, their family members, or their patients. Given the importance of being listed on this directory for SUDTCs, response rates for N-SSATS (which forms the survey frame for the NDDAATP) are very high: 91% to 96% over our study period. The NDDAATP directories include the name, exact street address (which we leverage in our study), offered services, and accepted forms of payments for all SUDTCs licensed to provide SUD treatment that are known to SAMHSA. In 2016, there were 18,087 known and licensed specialty SUDTCs in the U.S. (Substance Abuse and Mental Health Services Administration 2017). Thus, we are able to capture the vast majority of licensed specialty SUDTCs using these data. Moreover, the NDDAATP is the only dataset that includes exact location of specialty SUDTCs and is therefore the best available data for our study.

Specialty SUD treatment is defined by SAMHSA as a hospital, a residential facility, an outpatient treatment facility, or other facility with a SUD treatment program. For background,

[9] Data were accessed from the following website: https://wwwdasis.samhsa.gov/dasis2/nssats.htm (last accessed December 20, 2018).

this modality represents 75% of non-self-help SUD treatment and reflects the majority of SUD treatment expenditures in the U.S. (Center for Behavioral Health Statistics and Quality 2017).[10]

SUDTC opening and closings offer the variation that we use to identify SUDTC effects in our SDD model. Openings reflect the 'entrance' of an SUDTC into the neighborhood while closings capture SUDTC 'exit.' We use the NDDAATP information to construct a year-by-year panel of all licensed SUDTCs in Seattle. In particular, we link SUDTC entrance and exit information to residential property sales data using geographic information system (GIS) coordinates. Because of the annual structure of the NDDAATP directory (i.e., the N-SSATS, which forms the survey frame, is completed once per year and the NDDAATP is thus updated annually), SUDTC entry (exits) are coded in the year the SUDTC appeared (no longer appeared) in the NDDAATP directories.[11] This linking process likely introduces some measurement error into our analysis dataset. We explore the potential implications of such measurement error in robustness checking later in the manuscript.

Residential property sale transactions are matched to SUDTCs both in terms of geodetic distances and timing of the proximate SUDTCs. Over the study period there are 120 SUDTC openings and 69 SUDTC closings in Seattle. On average there are 54 operating SUDTCs in Seattle in a given year.[12] Figure 2 graphically displays all SUDTCs that operated in Seattle over

[10] Authors' calculations based on Table 5.18B. Self-help involves informal care such as religious counselling and Alcoholics Anonymous. Details on this calculation available on request. Details on specialty SUD treatment can be found at https://wwwdasis.samhsa.gov/dasis2/nssats.htm (last accessed December 20, 2018).

[11] In particular, as noted above, SUDTCs listed on NDDAATP must complete the above-noted N-SSATS survey. The N-SSATS is administered in the last week of March in each year of our study period and captures information on services offered by each SUDTC, including whether or not the facility is in operation. We use March 31st as the date on which SUDTCs opened and April 1st as the date on which they closed. Details available on request.

[12] During our study period, there are three non-psychiatric hospitals that provide SUD treatment listed on the NDDAATP: Swedish Medical Center- Ballard, VA Puget Sound Health Care System, and Seattle Children's Hospital. Although these hospitals provide SUD treatment, the primary focus of non-psychiatric hospitals is to provide general inpatient healthcare services to patients. We expect that non-psychiatric hospitals may affect residential property values through different mechanisms than outlined in our conceptual framework. We exclude non-psychiatric hospitals providing SUD treatment services from our analysis. Details available on request.

our study period. While there is some evidence of clustering of SUDTCs in the central portion of Seattle, SUDTCs appear to operate in a range of different neighborhoods in the city.

A concern with our analysis is that zoning regulations may limit the locations in which an SUDTC may operate. As is the case with businesses in general, SUDTCs must locate in commercial zones. However, as discussed by La Roche, Waller, and Wentland (2014), there are numerous Federal regulations that prohibit many forms of discrimination in center location (e.g., the Fair Housing Act, Rehabilitation Act, Americans with Disabilities Act). In addition, we have communicated with administrators at the Washington State Substance Abuse Agency regarding zoning regulations related to SUDTC location. Our conversations with administrators at this agency suggest that there are no such regulations that will limit SUDTC location choices. Overall, our review of the available evidences suggests that SUDTCs face no additional (legal) restrictions on location than other businesses.

5. Results

5.1 Summary statistics

Table 1 presents the summary statistics of characteristics for all properties within 0.2 miles of where an SUDTC has located, and properties within 0.2 and 0.4 miles of where an SUDTC locates. Between 2003 and 2016, there was a total of 131,862 residential property sales, 8,982 of which were within 0.2 miles of an SUDTC and 22,671 that were within 0.2 and 0.4 miles. Median sale prices in Seattle are relatively high ($554K in January of 2016) in comparison to the U.S. median cities ($182k in January of 2016).[13] However, Seattle residential property values are comparable to other large U.S. cities such as New York City ($567K), Los Angeles ($559K), and San Diego ($529K); values reflect median prices in January 2016.

[13] Median home prices are obtained from https://www.zillow.com/research/data/ (accessed December 20, 2018).

In our sample, the average sale prices for the treatment group ($471k in 2016 dollars) is approximately 3.4% lower than the full sample. Properties within 0.2 miles of an SUDTC and properties within 0.2 and 0.4 miles of an SUDTC are not identical, in terms of sales price or housing characteristics, but are more similar compared to the full sample. Importantly, we control for all characteristics listed in table 1 in our regressions.

5.2 Graphical evidence

Figure 3 presents a graph of the logarithm of daily sales prices using optimal Epanechnikov kernel smoothing for two-year periods before and after SUDTC entry,[14] for both properties within 0.2 miles of an SUDTC, and between 0.2 and 0.4 miles of an SUDTC. A necessary assumption for the SDD model to recover causal estimates is that the treatment and the comparison groups would have trended similarly in terms of outcomes (residential property sales prices in our context) had the treatment group not been treated (the entrance of an SUDTC in our study); i.e., 'parallel trends.' In figure 3, prior to SUDTC entry, we observe that the treatment and comparison groups exhibit generally similar trends, this pattern provides suggestive evidence that the data can satisfy the parallel trends assumption. We return to parallel trends more formally through estimation of an event-study model later in the manuscript. Examination of the trends post-SUDTC entry reveals no evidence of substantial differences between the two groups, which foreshadows our null findings for SUDTC effects on residential property values.

5.3 Non-SDD regression results

Table 2 presents the results for a naïve empirical model that does not account for endogenous SUDTC location choices. Column 1 presents selected parameter estimates from a model estimated with housing characteristics and year fixed effects, column 2 presents selected

[14] In particular, we use local polynomial smoothing with a bandwidth of 35 days. Details available on request.

parameter estimates for a model estimated with housing characteristics and year-zip code fixed effects, and column 3 additionally clusters standard errors at the zip code level. In all models coefficient estimates are negative and significant, suggesting that SUDTCs are associated lower residential property values. Coefficient estimates from table 2 imply that the entrance of an SUDTC in a neighborhood is associated with a 3.4% to 4.6% reduction in property values.[15]

5.4 SDD regression results

Table 3 presents testing for endogenous location choices by SUDTCs and the main regression results from our preferred SDD model. First, column 1 presents results from a test for endogenous location choice by SUDTC. In this test observations are dropped if the sale occurred within 0.4 miles of an SUDTC after the SUDTC becomes active (i.e., the only remaining SUDTC observations are before the SUDTC enters). This model allows us to test whether SUDTCs endogenously locate in areas with lower residential property values. Columns 2 and 3 present SDD models estimated using the full sample. Columns 4 and 5 present SDD estimates generated in the limited sales sample, where all observations are dropped that are outside of a 0.4 miles radius of an SUDTC. Columns 2 and 4 present results without the exit parameters, corresponding to Equation (2), and columns 3 and 5 present the results with the exit parameters included, corresponding to Equation (3). A full set of control variable coefficient estimates for the full sample model, including exit parameters, is reported in appendix table 1.

There are two main findings in table 3. First, in column 1 the $D^{0.4}$ parameter estimate is negative and statistically significant, documenting that on average SUDTCs endogenously locate in areas with lower residential property values. In particular, SUDTCs locate in areas with 2.2% lower property values. Second, once this endogeneity in location choice is accounted for through

[15] Semi-log point estimates are converted to percent changes using the following formula: $(exp^{\hat{\beta}} - 1) \times 100\%$.

the use of the SDD model, we find no statistically significant evidence that SUDTC entries and exits affect residential property values. In both the full and limited sales sample models the parameter estimates are statistically indistinguishable from zero and very small in magnitude. Similarly, exit parameter estimates are statistically indistinguishable from zero and small. Finally, joint *F*-tests for the joint significance of the entry and exit parameter estimates (which capture stigma effects) are not statistically different from zero.

Our standard errors are sufficiently small that we can rule out all but relatively modest decreases in residential property values following SUDTC entry. For instance, in the basic SDD model in the full sample model reported in column 2, we can rule out decreases in residential property values greater than 3.2% with 95% confidence. Similarly, in the basic SDD model in the limited sales sample, reported in column 4, we can rule out decreases in residential property values greater than 2.2% at this level of confidence. Results based on Equation (3), which incorporates SUDTC entrances and exits, provide similar results: 3.8% and 2.7% respectively.[16] Using these estimates, we can generate 95% confidence intervals for the maximum dollar value reduction in residential property values. Over our study period, the average property value in our treatment group is $471K (see table 1). Thus, using a 3.8% decline, we can rule out any more than a $18K in lost residential property values associated with SUDTC entry. Finally, we are able to rule out all but modest increases in values following SUDTC exit as well.

5.5 Robustness checks

We conducted a number of robustness checks to assess the stability of our findings. Overall, our results are highly stable across these additional analyses. First, as noted above, to mitigate bias from endogenous location choices of SUDTCs, we construct treatment and

[16] This specification is more data hungry than Equation (2) and thus our standard errors necessarily increase in size, which implies that larger values are included in our 95% confidence intervals.

comparison groups using geographic proximity to SUDTCs. To this end, in our main analysis, SUDTC distance bands for the treatment and comparison groups are defined as within 0.2 miles and within 0.2 to 0.4 miles of an SUDTC. We re-estimate Equation (2) in which we both expand and contract the distance based used to form the treatment and comparison groups. Results are presented for regressions using 0.1/0.3 miles, 0.1/0.4 miles, 0.1/0.5 miles, 0.2/0.4 miles (our baseline specification), 0.2/0.5 miles, 0.2/0.6 miles, 0.3/0.5 miles, and 0.3/0.6 miles distance band specifications. Table 4a presents results for the full sample and table 4b presents results for the limited sales sample. Treatment-entry and treatment-exit parameter estimates are statistically indistinguishable from zero in all specifications. Joint *F*-tests assessing stigma effects are also statistically indistinguishable from zero in every specification.

Second, we investigate time dynamics in the effects of SUDTC entry/exit on residential property values. As outlined by Wolfers (2006), in a study testing the effects of state unilateral divorce laws, it is plausible that the effect of an SUDTC entry/exit may change over time. Put differently, our primary specification, Equation (3), forces an abrupt change in property values at SUDTC entrance/exit than remains constant thereafter. This pattern may depart from real world SUDTC effects if the social disruption (e.g., crime, noise, traffic) or benefits (e.g., reduced SUD prevalence, increased economic activity) vary over time. To evaluate potential dynamics in the effect of SUDTCs on residential property values, we estimate an event-study model in the spirit of Autor (2003). In particular, we decompose the SUDTC entrance variable into one-year windows both before and after SUDTC entry. The omitted category is one year prior to SUDTC entrance. We impose endpoint restrictions: we assume that effects are not observable more than four years before or after SUDTC entrance (Kline 2012; McCrary 2007). We code all areas in which an SUDTC does not enter as zero for all lead and lag indicators (Lovenheim 2009). In addition to allowing for dynamic effects in the post-period, the event-study allows us to test a conditional version of the parallel trends tests by examining coefficient estimates on the lead variables. If lead variable coefficient estimates are small in magnitude and imprecise, that pattern of results supports the hypothesis that our data satisfies a conditional version of the parallel trends assumption.

We report event-study results for the full sample and the limited sales sample. As can be observed in figure 4, all event-study point estimates are small and statistically indistinguishable from zero, and no pre- or post-trends are evident. Overall, the event-study analysis suggests: (i) our data satisfy the parallel trends assumption and (ii) there are no dynamic SUDTC effects.

Third, recall that a limitation of the SUDTC data provided by the NDDAATP directory is that the data are only updated yearly (see Section 4.2). Thus, SUDTC entry and exits are only observed on an annual basis, and we will miss some entries/exits in the one-year period between surveys. This data feature may lead to some measurement error in our data; the bias from such error is difficult to sign (Bound, Brown, and Mathiowetz 2001).[17] To explore the empirical importance of this data limitation, we estimate ancillary models in which we exclude observations in the between-directory period where entry and exits could be mis-classified. Results generated in this ancillary analysis are presented in in appendix table 2. The results are not appreciably different from our core specification (table 3).

Fourth, we implement several robustness checks regarding SUDTC heterogeneity, and both fixed-effect and clustering specifications. Specifically, we (i) estimate the effect of multiple SUDTCs within a locality to assess whether there is a dose-response effect of SUDTC entrance;

[17] We attempted to locate exact opening and closing dates through SAMHSA (the agency that manages the NDDAATP) and the Washington State Substance Abuse Agency (the agency tasked with overseeing licensed SUDTCs in Seattle and that provides data to SAMHSA for management of NDDAATP). Collecting exact SUDTC opening and closing dates is not feasible based on our investigations into this issue. Details available on request.

(ii) estimate the effect of SUDTCs that provide methadone treatment;[18] (iii) estimate models using quarter-by-year fixed effects to better capture seasonality in housing sales prices (U.S. Census Bureau 2018); (iv) estimate limited sales sample models with standard errors clustered at the zip code level; and (v) estimate full-sample models using a wild cluster bootstrap approach to estimate standard errors (Cameron & Miller, 2015).[19] Results generated in these alternate specifications are presented in appendix tables 3 to 6. Findings are comparable to our main results (table 3). Finally, we exclude all residential property value variables and re-estimate Equations (2) and (3). We exclude the property-level controls as some of these could plausibly be influenced by SUDTC entrances/exists if – for instance – these entrances/exits alter the composition of residential properties listed for sale, thus leading to over-controlling bias in our estimates (Angrist and Pischke 2008). Results, reported in appendix table 7, are not appreciably different from our adjusted models (table 3).

6. Discussion

SUDs are prevalent and harmful health conditions within the U.S. and other developed countries. Treatment can effectively allow afflicted individuals to obtain abstinence, which additionally can reduce the associated negative societal costs of SUDs. However, SUDTCs require a physical space to occupy. There are anecdotal NIMBY concerns that these centers increase crime, littering, noise, and nuisance behaviors, which stigmatizes these centers and potentially reduces property values for residences in close proximity to the SUDTCs. On the

[18] We study centers that offer OUD treatment – specifically centers offering methadone – as the U.S. is in the midst of an opioid epidemic and how best to address this epidemic is a pressing question facing local, state, and federal governments. We note that buprenorphine is also indicated to treat OUD. However, this medication is generally prescribed in general physicians' outpatient offices and not specialty treatment facilities such as we study here.
[19] In our main specifications we cluster at the SUDTC area and zip code level respectively.

other hand, SUDTCs may increase property values by reducing SUD prevalence and associated behaviors and increasing employment opportunities within the neighborhood.

Given the scope of the SUD epidemic currently facing the U.S., the number of treatment facilities is expanding. For instance in 2003 (the first year of our study) there were 15,124 licensed specialty SUDTC facilities in the U.S. and by 2016 (the last year of our study) this number had risen to 18,087 (Substance Abuse and Mental Health Services Administration 2017, 2004), representing a 20% increase.[20] Thus, understanding the implications of SUDTC locations on the values of residential properties, which reflect major financial investments for many Americans, is of growing importance. Further, accurately understanding the effects of SUDTCs on property values is necessary to assess the overall costs of SUDs to society. While much of the literature that explores the costs of SUDs has focused on negative externalities such as crime and/or direct treatment costs, we explore a potential indirect treatment cost: financial spillovers to individuals who reside near an SUDTC.

In this study we provide new evidence on the effect of SUDTCs on residential property values using data from Seattle, Washington from 2003 to 2016, and an SDD estimator that mitigates bias from endogenous SUDTC location choices. We find that SUDTCs endogenously locate in areas with somewhat lower property values (2.2%). When we do not account for endogenous location choice, we find that SUDTCs reduce residential property values by 3.4% to 4.6%. However, after accounting for such location choices through the use of an SDD model, we find no statistically significant evidence that SUDTC entrance or exit influences residential property values. Moreover, our point estimates for both entrances and exits are very small in magnitude. Indeed, in our preferred SDD models we can rule out declines in property values

[20] Authors' calculations based on the 2003 and 2016 N-SSATS, details available on request.

following SUDTC entrance larger than 2.2% to 3.8% with 95% confidence. Our SDD estimates are robust to a wide range of specifications and sensitivity checks.

We note that our findings change when we apply the SDD model to account for endogenous location selection on the part of SUDTC owners and operators. In particular, we find no statistically significant evidence that SUDTCs affect property values when we apply the SDD estimator; coefficient estimates decline in magnitude and become statistically indistinguishable from zero. This pattern of results suggests that perhaps the perceived negative effects of SUDTCs on residential property values may be overstated. Previous economic research estimating dis-amenity effects also documents that failure to account for endogenous location choices can lead to estimates biased away from zero (Linden and Rockoff 2008). Our results thus link to a growing literature suggesting that empirical studies account for endogenous location choices when evaluating the effect of both amenities and dis-amenities on property values (Congdon-Hohman 2013; Dealy, Horn, and Berrens 2017; Linden and Rockoff 2008).

Local residents are often concerned that entrance of an SUDTC will impose costs on the neighborhood and, in turn, reduce residential property values. However, our findings suggest that the potential benefits of SUDTCs to the community may offset potential costs, leaving property values unchanged. Notably, SUDTCs reduce the prevalence of SUDs within the local area (Swensen 2015). Additionally, many studies document reductions in crime associated with SUDs treatment, and these effects have a considerable economic impact (Cohen and Piquero 2009; Doran 2008; McCollister et al. 2017; McCollister, French, and Fang 2010). In terms of SUDTCs, Bondurant et al., (2018) and Wen, Hockenberry, and Cummings (2017) show that that SUDTCs reduce both violent and financially motivated crimes in local areas. The social costs (e.g., legal system and healthcare costs) of one murder are very high: $11M (McCollister et al.

2017).[21] Finally, our study suggests that cost-benefit analyses of social goods (such as SUDTCs that reduce SUDs for individuals and associated harms to society) should incorporate the potential financial costs to individuals who reside near the location of the social good.

Our study has several limitations. First, we consider only SUDTCs licensed to deliver SUD treatment that are known to SAMHSA and complete the N-SSATS. We suspect that the number of SUDTCs that we miss is small given the importance of being listed on the NDDAATP for attracting patients and that SUDTCs are legally required to be licensed prior to delivering treatment to patients. Second, a critical step in application of the SDD model is selection of a suitable treatment and comparison group combination. In particular, the econometrician must locate a comparison group that can be used to estimate counterfactual trends in residential property values for the treatment group but is untreated by the event. While our results are robust to several alternative distance band specifications, we acknowledge that the most appropriate treatment-comparison group combination is unknown. Third, due to data limitations we are not able to determine the exact date at which SUDTCs enter and exit the market. However, our findings appear to be robust to several sensitivity analyses related to these limitations. Finally, we rely on a single city (Seattle). Moreover, Seattle experienced a large housing boom over our study period, which may alter the effects of dis-amenities. We note that our results are robust to numerous time and location fixed-effect specifications, which should account for non-linear changes in residential property values over time. Future studies are needed in more areas to fully understand the effect of SUDTCs on residential property values.

In summary, our findings shed new light on an important and relatively unstudied potential cost associated with SUDs, potential reductions in the value of housing values in close

[21] Inflated by the authors from the estimate reported in the original manuscript ($10,086,337 in 2016) to 2018 dollars using the CPI.

proximity to SUDTCs. We show that previous empirical evidence and anecdotes likely overstated the negative effects of SUDTCs on residential property values. While we did not study this question in our paper, it is possible that stigma against SUDTCs and NIMBY local efforts may have prevented these centers from optimally locating, which may impede treatment effectiveness and, in turn, patient outcomes and exacerbate social costs associated with SUDs.

Table 1: Residential Property Characteristics

Variable	Sample: Full sample	Treatment (0.2 miles)	Comparison (0.2 to 0.4 miles)
Sale Price ($1,000 in 2016 dollars)	487.56	471.02	479.14
	(283.80)	(259.49)	(270.10)
More than 1 No. of living unit (1= yes, 0 = no)	0.03	0.07	0.04
	(0.17)	(0.25)	(0.20)
No. of Stories	1.37	1.54	1.43
	(0.49)	(0.60)	(0.52)
No. of Bedrooms	3.23	3.13	3.20
	(1.00)	(1.05)	(1.00)
No. of Bathrooms	1.45	1.48	1.46
	(0.65)	(0.66)	(0.66)
Age	58.10	57.69	61.02
	(29.58)	(36.93)	(32.26)
Renovated (1= yes, 0 = no)	4.25	4.69	4.76
	(3.22)	(3.93)	(3.59)
Total Living (1,000 Square Feet)	1.83	1.71	1.77
	(0.77)	(0.74)	(0.73)
Total Basement (1,000 Square Feet)	0.67	0.61	0.63
	(0.53)	(0.48)	(0.49)
Total Garage (1,000 Square Feet)	0.17	0.14	0.15
	(0.22)	(0.20)	(0.20)
Total Porch (1,000 Square Feet)	0.05	0.05	0.05
	(0.09)	(0.08)	(0.09)
Total Deck (1,000 Square Feet)	0.11	0.08	0.10
	(0.17)	(0.14)	(0.16)
Percent Brick Stone	7.71	3.89	5.27
	(24.65)	(17.88)	(20.64)
Building Grade (quality)	7.25	7.23	7.20
	(0.94)	(0.93)	(0.91)
N	131,862	8,982	22,671

Notes: Residential properties can have more than one living unit.

Table 2: Effect of SUDTC Entrance and Exit on Residential Property values: Naïve OLS Model

Model:	(1)	(2)	(3)
Mean value of outcome variable ($1,000 in 2016 dollars):	487.56	487.56	487.56
$D^{0.2}$	-0.0467***	-0.0344***	-0.0344*
	(0.0054)	(0.0048)	(0.0181)
Constant	11.7253***	12.2773***	12.2773***
	(0.0566)	(0.0568)	(0.0740)
N	131,862	131,862	131,862
adj. R^2	0.533	0.646	0.646
Housing Characteristics	✓	✓	✓
Year FE	✓		
Year × Zip code Fixed Effects		✓	✓
Zip Code SE Cluster			✓

Notes: Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3: Effect of SUDTC Entrance and Exit on Residential Property values: SDD Results

Model:	(1) Test for Endogenous locations	(2) Full Sample	(3) Full Sample	(4) Limited Sales Sample	(5) Limited Sales Sample
Mean value of outcome variable ($1,000 in 2016 dollars):	486.65	487.56	487.56	476.84	476.84
$D^{0.2}$	-0.0101	-0.0079	-0.0080	-0.0302**	-0.0304**
	(0.0138)	(0.0136)	(0.0137)	(0.0138)	(0.0137)
$D^{0.4}$	-0.0223*	-0.0225*	-0.0228*		
	(0.0117)	(0.0126)	(0.0125)		
$D^{0.2}*\tau^{entry}$		-0.0055	-0.0111	0.0098	0.0064
		(0.0135)	(0.0143)	(0.0161)	(0.0172)
$D^{0.4}*\tau^{entry}$		0.0032	0.0008	-0.0094	-0.0086
		(0.0149)	(0.0177)	(0.0188)	(0.0184)
$D^{0.2}*\tau^{exit}$			0.0198		0.0134
			(0.0164)		(0.0142)
$D^{0.4}*\tau^{exit}$			0.0096		0.0291
			(0.0161)		(0.0177)
Constant	12.3972***	12.2954***	12.2923***	12.1320***	12.1371***
	(0.0703)	(0.0762)	(0.0761)	(0.1039)	(0.1074)
N	108,128	131,862	131,862	31,653	31,653
adj. R^2	0.651	0.646	0.646	0.630	0.630
Housing Characteristics	✓	✓	✓	✓	✓
Year × Zip code Fixed Effects	✓	✓	✓		
Year Fixed Effects				✓	✓
SUDTC Fixed Effect				✓	✓
Zip Code SE Cluster		✓	✓		
SUDTC area SE Cluster				✓	✓
Restricted to 0.4 miles				✓	✓
Observation within 0.4 miles after SUDTC entry dropped	✓				

Notes: Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4A: Effect of SUDTC Entrance and Exit on Residential Property values: SDD Results with Alternative Distance Band Specifications – Full Sample

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment group	0.1	0.1	0.1	0.2	0.2	0.2	0.3	0.3
Comparison group	0.3	0.4	0.5	0.4	0.5	0.6	0.5	0.6
Mean value of outcome variable ($1,000 in 2016 dollars):	487.56	487.56	487.56	487.56	487.56	487.56	487.56	487.56
$D^{Treatment}$	-0.0168	-0.0169	-0.0174	-0.0080	-0.0081	-0.0078	0.0019	0.0021
	(0.0177)	(0.0199)	(0.0204)	(0.0137)	(0.0153)	(0.0169)	(0.0155)	(0.0161)
$D^{Comparison}$	-0.0199	-0.0242*	-0.0297*	-0.0228*	-0.0288*	-0.0365*	-0.0295	-0.0370*
	(0.0142)	(0.0130)	(0.0162)	(0.0125)	(0.0165)	(0.0182)	(0.0182)	(0.0195)
$D^{Treatment} * \tau^{entry}$	0.0117	0.0092	0.0105	-0.0111	-0.0085	-0.0107	-0.0081	-0.0110
	(0.0172)	(0.0188)	(0.0205)	(0.0143)	(0.0164)	(0.0165)	(0.0178)	(0.0174)
$D^{Comparison} * \tau^{entry}$	-0.0044	-0.0017	-0.0025	0.0008	-0.0014	0.0013	-0.0022	0.0011
	(0.0209)	(0.0182)	(0.0192)	(0.0177)	(0.0192)	(0.0192)	(0.0194)	(0.0193)
$D^{Treatment} * \tau^{exit}$	-0.0035	0.0029	-0.0030	0.0198	0.0117	0.0123	0.0123	0.0132
	(0.0251)	(0.0280)	(0.0287)	(0.0164)	(0.0158)	(0.0157)	(0.0158)	(0.0157)
$D^{Comparison} * \tau^{exit}$	0.0181	0.0115	0.0195	0.0096	0.0196	0.0202	0.0202	0.0206
	(0.0183)	(0.0151)	(0.0155)	(0.0161)	(0.0160)	(0.0144)	(0.0154)	(0.0139)
Constant	12.2830***	12.2918***	12.2979***	12.2923***	12.2992***	12.3107***	12.2960***	12.3074***
	(0.0750)	(0.0758)	(0.0754)	(0.0761)	(0.0758)	(0.0745)	(0.0760)	(0.0748)
N	131,862	131,862	131,862	131,862	131,862	131,862	131,862	131,862
adj. R^2	0.646	0.646	0.646	0.646	0.646	0.646	0.646	0.646
Housing Characteristics	✓	✓	✓	✓	✓	✓	✓	✓
Year × Zip code Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Zip Code SE Cluster	✓	✓	✓	✓	✓	✓	✓	✓

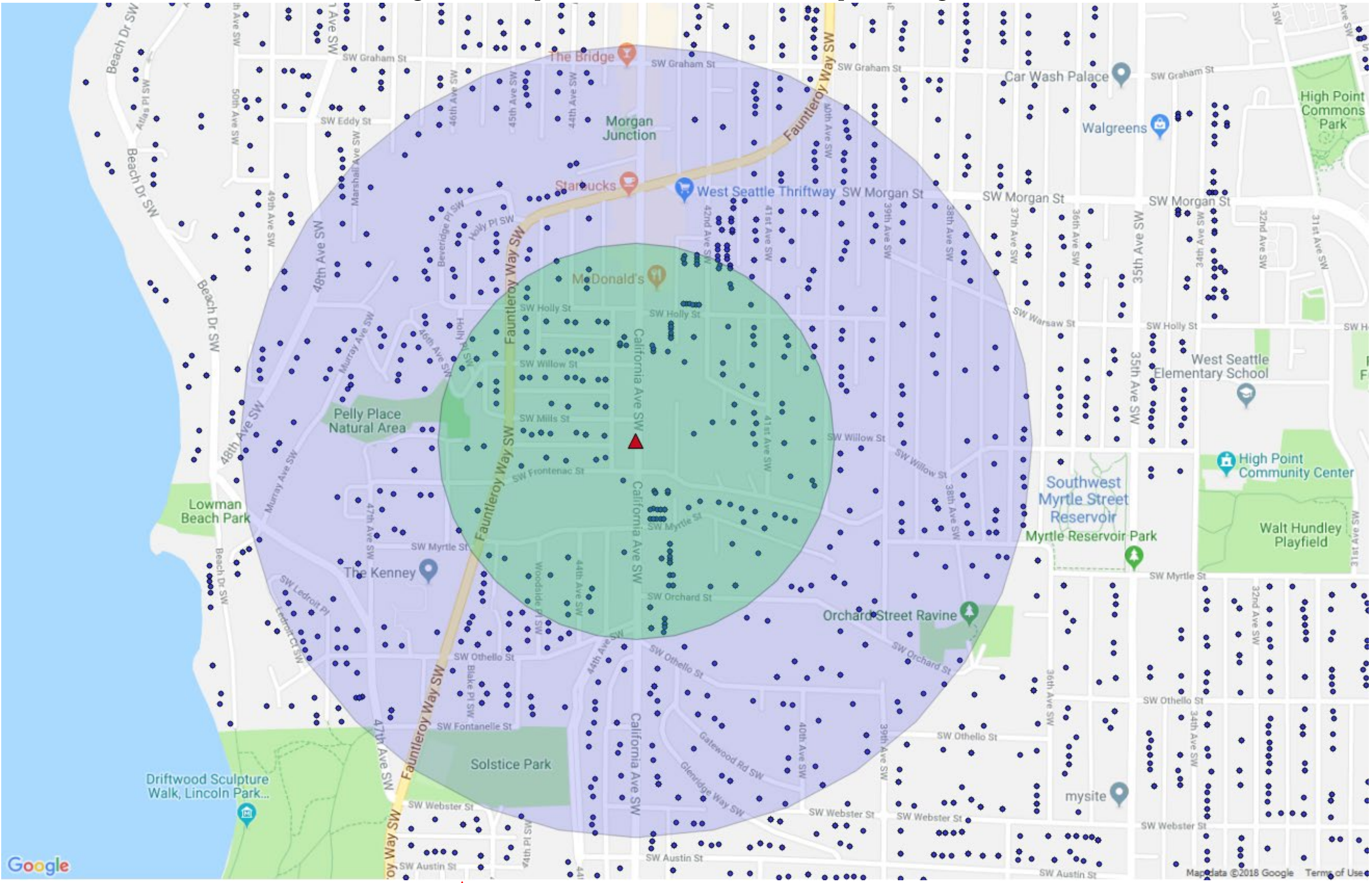
Notes: Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4B: Effect of SUDTC Entrance and Exit on Residential Property values: SDD Results with Alternative Distance Band Specifications – Limited Sales Sample

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment group	0.1	0.1	0.1	0.2	0.2	0.2	0.3	0.3
Comparison group	0.3	0.4	0.5	0.4	0.5	0.6	0.5	0.6
Mean value of outcome variable ($1,000 in 2016 dollars):	473.77	476.84	474.33	476.84	474.33	474.50	474.33	474.50
$D^{Treatment}$	-0.0406**	-0.0411**	-0.0436**	-0.0304**	-0.0323**	-0.0320*	-0.0097	-0.0096
	(0.0161)	(0.0173)	(0.0186)	(0.0137)	(0.0154)	(0.0163)	(0.0105)	(0.0114)
$D^{Treatment} * \tau^{entry}$	0.0214	0.0161	0.0184	0.0064	0.0093	0.0075	0.00001	-0.0025
	(0.0232)	(0.0246)	(0.0265)	(0.0172)	(0.0190)	(0.0190)	(0.0134)	(0.0131)
$D^{Comparison} * \tau^{entry}$	-0.0120	-0.0067	0.0003	-0.0086	-0.0014	-0.0009	-0.0017	-0.0005
	(0.0200)	(0.0184)	(0.0176)	(0.0184)	(0.0179)	(0.0174)	(0.0181)	(0.0175)
$D^{Treatment} * \tau^{exit}$	-0.0005	0.0073	0.0033	0.0134	0.0097	0.0133	0.0136	0.0171
	(0.0285)	(0.0297)	(0.0304)	(0.0142)	(0.0142)	(0.0135)	(0.0132)	(0.0127)
$D^{Comparison} * \tau^{exit}$	0.0331*	0.0288	0.0344**	0.0291	0.0353**	0.0382**	0.0321**	0.0346**
	(0.0192)	(0.0180)	(0.0168)	(0.0177)	(0.0164)	(0.0161)	(0.0157)	(0.0155)
Constant	11.8386***	12.1270***	12.1568***	12.1371***	12.1642***	12.1473***	12.1461***	12.1344***
	(0.3415)	(0.1083)	(0.1149)	(0.1074)	(0.1141)	(0.1010)	(0.1141)	(0.1014)
N	19,390	31,653	43,847	31,653	43,847	56,799	43,847	56,799
adj. R^2	0.636	0.630	0.622	0.630	0.622	0.622	0.622	0.622
Housing Characteristics	✓	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
SUDTC Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
SUDTC SE Cluster	✓	✓	✓	✓	✓	✓	✓	✓
Restricted to Comparison Region	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$.

Figure 1: Example SUDTC Treatment and Comapirision Region



Notes: ▲ is the SUDTC Center, ● are the residential properties sales.
First circle: within 0.2 miles of SUDTC, Second Circle: within 0.2-0.4 miles of SUDTC

Figure 2: SUDTC Locations in Seattle from 2003 to 2016

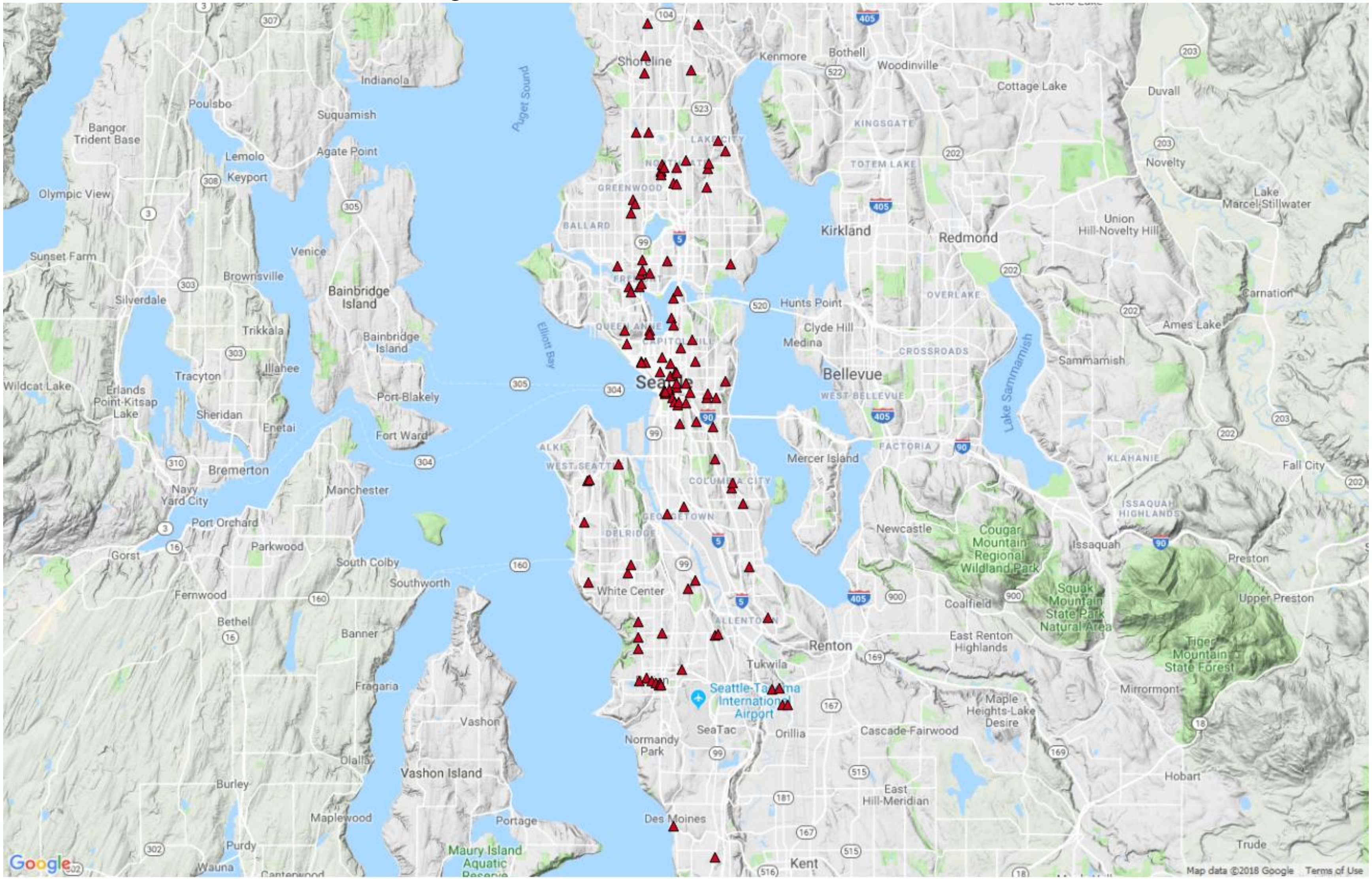
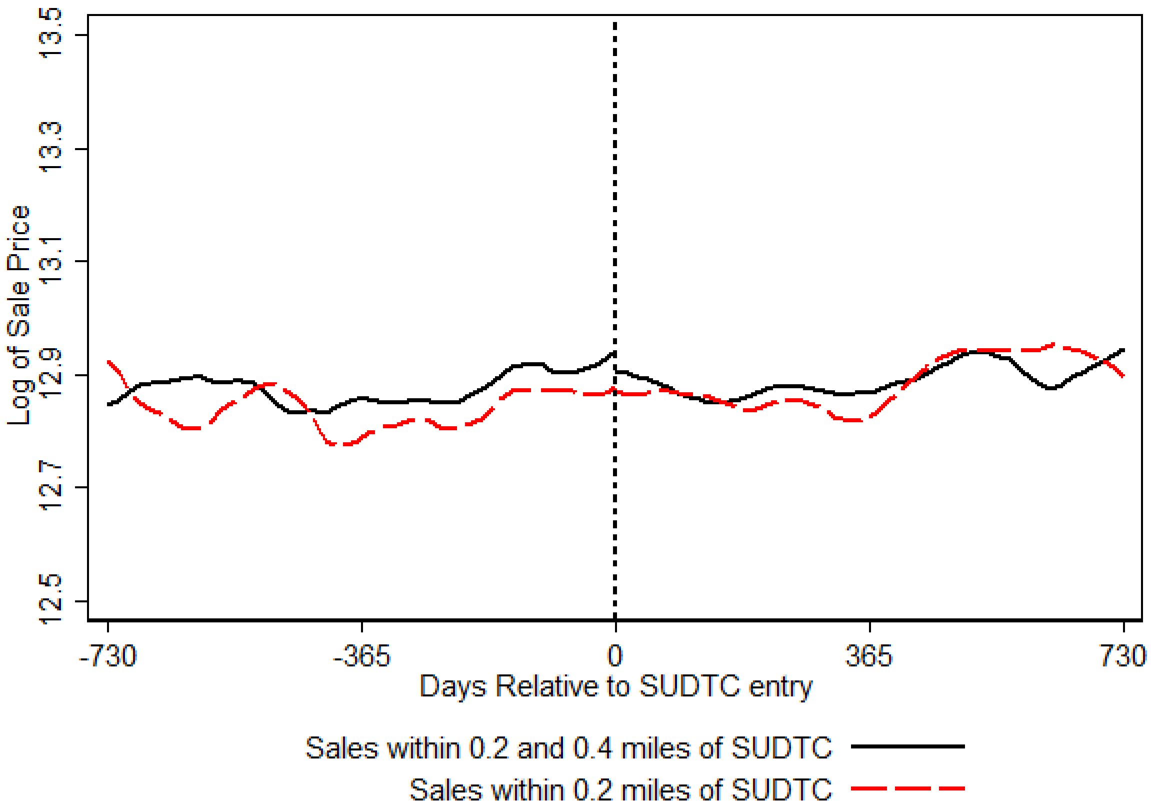
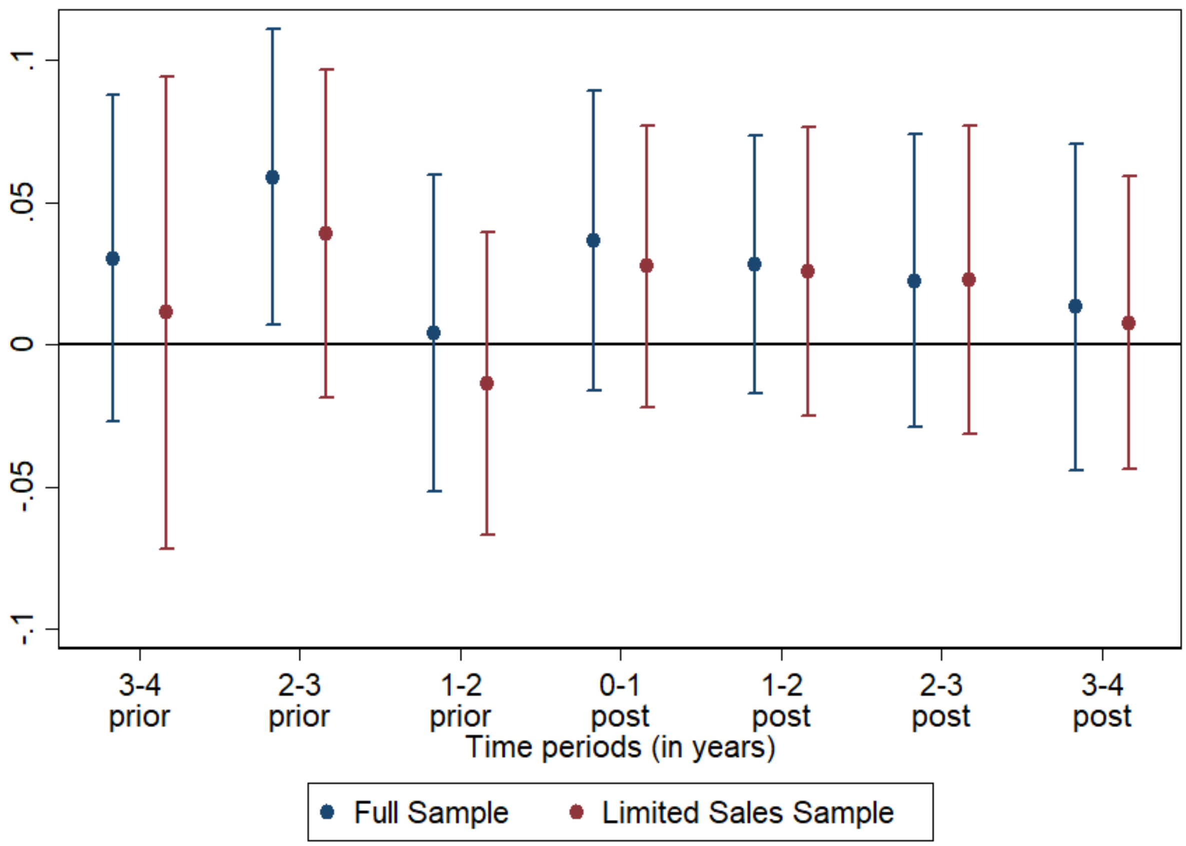


Figure 3: Trends in Residential Housing Prices in Seattle: Pre-and Post- SUDTC Entry



Notes: Data are centered around the SUDTC entry. The treatment group includes residential property sales that occur 0 to < 0.20 miles from an SUDTC. The comparison group includes residential property sales that occur 0.2 to 0.4 miles from an SUDTC. Epanechnikov local polynomial smoothing with bandwidth of 35 days.

Figure 4: Effect of SUDTC Entrance and Exit on Residential Property values: Event-study Coefficients Plotted for Treatment Region (0.2 miles from SUDTC)



Notes: Entry period defined as 0-1 years prior to survey date. Observations restricted to 4-years prior and 4-years post SUDTC entry. The omitted category is 0-1 years prior to SUDTC entry. Mean value of the outcome variable ($1,000 in 2016 dollars): 487.

Appendix Table 1: Effect of SUDTC Entrance and Exit on Residential Property values: SDD Model Full Set of Control Variable Coefficient Estimate

Control Variable Coefficient Estimates for Column (3) in Table 3	Beta (Standard error)
Mean value of outcome variable ($1,000 in 2016 dollars):	487.56
More than 1 No. of living unit (1= yes, 0 = no)	-0.0266**
	(0.0116)
No. of Stories	0.0257***
	(0.0079)
No. of Bedrooms	-0.0115***
	(0.0033)
No. of Bathrooms	-0.0024
	(0.0033)
Age	0.0018***
	(0.0005)
Age-squared	-0.0035
	(0.0045)
Renovated (1= yes, 0 = no)	0.0578***
	(0.0079)
Total Living (1,000 Square Feet)	0.1726***
	(0.0060)
Total Basement (1,000 Square Feet)	0.0345***
	(0.0063)
Total Garage (1,000 Square Feet)	0.0904***
	(0.0104)
Total Porch (1,000 Square Feet)	0.1252***
	(0.0199)
Total Deck (1,000 Square Feet)	0.1611***
	(0.0146)
Percent Brick Stone	0.0004***
	(0.0001)
Constant	12.2923***
	(0.0761)
N	131,862
adj. R^2	0.646
Building Grade Variables	✓

Notes: All models estimated with OLS. Standard errors clustered at Zip Code level reported in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$.

Appendix Table 2: Effect of SUDTC Entrance and Exit on Residential Property values: SDD Results Dropping Observations in the Between-N-SSATS Survey Period

Model:	(1) Full Sample	(2) Full Sample	(3) Limited Sales Sample	(4) Limited Sales Sample
Mean value of outcome variable ($1,000 in 2016 dollars):	487.56	487.56	476.84	476.84
$D^{0.2}$	-0.0008	-0.0008	-0.0267	-0.0269
	(0.0147)	(0.0147)	(0.0167)	(0.0166)
$D^{0.4}$	-0.0236*	-0.0241*		
	(0.0123)	(0.0121)		
$D^{0.2}*\tau^{entry}$	-0.0135	-0.0184	0.0056	0.0028
	(0.0136)	(0.0142)	(0.0186)	(0.0195)
$D^{0.4}*\tau^{entry}$	0.0047	0.0016	-0.0074	-0.0050
	(0.0145)	(0.0172)	(0.0209)	(0.0206)
$D^{0.2}*\tau^{exit}$		0.0178		0.0122
		(0.0151)		(0.0143)
$D^{0.4}*\tau^{exit}$		0.0125		0.0332*
		(0.0153)		(0.0175)
Constant	12.2952***	12.2918***	12.1243***	12.1299***
	(0.0765)	(0.0764)	(0.1052)	(0.1087)
N	130,380	130,380	30,171	30,171
adj. R^2	0.647	0.647	0.632	0.632
Housing Characteristics	✓	✓	✓	✓
Year × Zip code Fixed Effects	✓	✓		
Year Fixed Effects			✓	✓
SUDTC Fixed Effect			✓	✓
Zip Code SE Cluster	✓	✓		
SUDTC area SE Cluster			✓	✓
Restricted to 0.4 miles			✓	✓
Observation dropped within 0.4 miles for 365 days before entry	✓	✓	✓	✓

Notes: Standard errors in parentheses. Sale observations 365 days before the survey date dropped at control level (0.4 miles). * $p < .1$, ** $p < .05$, *** $p < .01$.

Appendix Table 3: Effect of SUDTC Entrance and Exit on Residential Property values: SDD Results with Alternate Fixed Effect and Clustering Specifications

Model:	(1) Full Sample	(2) Full Sample	(3) Full Sample	(4) Limited Sales Sample	(5) Limited Sales Sample	(6) Limited Sales Sample
Mean value of outcome variable ($1,000 in 2016 dollars):	487.56	487.56	487.56	476.84	476.84	476.84
$D^{0.2}$	-0.0080	-0.0043	-0.0080	-0.0036	-0.0295**	-0.0295**
	(0.0137)	(0.0157)	(0.0120)	(0.0141)	(0.0135)	(0.0135)
$D^{0.4}$	-0.0228*	-0.0246	-0.0228*			
	(0.0125)	(0.0149)	(0.0124)			
$D^{0.2}*\tau^{entry}$	-0.0111	-0.0158	-0.0111	-0.0156	0.0073	0.0073
	(0.0143)	(0.0158)	(0.0173)	(0.0138)	(0.0142)	(0.0169)
$D^{0.4}*\tau^{entry}$	0.0008	-0.0034	0.0008	-0.0184	-0.0148	-0.0148
	(0.0177)	(0.0192)	(0.0046)	(0.0204)	(0.0214)	(0.0181)
$D^{0.2}*\tau^{exit}$	0.0198	0.0193	0.0198	0.0194	0.0119	0.0119
	(0.0164)	(0.0173)	(0.0176)	(0.0168)	(0.0170)	(0.0139)
$D^{0.4}*\tau^{exit}$	0.0096	0.0275	0.0096	0.0113	0.0216	0.0216
	(0.0161)	(0.0171)	(0.0194)	(0.0222)	(0.0167)	(0.0175)
Constant	12.2923***	12.2558***	12.4368***	12.1275***	12.0576***	12.0576***
	(0.0761)	(0.0736)	(0.0000)	(0.1785)	(0.1685)	(0.1091)
N	131,862	131,862	131,862	31,653	31,653	31,653
adj. R^2	0.646	0.639	0.646	0.616	0.636	0.636
Housing Characteristics	✓	✓	✓	✓	✓	✓
Year × Zip code Fixed Effects	✓		✓			
Quarter Year Fixed Effects		✓		✓	✓	✓
Zip Code Fixed Effects		✓	✓	✓		
SUDTC fixed effects					✓	✓
Zip Code SE Cluster	✓	✓	✓	✓	✓	
SUDTC SE Cluster						✓
Wild Cluster Boot Strap at Zip Code level			✓			
Restricted to 0.4 miles				✓	✓	✓

Notes: All models estimated with OLS. Standard errors reported in parentheses. Treatment group is defined as all properties sold 0 to <0.2 miles from an SUDTC. Comparison group is defined as all properties sold 0.2 to 0.4 miles from an SUDTC. * $p < .1$, ** $p < .05$, *** $p < .01$.

Appendix Table 4: Effect of SUDTC Entrance and Exit on Residential Property values: SDD Result using Methadone Maintenance and Methadone Detoxification SUDTCs Only

Model:	(1) Full Sample	(2) Full Sample	(3) Limited Sales Sample	(4) Limited Sales Sample
Mean value of outcome variable ($1,000 in 2016 dollars):	487.56	487.56	476.84	476.84
$D^{0.2}$	-0.0080	-0.0080	-0.0303**	-0.0306**
	(0.0137)	(0.0137)	(0.0137)	(0.0135)
$D^{0.4}$	-0.0225*	-0.0229*		
	(0.0126)	(0.0126)		
$D^{0.2}*\tau^{entry}$	-0.0084	-0.0160	0.0075	0.0027
	(0.0139)	(0.0145)	(0.0166)	(0.0178)
$D^{0.2}*\tau^{entry}*\theta^{Methadone}$	0.0359	0.0437	0.0256	0.0305
	(0.0397)	(0.0383)	(0.0410)	(0.0414)
$D^{0.4}*\tau^{entry}$	0.0027	-0.0004	-0.0122	-0.0129
	(0.0135)	(0.0163)	(0.0199)	(0.0191)
$D^{0.4}*\tau^{entry}*\theta^{Methadone}$	0.0049	0.0084	0.0214	0.0358
	(0.0353)	(0.0354)	(0.0217)	(0.0241)
$D^{0.2}*\tau^{exit}$		0.0246		0.0169
		(0.0157)		(0.0138)
$D^{0.4}*\tau^{exit}$		0.0108		0.0316*
		(0.0158)		(0.0184)
Constant	12.2955***	12.2918***	12.1325***	12.1389***
	(0.0765)	(0.0763)	(0.1026)	(0.1062)
N	131,862	131,862	31,653	31,653
adj. R^2	0.646	0.646	0.630	0.630
Housing Characteristics	✓	✓	✓	✓
Year × Zip code Fixed Effects	✓	✓		
Year Fixed Effects			✓	✓
SUDTC Fixed Effect			✓	✓
Zip Code SE Cluster	✓	✓		
SUDTC area SE Cluster			✓	✓
Restricted to 0.4 miles			✓	✓

Notes: Standard errors in parentheses. $\theta^{Methadone}$ represents SUDTC providing Methadone maintenance and Methadone detoxification service in operation. * $p < .1$, ** $p < .05$, *** $p < .01$.

Appendix Table 5: Effect of SUDTC Entrance and Exit on Residential Property values: SDD Results Accounting for Multiple SUDTCs in Proximity to Property

Model:	(1) Full Sample	(2) Full Sample	(3) Limited Sales	(4) Limited Sales
Mean value of outcome variable:	487.56	487.56	476.84	476.84
$D^{0.2}$	-0.0079	-0.0080	-0.0302**	-0.0303**
	(0.0136)	(0.0137)	(0.0138)	(0.0137)
$D^{0.4}$	-0.0224*	-0.0228*		
	(0.0126)	(0.0125)		
$D^{0.2}*\tau^{entry}$	-0.0050	-0.0110	0.0105	0.0066
	(0.0131)	(0.0134)	(0.0161)	(0.0173)
$D^{0.2}*\tau^{entry}*\theta^{Secondary\ SUDTC}$	-0.0099	-0.0009	-0.0167	-0.0057
	(0.0347)	(0.0334)	(0.0238)	(0.0237)
$D^{0.4}*\tau^{entry}$	0.0031	0.0007	-0.0097	-0.0087
	(0.0149)	(0.0177)	(0.0189)	(0.0185)
$D^{0.2}*\tau^{exit}$		0.0197		0.0131
		(0.0155)		(0.0139)
$D^{0.4}*\tau^{exit}$		0.0096		0.0290
		(0.0161)		(0.0178)
Constant	12.2952***	12.2923***	12.1314***	12.1369***
	(0.0762)	(0.0761)	(0.1041)	(0.1076)
N	131,862	131,862	31,653	31,653
adj. R^2	0.646	0.646	0.630	0.630
Housing Characteristics	✓	✓	✓	✓
Year × Zip code Fixed Effects	✓	✓		
Year Fixed Effects			✓	✓
SUDTC Fixed Effect			✓	✓
Zip Code SE Cluster	✓	✓		
SUDTC area SE Cluster			✓	✓
Restricted to 0.4 miles			✓	✓

Notes: Standard errors in parentheses. $\theta^{Secondary\ SUDTC}$ represents other SUDTCs in operation within 0.2 miles.
* $p < .1$, ** $p < .05$, *** $p < .01$.

Appendix Table 6: Effect of SUDTC Entrance and Exit on Residential Property values: SDD Results for Sample with Exit Parameter Suppressed for SUDTC that Entered Multiple Times

Model:	(1) Full Sample	(2) Full Sample	(3) Limited Sales Sample	(4) Limited Sales Sample
Mean value of outcome variable:	487.56	487.56	476.84	476.84
$D^{0.2}$	-0.0079	-0.0080	-0.0302**	-0.0300**
	(0.0136)	(0.0137)	(0.0138)	(0.0139)
$D^{0.4}$	-0.0225*	-0.0230*		
	(0.0126)	(0.0125)		
$D^{0.2}*\tau^{entry}$	-0.0055	-0.0070	0.0096	0.0091
	(0.0135)	(0.0147)	(0.0161)	(0.0169)
$D^{0.4}*\tau^{entry}$	0.0032	-0.0020	-0.0094	-0.0073
	(0.0149)	(0.0173)	(0.0189)	(0.0188)
$D^{0.2}*\tau^{exit}$		0.0069		0.0038
		(0.0142)		(0.0143)
$D^{0.4}*\tau^{exit}$		0.0205		0.0424**
		(0.0153)		(0.0193)
Constant	12.2954***	12.2916***	12.1321***	12.1368***
	(0.0762)	(0.0761)	(0.1041)	(0.1085)
N	131,862	131,862	31,653	31,653
adj. R^2	0.646	0.646	0.630	0.630
Housing Characteristics	✓	✓	✓	✓
Year × Zip code Fixed Effects	✓	✓		
Year Fixed Effects			✓	✓
SUDTC Fixed Effect			✓	✓
Zip Code SE Cluster	✓	✓		
SUDTC area SE Cluster			✓	✓
Restricted to 0.4 miles			✓	✓
Exit parameter suppressed for SUDTC with multiple entry	✓	✓	✓	✓

Notes: Standard errors in parentheses. SUDTC with multiple entry at the same locations are considered to have never left the location. * $p < .1$, ** $p < .05$, *** $p < .01$.

Appendix Table 7: Effect of SUDTC Entrance and Exit on Residential Property values: SDD Results Excluding Residential Property Controls

Model:	(1) Full Sample	(2) Full Sample	(3) Limited Sales Sample	(4) Limited Sales Sample
Mean value of outcome variable ($1,000 in 2016 dollars):	487.56	487.56	476.84	476.84
$D^{0.2}$	-0.0343	-0.0344	-0.0639***	-0.0641***
	(0.0235)	(0.0235)	(0.0222)	(0.0220)
$D^{0.4}$	-0.0728***	-0.0734***		
	(0.0257)	(0.0257)		
$D^{0.2}*\tau^{entry}$	-0.0003	-0.0095	0.0291	0.0226
	(0.0203)	(0.0237)	(0.0259)	(0.0277)
$D^{0.4}*\tau^{entry}$	0.0199	0.0158	-0.0028	-0.0011
	(0.0302)	(0.0329)	(0.0206)	(0.0203)
$D^{0.2}*\tau^{exit}$		0.0324		0.0235
		(0.0419)		(0.0336)
$D^{0.4}*\tau^{exit}$		0.0162		0.0258
		(0.0285)		(0.0211)
Constant	13.4539***	13.4490***	12.8962***	12.9038***
	(0.0145)	(0.0154)	(0.0101)	(0.0106)
N	131,862	131,862	31,653	31,653
adj. R^2	0.403	0.403	0.466	0.467
Year × Zip code Fixed Effects	✓	✓		
Year Fixed Effects			✓	✓
SUDTC Fixed Effect			✓	✓
Zip Code SE Cluster	✓	✓		
SUDTC area SE Cluster			✓	✓
Restricted to 0.4 miles			✓	✓

Notes: Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

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