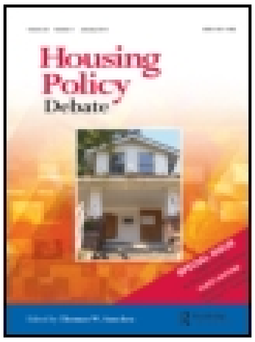

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The Commodity Effects of Decommodification: Community Land Trusts and Neighborhood Property Values

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ABSTRACT

This article explores the impacts of community land trust (CLT) properties on the real estate prices of nearby homes through a case study of a relatively large CLT in Minneapolis, Minnesota. We use hedonic regression and a difference-in-difference estimation with spatial error correction to measure price effects. The number of developments citywide is insufficient to yield significant results. However, we find evidence that clustering CLTs stemmed the decline in sales prices during the foreclosure crisis. The introduction of the first nearby CLT had no measurable price impact, but each additional CLT was associated with a 5% higher sales price in North Minneapolis, and 3% higher in Central Minneapolis. In the postrecession period, we estimate that the introduction of CLTs in North Minneapolis was associated with a 10.9% increase in nearby sales prices. These results suggest that, contrary to common assumptions, price effects are strongest when affordable properties are spatially clustered.

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community land trust (CLT); community development and revitalization; housing; neighborhoods; foreclosure

> Neighborhood impacts can be diverse and difficult to measure, but they are likely to be reflected in impacts on property values, which become a surrogate measure for any combination of negative externalities associated with affordable housing. Simply stated, the fear of adverse impacts is that affordable housing will reduce values of adjacent and nearby properties. –Koebel and Lang (2004, p. 3)

The construction of affordable housing is often resisted by neighbors and others in the community because of the fear of the property value impacts of being close to such developments. There are, of course, other reasons why affordable housing is opposed. Most often it is because of the stereotyped assumptions and mental associations sometimes made about those who reside within affordable housing developments (Tighe, 2010), or from political ideologies and levels of trust in the government (Pendall, 1999). In the end, those are more difficult to counter, and often get masked in a cloak of concern over property values. Accordingly, there is a large literature on the impacts of affordable housing developments on the property values of nearby homes, spanning many kinds of housing programs (publicly owned, privately owned and publicly subsidized, Low-Income Housing Tax Credit), which has come to many different conclusions (Nguyen, 2005). The answer, in short, is that it depends. It depends on both the characteristics of the affordable housing and the characteristics of the neighborhoods in which it is sited.

Despite this large body of work, housing in community land trusts (CLTs) has not been studied. To some extent, this is understandable given that CLTs are still a small part of the affordable housing landscape. But it is a rapidly growing segment, and it is important to understand how this form of

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Supplemental data for this article can be accessed here.

affordable housing is similar to, or different from, other forms of affordable housing. Although the structure, design, and even tenure of CLTs vary widely, all CLTs provide affordable housing in perpetuity by removing land from speculative real estate markets and holding it in a trust. This study explores the relationship between home sale prices and CLTs using the case study of a relatively large CLT with 261 units in Minneapolis, Minnesota. The CLT properties analyzed here are single-family homes scattered throughout the city, although they are generally clustered in lower income areas in North and Central Minneapolis. Whereas the land is held in a trust, the houses are privately owned, and the units are not generally physically identifiable from the surrounding housing stock.

We use the now well-developed difference-in-differences approach with a hedonic regression model to analyze the impacts of siting CLTs on adjacent and nearby property values. We find some evidence citywide using ordinary least squares (OLS) regression that CLTs are positively associated with nearby sales prices, but this finding is not robust to a spatial error model (SEM) specification. We attribute this result to the small number of CLT housing developments being measured relative to the size and variation in real estate. When we replicated our analysis in two subareas where CLTs were most often sited, our analysis yielded robust results. These findings suggest that clustering multiple CLT properties in an area is positively associated with nearby sales prices. Furthermore, this finding is related to the foreclosure crisis and its aftermath, which coincided with the study, and in particular to a foreclosure diversion program operated by the CLT studied here.

We find that in North and Central Minneapolis, when sales prices were plummeting amid the foreclosure crisis from 2006 through 2010, clustering CLT properties was associated with smaller decreases of nearby home sale prices. The introduction of the first nearby CLT during this time had no measurable impact, but each additional CLT within 1,000 feet of the home being sold was associated with a 5% higher sales price in North Minneapolis, and a 3% higher sales price in Central Minneapolis. Further, we find evidence that since 2010, the introduction of CLT properties was associated with an increase of 10.9% in nearby sales prices within 500 feet in North Minneapolis. We detect no price impacts in Central Minneapolis during this time period, which we attribute to a decline in CLT activity in this part of the city. A closer analysis of North Minneapolis suggests that the price increase was driven by properties acquired through the CLT foreclosure program called Project Reclaim (which we discuss below).

The data for this analysis come from several sources. First, the geographic locations and date of sale for all the land trust properties were acquired from the City of Lakes Community Land Trust (CLCLT) in Minneapolis from 2002 through 2017. Second, sales price transaction data for all housing sales in the City of Minneapolis since 2002 were acquired from the Minneapolis Assessor's Office. These transaction data included the sales price as well as the year, date, and location of sale. As is common when working with home sale data, we identified arms-length transactions by removing all one-dollar sales. We also removed all sales with nonresidential uses, and all sales in excess of $1 million. To develop our hedonic regressions we acquired additional data sets from Open Data Minneapolis, including databases of building and parcel characteristics from the Assessor's Office. These city databases were joined to the home sale transaction data using the city's parcel identification number. Neighborhood variables were appended to our data set using spatial join procedures in a Geographic Information System (GIS). We used GIS for our spatial and density analysis, and open-source R software for our regression analysis.

We faced two particular methodological challenges in applying the difference-in-differences approach in this case study. First, CLCLT's portfolio is dominated by single-family properties, many of which are clustered in a handful of neighborhoods, and which enter the portfolio in a staggered way over many years. To address this, the introduction of each CLT property is used as a point of demarcation in the model, with nearby property values compared in the years following the introduction of the property with the years preceding it. Furthermore, we consider the effects of both the introduction of the new CLT property and the density of nearby CLTs at the time of sale on nearby sales prices. A second major hurdle was presented by the wild fluctuations in the housing and real estate markets over the life span of the study. Accordingly, we chose to run separate regressions for two time periods based on the city's sales price trends. The first regression covers the period of price decline during the foreclosure crisis from 2006 to 2010. The second one covers the postcrisis recovery period, when prices were increasing, from 2011–2016.[1]

1. Housing in CLTs

A CLT is a form of land tenure in which an organization (usually formalized as a 501(c)3 not-for-profit corporation) owns the land in perpetuity, but leases out the improvements on the land (housing, businesses, community facilities, agriculture, etc.) to users who agree to abide by the agreements in the lease that limit the property's use and transferability. In practice, it is most often used as a form of affordable housing, which, because of the nonprofit's ownership of the land, allows for the affordability of the housing to exist permanently and the subsidies that enable that affordability to be retained in the land. The permanent affordability of the housing comes not just from retention of the land and the removal of the land from the sales price of the housing, but also from resale restrictions that are part of the ground leases that owners of the improvements sign. These restrictions take the form of formulas that vary from one CLT to another, but all limit the prices that houses can be sold for when it is time for an owner to sell, and share any sales profit between the owner of the improvements and the land trust (the owner of the land).

The first CLT (New Communities, Inc.) was created in 1969 in Albany, Georgia, and a few rural CLTs were created in the 1970s following the New Communities example. In the 1980s the CLT movement came to cities, and the creation of the first urban CLT occurred in Cincinnati, Ohio, in 1980. This movement into urban areas is when CLTs began to be discussed and understood as a way of providing permanently affordable housing. CLTs would thereafter become connected to, and often folded into, the larger field of community development, with its emphasis on affordable housing construction. The last 15–20 years have been a period of significant growth, building upon the developments of the 1980s and 1990s. There are now around 260 CLTs operating in the United States, and they have been developed or are being developed in the United Kingdom, Western Europe, and Australia (see, e.g., Crabtree et al., 2013; Thompson, 2015). The CLT model also shares many features with other models in other contexts, most notably the model of shared ownership through a housing association that is common in the UK.[2] Thus the CLT model has, in many senses, become part of the mainstream affordable housing industry. Although there are still precious few units attached to these CLTs—Thaden (2018) estimates that there are only 12,000 units in CLTs in the United States—the growth in their numbers and their acceptance by the mainstream affordable housing industry suggest that their role in providing housing will grow substantially in the next 10 years.

2. Minneapolis and CLCLT

For this study we use Minneapolis and the CLCLT portfolio of CLT properties. Minneapolis is a city that experienced a very pronounced housing boom and bust and boom again cycle in this century (see Figure 1). Sales prices increased from $160,000 in 2002 to $220,000 in 2006, before plunging to $133,000 in 2009 and racing back up to $216,000 in 2016.

Minneapolis, and the Twin Cities area more generally, also has a reputation for being a progressive metropolitan area, with significant support—both public and philanthropic—for social service providers in general, and housing in particular. This support is part of why the area has become home to a significant number of CLTs. In the leadup to the housing crisis in 2007, the region was also giving birth to a set of CLTs designed to provide affordable housing. In the Twin Cities metropolitan area, there are six different CLTs. The largest of these is CLCLT in Minneapolis.

CLCLT was formed out of a collaboration between some neighborhood and tenant organizing groups and two community development corporations (CDCs). The growing pressures of the real

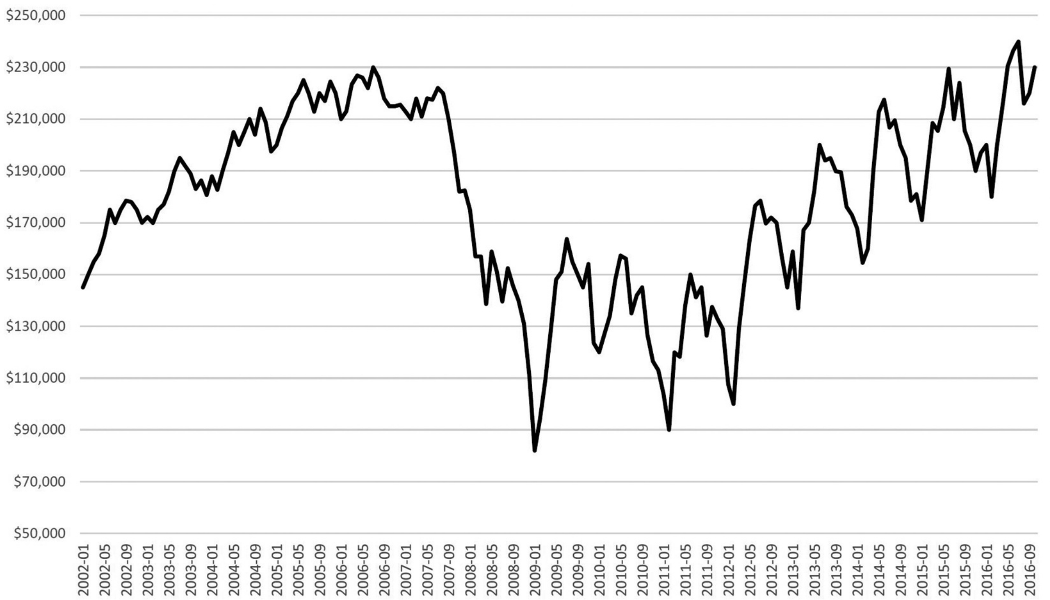

Figure 1. Average sales price in unadjusted dollars from 2002–2016, Minneapolis Assessor's Office.

estate market in south Minneapolis led to the creation of the Minneapolis Community Land Trusts Initiative (MCLTI) in 2001. Through a set of discussions and research, the initiative decided that the CLT created would not focus only on south Minneapolis, but instead be citywide. As we discuss below, many of CLCLT's early properties are in the southern part of central Minneapolis, in the Phillips and Powderhorn community areas.

The first CLCLT property was sold in 2004. Growth in the portfolio was steady for the first few years, before slowing down during the foreclosure crisis, and reaccelerating. As of 2017, there are 261 CLTs in CLCLT's portfolio. Although the CLT has the entire city as its service area, in practice its properties are concentrated in four community areas[3] called Phillips and Powderhorn (Central Minneapolis) and Near North and Camden (North Minneapolis). These two subsections contain 85% of the CLT's properties (see Figure 2). House prices in these areas are significantly lower than those in Minneapolis as a whole, and generally they experienced much greater price declines than did the city overall during the foreclosure crisis. CLCLT's early properties (pre-2007) were primarily in Central Minneapolis, but over time, CLCLT's geographic footprint shifted to focus more in North Minneapolis.

In addition, over the last few years, more CLCLT properties have also been scattered across different sections of the city. CLCLT's Homebuyer Initiated Program (HIP) allows a potential homebuyer to look anywhere within the City of Minneapolis for a home to purchase. If she finds one but cannot afford it, she can approach the CLT, which will provide some subsidy to make up for the affordability gap. She will become the owner of that home, whereas the land underneath it becomes part of the CLT's portfolio. HIP properties tend to be less spatially clustered, and constitute the majority of newer additions to the portfolio. Of the 117 CLT properties added between 2011 and 2016, 72 were homebuyer initiated.

CLCLT also has the Project Reclaim program, a foreclosure mitigation program that plays an important role in our analysis. Reclaim is rooted in a partnership between CLCLT and Urban Homeworks, a faith-based CDC in North Minneapolis. This is a contract-for-deed program with Urban Homeworks acting as the seller and CLCLT providing long-term stewardship of the land and the affordability of the housing. Urban Homeworks acquired and rehabbed the properties using Neighborhood Stabilization Program dollars. The properties became land trust homes at the time of

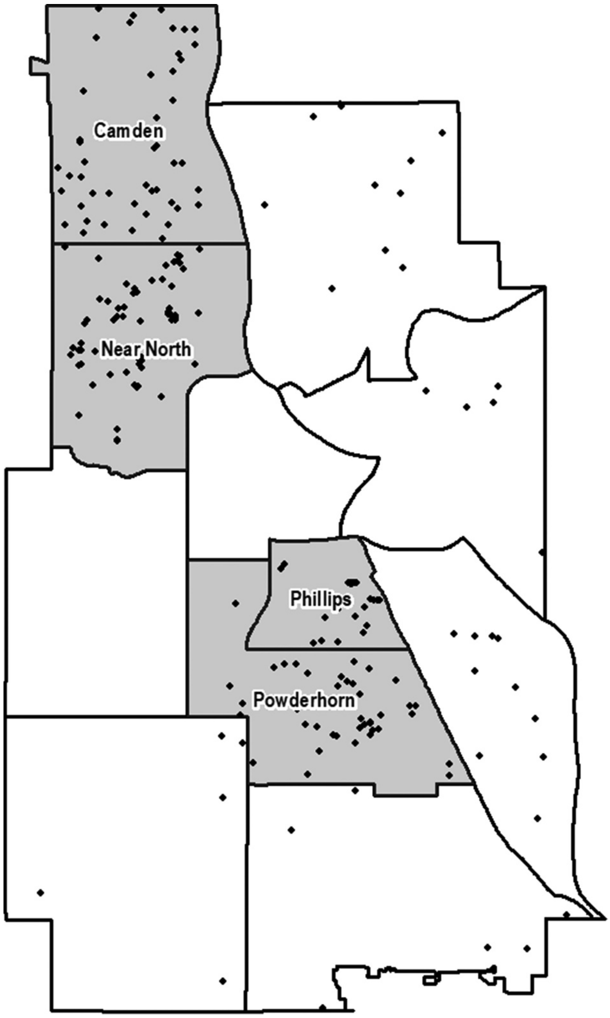

Figure 2. Map of City of Lakes Community Land Trust properties as of 2017.

signing of the contract. The properties have a deed restriction that maintains their affordability and keeps them in the land trust portfolio. When the homeowners refinance into a conventional mortgage, the deed restriction is terminated and the homeowners sign a ground lease with the land trust, like all other homeowners. Project Reclaim properties are concentrated where the foreclosure crisis hit the hardest in North Minneapolis. The program first started at the height of the foreclosure crisis in 2009, and CLCLT added on average five new properties this way each year through 2016. As of 2017, roughly half of CLCLT properties are homebuyer initiated and 18% are Project Reclaim.

3. Methods

This analysis follows a well-established literature that employs hedonic price modeling to isolate the effect of proximity to affordable housing sites on sales prices. This procedure is popular not only in affordable housing but more broadly, in quantifying the impact of various amenities and disamenities on the real estate market such as green spaces, train lines, pollution, or climate change (Bohmana & Nilsson, 2016; Galinato & Tantihkarnchana, 2018; Smith & Chin Huang, 1993; Wüstemann & Kolbe, 2017). Then, a pre/post analysis compared the price level and the price trend in the surrounding neighborhood before and after the new housing project went on the market. This approach is called difference-in-differences or adjusted-interrupted time series (Deng, 2011; Ellen, 2007; Ellen, Scott, Schwartz, & Schill, 2001; Galster, Santiago, Smith, & Tatian, 1999a; Galster, Tatian, & Smith, 1999b; Galster, Tempkin, Walker, & Sawyer, 2004; Koschinsky, 2009; Schwartz, Gould, Voicu, & Schill, 2006).[4] The pre/post analysis uses the date of the CLT sale as the point of demarcation, comparing nearby sales prices before and after the introduction of each CLT.

3.1. Approach

A hedonic regression decomposes home sales price into various component parts to isolate the impact of the factor of interest, in this case the impact of proximity to a CLT. Our model includes structural, neighborhood, and time and space variables, with coefficients representing willingness to pay for different housing attributes. For our hedonic model, the structural variables came primarily from the city's Building Characteristics and Parcel Characteristics databases. These databases were joined to the home sale transaction data using the homes' unique geographic number. We considered all of the potentially relevant variables in those databases and ultimately included the following: year built, building use, building material, zoning, presence of fireplace, assessed building value, and assessed land value. We considered using the size of the building in square feet, but found it correlated almost perfectly with the assessed values and thus chose the ones with greater explanatory power. The neighborhood variables included proximity to light rail, which we calculated with GIS, and a combination variable for unique community area and year of sale.[5] We then added variables for the year of sale and quarter of sale, for the census tract location, and for longitude and latitude.

Then, a difference-in-difference process was used to measure the relationship between CLTs and nearby sales prices before and after the introduction of the CLT, controlling for all the other characteristics described above. Intuitively, the impact of a CLT on nearby prices is the difference between property values in the vicinity of a CLT before and after a new land trust property is added, relative to price changes of comparable homes in comparable places. Difference-in-differences mirrors experimental design by comparing an experimental group (properties within 500 feet of a CLT) with a control group (properties similar to the experimental group except for being farther away from the CLT). We assume the trajectory of the control group would have occurred in the experimental group but for the treatment, in this case the introduction of the CLT. The difference between what we predict using control group trends and what actually occurred in the treatment group is the difference-in-difference estimator and captures the impact of the CLT on sales price.

We define *nearby* to mean any home sale occurring within 500 feet of a CLT.[6] We refer to these areas as subneighborhoods, and all the sales within 500 feet of an existing CLT can be thought of as our experimental group. Of just over 100,000 total home sales over the 2005–2016 time period, 3,930 occurred within 500 feet of a completed CLT. An additional 6,805 occurred within 500 feet of a site that would later be a CLT location. This second group is used to control for site selection bias to allow us to isolate the causal impact of the CLT. The main control group in this study is all home sales in the same neighborhood (census tract) except for those sales that occurred within the subneighborhood.

Most analyses measuring the real estate impact of affordable housing interventions have focused on larger multiunit projects, where distance to nearest development was of primary interest. By contrast, the CLT portfolio analyzed here is almost exclusively a scattered-site single-family model,[7] so the density of CLTs in the vicinity was as important in the analysis as the distance to the nearest CLT. Within our experimental group of 3,930 sales within 500 feet of a CLT, 1,130 sales occurred near more than one CLT, and 810 sales occurred near more than three CLTs. In North Minneapolis, where CLTs were most spatially clustered, it was most common to see multiple CLTs occurring nearby. Here, there were 1,092 sales within 500 feet of a CLT, and roughly half of those (513 sales) occurred near more than one CLT; 203 sales in North Minneapolis had more than three nearby CLTs.

Our model tests for density using the number of CLTs within 1,000 feet of the home at the time of the sale.[8] The coefficient of the density variable can be interpreted as the relationship between nearby sales prices and the addition of each subsequent CLT after the first. In practice, the density term is an interaction effect with the difference-in-difference price level coefficient, which measures the overall effect of a CLT on nearby prices. We also add interaction terms for the CLT's Homebuyer Initiated and Project Reclaim programs. These variables test whether the properties associated with these programs have distinct impacts on nearby prices, and are only included in the 2011–2016 time period because of small sample sizes for the earlier period.

3.2. Model Specification

Our OLS model is given by the following equation:

$$
\begin{aligned}
\mathrm{Ln}(P)_{int} = {} & \alpha + \beta \mathrm{S_i} + \delta \mathrm{T_{it}} + \gamma \mathrm{N_n} + \eta \mathrm{L_{it}} && \text{(control variables)} \\
& + \zeta \mathrm{PreLevel_i} + \rho \mathrm{PreTrend_i} + \lambda \mathrm{PostLevel_{it}} + \nu \mathrm{PostTrend_{it}} && \text{(DID variables)} \\
& + \mathrm{NUMBR} * \lambda \mathrm{PostLevel_{it}} + \mathrm{HIP} * \lambda \mathrm{PostLevel_{it}} + \mathrm{PR} * \lambda \mathrm{PostLevel_{it}} && \text{(interaction effects)} \\
& + \varepsilon_{\mathrm{int}} && \text{(error)}
\end{aligned}
$$

The control variables predict the sales price using structural, neighborhood, and time characteristics. $\mathrm{Ln}(P)_{\mathrm{int}}$ is the log of the sales price for property *i* in neighborhood *n* at time *t*. $\beta \mathrm{S_i}$ is a structural matrix containing property-related characteristics, $\delta \mathrm{T_{it}}$ contains time-related characteristics, $\gamma \mathrm{N_n}$ are neighborhood characteristics, and $\eta \mathrm{L_{it}}$ are space or location characteristics.

Following the literature, the four difference-in-differences variables are *PreLevel, PostLevel, PreTrend*, and *PostTrend*. We have also added, as is common in the literature, three interaction terms using the *PostLevel* variable.

- The *post* variables (*PostLevel* and *PostTrend*) measure the impact of introducing CLTs on nearby property values. PostLevel captures the general impact of the introduction of a CLT on nearby house prices, and PostTrend captures home price change patterns over time since the introduction of the first nearby CLT.
- The *pre* variables (PreLevel and PreTrend) control for site selection.
- A density variable was developed by interacting PostLevel with the count of CLTs within 1,000 feet.
- Two variables capture whether the nearby CLT is part of the HIP or Project Reclaim.

Clear definitions of these coefficients are included in Figure 3.[9] (See Online Appendix 1 for baseline regression results.)

The data used in this analysis (2006–2016) cover some of the largest fluctuations in real estate prices in memory. To reduce temporal dependencies, we run separate regressions for the peak to trough during the crisis, and then for the recovery period. Whereas home sale prices citywide began to recover in 2010, sales prices in North and Central Minneapolis, where the CLTs predominate, rebounded a bit later. Accordingly, we used 2011 as the starting year for the postcrash rebound. We took additional steps to minimize temporal noise, including sale year and sale quarter control variables, and an interaction variable for unique community area and year of sale. As discussed in Schwartz et al. (2006), this interaction term helps account for temporal differences across various market subareas, and including it improved our spatio-temporal dependency diagnostics.

In the last decade, there has been a growing awareness of the need and ability to better correct for spatial autocorrelation and spatial dependence in applied regression modeling. Previous studies on the real estate effects of housing projects generally rely on two strategies to control for spatial heterogeneity: first, a fixed-effects approach that uses census tracts as dummy variables to control

Impact of CLT on Sub-Neighborhood Real Estate Prices

- Price Level (*PostLevel*): A (1/0) dummy variable describing the property value impacts from the introduction of a generic CLT. Equals 1 if the single-family property is located in a CLT sub-neighborhood and its sale occurred after the CLT was introduced. This coefficient measures systematic impacts associated with CLT properties.
- Price Trend (*PostTrend)*: A trend variable that equals the number of years between the sale date and the introduction of the CLT. If the property is not located in a CLT sub-area, or if the sale predates the CLT, it equals 0. This coefficient measures whether CLTs impacts nearby price changes over time.

Systematic Differences of CLT Sub-Neighborhoods (siting differences)

- Price Level (*PreLevel*): A dummy variable (1/0) that describes whether the single-family property being sold is located within 500 feet of a CLT property, regardless of whether the sale preceded the introduction of the CLT. Its coefficient tells us whether the sub-neighborhood has systematically lower or higher price levels than the rest of the Census tract prior to the CLT entering the portfolio.
- Price Trend (*PreTrend*: A trend variable measuring the annual price appreciation in the CLT sub-neighborhood. This variable is the number of years difference between the transaction year and 2004 (the year before our dataset starts). If the home is not located in a CLT sub-neighborhood, the value is 0. The value of this coefficient indicates whether the price appreciation trend in the sub-neighborhood is faster or slower than the rest of the Census tract prior to CLT.

Interaction Terms

- CLT Density Impact: This is the count of CLTs within 1000 feet multiplied by the 1/0 *PostLevel* dummy variable. The value of this coefficient tells us the impact of each additional proximate CLT on prices.
- Homebuyer Initiated: This term measures the real estate effects of Homebuyer Initiated Program (HIP) properties. HIP is a 1/0 binary dummy variable that equals 1 if it is an HIP property, and is multiplied by the *PostLevel* dummy variable. This coefficient tells us the impact of HIP properties on price level.
- Project Reclaim: This term measures the real estate effects of CLTs that are part of foreclosure program, Project: Reclaim. PR is a 1/0 binary dummy variable that equals 1 if it is a PR property, and is multiplied by the *PostLevel* dummy variable. This coefficient tells us the impact of PR properties on price level.

Figure 3. Definitions of coefficients.

for neighborhood differences; second, a spatial trend approach that includes latitude and longitude information as explanatory variables in the regression. The more well-known spatial models, such as the spatial lag or spatial error model, have so far not been incorporated into this literature.[10] In this analysis, we estimate a hedonic price model with a difference-in-differences estimation using both OLS and SEM. The SEM corrects for spatial patterns in the residuals.

After initially running the OLS model, we tested the results to determine whether running a spatial model was necessary. Our general procedure involved three steps: (a) run the OLS regression; (b) run diagnostics on the results to test for spatial autocorrelation and identify an appropriate spatial model if necessary; and (c) run the spatial model as necessary. We found that although the neighborhood dummy variables and spatial trend terms reduced the spatial dependency, spatial autocorrelation remained. Moran's I values were still large and highly significant. Based on the spatial dependence diagnostics (see Online Appendix 2), we decided to run an SEM in lieu of the spatial lag model popular in real estate analysis. We did so because the robust LaGrange multiplier results strongly indicated SEM was a better model to fit these data. We followed this procedure using data for the whole city, and then reproduced it for North Minneapolis and Central Minneapolis. In all three cases, the diagnostics supported running an SEM.

A detailed explanation of the SEM is outside of the scope of this article (see Anselin & Rey, 2014). Briefly, spatial autocorrelation is assumed to lie in the error term of the model, because of unmeasured spatial dependencies in the data. These dependencies are corrected for using a spatial weight matrix that is constructed using values of the dependent variable and its geographic location. In this study, we relied on a nearest neighbor approach to build the weight matrix, and constructed it using the three closest sales that occurred during the previous year. Mathematically, the SEM model in matrix notation is:

$$y = X\beta_0 + u, \;\; u = \lambda W u + \varepsilon$$

where the u error vector is assumed to follow a spatial autoregressive process, $\lambda$is the spatial autoregressive parameter (called lambda in the results section), Wis a spatial weight matrix, and ε is a vector of idiosyncratic errors.

Spatial models require intensive processing time because of the incorporation of weight matrices. To run the spatial models at a citywide level, we drew a random sample of 15,000 from our full universe of home sale transactions. As described above, we acquired a data set with the sales price, location, and date of each home sale transaction in Minneapolis throughout the time period. To run the SEM model, we thinned the data by choosing a random sample from the universe of home sale transactions for each year, retaining the hedonic and experimental variables joined to them from the various other data sources.

4. Descriptive Statistics

4.1. CLT Portfolio and the Foreclosure Crisis

Over the course of the study period, CLCLT shifted its geographic focus to work increasingly in weaker real estate markets in North Minneapolis. As shown in the maps in Figure 4, in the early years most land trust properties were in Central Minneapolis, where average sales prices are slightly below the city average of $200,000. Between 2012 and 2015, they added 16 properties per year in North Minneapolis, where average sales prices are roughly $125,000. The maps below show CLCLTs portfolio growth over time against the median sales price of single-family homes by census tract in 2006, 2010, and 2016. Darker shades on the maps indicate higher sales prices, with the darkest (black) showing median sales prices above $350,000. The land trust properties are clearly concentrated in the lighter shades with lower sales prices, particularly by the 2016 snapshot.

The 2006 map captures a period when prices were rising unsustainably. CLCLT was adding roughly 20 properties per year, almost all of them in Central Minneapolis. The 2010 snapshot captures the period of declining prices when CLCLT was adding fewer new properties each year, roughly 15 annually. North Minneapolis experienced the greatest drop in prices during the recent foreclosure crisis, and the 2016 snapshot shows lots of new CLT activity in North Minneapolis where CLCLT is expanding its footprint. Whereas sales prices in Central Minneapolis have largely recovered since the trough, North Minneapolis sales prices remain below their precrisis levels. The 2016 map also shows many more dots scattered outside of the two main clusters, reflective of increased homebuyer-initiated activity throughout the city.

Minneapolis' foreclosure rate peaked in 2008 with 18 foreclosures per 1,000 housing units; however, the crisis was much worse in North and Central Minneapolis. Foreclosure hit Near North

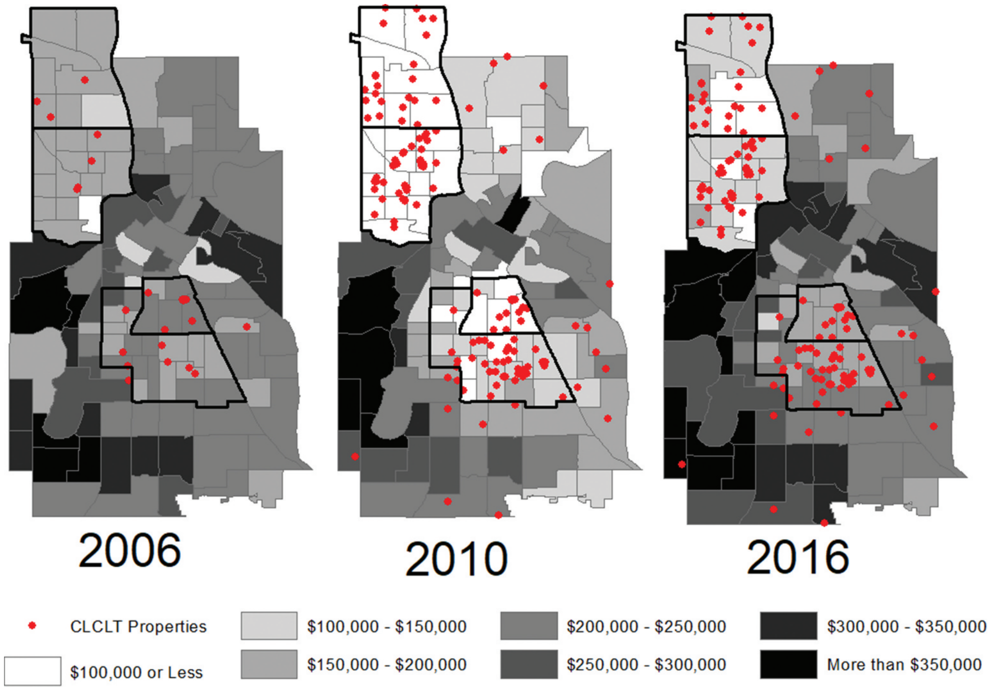

Figure 4. Map of CLCLT portfolio and median sales prices.

Minneapolis the hardest, peaking at 71 foreclosures per 1,000 housing units.[11] Foreclosure, particularly the presence of multiple foreclosures in a neighborhood, can dampen nearby property values. Research indicates these negative spillover effects of concentrated foreclosure are particularly strong in lower income neighborhoods (Bidanset, McCord, & Davis, 2016).

Most of CLCLT's recent units are in North Minneapolis, where the foreclosure problem was most acute. The map in Figure 5 shows the density of foreclosures per square mile as of 2009, along with CLCLT's portfolio of properties. It clearly demonstrates that the CLTs were often sited in places most hard hit by foreclosure. The red dots on the map are Project Reclaim properties, acquired through foreclosure. These cluster strongly in the black areas of the map, where the foreclosure crisis was most severe. The first Project Reclaim property was not added to the portfolio until 2009. CLCLT added five Project Reclaim properties each year since then, and they now make up 18% of the portfolio. As will be described in our results section, the foreclosure crisis appears to be closely tied to the CLT price impacts that we detect. This is true for the earlier time period (2006–2010), when these areas were experiencing widespread foreclosure, and for the postcrisis period, when CLCLT was acquiring foreclosed properties and returning them to productive use as part of Project Reclaim.

4.2. CLT Subneighborhoods and Comparables

The houses in CLCLT's portfolio are not meaningfully different from those around them. The vast majority of CLCLT properties are preexisting homes either bought through the HIP or rehabbed through the Project Reclaim program. Structurally, they do not stand out from other real estate in the area. Much of the remainder of their portfolio is simply regular (for their neighborhoods) homes that the CLCLT worked with contractors to rehab. Therefore, it is very easy to walk down a block with one or two CLCLT homes and not know it, since to all appearances they are like all the other houses on the block.

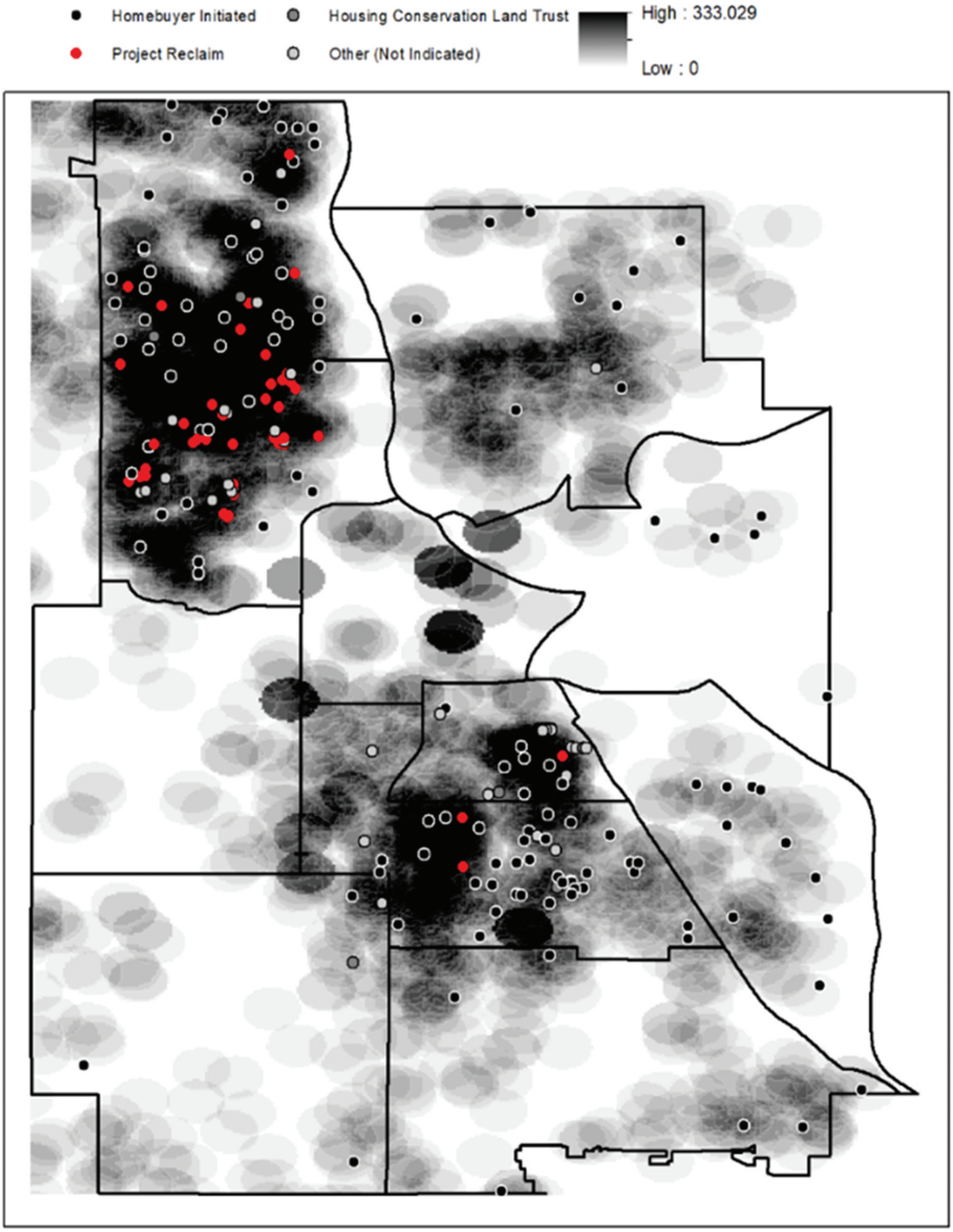

Figure 5. Map of CLCLT properties and density of foreclosure per square mile as of 2009.

Policy and housing literatures commonly treat census tracts as neighborhoods. In this analysis, we focus on the concept of a somewhat smaller subneighborhood, which we take to mean areas within 500 feet of a CLT property. The analysis compares the price levels and price trends in these CLT subneighborhoods with sales of homes that are similar but for their proximity to the CLT. In the chart below, we compare median sales prices of homes sold in CLT 500-foot subneighborhoods with the city as a whole. To create the chart, we take a snapshot of subneighborhoods each year and compare the median home sale price with the median price in the city as a whole. The chart captures annual

Figure 6. Median sales price of experimental subneighborhoods.

snapshots of nearby properties for the portfolio of CLTs at that time. So, since there are more CLTs entering the portfolio over time, the number of subneighborhoods—and of potential nearby sales—increases over time.

The chart in Figure 6 indicates that median sales prices near CLTs were 75–85% as high as those in the city overall from 2004 to 2007. However, by 2010 and continuing to the present, sales prices in CLT subneighborhoods were half those of the city overall. Two interrelated trends are captured here. First, CLCLT began acquiring more properties in lower income North Minneapolis neighborhoods, which reduced the average sales price of a CLT property relative to the city overall. Second, sales prices near existing CLTs declined faster and further than those in the city overall during the housing crisis. Taken together, these trends explain the gap between CLT subneighborhood prices and prices citywide. Since 2010, sales prices in CLT subneighborhoods have been rising, but they are only keeping pace with the city. Prices in CLT subneighborhoods remain roughly half of the city's median sales price.

Table 1 presents some summary descriptive statistics comparing the properties sold in CLT subneighborhoods with the broader database of property sold throughout the city. It is a very rough sketch, covering many years of data, but it provides a snapshot of how these areas compare with the city overall. The share of sales in North Minneapolis is 22%, equivalent in both groups. However, CLT subneighborhoods are heavily represented in Central Minneapolis. CLT subneighborhoods also have a newer housing stock. More have been built since 2000, and fewer properties date to before World War II. Finally, the property-type makeup is somewhat different, with many more condominiums near the CLTs relative to the broader housing stock. This is likely related to the fact that there is more recent construction as well.

5. Results

We ran our analysis first at the citywide level, looking at the 2006–2010 and 2011–2016 time periods separately to account for major fluctuations in sales prices. We then replicated the analysis for the

Table 1. Characteristics of properties sold.

	All property sales (%)	Sales within 500 feet of a community land trust (%)
Community areas		
North Minneapolis	22	22
Central Minneapolis	16	23
Other areas	62	55
Year built		
Average year built	1936	1949
Pre-World War II	65	47
Since 2000	9	16
Property type		
Condominium	18	32
Double bungalow	10	7
Townhouse	1	3
Triplex	1	1
Residential—other	71	57

two time periods in the sections of the city where CLT properties were clustered, in North and Central Minneapolis. Our three main findings are the following.

At the city level, we do not detect any association between CLTs and nearby home sale prices from 2006–2010. The model for 2011–2016 provides some evidence that CLTs lead to higher nearby sales prices using the OLS model. However, these findings are not robust to the spatial error model specification. We interpret this to mean that the sample is too small for such a large and varied real estate market.

In North and Central Minneapolis, from 2006 to 2010, we detect a significant positive effect of CLT density on sales prices. We find that the presence of a single nearby CLT within 500 feet does not affect price levels, but each additional CLT within 1,000 feet is associated with higher prices.[12] We estimate the density effect is a 5% increase in sales price in North Minneapolis for each additional CLT, and a 3% increase in sales price for each additional CLT in Central Minneapolis. We interpret this to mean that CLTs played a role in stabilizing sales prices in these neighborhoods during the foreclosure crisis.

In North Minneapolis only, from 2011 to 2016, we estimate that the presence of CLTs is associated with a 10% increase in sales prices within 500 feet, with most of this driven by the Project Reclaim foreclosure diversion program. During this postcrisis period, it was the presence of a nearby CLT, rather than the density of CLTs in the surrounding area, that was statistically significant. The strong positive association with Project Reclaim properties suggests that the relationship between CLTs and nearby sales prices was still closely linked to the foreclosure crisis. Taken together, our results suggest that CLTs can be effective tools in stabilizing and improving neighborhood housing markets plagued by foreclosure.

5.1. Citywide Results

Table 2 shows the regression results for our OLS model with fixed effects and spatial trend terms for longitude and latitude. All the structural and control variables were consistent with expectations (see Online Appendix 1), and the regressions yielded relatively high R^2 values (0.69 for 2006–2010, 0.71 for 2011–2016).

We find evidence that during the postcrisis period from 2011 to 2016, the introduction of a CLT is associated with a 6% increase in sales prices within 500 feet, with 95% confidence. No pattern is detected in the clustering of CLTs in an area or in longer term price trends over time, nor do we detect any significant relationship between sales price effects and either the HIP or Project Reclaim. During the earlier period from 2006 to 2010, when prices were declining, our results do not indicate any systematic impacts of the introduction of CLTs on sales prices. We suspect this may be due to the smaller total number of CLTs citywide during that time.

Table 2. Citywide results: Ordinary least squares model with fixed effects/spatial trend.

	2006–2010			2011–2016		
Coefficients	Estimate	*p* value	Significance	Estimate	*p* value	Significance
Siting differences—price level	0.01119	.2397		0.00464	.84113	
Siting differences—price trend	−0.04264	8.40E-10	>99.9% confidence	0.06982	.00000	>99.9% confidence
CLT impact—price level	−0.00474	.79127		0.0609	.03908	>95% confidence
CLT impact—price trend	0.00684	.34549		−0.00991	.05496	
CLT density impact	0.002247	.35899		−0.00394	.32424	
Homebuyer Initiated Program	NA	NA		−0.07507	.05825	
Project Reclaim program	NA	NA		−0.04458	.36099	
Diagnostics						
R^2 (adjusted)	0.69			0.7		
Akaike information criterion	19,382			18,449		

Note. CLT = community land trust. NA = not applicable.

The strongest statistical finding from these models is related to siting patterns of CLTs. In the earlier time period, CLTs were sited in areas where prices were falling 4% faster than in otherwise comparable neighborhoods. By contrast, we find that since 2011, CLTs were sited in areas where prices are increasing 7% faster than in otherwise comparable neighborhoods. It is impossible to tell from the data why these siting differences occurred.

Table 3 shows the results for the SEM, which better accounts for spatial autocorrelation in the data. Because the SEM relies on maximum likelihood estimation, it does not report an R^2 value. However, the large and significant lambda and likelihood ratio test diagnostics suggest that this model is an improvement over OLS. Furthermore, the Akaike information criterion (AIC) is smaller, albeit only somewhat smaller: 18,432 compared with 18,851 for 2011–2016.

Theory tells us that the magnitudes of the coefficients should be similar in our SEM and OLS models, and they are. Theory also tells us that results may lose significance as the SEM model corrects for additional error, and they do. The value of the coefficient for the price effect is the same (6.2%), but the significance of the finding disappears. To check for biased coefficients, we ran a spatial Hausman test, which has a null hypothesis that these two models are the same. If the null hypothesis had been true, this would indicate that OLS might be preferable because it is more efficient.[13] However, the *p* value was small and significant at a 99% confidence level. We conclude that there is only weak evidence that CLTs are associated with an increase of roughly 6% in nearby sales prices.

5.2. North Minneapolis

We followed the same pattern of analysis as above for North Minneapolis, running first the OLS, then the spatial dependence diagnostics, and finally the SEM. The spatial dependence diagnostics for OLS

Table 3. Citywide results: Spatial error model.

	2006–2010			2011–2016		
Coefficients	Estimate	*p* value	Significance	Estimate	*p* value	Significance
Siting differences—price level	−0.00769	.63253		0.00784	.73959	
Siting differences—price trend	−0.05442	.00000	>99.9% confidence	0.07288	.00000	>99.9% confidence
CLT impact—price level	0.01582	.63812		0.06156	−.15586	
CLT impact—price trend	−0.00203	.88176		−0.00604	.23650	
CLT density impact	0.00439	.29171		0.00302	.47101	
Homebuyer Initiated Program	NA	NA		−0.00164	.91317	
Project Reclaim program	NA	NA		0.00959	.66968	
Diagnostics						
Lambda	0.192, *p* value: .00000			0.16, *p* value: .00000		
Likelihood ratio test	339.49, *p* value: .00000			241, *p* value: .00000		
Akaike information criterion	18,851			18,432		

Note. CLT = community land trust. NA = not applicable.

(see Online Appendix 2) indicated the presence of spatial autocorrelation, with a Moran's I value of 20 and statistically significant LaGrange multiplier results. As in the citywide regression, robust LaGrange statistical tests suggested the SEM was the appropriate spatial model to use. Our results strongly indicate that SEM shows an improvement over OLS here, with large and significant lambda values and likelihood ratio test results. The AIC goes down from 15,189 to 14,871. The coefficients for the OLS and SEM models were very similar, and since the spatial model provided equally significant coefficient results, we focus our discussion here on the SEM results. Our findings are shown in Table 4. They are stronger and more significant than those for the city as a whole, most likely because of the increased density of CLT properties.

The results for 2006–2010 indicate that although the price effects of the CLT are not statistically significant, the interaction term with the number of nearby CLTs is statistically significant. Specifically, the introduction of each additional CLT after the first, within 1,000 feet of the home being sold, is associated with a 5% increase in the sales price, with 99% confidence. This result suggests that during this difficult time when prices were precipitously declining, a single CLT would exert little impact on price. However, the clustering of more than one CLT was able to help curb declines in nearby home sales price. It is also worth mentioning that the coefficients on the price impact and price trend variables are both nearly significant.

The most interesting findings since 2011 relate to price effects from the introduction of a CLT nearby rather than from density. We estimate that the introduction of a Project Reclaim CLT in North Minneapolis is associated with an 8.6% increase in nearby sales prices, with 99.9% confidence. The overall CLT price effect (associated with CLTs that are not part of the foreclosure mitigation program) is not statistically significant. But there is a small negative density effect. Each additional CLT property within 1,000 feet of a home is associated with a 1.5% decline in sales price. We found the negative density coefficient somewhat surprising given the 2006–2010 findings, and decided not to draw conclusions from it given the small size of the coefficient and the smaller confidence level relative to the other findings.

To disentangle the general effect of introducing CLTs from the foreclosure-related Project Reclaim, we reran the 2011–2016 regression with an alternative specification that removed the program interaction terms. These results are shown in Table 5.

We estimate that during the postcrisis period, the introduction of a CLT is generally associated with a 10% increase in sales prices, with 95% confidence. Combining this with the results from Table 4, we conclude that most of this association is driven by the foreclosure mitigation program. This specification detects no significant density relationship, which supports our decision to deemphasize this result in our conclusions.

As in our citywide results, North Minneapolis reveals strong and significant findings related to the siting of CLT properties. From 2006 to 2010, CLTs were sited in areas with property values declining 20% faster than those in the broader neighborhood in which they sit, with 99.9% confidence. We

Table 4. Results for North Minneapolis, Minnesota: Spatial error model.

	2006–2010			2011–2016		
Coefficients	Estimate	*p* value	Significance	Estimate	*p* value	Significance
Siting differences—price level	0.0352	.0840		0.0099	.7335	
Siting differences—price trend	−0.2026	.00000	>99.9% confidence	0.1578	.0000	>99.9% confidence
CLT impact—price level	0.0880	.0569		0.0866	.0646	
CLT impact—price trend	−0.0378	.0552		−0.005	.4756	
CLT density impact	0.0520	.0019	>99% confidence	−0.0157	.0399	>95% confidence
Homebuyer Initiated Program	NA	NA		0.0084	.7208	
Project Reclaim program	NA	NA		0.0862	.0048	>99.9% confidence
Diagnostics						
Lambda	0.1756, *p* value: .00000			0.226, *p* value: .00000		
Likelihood ratio test	290.49, *p* value: .00000			320.5, *p* value: .00000		
Akaike information criterion	24,479			14,871		

Note. CLT = community land trust. NA = not applicable.

Table 5. Results for North Minneapolis, Minnesota: Spatial error model (program variables removed).

	2006–2010			2011–2016		
Coefficients	Estimate	*p* value	Significance	Estimate	*p* value	Significance
Siting differences—price level	0.0352	.0840		0.01354	.63871	
Siting differences—price trend	−0.2026	.00000	>99.9% confidence	0.15895	.00000	>99.9% confidence
CLT impact—price level	0.0880	.0569		0.10977	.01398	>95% confidence
CLT impact—price trend	−0.0378	.0552		−0.00823	.23598	
CLT density impact	0.0520	.0019	>99% confidence	−0.00922	.20257	
Homebuyer Initiated Program	NA	NA		Not included		
Project Reclaim program	NA	NA		Not included		
Diagnostics						
Lambda	0.1756, *p* value: .00000			0.225, *p* value: .00000		
Likelihood ratio test	290.49, *p* value: .00000			319.35, *p* value: .00000		
Akaike information criterion	24,479			14,874		

Note. CLT = community land trust. NA = not applicable.

suspect the negative spillover effects from the wave of local foreclosures may explain this result. By contrast, from 2011 to 2016, we find with 99.9% confidence that CLTs are located in subneighborhoods where sales prices are increasing a remarkable 15.5% faster than prices in the broader census tract. Our model accounts for the price impact of multiple CLTs near the location of the sale, but it is possible some of this preexisting trend may be attributable to the earlier presence of nearby CLTs.

5.3. Central Minneapolis

As with the other analyses, we first ran OLS, and the subsequent regression diagnostics indicated that an SEM was appropriate (see Online Appendix 2). We therefore focus the discussion on the findings from the SEM for the two time periods, shown in Table 6.

Similar to our results from North Minneapolis, the regression for 2006–2010 shows no general price effects from CLTs, but does pick up a positive association with CLT density. The coefficient is slightly smaller than in North Minneapolis, but still positive and highly significant (> 99.9%). We estimate that during this time of falling prices, proximity to a single CLT had no systematic impact on home prices. However, the clustering of each additional CLT within 1,000 feet was associated with a 3.6% increase in sales price.

Our 2011–2016 regression finds only weak evidence that this density pattern continued into the postcrisis period (*p* value 0.0865). Given the similarity to the finding from 2006–2010, we take this to be an encouraging sign of an ongoing cluster effect. However, the finding is not statistically strong.

Table 6. Results for Central Minneapolis, Minnesota: Spatial error model.

	2006–2010			2011–2016		
Coefficients	Estimate	*p* value	Significance	Estimate	*p* value	Significance
Siting differences—price level	0.06647	.01151	>95% confidence	−0.07451	.26418	
Siting differences—price trend	−0.22648	.00000	>99.9% confidence	0.15754	.00000	>99.9% confidence
CLT impact—price level	−0.0719	.27281		0.08077	.52735	
CLT impact—price trend	−0.0097	.74044		−0.01879	.42986	
CLT density impact	0.03623	.000841	>99% confidence	0.03223	.08650	
Homebuyer Initiated Program	NA	NA		−0.07083	.14571	
Project Reclaim program	NA	NA		−0.04420	.64729	
Diagnostics						
Lambda	0.28394, *p* value: .00000			0.24538, *p* value: .00000		
Likelihood ratio test	447.64, *p* value: .00000			302.38, *p* value: .00000		
Akaike information criterion	11,252			8,620		

Note. CLT = community land trust. NA = not applicable.

Finally, across both time periods we detect very similar siting patterns in Central Minneapolis to those we found in North Minneapolis. In the precrisis period, real estate prices declined 22% faster, and postcrisis prices increased 16% faster, than those in otherwise comparable areas. We can only hypothesize about the cause of this persistent result. During the postcrisis period, the rehabilitation of properties in anticipation of sale may impact nearby prices and confound our results. Alternatively, the clustering effect of existing CLTs in the vicinity may also be impacting price.

6. Summary and Conclusion

Our analysis of Minneapolis suggests that CLTs are generally associated with increases in nearby sales prices, and that the concentration of these affordable properties was associated with market stabilization. However, the precise magnitude and strength of these associations depends on the geography or scale of the analysis, the density of CLT properties in the area, real estate trends occurring over time, and the type of CLT program involved. Citywide, we find a positive association using an OLS model, but the statistical significance disappears with an SEM. We conclude this is only weak evidence citywide of a relationship between the introduction of a CLT and nearby sales prices. The story is different, however, when we focus on particular neighborhoods with significant densities of CLT homes, both during the foreclosure crisis and after the worst of the crisis had passed.

The real estate impacts of CLTs in this case were closely tied to the foreclosure crisis. Between 2006 and 2010, we find a significant positive relationship between CLT density and sales prices. The presence of a single CLT within 500 feet does not seem to affect price levels. However, each subsequent CLT within 1,000 feet increases the sales price, or more accurately lessens the price decline occurring in the vicinity. The density effect in North Minneapolis is a 5% boost in sales price for each subsequent CLT, and the density effect in Central Minneapolis is a 3% boost in sales price for each additional CLT. This is strong evidence that CLTs played a role in stabilizing the city's neighborhoods that were hit hardest by the foreclosure crisis. CLTs very rarely go into foreclosure (Thaden & Rosenberg, 2010), so we propose that the presence of CLT homes in an area operated as a bulwark against the instability and neighborhood disruptions caused by foreclosures. We see CLTs as a mechanism that can be fruitfully used as a countercyclical market stabilizing tool in times of recession or other significant downturns. Our methods did not allow us to identify the causal mechanism for this, but in addition to the stability of the CLT properties themselves, we suspect that multiple CLT sales in a single area served as a signal to markets that neighborhood real estate prices were stabilizing, which kept area prices from declining further.

The importance of the foreclosure crisis in this case continued into the postcrisis period. Post crisis, the introduction of a new CLT property within 500 feet is what impacted sales prices. In fact, we detected a small negative density effect, but it was not robust to different specifications. Our findings show that between 2011 and 2016 in North Minneapolis, the introduction of a CLT is associated with a 10% increase in nearby sales prices, with 95% confidence. This finding was largely driven by the organization's foreclosure mitigation program. When the price effects of Project Reclaim properties are isolated from the rest, the general price effects of CLTs disappear. We can only speculate about the causal mechanisms at work here. We suspect that by addressing blighted properties, the CLT is removing a negative externality depressing nearby prices. We doubt that our analysis is detecting a reduction in available housing supply driving up prices, because there are too few CLTs (261 units) to have that kind of market impact.

Our results suggest there is more to unpack with respect to the influence of CLT density on sales prices. It is clear that clustering CLTs in particular places can have both stabilizing effects in downtimes in the market and market-strengthening effects in periods of growth. The clustering in North Minneapolis was, to no small degree, a result of the specifics of Project Reclaim. Since that program was the result of a collaboration with a neighborhood-focused CDC, its efforts were bound to be place-focused. The HIP, conversely, is an intervention at the scale of a relatively mobile (in the moment of searching for a home) household. It is not place specific, beyond having to be a home within the city of Minneapolis. Neighborhood effects of such a program and such a geography are likely to be smaller, since the program is not neighborhood-focused. It is impossible to predict the transferability of these results to CLTs in other places, but the neighborhood stabilization effects we found strongly support the need for investigation in similar neighborhood markets in other places.

Finally, our results strongly indicate that any concerns of policymakers, neighborhood associations, or individuals about CLTs being a form of affordable housing that hurts nearby property values are simply misplaced. The property value impacts of CLTs on nearby homes that we detected were overwhelmingly positive. And, contrary to what is commonly assumed in the affordable housing policy realm, and the American public sphere more generally, the greater the concentration of these permanently affordable units, the greater the impacts on the property values of nearby homes.

Notes

1. Citywide home sale prices began to rebound by 2010. However, in North and Central Minneapolis, where the CLTs were primarily sited, prices rebounded a bit later. For this reason, we ran the analysis using 2011 rather than 2010 as the start of the recovery period. To test the impact of this decision, we also ran citywide results using 2010 as the cutoff, and results were similar.
2. Whereas the shared ownership model in the UK has many similar programmatic features to the CLT—particularly its making the property affordable by dividing the ownership of the property into pieces owned by different entities—it is also rather different in some ways, as there is not permanent affordability built into that model, nor is there any community engagement (certainly not a legacy of community control) as there is for CLTs. For more on shared ownership in the UK, see Munro (2007) who situates it in the context of UK housing policy more generally or Wallace (2012) who focuses on the ways in it works, or does not work, for the people in the housing.
3. Minneapolis has designated community areas.
4. Koschinsky (2009) and Deng (2011) call this approach the adjusted interrupted time series model with a difference-in-difference estimation, or the AITS-DID modeling approach. The AITS terminology comes from Galster et al. (2004). However, the DID approach has been popular in the economics literature for more than 40 years.
5. We considered several other neighborhood variables, including crime rate and school quality, but none added anything to the explanatory power of the model.
6. The standard in the literature is 500 or 1,000 feet, and given the scattered nature of CLCLTs portfolio, the smaller threshold was more appropriate. We considered both thresholds, and descriptive analysis suggests that they would yield similar results.
7. There was one multifamily project, which was not included in this analysis.
8. We considered several other density specifications, including the distance to the nearest three CLTs; the density of CLTs per square mile (measured using a raster density process that calculated a smooth surface using the number of CLTs within ¼ mile); and the density of CLTs per 1,000 housing units (calculated using the city's parcel file and census data). Ultimately, we decided to stick with the first specification because the results were generally consistent across models and because of the intuitiveness of the coefficients.
9. Variable definitions inspired by Deng (2011).
10. Galster et al. (2004) consider a spatial lag model, but determine that the fixed effects and spatial trend terms effectively control for spatial autocorrelation.
11. Foreclosure data were acquired from Hennepin County and analyzed by the authors.
12. We conducted the density analysis using a 1,000-foot threshold in GIS. This is why the density variable uses this threshold, whereas the difference-in-difference analysis is based on a 500-foot distance to a new CLT.
13. See Pace and LeSage (2008) for a discussion of the spatial Hausman test as it relates to the SEM.

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