The Effect of Community Land Trusts on Neighborhood Outcomes*

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Abstract

This paper studies the effect of community land trusts (CLTs) on neighborhood composition and affordability. CLTs are non-profit organizations that buy and resell houses at subsidized prices with one unique feature: the trust keeps the land deed and leases it to homeowners who sign a long-term agreement to limit the home's resale price, maintaining its affordability indefinitely. CLTs have been rediscovered in recent years as a popular solution to maintaining the stock of affordable housing, in part because they also create pathways from renting to homeownership. An important question is whether a CLT - aside from making the purchased dwelling permanently affordable - generates spillover effects on surrounding house prices through improvements in neighborhood amenities. We create the first national dataset of CLT housing transactions from 2000 to 2016 and combine it with panel data on individual migration histories to estimate the effects of CLT purchases on home prices and displacement in the surrounding neighborhood. We find preliminary evidence that neighborhood housing values do increase within 200 meters of new CLTs purchases, while the probability of a household moving decreases, implying that CLTs help to revitalize declining neighborhoods.

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1 Introduction

Widespread affordable housing shortages and gentrification of historically low-income neighborhoods are a growing concern in US housing policy. Indeed, while the price of shelter relative to other goods has increased by 120 percent between 1970 and 2016 (Albouy, Ehrlich, and Liu 2016), there is considerable heterogeneity in the extent of house price appreciation across places. Coastal cities that experienced a rise in incomes coupled with a restrictive regulatory regime for housing exhibit the largest increase in prices (**glaeser˙economic˙2018**). Regardless of the underlying causes, the increase in housing costs has been linked to the displacement of low-income renters (**qiang˙displacement˙2020**). In principle, aspiring home buyers, as well as low-income home-owners may also be adversely affected. Displacement of lower-income, long-term residents has become a key concern for communities and local governments, spurring a movement to find creative and community-based solutions to tackle these problems and increase the stock of affordable housing (**hwang˙unequal˙2020**).

It is in this context that the long-used model of community land trusts has been rediscovered. Community land trusts (CLTs) are non-profit organizations that buy and resell dwellings at subsidized prices with one unique feature: the trust keeps the land deed and leases it to homeowners who sign a long-term agreement to limit the home's resale price, maintaining its affordability indefinitely. This arrangement seeks to balance between two competing objectives: allowing the present occupant to build wealth through their home, while keeping the resale price affordable for the next buyer.[1]

Whether this is a model worth pursuing in response to the shortage of affordable housing is ultimately an empirical question. Dwellings that enter the CLT model remain permanently affordable, but neighborhood amenities may improve and increase surrounding property prices, ultimately undermining affordability. Therefore, when housing costs are driven by shortages in the supply of dwellings, acquisition of properties by a CLT may result in higher housing costs. This, in turn, may lead to the displacement of lower income residents in the neighborhood. What is the effect of a trust's acquisition of properties on neighborhood property prices and incumbent residents? In what context should CLTs be used to meet the affordable housing challenge?

Why might CLTs have a deleterious effect on the affordability of neighborhood properties? CLTs generally have a negligible effect on the total housing stock, since they seek to acquire

1. Some community land trusts also manage affordable rental housing. This paper only focuses on properties acquired by a CLT for owner-occupancy and those acquired for renting.

existing properties.[2] The properties they acquire, however, are no longer available on the private market, resulting in a reduction in the supply of housing units for sale. When demand for housing is either unchanged or increasing, a reduction in the supply of homes will lead to rising prices for the remaining units. To the extent that properties within the same neighborhoods are substitutes for one another, we would expect acquisitions by a CLT to increase surrounding house prices, making housing less affordable.

Furthermore, CLTs in practice tend to organize members together with their local community to undertake projects that improve neighborhood amenities, such as the construction and maintenance of community gardens. CLTs also increase civic activity in the neighborhoods where they operate cite source, which may increase the community's capacity to effectively petition local authorities for better services and amenities. Finally, properties acquired by a CLT and leased to an owner-occupant are more likely to be maintained, compared to that same property when it is occupied by a renter. All of these reasons would improve the neighborhood amenities where CLTs are active, and, therefore, increase demand for housing in that neighborhood.

4. Motivate why we look at the price effect on average ==¿ it's not obvious. e.g. a vacant is usually very bad for property prices. The "resident mobility" component should be more motivated.

On the other hand, CLTs might in theory exert negative pressure on surrounding house prices through their purchases. Eligibility for occupying CLT homes (either as home-owners or renters) is determined by income. In particular, households usually meet conditions that limit their incomes to around 80% of area median income, with the precise threshold differing by organization. To the extent that residents prefer richer neighbors (cite source), an influx of lower-income residents would make a neighborhood less desirable and, in turn, reduce demand for local residential properties. Should this effect overcome the upward pressure on house prices described above, we would expect prices of properties surrounding a unit acquired by a CLT to decline, relative to similar properties further away.

To study these questions, we create the first comprehensive national data set of CLT real estate transactions between 2000 and 2016 and combine it with panel data on household migration histories. These data allow us to study the effect of property acquisitions by CLTs on the value of surrounding properties, as well as the likelihood that a neighboring household relocates. We also explore the effect of CLTs on home-ownership and income. It is important

2. Some organizations purchase and develop vacant lots, or rehabilitate dilapidated buildings, thereby adding to the local housing supply. However, the vast majority of acquisitions by CLTs are of existing housing units (Check this).

to note that our paper measures affordability using property sales prices and estimated home values, but not rental prices. To the extent that home values are a measure of housing costs that is correlated with rents, the results we find on affordability may extend to the rental market.

Identification challenges and methods: The ideal data set for credibly estimating the effect of CLT acquisitions on neighborhood outcomes would be composed of the following: the location of individual properties randomly acquired by CLTs, outcomes (transaction prices, displacement, tenancy) for properties in their immediate vicinity, and outcomes for properties outside of the known treatment radius. Treatment would then be estimated through a difference-in-differences specification, with the pre and post periods defined by the time of the random CLT acquisition, and the treatment and control groups defined by the treatment radius. While our data include comprehensive outcomes by address and the location of CLT acquisitions, these were not acquired randomly by CLTs. Furthermore, we lack definitive information about the likely treatment radius. These drawbacks constitute the identification challenges we face.

CLTs make deliberate decisions about where to look for properties, exactly which properties to acquire, and when to acquire them. As a result, the sample of CLT properties is by no means random. We overcome this hurdle by exploiting rich geocoded microdata on housing transactions and household characteristics. Our identification strategy relies on the fact that within a given neighborhood where CLTs are active, the exact location of the home that they purchase is credibly exogenous. In particular, CLTs tend to be cash-constrained and the exact property they acquire is determined by the set of properties available for sale at the precise time when organizations can afford to make a purchase. Within a target neighborhood, the set of properties available for sale is likely to be independent of a CLT's purchase timeline.

The second identification challenge requires that we correctly identify how far treatment effects extend beyond a CLT property. Mis-specifying the treatment radius results in biased estimates of the treatment effect (Butts 2021). If the treatment radius is significantly different from 200m, our results may be biased.

Main results: We find that acquisitions by CLTs lead to an increase of roughly $14,000 in the estimated home value of surrounding properties, relative to the control group. Using data on sales prices over the three years after the purchase, we find that acquisitions lead to a 10% increase in the sales price of surrounding properties, relative to the control group. To put these findings in context, the average sales price within CLT micro-neighborhoods over the three years following a CLT purchase is $XXX,XXX, while the mean estimated home value at the time of purchase is $XXX,XXX. Turning to the effect on relocation, we find that CLT acquisition reduces the likelihood of a move from a surrounding home by 1.4 percentage points over a baseline likelihood of XX %. Taken together, these results suggest that CLTs make properties in target neighborhoods more valuable, but that does not precipitate the displacement of residents. One interpretation of these findings is that CLTs arrest the decline and abandonment of neighborhoods where they operate.

Additional results tend to support this conclusion. For example, we find that estimated home-ownership increases by 14 percentage points (over a baseline of XXX), while incomes increase by 2.4 %. These results must not be interpreted as the effect of CLT activity on the home-ownership and income of existing neighbors, since the composition of residents likely changes over the study period.

Related Literature: This paper contributes to several strands of literature. First, it adds to the literature on Community Land Trusts (CLTs). and the majority of the available studies focus on the impacts that CLTs have on their residents[3]. This paper contributes to the literature on the neighborhood effects of CLTs, **which is still pretty limited**. **nelson˙commodity˙2020** focus on the City of Lakes Community Land Trust in Minneapolis and find that its presence in a neighborhood is associated with stably higher housing prices, stabilizing neighborhoods affected by foreclosure. Choi, Zandt, and Matarrita-Cascante n.d. use data from 46 CLTs across the country and demographic data at the census tract to find evidence that CLTs can slow displacement and turnover in gentrifying neighborhoods. Our study leverages extensive micro data to study highly local effects of CLT housing across the United States. Previous studies either focus on a single CLT (**nelson˙commodity˙2020**) or rely on CLTs to voluntarily provide information on the units they own (Choi, Zandt, and Matarrita-Cascante n.d.). We contribute to the literature by bringing in a comprehensive new dataset on public-records CLTs transactions until 2016, paired with transaction and demographic data at the address level: this allows us to study the microneighborhood effects of CLTs instead of having to restrict our attention to those tracts that have enough CLT homes to see an effect.

Second, this paper is part of the literature examining the effects the affordable housing has

3. This literature finds conflicting results on whether CLTs create lasting affordability for the homes in the model (**lauria˙effectiveness˙2007**, **davis˙lands˙2009**, Bourassa 2007)[4], but pretty consistent results on the fact that they do increase wealth-building opportunities for low-income households (**temkin˙balancing˙2010**, **thaden˙stable˙2011**).

on local neighborhoods. With this focus, scholars have previously studied the Low Income Housing Tax Credit (LIHTC) (**eriksen˙crowd˙2010**; **diamond˙who˙2019**; Baum-Snow and Marion 2009), Section 8 vouchers (**davis˙neighborhood˙2021**, **susin˙rent˙2002**), rent control (**diamond˙effects˙2019**; Autor, Palmer, and Pathak 2014, 2017) and inclusionary zoning (**schuetz˙silver˙2011**; **soltas˙price˙2021**, [**singh2020**]). Despite their expanding role in the affordable housing landscape, Community Land Trusts (CLTs) are relatively understudied and we contribute to filling this gap.

More broadly, our paper is related to a literature examining the neighborhood spillover effects of housing policies. **pennington˙does˙2021** exploits the random variation in the location of serious building fires in San Francisco, and finds that new construction of market rate housing reduces rents and displacement pressures while improving neighborhood quality thus benefiting incumbent residents. **hornbeck˙creative˙2017** find that negative spillover effects on property values from outdated buildings dampened renovation incentives in Boston until the Great Fire in 1872 removed wide swaths of outdated housing stock and spurred new construction. **rossihansberg˙housing˙2010** study the impact of urban revitalization programs implemented in the Richmond, Virginia area on local land prices. Campbell, Giglio, and Pathak 2011 examine the effects of housing foreclosure on housing prices nearby. **one key mechanism through which CLTs operate is by increasing incentives to making improvement on the house, wihch has positive spillovers on neighrborhing prices. Interestingly, the probability of moving goes down. frame contribution**

The paper proceeds as follows. Section 2 gives background information on community land trusts. Section 3 describes the data we use. Section 4 presents research design and estimation procedure. Section 5 gives the estimation results for the effect on housing prices and moving probability. Section 6 discusses the policy implications. Section 7 concludes.

2 Community Land Trusts

Community land trusts (CLTs) seek to remove land from the private market by purchasing it and leasing it to qualified residents at below-market rate. They maintain affordability by limiting resale prices through formulae that compensate leaseholders based on inflation, local house prices, and length of tenure. Most CLTs obtain a 501(c)(3) designation from the IRS, though in a few cases, programs similar to CLTs are administered by local governments or public housing authorities. In this paper, we focus on CLTs that have been registered as

501(c)(3) organizations at some point between 1990 and 2016.[5]

The earliest CLTs were formed in primarily rural areas in the 1960s and 70s, with the first arising to provide black households with greater access to land and asset ownership. Urban CLTs emerged in the 1980s as a way to provide permanently affordable housing for low- and medium-income households (see **davis˙community˙2010**). Since the 1990s, the number of CLTs has grown significantly in the United States, driven by the support of local governments and municipalities. A 2006 survey by the Lincoln Land Institute showed that the majority of CLTs serve urban areas, followed by rural or small towns. Though CLTs are diverse and form in response to specific local conditions, the majority share a mission of promoting affordable housing (**sungu-eryilmaz˙national˙2007**).

CLTs are usually governed by a board of CLT-properties residents, community residents and public representatives. They incorporate a variety of governance structures, policies, and practices to ensure community engagement and that community interests are prioritized (**thaden˙resident˙2014**). They can carry out a variety of projects in a community (such as agriculture projects, affordable commercial spaces, green spaces conservation), but the heart of their work is the creation of homes that remain permanently affordable, providing homeownership opportunities for lower income families. While there is a lot of variability in the details of CLTs' activity, we describe the general structure of their program in the following subsection.

2.1 Overview of CLTs' program structure

The most common configuration of the program begins with the Community Land Trust (CLT) purchasing a lot of land with the purpose of retaining ownership forever. Any structure sitting on the lot is then sold to a qualified family or individual who leases the land from the CLT in a long-term (usually 99 years) contract that can be renewed and inherited. The purchase price is therefore more affordable because the homeowner is buying the house but not the land. Homes are usually priced at a cost so that monthly mortgage payments are affordable to households with income below 80% of Area Median Income (AMI). Buyers will still need to be eligible for a mortgage from a third-party lender and a minimal down payment will be required from the home buyer, with the balance subsidized by a no- or low-interest gap loan. This means that the population that CLTs target for their homeownership

5. While we do have some financial information on Community Land Trusts created after 2016, our CLT transaction dataset - and therefore our main analysis - stops in 2016.

programs is low-to moderate income residents.[6]

CLTs usually operate as a shared-equity homeownership program, with homeowners agreeing to re-sell the home at a restricted price to keep it affordable for future buyers. The property could be sold back to the CLT or sold directly by one homeowner to another and the resale price is established by a resale formula that varies across CLTs rather than by the property's market value.

Resale formulas are usually designed to allow homeowners to recover their original down payment and to realize a "reasonable return" on the home-owner's investment.[7] In general, however, resale formulas set an upper limit and there is no guarantee that a homeowner will receive the formula-determined price: for instance if the property's value has plummeted, its condition has deteriorated, or if the formula itself has failed to keep the resale price within financial reach of the targeted, income-eligible population, the actual resale price may be lower.

[**Davis2006**] describes four common approaches to determining the resale price of a CLT home: indexed formulas, itemized formulas, appraisal-based formulas and mortgage-based formulas. Indexed formulas link upward adjustments in the original purchase price of a house to changes in a specified index, such as percentage change in Area Median Income. Itemized formulas adjust the original purchase price by adding or subtracting specific factors that change the value of the home, such as capital improvements or unusual damages made by the owner, inflation, maintenance, repair and depreciation. Appraisal-based formulas, adjust the original purchase price by giving the owner a specified percentage of market appreciation, as measured by appraisals that are done at the time of purchase and at the time of resale. Finally, mortgage-based formulas determine the resale price by calculating the maximum amount of mortgage financing that a home buyer at a targeted level of income can afford at current interest rates. All of these formula types are used by different CLTs, but it is outside the purpose of this paper to distinguish how they affect CLT residents' incentives.

6. According to the definition provided by the department of Housing and Urban Development, *low-income* refers to households earning less than 80% of the Area Median Income (AMI), *very low-income* to households earning between 31% and 50% and *extremely low-income* to households earning less than 30% of the AMI. While private nonprofits can provide affordable housing to low-income households, it is usually hard for them to serve very- and extremely low-income households without the deep subsidies of public housing assistance.

7. As [**Davis2006**] highlights, "What constitutes a return that is "reasonable" or "fair" is a subject of considerable debate among the organizers and supporters of shared equity housing", (page 65).

3 Data

We use three main panel datasets for our analysis: a community land trust (CLT) panel, an address-level panel to study housing prices and one panel at the household level to study residential mobility. We build the panels by combining data from several different sources for the years 2000-2016.

3.1 Community Land Trusts Data

First, we scraped the CLT directory put together by the Schumacher Center for a New Economics to identify which CLTs are active in every state.[8] CLTs are usually 501(c) nonprofit organizations but they do not have a dedicated subsection of the tax code allowing researchers to identify them from the national Tax Exempt Organization databases.

Once we identified the names of the organizations that fall into the CLT definition, we obtained their tax returns from the Nonprofit Explorer provided by ProPublica.[9] The dataset reports each organization's financial details such as their executive compensation, revenues and expenses. This tool allows us to identify additional CLTs that do not appear in our initial list, mainly because they are no longer active.

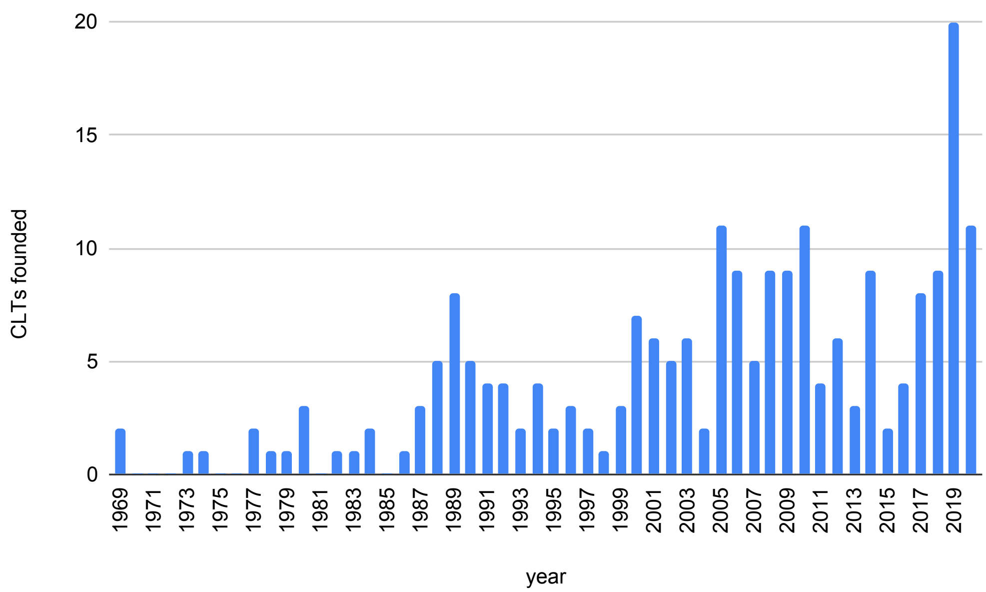


Figure 1: Number of community land trusts over time

8. Source: https://centerforneweconomics.org/apply/community-land-trust-program/directory/
9. Accessible here: https://projects.propublica.org/nonprofits/

We identified a total of 220 CLTs founded between 1969 and 2021.[10] The founding date and location of these organizations are summarized in figures 1, 2 and 3. The establishment of CLTs accelerated in the 1980s, peaking in 1989 before declining over the next decade. The middle of the 2000's saw a rise in activity, a large proportion of which occurred in the aftermath of the housing crisis and recession of 2007-08. However, the year with the most CLTs founded is 2019. While many of these organizations are unlikely to have a large portfolio of properties so soon after their founding, this peak suggests growing interest in the CLT model in the US, as urban areas struggle to maintain a reliable stock of affordable housing. Figure 3 shows that the states with the most CLTs - Washington, Massachusetts, California, and New York - also happen to be those with the largest urban population centers.

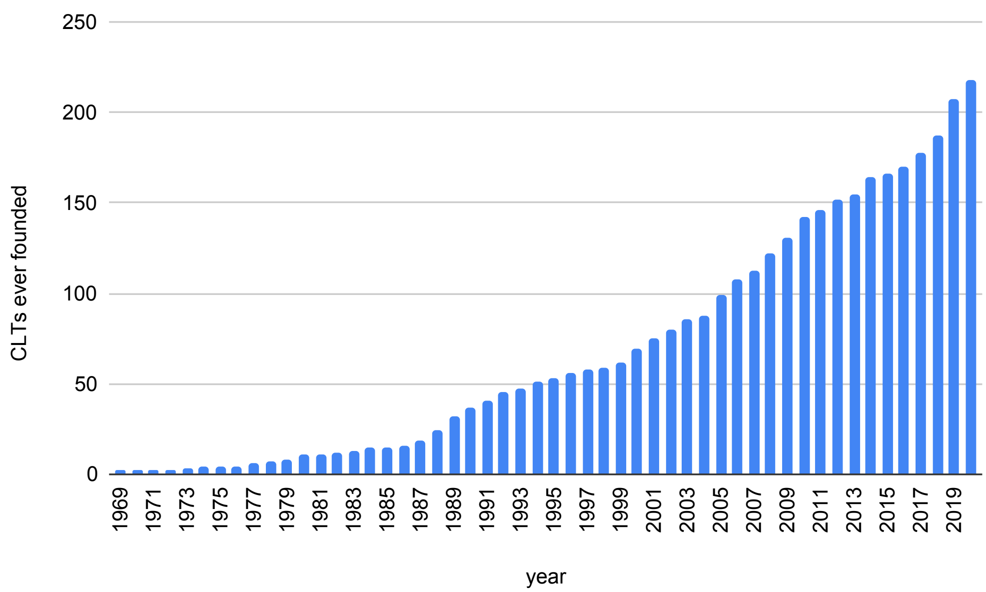


Figure 2: Cumulative number of community land trusts over time

3.2 Address-level Data

The second dataset that we use is provided by CoreLogic and includes detailed public records on housing characteristics and transactions data collected from county assessor and register of deeds officers. We merge this dataset with the CLT dataset, which allows us to identify exactly which homes were purchased by each organization and on what date. We are also able to identify subsequent sales of CLT properties and the price at which they are transacted.

10. **thaden˙state˙2018** estimates that by 2018 there were 225 CLTs (60 of which had no units) with 12,000 home-ownership units.

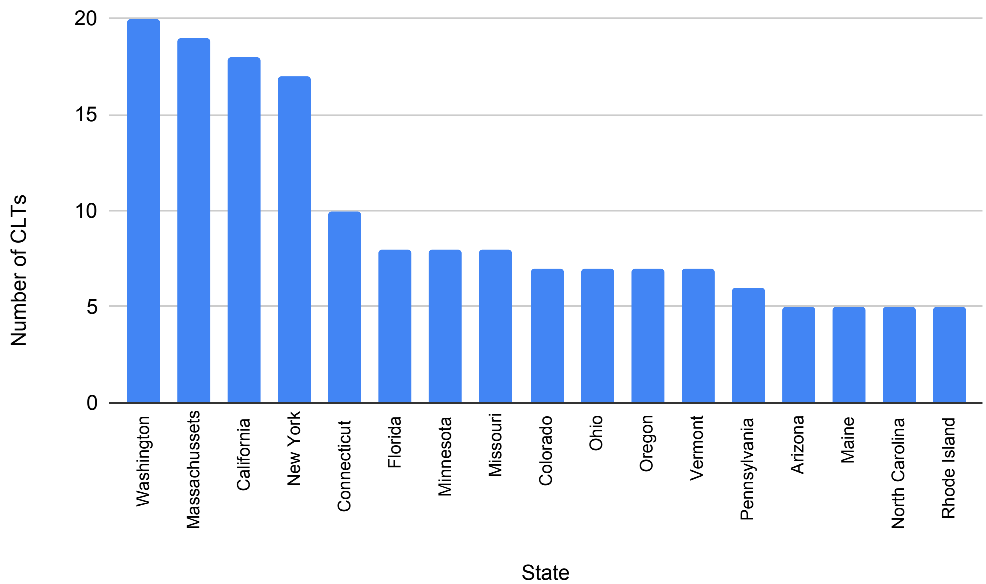


Figure 3: Number of community land trusts by state for those with more than 5 CLTs

The CoreLogic data are at the transaction level and provide us with a transaction's price and date, as well as property characteristics, such as whether the property is a single-family or multifamily home, the year it was built, the property's square footage and number of bedrooms. For each property, we are able to construct its transaction history for the period 2000-2016, including the buyer's and seller's names and transaction type (arm-length versus nominal transfer).

The quality of the data is not uniform across the counties in our sample for two main reasons. First, not all states have the same requirements in terms of what information must be included in public records. Second, coverage doesn't start at the same time in all counties. While there are some transactions in the data as early as the 1990's, it is only after the year 2000 that coverage allows for meaningful inference. For this reason, we focus on transactions that happened between 2000 and 2016. As explained in detail in section 4, we restrict our analysis to properties within 500 meters of a CLT home.

Constructing the analysis file requires identifying addresses in the home sales data that were bought by CLTs. Unfortunately, CoreLogic data do not include identifiers for whether a transaction involves a CLT. Furthermore, idiosyncrasies in each CLT's operating model generate patterns in the home sales data that may be unique.[11] As a result, relevant transactions must be identified by conducting a search for the CLT through the buyers' names.

11. For example, in some cases, a CLT will subsidize the sale price of the home with the subsidy being recorded as a separate transaction. The sale of an address would then generate two records. In other cases, a sale is recorded in a more standard manner as a single record.

CLTs may be recorded as parties in a transaction under a number of different iterations of their official name.[12] This work must proceed one organization at a time, and to date has been completed for the 15 largest CLTs by number of units according to the information in the Schumacher Center for a New Economics's directory.

Table 1 reports information for the transactions that took place between 2000 and 2016 for the CLTs in our current sample. Restricting our analysis to those properties within 500 meters of a CLT home leaves us with a sample of more than 47,000 transactions in a total of 19 counties in 11 states.

Table 1: Community land trusts included in the analysis to date

CLT Name	Location	Transactions	Unique Properties
Champlain	Brington, VT	204	98
Orange	Chapel Hill, NC	39	33
City of Lakes CLT	Minneapolis, MN	117	89
Community Partners for Affordable Housing	Highland Park, IL	11	11
Durham CLT	Durham, NC	48	43
Diamond State CLT	Dover, DE	11	9
First Homes	Rochester, MN	137	87
Guadalupe NDC	Austin, TX	43	27
Homes within Reach	Minnetonka, MN	55	49
Homestead	Seattle, WA	100	72
Newtown	Tempe, AZ	136	82
Oakland CLT	Oakland, CA	18	18
Pima County	Tucson, AZ	64	60
Proud Ground	Portlad, OR	30	23
Rocky Mountain	Colorado Springs, CO	224	148

3.3 Household-level Data

Our third panel is from Data Axle USA (formerly known as Info USA), which provides information on the household residing at a given address in a given year from 2006 to 2019. The data is collected by Data Axle using records from over 100 different sources including real estate and tax assessments, voter registration files, utility connects, bill processors, behavioral data, integrated with "dozens of proprietary enrichment sources [*and*] proprietary ethnic research and thousands of linguistic rules to identify an individual's affiliation with a particular racial or cultural group."[13]

We finally collect information from the 2000 Census as well as multiple American Community Survey (ACS) waves. These data provide information on median income levels,

12. For example, "Durham Community Land Trustees", "Durham Community Land Trust", "Durham Cmnty Land Trust", "Durham CLT", or "DCLT".

13. https://www.dataaxleusa.com/lists/ethnicity-marketing-list/

median home values and minority population shares.

4 Research Design

Our goal is to study the effect of Community Land Trusts' (CLTs) activity on local house price and probability of moving. In order to causally identify such effects, we use a spatial difference-in-differences strategy commonly known as the "ring method". Intuitively, we compare units very close to a CLT home before and after the home was purchased by the CLT to units slightly further away from the CLT home.

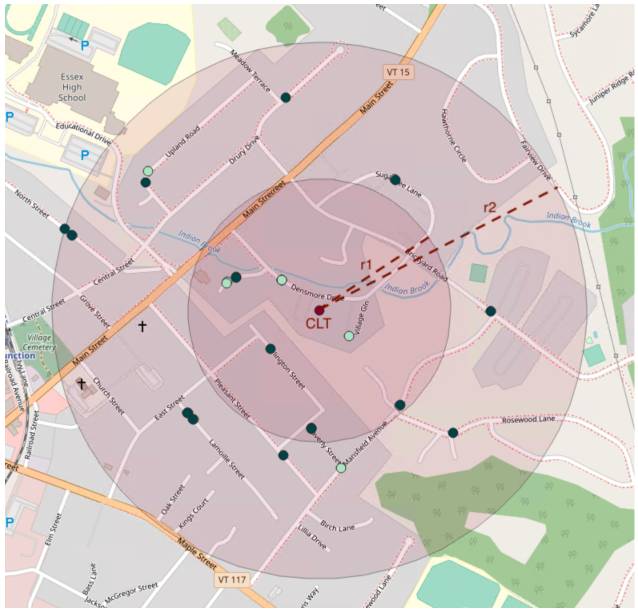
Figure 4 illustrates the intuition behind the method. The center of the figure is marked with a CLT home purchased in year t_0, which represents the treatment. Two rings are then drawn around the treatment location: an inner ring of radius r_1 and an outer ring of radius r_2. Units within the inner circle, are considered treated due to their proximity to the CLT home, while units between the inner and outer circles are considered control units. The remaining units are removed from the sample. Observations across the two groups for periods $t < t_0$ constitute the "pre" period, while those for periods $t \geq t_0$ constitute the "post" period. Throughout the paper we use the term "microneighborhood" to indicate the area included within the larger ring around a CLT home.

4.1 Identification

The main identification challenge is that CLTs do not purchase their homes randomly. Instead, their activity is geographically targeted to specific neighborhoods. We overcome this concern by exploiting the rich geocoded microdata on housing transactions and household characteristics. Our identification strategy relies on the fact that within a given neighborhood where CLTs are active, the exact location of the home that they purchase is exogenous. In particular, CLTs tend to be cash-constrained and the exact purchase location depends on what parcels are available for sale at the time when the organization can afford to make a purchase.

Butts 2021 formalizes the identifying assumptions that are needed for the estimated average treatment effect to be unbiased. The first assumption is the usual parallel trends assumption for the treated and control units: the average change over time in outcomes in the treated ring had it not been treated is equal to the average change in outcomes in the control ring. The high spatial frequency of our data allows us to compare treated and control units that are proximate to one another, have access to the same local amenities

Figure 4: Illustration of the ring method using a microneighborhood in XXX, Vermont



The red dot represents a home purchased by the Champlain CLT in year XXX. Homes located in the smaller ring of radius r_1 constitute the treatment group, while those located in the larger ring of radius r_2 are the control group. The light blue dots represent homes that were transacted in the 356 days before the CLT purchased the home, while the dark green dots represent homes transacted in the 365 days after.

and therefore are likely on the same house prices and household mobility trends. **FIGURE ADD EVENT STUDY** also provide some reassurance that this condition is verified.

The second assumption requires that we correctly identify the radius of the inner ring, i.e. how far treatment effects are experienced. As highlighted by Butts 2021, when this assumption is not satisfied, the estimates of the treatment effect are biased.

4.2 Estimation

We estimate the following model for observation i in micro-neighborhood c and time period t:

$$Y_{i,c,t} = \beta_1 In - ring_{i,c} + \beta_2 Post_{i,t} + \beta_3 (In - ring_{i,c} \times Post_{i,t}) + \gamma_c + \tau_{YM} + \epsilon_{i,c,t} \tag{1}$$

$Y_{i,c,t}$ is the outcome of interest, $In - ring_{i,c}$ is a dummy variable equal to 1 if unit i is within 250m of a CLT home and Post$_{i,t}$ is a dummy variable equal to 1 for periods after the CLT purchases a house in the microneighborhood. We also include a vector of micro-neighborhood fixed effects, γ_c, and a vector of year-month fixed effects τ_{YM}. Like in a standard difference-in-differences specification, β_3 is the coefficient of interest and, under the assumptions articulated in the previous sections, captures the average treatment effect of proximity to a CLT home.

This method is well-established in the literature, although it has some shortcomings. We are currently working on addressing them

5 Results

This section presents the main results from investigating how community land trusts' (CLTs) new purchases affect the surrounding residents and their property values. Section 5.1 summarizes our results or the effect of CLTs on property values, while 5.2 investigates the effects on surrounding residents' mobility.

5.1 House prices

Table 2 presents results from estimating Equation (1), the specification discussed in the previous section. The outcome variable is the logarithm of the public-records transaction price reported from the CoreLogic dataset. Columns (1) through (3) progressively add microneighborhood and year-month fixed effects. Throughout the specifications, we cluster standard errors by address.

The in-ring coefficient is negative, as expected, indicating that CLTs target the neighborhood's lowest-valued areas. The estimate in Column 3 implies that, on average, properties within 250 meters from a CLTs property sell for 13.6% less than properties located slightly further away, between 250 and 500 meters.

The main coefficient of interest is the interaction of the in-ring and post variables. The positive sign means that a CLT's home purchasing activity increases property prices in the immediate surroundings. The coefficient in Column 3 indicates that this effect is a sizable 10.14%.

A key concern using the CoreLogic transaction-level dataset is that the composition of houses that sell at a specific time and place may be selected along dimensions we cannot control for. In this case the estimate for the effect of CLT activity on housing prices would be biased. To ease this concern we could use address fixed effects, but this would lead us to throw out a large amount of data since not many of the houses in our sample sell twice within the relatively short period that we consider. Moreover, the houses that do sell twice

Table 2: Effect of CLT acquisitions on sales prices (% change)

Dependent Variable:	log(Transaction Price)		
Model:	(1)	(2)	(3)
Variables			
In-ring	-0.1367***	-0.1457***	-0.1359***
	(0.0304)	(0.0206)	(0.0191)
Post	-0.0263	-0.0632***	-0.0692***
	(0.0340)	(0.0236)	(0.0193)
In-ring × Post	0.0592	0.1282***	0.1014***
	(0.0396)	(0.0283)	(0.0249)
Fixed-effects			
Microneighborhood		Yes	Yes
Year-Month			Yes
Fit statistics			
Observations	47,202	47,202	47,202
R^2	0.00238	0.28584	0.30979

Clustered (address) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

in a short time frame could themselves be systematically different from those that don't. Instead, we use the Data Axle USA dataset to run a robustness check.

Table 3 reports results from estimating Equation (1) using the estimated home value variable from Data Axle USA. The signs and magnitudes of the coefficients are reassuringly consistent with the results we found in Table 2. The main advantage of this exercise is that we have a balanced panel: all addresses are observed every year, independently of whether they are transacted of not. This minimizes our concerns about the different composition of houses that sell in a given time frame. However, the main shortcoming is that the dependent variable is an estimate provided by the company, rather than the true market value. Moreover, our time-of-sale fixed effects are less precise because we only observe the year in which the observation was collected instead of the exact date.

Overall, we believe that Table 2 and Table 3 together provide strong support for the fact that CLTs' home purchasing activity leads to sizeable increases in the immediate surroundings in the period following the purchase.

5.2 Resident Mobility

Our second set of results focuses on the effect of CLTs home purchases on the mobility of residents living in the surrounding properties. Table 4 presents results of a linear probability model estimated using Equation (1). The outcome variable is a binary variable equal to one

Table 3: Effect of CLT acquisitions on estimated home values ($)

Dependent Variable:	Estimated Home Value		
Model:	(1)	(2)	(3)
Variables			
In-ring	5,581.0**	-10,121.4***	-11,916.7***
	(2,420.8)	(2,028.7)	(2,039.9)
Post	-13,178.7***	-9,915.9***	-1,088.6
	(1,442.9)	(1,528.7)	(1,288.3)
In-ring × Post	16,839.5***	10,539.4***	14,282.8***
	(1,684.7)	(1,650.7)	(1,686.1)
Fixed-effects			
Microneighborhood		Yes	Yes
Year			Yes
Fit statistics			
Observations	192,552	192,552	192,552
R^2	0.00237	0.45845	0.46429

Clustered (address_id_unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

if the household has moved from the previous year. Column (1) through (3) progressively add year and microneighborhood fixed effects. Throughout the specifications, we cluster standard errors by address and we control for the length of residence of a household at its current address.

The coefficient on length of residence is unsurprisingly negative, suggesting that the longer a household has been living in its current location, the more likely it is to be found in the same location the following year. To be precise, for each year that the household has been living at its current address, the probability of moving decreases by almost 1 percentage point.

As in the previous section, the main coefficient of interest is the interaction of the in-ring and post variables. The negative sign means that a CLT's home purchasing activity decreases the probability of moving for households living in the immediate surroundings. The coefficient in Column 3 indicates a decrease by 1.4 percentage points in the probability of moving for households located within 250 meters of a newly purchased CLT home compared to households located slightly further away.

CLTs seem to have a positive impact in the likelihood of a neighborhood to retain current residents. To assess possible mechanisms, we look at whether we observe any change in homeownership rates in the area. Table 5 this channel using the probability that a household owns the house in which it resides provided by Data Axle USA. The variable takes

Table 4: Effect of CLT acquisition on likelihood of moving

Dependent Variable:	Moved		
Model:	(1)	(2)	(3)
Variables			
In-ring	-0.0017	-0.0028	-0.0008
	(0.0036)	(0.0035)	(0.0037)
Post	0.0065*	-0.0022	-0.0272***
	(0.0035)	(0.0035)	(0.0044)
In-ring × Post	-0.0036	-0.0072*	-0.0140***
	(0.0041)	(0.0041)	(0.0046)
Length of Residence	-0.0098***	-0.0097***	-0.0090***
	(0.0001)	(0.0001)	(0.0001)
Fixed-effects			
Year		Yes	Yes
Microneighborhood			Yes
Fit statistics			
Observations	164,385	164,385	164,385
R^2	0.13348	0.13923	0.16491

Clustered (address_id_unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

values between 1 (confirmed renter) and 9 (confirmed homeowner), with intermediate values different levels of certainty about the household's tenure[14].

Unsurprisingly, households that have lived at the same address for longer are more likely to be homeowner. The coefficient of interest, the interaction between in-ring and post, suggests that CLT activity increases the likelihood that households own the home they are living in. This effect seems consistent with CLTs making a neighborhood more desirable for people to live in long-term and therefore buying a house, but it also indicates that further analysis on whether renters can benefit from such increase in desirability is a necessary next step.

6 Conclusion

Community land trusts seek to remove residential properties from the private market in order to maintain a permanent stock of affordable housing for low-income households. Eligible members lease these properties as the trust continues to own the land. The governance structure of CLTs ensures that relevant stakeholders, including the surrounding community

14. We are currently in the process of obtaining a more precise measurement by comparing the household's names in Data Axle USA to the administrative transaction records in CoreLogic.

Table 5: Effect of CLT acquisition on composition of home-owners

Dependent Variable:	Ownership Likelihood		
Model:	(1)	(2)	(3)
Variables			
In-ring	0.4369***	0.2002***	0.1659***
	(0.0365)	(0.0311)	(0.0312)
Post	-0.1913***	-0.0226	0.1145***
	(0.0227)	(0.0186)	(0.0184)
In-ring × Post	0.1965***	0.0996***	0.1391***
	(0.0277)	(0.0220)	(0.0226)
Length of Residence	0.1284***	0.0841***	0.0840***
	(0.0011)	(0.0011)	(0.0011)
Fixed-effects			
Microneighborhood		Yes	Yes
Year			Yes
Fit statistics			
Observations	192,552	192,552	192,552
R^2	0.29427	0.53927	0.54027

Clustered (address_id_unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

and local government, participate in the trust's decision-making.

Despite widespread concerns about the provision and maintenance of affordable housing in urban areas across the US, the CLT model has only been sparingly used. It is estimated that only around 226 CLTs were founded since the 1960s, and they control roughly 12,000 residential units. Should the community land trust be more widely adopted as a tool to address the affordable housing challenge? One key consideration that must be taken into account to answer this question is the spillover effect of CLT activity. While properties managed by the trusts remain perpetually affordable, their impact on neighboring properties is less clear. Indeed, CLTs tend to improve neighborhood amenities, which may serve as upward pressure on house prices. Furthermore, the fact that CLTs remove housing units from the market may exacerbate housing supply shortages (**glaeser˙economic˙2018**). On the other hand, residents of CLT properties typically earn lower incomes than the area median. To the extent that house prices are affected by the socioeconomic composition of residents, prices of surrounding homes may decline in response to CLT activity.

This paper estimates the effect of CLT activity on neighborhood outcomes. More specifically, we study the impact of CLT purchases on sales prices and displacement in the micro-neighborhood surrounding an address. The method we employ effectively compares the outcomes of homes within 200m of a CLT property, to those of homes between 200m and

400m of the same property. The proximity of the treatment group to the control group allows us to credibly assign changes in sales prices and displacement to CLT activity, since all properties in the micro-neighborhood are subject to the same local trends.

We find that CLT acquisition of a property leads to an increase of XXXX % in the sales price of surrounding properties over the following year, relative to the control group. At the same time, acquisition reduces the likelihood of a move from surrounding addresses by XXX %.

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A Appendix

A.1 Tables

Table 6: Effect of CLT acquisition on incomes (% change)

Dependent Variable:	I(log(income))		
Model:	(1)	(2)	(3)
Variables			
In-ring	0.1557***	0.0003	9.25×10^{-6}
	(0.0137)	(0.0096)	(0.0096)
Post	-0.0305***	0.0182***	0.0135*
	(0.0094)	(0.0071)	(0.0069)
In-ring × Post	0.0772***	0.0192**	0.0240***
	(0.0111)	(0.0084)	(0.0085)
Length of Residence	0.0228***	0.0081***	0.0080***
	(0.0005)	(0.0003)	(0.0003)
Fixed-effects			
Microneighborhood		Yes	Yes
Year			Yes
Fit statistics			
Observations	192,552	192,552	192,552
R^2	0.09836	0.53331	0.53622

Clustered (address_id_unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.2 Figures