The Effects 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 a unique feature: the trust retains ownership of the land and leases it to homeowners with long-term agreements to limit resale price and maintain affordability. CLTs have gained renewed attention as a possible solution to the shrinking 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 changes in neighborhood amenities. We create a novel 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 evidence that neighborhood housing values decrease in the vicinity of CLT properties and so does the probability of a household moving out of the neighborhood, especially for Black and Hispanic households. These results suggest that CLTs help current resident traditionally at higher risk of displacement to remain in their neighborhood.

Keywords: Affordable housing, Community land trust (CLT), Neighborhood change, House price, Displacement

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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 et al., 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 and Gyourko, 2018). Regardless of the underlying causes, the increase in housing costs has been linked to the displacement of low-income renters (Qiang et al., 2020). Aspiring home buyers and 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 and Ding, 2020).

It is in this context that the long-used model of Community Land Trusts (CLTs) has been rediscovered. 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.

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. However, CLTs may have an impact on surrounding housing prices as well. The cost of neighborhood housing may increase if CLT purchases restrict housing supply by occupying properties or improve neighborhood amenities. Alternatively, housing prices could go down if the influx of lower-income residents reduce demand for the neighborhoods in which CLTs are working, a well-documented pattern in the affordable housing literature. If price effects are positive, this may lead to the displacement of lower-income residents in the neighborhood. In this paper we ask the following: what is the effect of a CLT's acquisition of properties on neighborhood property prices and incumbent residents' likelihood to move? In what context should CLTs be used to meet the affordable housing challenge?

CLTs generally have a negligible effect on the total housing stock, since they seek to acquire existing properties.[1] 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. While CLTs don't usually own enough units to make a difference at the city level, their property tend to be clustered in specific neighborhoods, so that this effect could be sizeable at the local level. Moreover, most CLTs organize members together with their local community to undertake projects that improve neighborhood amenities, such as the construction and maintenance of community gardens and they create incentives for homeowners to make visible improvements to their home and. Properties acquired by a CLT and leased to an owner-occupant are more likely to be maintained, either by the occupant or the CLT itself. All of these reasons would improve the neighborhood quality where CLTs are active, and, therefore, increase demand for housing in that neighborhood.

On the other hand, CLTs might 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. Households usually meet conditions that limit their incomes to around 80% of area median income, with the precise threshold differing by organization. If affordable housing developments are viewed as a disamenity, as Diamond and McQuade, 2019 find to be the case for higher-income households in higher-income areas, 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 farther away.

CLT activity may affect other neighborhood outcomes related to affordability, in addition to house prices. Many municipalities in the United States are experiencing the effects of gentrification and the displacement of low income residents as long-neglected neighborhoods undergo revitalization through an influx of businesses and new residents. If CLT activity contributes to slowing displacement, we would expect to see an decrease in the likelihood that residents in the surrounding neighborhood move elsewhere.

To study the local price and demographic effects of CLTs, we create a novel data set of CLT real estate transactions between 2000 and 2016 and combine it with panel data on household migration histories. This paper focuses on the top 10% of CLTs by properties owned in the United States.

[1] Some organizations purchase and develop vacant lots, or rehabilitate dilapidated buildings, thereby adding to the local housing supply. This occurrence is not very common in our data and we do not account for this activity explicitly in the analysis. The purchase of a vacant lot is therefore treated in the same way as the purchase of an existing unit.

These datasets allow us to overcome some of the limitations faced by previous literature on the topic and study the effect of property acquisitions by CLTs on surrounding property values and resident mobility. We also explore the effect of CLTs on homeownership and demographic composition. It is important to note that our paper measures affordability using property sale 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.

We identify the effects of CLTs on surrounding housing prices and residents' mobility by exploiting the fact that 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, so that the exact geographic location of the home that they purchase is credibly exogenous. We therefore use a spatial difference-in-differences estimator, to evaluates the effects of a CLT acquisition on immediately surrounding homes relative to the homes slightly farther away within the target neighborhood. While our research design provides a step forward with respect to previous analyses, we still find some evidence that there may still be within-neighborhood sorting of CLTs into specific properties, and we discuss our identification strategy and the challenges we face in more detail in section 4.

Our results on the impact of CLTs on home sale prices suggest that the effects depend on the intensity of CLT activity in the neighborhood. Initially, a CLT purchase is associated with a decrease in surrounding transaction prices (-2.5% for homes within 300m of the CLT home and -3.65% for homes between 300m and 600m), but this effect is mitigated and even reversed as CLT activity increases. We also find that the magnitude of the effect of CLTs on estimated home values provided by Data Axle USA is generally lower than the effect on sale price, but the same patterns hold. This could be a result of the fact that once the CLT starts its activity and neighbors become more familiar with the model, it becomes more desirable to live near the nonprofit's property. We also find that the effect of CLTs on prices varies depending on the housing market. CLTs in high cost markets may have as their main mission to preserve housing affordability, and therefore, the negative effects on sale prices are larger in these markets. However, in markets that are not facing high housing costs, CLTs have a more positive effect on the sale prices of houses around them, consistent with the idea that their focus in those areas may be to neighborhood revitalization.

We also find that CLT activity reduces the moving probability of households in the surroundings (-0.85 percentage points for residents within 300m and -1.17 percentage points for residents between 300m and 600m, compared to residents living between 600m and 1000m from a CLT property). However, we find that CLT activity is associated with a decrease in the likelihood that households own the home they are living in. This suggests that the increased likelihood of a neighborhood to retain current residents is accompanied by an influx of renters in the areas around CLTs, likely due to increased affordability.

The paper also explores the effects of CLTs on the demographic composition of a neighborhood. Our results showed an increase in the probability that the head of a household near a CLT property is Black or Hispanic, especially outside the areas that are experiencing high housing costs. These effects are also increasing in the intensity of CLT activity in the area. We find opposite effects on the probability that the head of the household is White, with an increase in the immediate surroundings of a CLT property in high-cost markets and a decrease in other markets. The probability that the head of a household is Asian differs across market types are also mostly positive, although with lower magnitudes in areas with higher home prices.

Overall our results suggest that CLTs may yield higher neighborhood affordability and ability to retain current residents, although this does not translate in an increase in the local homeownership rates. The composition of the neighborhood seem to suggest slight increases in racial and ethnic groups traditionally more affected by displacement, providing some encouragement in the role that CLTs can play to prevent it. However, our results also provide suggestive evidence that, while CLTs may help maintain affordability and prevent displacement in more affordable areas, they may not be able to achieve the same results in higher-cost areas.

Related Literature: This paper contributes to several strands of literature. First, it adds to the literature on Community Land Trusts (CLTs). Despite the increasing attention that the model has received in the public debate, evaluations of CLTs are still limited and the majority of the available studies focus on the impacts that CLTs have on the residents of their properties.[2]. Less attention has been paid to the effects that CLTs have on the neighborhoods in which they are active, which is the focus of this paper. Two notable exceptions are Nelson et al., 2020 and Choi et al., 2018. Nelson et al., 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, particularly

[2]This literature is largely consistent in finding that CLTs do increase wealth-building opportunities for low-income households (Temkin et al., 2010, Thaden, 2011), while results are less consistent regarding whether they create lasting affordability for the homes in the model (Lauria and Comstock, 2007, J. E. Davis and Stokes, 2009) Bourassa, 2007 highlights how the ability to create lasting affordability depends on conditions such as prevailing interest rates, housing price appreciation and CLT-specific characteristics.

in neighborhoods affected by foreclosure. Choi et al., 2018, using data from 46 CLTs across the United States and demographic data at the Census tract level, find evidence that CLTs can slow displacement and turnover in gentrifying neighborhoods. These studies either focus on a single CLT (Nelson et al., 2020) or rely on CLTs to voluntarily provide information on the units they own (Choi et al., 2018). We contribute to the literature by bringing in a new public-records dataset on the housing transactions of the top 10% of CLTs across the United States by properties owned, paired with mobility and demographic data at the address level. Our dataset allows us to study the microneighborhood effects of CLTs instead of having to restrict our attention to Census tracts that have enough CLT homes to detect effects at such an aggregate level.

Second, this paper contributes to the literature examining the effects of affordable housing on the property values of surrounding homes. With this focus, scholars have previously studied the Low Income Housing Tax Credit (LIHTC) (Baum-Snow and Marion, 2009; Deng, 2011; Diamond and McQuade, 2019; Eriksen and Rosenthal, 2010), Section 8 vouchers (M. A. Davis et al., 2021, Susin, 2002), rent control (Autor et al., 2014, 2017), inclusionary zoning (Schuetz et al., 2011; Soltas, 2021, Singh, 2020) and the relaxation of existing zoning regulation (Kulka et al., 2022). These studies have arrived at different conclusions, suggesting that ultimately the answer depends on the attributes of the affordable housing and the features of the surrounding neighborhoods. Despite their expanding role in the affordable housing landscape, Community Land Trusts (CLTs) are relatively understudied and we contribute to filling this gap.

Finally, our paper contributes to the literature on housing affordability and displacement. Multiple studies show that building market-rate housing eases the middle and low-income housing market, lowering rents and preventing displacement (Mast, 2021; Pennington, 2021). Diamond et al., 2019 find that rent control in San Francisco limited the displacement of minorities in the short run, but prompted a shift towards higher-income housing, resulting in higher rents and gentrification. We contribute to this literature by showing that CLTs, which slow down sale price increases especially in high-cost markets have positive spillovers on current residents' willingness and ability to remain in their neighborhood. We find that the effect is particularly pronounced for Black and Hispanic households, traditionally considered more at risk of being displaced.

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, moving probability and demographic composition of the neighborhood. 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.[3]

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 J. E. Davis, 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 Institute of Land Policy 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 and Greenstein, 2007).

CLTs are usually governed by a board of residents of CLT properties, 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 and Lowe, 2014). Their work primarily focuses on creating permanently affordable homes, offering homeownership opportunities to low-income families, although they may also undertake other community projects like urban agriculture, commercial spaces and green space preservation. 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 permanently. Any structure sitting on the lot is then sold to a qualified family or individual who leases the land from the CLT in a

[3]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.

long-term (usually 99 years) contract that can be renewed and inherited.[4] 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 programs is low-to moderate income residents.[5]

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 with the resale price determined 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.[6] 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.

J. E. Davis, 2006 describes four common approaches to determining the resale price of a CLT home: indexed formulas, itemized formulas, appraisal-based formulas and mortgage-based formulas[7]. 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

[4]Some community land trusts also manage affordable rental housing. In this paper, we do not distinguish between properties acquired by a CLT for owner-occupancy and those acquired for renting.

[5]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.

[6]As J. E. Davis, 2006 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).

[7]See J. E. Davis, 2006 (pages 65-69) for detailed descriptions of each resale formula.

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.

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)(3) 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.

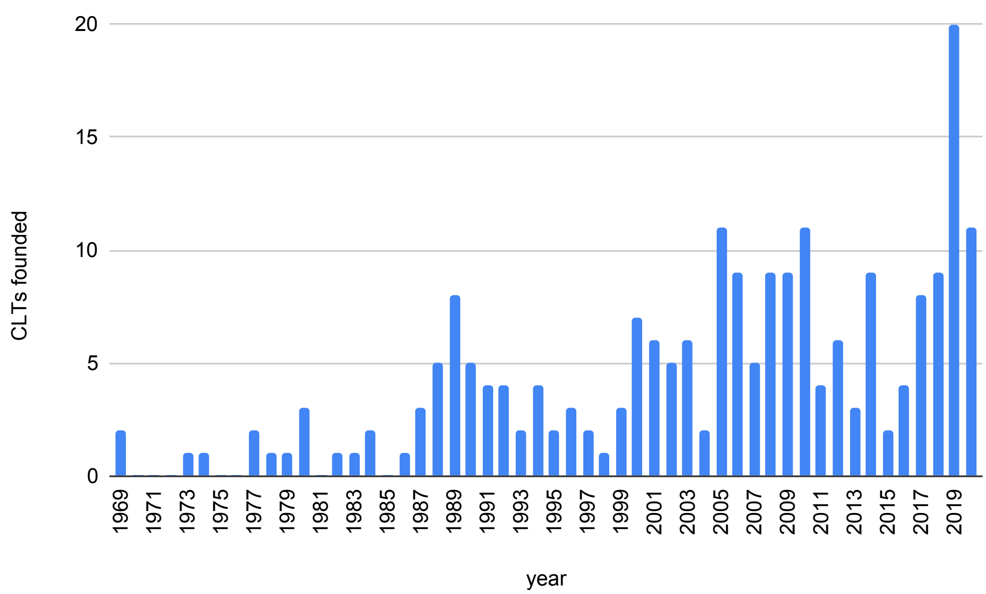


Figure 1: Number of newly-founded community land trusts over time.

Once we identified the names of the organizations that fall into the CLT definition, we obtained

[8]Source: https://centerforneweconomics.org/apply/community-land-trust-program/directory/

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.

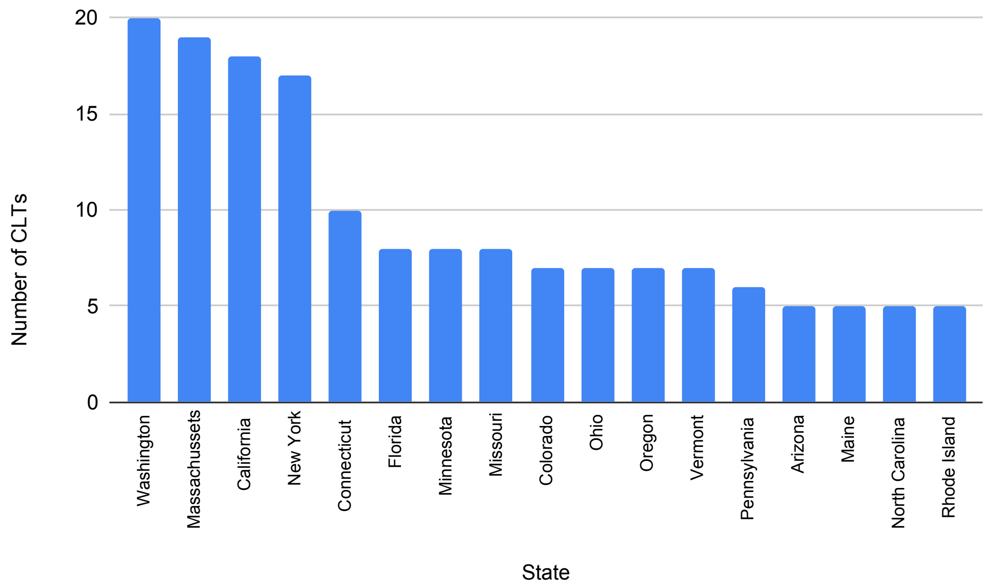


Figure 2: Number of community land trusts by state for those with more than 5 CLTs.

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 and 2. 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 2 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.

[9] Accessible here: https://projects.propublica.org/nonprofits/

[10] Thaden, 2018 estimates that by 2018 there were 225 CLTs (60 of which had no units) with 12,000 homeownership units.

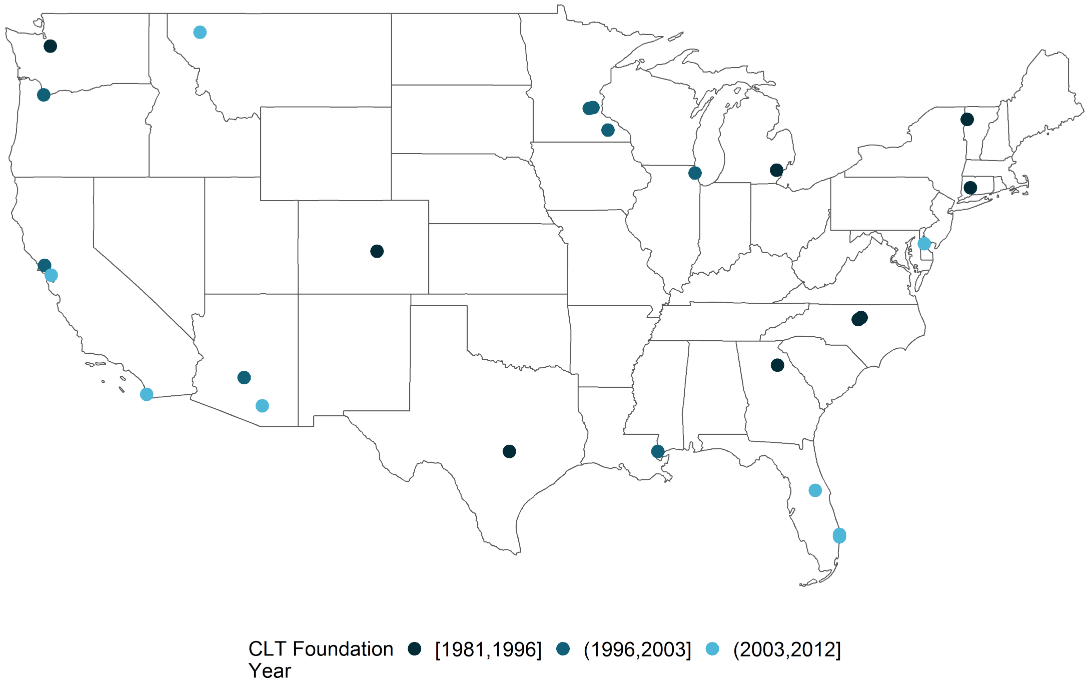


Figure 3: Location of Community Land Trusts included in the analysis, by year in which they were founded.

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 assessors 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.

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 arm-length transactions that happened between 2000 and 2016. As explained in detail in section 4, we restrict our analysis to properties within 1000 meters of a CLT home. Table 1 shows the mean of selected characteristics at the 2010 Census tract level, by number of properties that we identify as owned by CLTs in the tract.

Table 1: Mean characteristics for 2010 Census tracts, by number of CLT properties

	Tracts with No CLT Property	Tracts with at Least 1 CLT Property	Tracts with More than 1 CLT Property
Total Census Tracts	2684	405	245
Tract Median HH Income	$68,785	$57,196	$56,791
Tract Average Poverty Rate	7.59%	8.61%	8.85%
Tract % Black or African American	7.57%	10.90%	10.05%
Tract Median Home Value	$297,128	$224,894	$225,843
Tract Median Vacancy Rate	4.35%	3.36%	3.15%
Tract Share of Owner-Occupied Units	60.60%	58.23%	58.32%
Tract Median Housing Burden	24.93%	26.01%	26.11%

Constructing the analysis file requires identifying addresses[11] in the home sales data that were bought by CLTs. Unfortunately, CoreLogic data do not include identifiers for whether a transaction involves a CLT and idiosyncrasies in each CLT's operating model generate patterns in the home sales data that may be unique.[12] As a result, relevant transactions must be identified by conducting a search for the CLT through the buyers' names. CLTs may be recorded as parties in a transaction under a number of different iterations of their official name.[13] 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.

While our data collection could be scaled up to cover the universe of CLTs in the United States, we focus on the top 10% of CLTs by number of properties owned. Figure 3 shows the geographic location of the CLTs in our sample and Table 2 reports information for the transactions that took

[11]Throughout the paper, we use the term "address" as a synonym of "housing unit", as we control for unit number in duplexes and multifamily buildings.

[12]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.

[13]For example, "Durham Community Land Trustees", "Durham Community Land Trust", "Durham Cmnty Land Trust", "Durham CLT", or "DCLT".

place between 2000 and 2016 for the largest CLTs in our current sample. Restricting our analysis to those properties within 1000 meters of a CLT home that were sold within 5 years from the date the CLT purchase date leaves us with a sample of more than 230,000 transactions in a total of 19 counties in 11 states. Figure 4 plots the location of CLT houses for four CLTs in our sample.

Table 2: Community land trusts included in the analysis

CLT Name	Location	Transactions	Unique Properties
Champlain	Burlington, 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

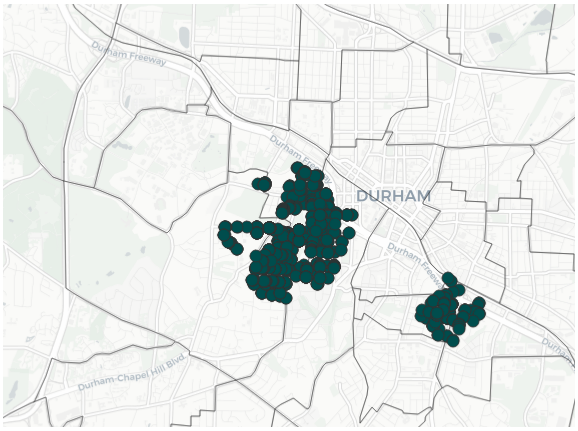
3.3 Household-level Data

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 every 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".[14]

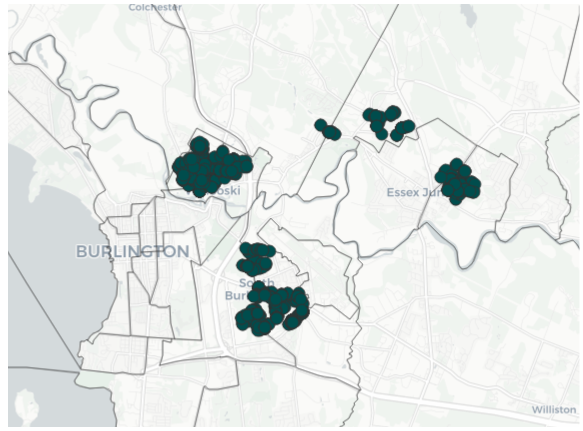
The Data Axle USA data provide a balanced panel of the demographic characteristics of residents around CLT properties, including estimates of their home's value and income and the length of residence at their current address. To study the effects of CLT home purchases on surrounding residents' mobility, we construct the variable "moved" to be equal to 1 if we observe a change in the residents' names from the previous year. Table 3 shows average characteristics for different group of observations in both our datasets.

[14]Source: https://www.dataaxleusa.com/lists/ethnicity-marketing-list/

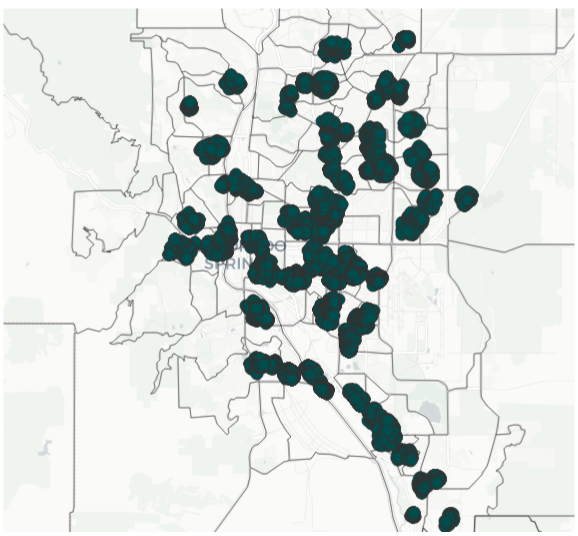
Figure 4: Properties of 4 Community Land Trusts



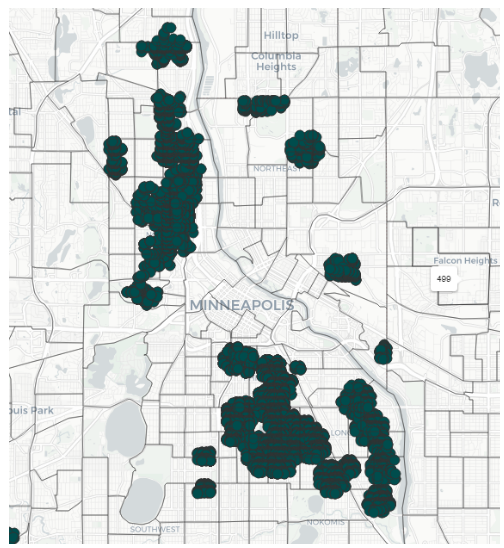
(a) Durham CLT, Durham NC



(b) Champlain, Burlington, VT



(c) Rocky Mountain CLT, Colorado Springs, CO



(d) City of Lakes CLT, Minneapolis, MN

4 Empirical Strategy

Our goal is to study the effect of Community Land Trusts' (CLTs) activity on local house price and demographic composition. A simple comparison of large neighborhoods with and without CLT properties would yield a biased estimate of the effect of CLTs, since the neighborhoods in which CLTs are active are likely different from neighborhoods in which they are not. Controlling for observable neighborhood characteristics would also not guarantee a causal interpretation of the estimates. CLTs could, for instance, require a specific social fabric to be present in the community for people to organize and found such an organization. Most of the previous studies on CLTs have

Table 3: Summary statistics

	Within 300m			
	Prior to CLT	**1 CLT**	**2 CLTs**	**3+ CLTs**
Mean Transaction Price	$260,833	$216,161	$305,233	$234,828
N CoreLogic	8418	8054	298	718
Mean Estimated Home Value	$198,915	$177,392	$128,395	$120,179
% Moved	9.33%	14.58%	17.77%	17.75%
% Owner	78.13%	69.63%	44.36%	41.34%
% Black	3.85%	5.08%	3.77%	4.05%
% Hisp	5.33%	6.99%	6.62%	6.80%
% Asian	2.50%	4.02%	2.46%	7.62%
% White	57.72%	64.64%	56.96%	68.47%
N Data Axle USA	10625	18939	1262	1891

	300m-600m			
	Prior to CLT	**1 CLT**	**2 CLTs**	**3+ CLTs**
Mean Transaction Price	$238,687	$267,056	$246,474	$258,596
N CoreLogic	49713	58609	7159	14756
Mean Estimated Home Value	$195,089	$180,833	$131,391	$123,723
% Moved	11.10%	14.75%	20.56%	21.44%
% Owner	71.03%	65.30%	49.80%	41.15%
% Black	3.54%	4.41%	3.95%	5.30%
% Hisp	5.65%	6.91%	9.03%	10.04%
% Asian	2.59%	3.71%	4.43%	5.03%
% White	54.48%	62.17%	60.96%	57.13%
N Data Axle USA	102086	117588	15381	20716

Note: The table reports the mean values and number of observations of the variables used in our analysis. The first panel reports data from Corelogic, so that each observation is a house transaction. The second panel reports data from Data Axle USA, so that each observation is an address in a given year.

been limited by the data availability to comparing Census tracts with and without CLTs (or even focus on tracts with particularly intense CLT activity), while thanks to the rich geocoded microdata on housing transactions and household characteristics described in Section 3 we can use methods that exploit the fine geographic level.

A standard candidate method to estimate the local impact of CLTs could be a strategy commonly known as the "ring method". This method is a type of spatial difference-in-differences model and it consists in comparing units very close to a CLT home before and after the home was purchased by the CLT to units slightly further away. Figure 5 in Appendix A illustrates the intuition behind the method. Butts, 2022 formalizes the assumptions that are necessary for identification in the ring method: local parallel trends and correct identification of the radius of the inner and outer rings. The first assumption requires that treatment and control units are on parallel trends: 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 and therefore are likely on the same house prices and household mobility trends. Moreover, we can exploit 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 purchase location depends on what parcels are available for sale at the time when the organization can afford to make a purchase.

While a good starting point, and while the underlying identification arguments that we use are the same, our context has two features that make it desirable for us to slightly modify this specification. First of all, we are concerned that estimating a single average treatment effect would mask the fact that the effect of CLTs may not be constant. Therefore, we decide to estimate a treatment effect curve, using multiple rings to estimate treatment effects at different distances.[15] We focus on houses that are located within 1000m from a CLT property within a time frame of 5 years before or after the CLT purchase and run the following specification ("Model 1" - extensive margin):

$$Y_{itk} = \sum_{d \in D} \alpha_{0d} Pre_{idt} + \sum_{d \in D} \alpha_{1d} Post_{idt} + \beta X_{it} + \mu_k + \tau_t + \epsilon_{itk} \tag{1}$$

where Y_{itk} is the outcome of interest for unit i at time t in Census track k; D is a set of distance bands d, where $D = \{0-300\text{m}, 300-600\text{m}\}$. Pre_{idt} is a dummy variable equal to 1 if the observation i in distance band d at time t is prior to the purchase of the first property by a CLT; $Post_{idt}$ is a dummy variable equal to 1 if the observation i in distance band d at time t is after the purchase of the first property by a CLT; X_{it} is a vector of controls; μ_k is a vector of Census tracts fixed effects[16], τ_t is a vector of time fixed effects; and ϵ_{itk} is a random error variable. Just like in Voith et al., 2022, the "average treatment effect" is the average difference between the coefficients for the Pre and $Post$ variables within a given distance from a CLT property and is interpreted with respect to the excluded category: properties between 600m and 1000m of the CLT property.[17]

[15] Both Alexander et al., 2019 and Voith et al., 2022 use a similar methodology.

[16] We use Census tracts in our main specification because their boundaries are consistent over time. We ran the same specification using 2010 Census block group fixed effects and the results, also included in Appendix B, are mostly robust.

[17] In contrast to the basic DID approach, this specification includes the Pre variable in the regression, so that we cannot simply use the interaction between $Post$ and the treatment dummy to estimate the treatment effect. We need

Our second concern is that, like in Voith et al., 2022 and Pennington, 2021, CLTs' properties tend to be spatially clustered. Figure 4 shows the distribution of different CLTs' properties and highlights how it is not uncommon for houses to be treated more than once in different distance rings. We therefore specify a second model ("Model 2" - intensive margin) to take into account the effect of concentrated CLT properties and overlapping treatments:

$$Y_{itk} = \sum_{d \in D} \alpha_{0d} Pre_{idt} + \sum_{d \in D} \alpha_{1d} Post1_{idt} + \sum_{d \in D} \alpha_{1d} Post2_{idt} + \sum_{d \in D} \alpha_{1d} Post3_{idt} + \beta X_{it} + \mu_k + \tau_t + \epsilon_{itk} \quad (2)$$

where Y_{itk} is the outcome of interest for unit i at time t in Census tract k; D is a set of distance bands d, where $D = \{0-300\text{m}, 300-600\text{m}\}$. Pre_{idt} is a dummy variable equal to 1 if the observation i in distance band d at time t is prior to the purchase of the first property by a CLT; $Post1_{idt}$ is a dummy variable equal to 1 if observation i in distance band d at time t is after the purchase of at least one property by a CLT; $Post2_{idt}$ is a dummy variable equal to 1 if observation i in distance band d at time t is after the purchase of at least two properties by a CLT; $Post3_{idt}$ is a dummy variable equal to 1 if observation i in distance band d at time t is after the purchase of at least three properties by a CLT; X_{it} is a vector of controls; μ_k is a vector of Census tracts fixed effects, τ_t is a vector of time fixed effects; and ϵ_{itk} is a random error variable.

Like in the previous specification, we need an extra step to calculate the average treatment effects. The difference between Pre and $Post1$ captures the effect of the first CLT being purchased at a given distance, the difference between Pre and ($Post1$ + $Post2$) captures the cumulative effect of 2 CLTs being purchased at a given distance, and the difference between Pre and ($Post1$ + $Post2$ + $Post3$) captures the cumulative effect of 3 or more CLTs being purchased.

5 Neighborhood Effects of Community Land Trusts

This section presents our estimates of the effect of Community Land Trusts (CLTs) on local neighborhood outcomes. In subsection 5.1 we estimate the effect of CLT acquisitions on the sale prices and estimated home values of neighboring properties. In subsection 5.2 we estimate the effects of CLT acquisitions on surrounding residents' mobility and demographics. In each subsection we also explore some potential heterogeneity of CLTs in different housing markets and present results

to manually calculate the difference between Pre and $Post$, but this allows us to estimate the cumulative effects of multiple CLTs.

obtained by splitting the sample based on market-level affordability.

5.1 House prices

Table 4 presents estimates of the effect of CLT acquisition on house transaction prices reported in the CoreLogic dataset. To facilitate the reading of our results, we include our estimates for the average treatment effects of different types of CLT purchases, but tables with the full set of Pre and $Post$ coefficients can be found in Appendix D. Throughout the analysis, we cluster standard errors by address and control for number of bedrooms, age at sale and square footage of the property.

Columns (1) through (3) progressively add year-month and Census tract fixed effects to our "Model 1" specification. These estimates suggest a negative responses of housing prices to CLT purchases, although the magnitude of the effect is greatly reduced once we include Census tract fixed effects. Our extensive margin analysis suggests that CLT purchases have a negative but statistically insignificant effect on the transaction price of houses within 300m of the CLT property compared to houses located between 600m and 1000m from the property (our control group). We also estimate that a CLT purchase is associated to a 3.74%[18] decrease in housing transaction prices for houses located between 300m and 600m compared to houses located between 600m and 1000m.

Columns (4) through (6) progressively add the same set of fixed effects to our "Model 2" specification. We find that an initial CLT purchase is associated to a decrease in surrounding transaction prices compared to homes located between 600m and 1000m of the CLT home (-2.5% for homes within 300m of the CLT home and -3.65% for homes between 300m and 600m). Interestingly, this effect is attenuated by subsequent purchases and even reversed for houses within 300m of the CLT property. While we do not have the data to confirm the mechanism driving this pattern, it is possible that once the CLT starts its activity and neighbors become more familiar with the model, it becomes more desirable to live near the nonprofit's property.

A key concern using the CoreLogic transaction-level dataset is that the composition of properties that sell at a specific time and location may be selected along dimensions we cannot control for. 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 in a short time frame could themselves be systematically different from those that don't. Instead, we use the Data Axle USA

[18] Throughout the paper, we convert model coefficients from natural logarithms to percentages, which may result in slight discrepancies between the percentages in the text and the coefficients in the tables (e.g. $e^{(-0.0381)}-1 = -3.74\%$).

Table 4: Effect of Nearby CLT Acquisitions on Sale Price (% Change)

Dependent Variable:	log(Transaction Price)					
		Model 1			Model 2	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any $CLT_{d\in(0,300]}$	-0.1298***	-0.1907***	-0.0286			
	(0.0274)	(0.0263)	(0.0289)			
First $CLT_{d\in(0,300]}$				0.0407***	-0.0301**	-0.0253**
				(0.0155)	(0.0137)	(0.0115)
Second $CLT_{d\in(0,300]}$				0.0728*	0.0236	0.0659**
				(0.0426)	(0.0390)	(0.0293)
Third+ $CLT_{d\in(0,300]}$				-0.0206	-0.0427*	0.0089
				(0.0268)	(0.0249)	(0.0211)
Any $CLT_{d\in(300,600]}$	-0.1404***	-0.2137***	-0.0381**			
	(0.0133)	(0.0130)	(0.0167)			
First $CLT_{d\in(300,600]}$				-0.0124**	-0.0872***	-0.0372***
				(0.0054)	(0.0062)	(0.0061)
Second $CLT_{d\in(300,600]}$				-0.0034	-0.0945***	-0.0288**
				(0.0150)	(0.0144)	(0.0118)
Third+ $CLT_{d\in(300,600]}$				0.0374*	-0.0516***	0.0117
				(0.0192)	(0.0196)	(0.0123)
Fixed-effects						
Year-Month		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	233,037	233,037	233,037	233,037	233,037	233,037
R^2	0.12786	0.21337	0.39680	0.12914	0.21589	0.39972

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

dataset to provide a related set of results.

Table 5 presents estimates of the effect of CLT acquisition on an estimate of the home value included in the Data Axle USA dataset. We include controls for the length of residence of the household in its current home as well as an estimate of household income. The main advantage of this exercise is that we have a balanced panel: all addresses are observed every year, independently of whether or not the house is sold. This minimizes our concerns about the different composition of houses that sell in a given time frame. However, there are some differences in the two datasets that make a direct comparison of the estimates difficult. First of all, the time coverage of the two datasets is not the same: CoreLogic covers the period between 2000 and 2016, while Data Axle USA only starts in 2006. The results for home prices therefore include rings around CLTs that are excluded from Data Axle USA. Moreover, the time the fixed effects in Data Axle USA are less precise because we only observe each address once a year. Finally, the dependent variable in Data Axle USA is an estimate provided by the company, rather than the true market value.

Table 5: Effect of Nearby CLT Acquisitions on Estimated Home Value (% Change)

Dependent Variable:	log(Estimated Home Value)					
		Model 1			Model 2	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any $\text{CLT}_{d\in(0,300]}$	2.63×10^{-5}	0.0136^{***}	-0.0193^{***}			
	(0.0044)	(0.0045)	(0.0036)			
First $\text{CLT}_{d\in(0,300]}$				-0.0087^{***}	-0.0006	-0.0101^{***}
				(0.0033)	(0.0034)	(0.0026)
Second $\text{CLT}_{d\in(0,300]}$				-0.0491^{***}	-0.0470^{***}	-0.0656^{***}
				(0.0123)	(0.0123)	(0.0109)
Third+ $\text{CLT}_{d\in(0,300]}$				0.0712^{***}	0.0763^{***}	0.0277^{***}
				(0.0106)	(0.0108)	(0.0096)
Any $\text{CLT}_{d\in(300,600]}$	0.0333^{***}	0.0513^{***}	0.0067^{**}			
	(0.0033)	(0.0036)	(0.0026)			
First $\text{CLT}_{d\in(300,600]}$				0.0134^{***}	0.0257^{***}	0.0051^{**}
				(0.0026)	(0.0028)	(0.0021)
Second $\text{CLT}_{d\in(300,600]}$				-0.0530^{***}	-0.0377^{***}	-0.0056
				(0.0070)	(0.0071)	(0.0049)
Third+ $\text{CLT}_{d\in(300,600]}$				0.0311^{***}	0.0548^{***}	0.0192^{***}
				(0.0110)	(0.0117)	(0.0073)
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	652,022	652,022	652,022	652,022	652,022	652,022
R^2	0.40565	0.43801	0.68569	0.40689	0.43893	0.68605

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

The magnitude of the effect of CLT purchases on estimated home values is generally lower than the effect on sale price, but the same pattern of a reverse in the direction of the effect as CLT activity increase holds when we look at estimated home values. Overall, Table 4 and 5 together seem to suggest that the composition of houses that are sold after the CLT purchase properties matters: it is possible that houses in potentially worse condition are sold, making the effect more negative. Both sets of results, however, seems to support the idea that CLTs keep the area more affordable and that we only start seeing some positive price effects in those areas where CLT activity is particularly intense.

5.1.1 Treatment Effect Heterogeneity

The average treatment effects estimated in the previous section may mask interesting heterogeneity in the effect of CLTs in different housing markets. In particular, CLTs that are active in markets experiencing high housing costs may have as their main mission to preserve housing affordability.

Table 6: Effect of Nearby CLT Acquisitions on Sale Price by Market Type (% Change)

Dependent Variable:	log(Transaction Price)			
Model	Model 1		Model 2	
Sample	High Cost	Rest	High Cost	Rest
Model:	(1)	(2)	(3)	(4)
Variables				
Any $CLT_{d\in(0,300]}$	-0.0470***	-0.0180		
	(0.0152)	(0.0126)		
First $CLT_{d\in(0,300]}$			-0.0612***	-0.0194
			(0.0152)	(0.0126)
Second $CLT_{d\in(0,300]}$			-0.1045**	0.0810**
			(0.0493)	(0.0319)
Third+ $CLT_{d\in(0,300]}$			-0.1420***	0.0266
			(0.0516)	(0.0223)
Any $CLT_{d\in(300,600]}$	-0.0541	0.0751***		
	(0.0386)	(0.0195)		
First $CLT_{d\in(300,600]}$			-0.0205*	-0.0369***
			(0.0118)	(0.0066)
Second $CLT_{d\in(300,600]}$			-0.0578***	-0.0258*
			(0.0183)	(0.0134)
Third+ $CLT_{d\in(300,600]}$			-0.0303	0.0138
			(0.0190)	(0.0134)
Fixed-effects				
Year-Month	Yes	Yes	Yes	Yes
Census Tract	Yes	Yes	Yes	Yes
Fit statistics				
Observations	22,372	210,665	22,372	210,665
R^2	0.56707	0.37335	0.56993	0.37458

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

On the other hand, CLTs working in more divested areas may aim at increasing property values. We therefore split our sample between CLTs that operate in "high cost" markets (the top 25% urban areas by housing cost in our full sample) and the other markets.

Table 6 shows the extensive and intensive response of sale prices to CLT activity within 300m and between 300m and 600m in each market type. Our estimates suggest that the negative effects on sale prices are larger in higher cost markets, especially in the immediate surroundings of a newly purchased CLT property (-4.5% compared to a statistically insignificant -1.78%). Interestingly, we find that in the not "high cost" sample, CLTs may have positive effects on the sale prices of houses around them (up to 7.78% within 300m and 7.79% within 600m). This effect is consistent with the idea that the main focus of CLTs in those areas may be to revitalize the neighborhood, rather than mitigate increases in housing prices.

Table 7 shows the extensive and intensive response of estimated home values to CLT activity within 300m and between 300m and 600m in each market type. The positive effects on the values

Table 7: Effect of Nearby CLT Acquisitions on Estimated Home Values by Market Type (% Change)

Dependent Variable:	log(Estimated Home Value)			
Model	Model 1		Model 2	
Sample	High Cost	Rest	High Cost	Rest
Model:	(1)	(2)	(3)	(4)
Variables				
Any $\text{CLT}_{d\in(0,300]}$	-0.0171**	-0.0201***		
	(0.0073)	(0.0040)		
First $\text{CLT}_{d\in(0,300]}$			-0.0171***	-0.0081***
			(0.0054)	(0.0029)
Second $\text{CLT}_{d\in(0,300]}$			-0.0492***	-0.0712***
			(0.0118)	(0.0142)
Third+ $\text{CLT}_{d\in(0,300]}$			0.0400***	0.0343**
			(0.0119)	(0.0153)
Any $\text{CLT}_{d\in(300,600]}$	0.0083	0.0016		
	(0.0055)	(0.0029)		
First $\text{CLT}_{d\in(300,600]}$			0.0019	0.0022
			(0.0042)	(0.0024)
Second $\text{CLT}_{d\in(300,600]}$			0.0191**	-0.0141**
			(0.0089)	(0.0058)
Third+ $\text{CLT}_{d\in(300,600]}$			0.0298**	-0.0036
			(0.0122)	(0.0085)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Census Tract	Yes	Yes	Yes	Yes
Fit statistics				
Observations	183,839	468,183	183,839	468,183
R^2	0.65146	0.66639	0.65256	0.66658

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

of the properties within 300m of a CLT in the not "high cost" sample don't kick in until there is a high concentration of CLTs (+3.48% from the third CLT on).

As mentioned before, the difference in time coverage may help explain the discrepancies that we find across the two data sources: the magnitudes of the negative effects on estimated home values are generally reduced compared to the effects on sale prices. Another difference across the two datasets is that we observe positive effects on estimated property values in the high-cost sample. This suggests that earlier observations in the Corelogic dataset may be bringing down the overall effect and that future research should explore heterogeneity by waves of CLT activity, as the main focus of these organizations may have evolved over time.

5.2 Resident Mobility and Demographic Composition

Our second set of results focuses on the effect of CLTs home purchases on the mobility and demographic composition of residents living in the surrounding properties. Throughout the analysis we cluster standard errors by address and control for the length of residence of a household at its current address as well as an estimate of household income.

Table 8: Effect of Nearby CLT Acquisitions on Likelihood of Moving

Dependent Variable:	Moved					
		Model 1			Model 2	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any $\text{CLT}_{d\in(0,300]}$	0.0364***	0.0068***	-0.0085***			
	(0.0023)	(0.0024)	(0.0025)			
First $\text{CLT}_{d\in(0,300]}$				0.0352***	0.0073***	-0.0051***
				(0.0018)	(0.0019)	(0.0019)
Second $\text{CLT}_{d\in(0,300]}$				0.0284***	0.0040	-0.0019
				(0.0057)	(0.0057)	(0.0057)
Third+ $\text{CLT}_{d\in(0,300]}$				0.0289***	-0.0016	-0.0071
				(0.0049)	(0.0049)	(0.0056)
Any $\text{CLT}_{d\in(300,600]}$	0.0329***	0.0035**	-0.0117***			
	(0.0016)	(0.0017)	(0.0017)			
First $\text{CLT}_{d\in(300,600]}$				0.0275***	-6.44×10^{-5}	-0.0129***
				(0.0013)	(0.0014)	(0.0015)
Second $\text{CLT}_{d\in(300,600]}$				0.0583***	0.0275***	0.0022
				(0.0035)	(0.0036)	(0.0037)
Third+ $\text{CLT}_{d\in(300,600]}$				0.0501***	0.0192***	0.0115**
				(0.0047)	(0.0048)	(0.0051)
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	769,964	769,964	769,964	769,964	769,964	769,964
R^2	0.13479	0.14279	0.16247	0.13570	0.14317	0.16262

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

Table 8 presents results of a linear probability model estimated using "Model 1" and "Model 2". The outcome variable is a binary variable equal to one if the household is not living in the same location as the previous year. Columns (1) through (3) progressively add year and Census tract fixed effects to our "Model 1" specification. Once we include geographical fixed effects, these estimates suggest CLT activity reduces the probability that households in its surroundings move compared to households located between 600m and 1000m. Our extensive margin analysis suggests that CLTs reduce the probability of moving by 0.85 percentage points for households that live within 300m and by 1.17 percentage points for households located between 300m and 600m. For

Table 9: Effect of Nearby CLT Acquisitions on Likelihood of Owner-Occupied

Dependent Variable:	Owner-Occupied					
		Model 1			Model 2	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any CLT$_{d\in(0,300]}$	-0.0679***	-0.0498***	-0.0093**			
	(0.0040)	(0.0041)	(0.0039)			
First CLT$_{d\in(0,300]}$				-0.0416***	-0.0259***	-0.0088***
				(0.0028)	(0.0029)	(0.0027)
Second CLT$_{d\in(0,300]}$				-0.1102***	-0.1032***	-0.0567***
				(0.0093)	(0.0093)	(0.0090)
Third+ CLT$_{d\in(0,300]}$				-0.1800***	-0.1692***	-0.0713***
				(0.0076)	(0.0076)	(0.0094)
Any CLT$_{d\in(300,600]}$	-0.0820***	-0.0640***	-0.0190***			
	(0.0025)	(0.0028)	(0.0025)			
First CLT$_{d\in(300,600]}$				-0.0575***	-0.0401***	-0.0133***
				(0.0020)	(0.0022)	(0.0019)
Second CLT$_{d\in(300,600]}$				-0.1258***	-0.1131***	-0.0156***
				(0.0050)	(0.0052)	(0.0046)
Third+ CLT$_{d\in(300,600]}$				-0.1605***	-0.1426***	-0.0176***
				(0.0066)	(0.0068)	(0.0067)
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	874,046	874,046	874,046	874,046	874,046	874,046
R^2	0.37597	0.38031	0.52751	0.37951	0.38394	0.52769

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

what concerns the intensive margin, this negative is attenuated in areas with higher intensity of CLT activity: for homes between 300m and 600m this effect even reverses after 3 or more CLT homes have been purchased.

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 9 explores this channel using a binary variable that equals to 1 if the house is owner-occupied provided by Data Axle USA. We would have expected an increase in homeownership probability to be associated with the higher desirability of the neighborhood for current residents.

To our surprise, we find that CLT activity is associated to a decrease in the likelihood that households own the home they are living in by 0.93 percentage points for households that live within 300m and by 1.9 percentage points for households located between 300m and 600m compared to those that live between 600m and 1000m. Moreover, differently from the effects on house transaction prices and estimated home values, the intensity of the effect increases with the intensity of CLT activity. This effect on homeownership suggests an influx or renters in the areas around CLTs, likely as a consequence of increased affordability.

Table 10: Effect of Nearby CLT Acquisitions on Demographic Composition

Dependent Variables:	Black	Hispanic	White	Asian	Black	Hispanic	White	Asian
	Model 1				Model 2			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Any $CLT_{d\in(0,300]}$	-0.0011	0.0075^{***}	-0.0126^{**}	0.0022				
	(0.0018)	(0.0024)	(0.0050)	(0.0020)				
First $CLT_{d\in(0,300]}$					0.0005	0.0046^{***}	-0.0016	0.0008
					(0.0012)	(0.0017)	(0.0036)	(0.0014)
Second $CLT_{d\in(0,300]}$					0.0133^{***}	0.0122^{*}	-0.0397^{***}	-0.0065^{**}
					(0.0043)	(0.0068)	(0.0109)	(0.0032)
Third+ $CLT_{d\in(0,300]}$					0.0097^{**}	0.0048	0.0255^{**}	0.0047
					(0.0039)	(0.0063)	(0.0107)	(0.0048)
Any $CLT_{d\in(300,600]}$	4.94×10^{-5}	0.0045^{***}	-0.0022	0.0047^{***}				
	(0.0012)	(0.0016)	(0.0034)	(0.0014)				
First $CLT_{d\in(300,600]}$					0.0016^{*}	0.0078^{***}	-0.0012	0.0016
					(0.0009)	(0.0012)	(0.0027)	(0.0010)
Second $CLT_{d\in(300,600]}$					0.0041^{*}	0.0072^{**}	-0.0010	0.0079^{***}
					(0.0021)	(0.0033)	(0.0060)	(0.0025)
Third+ $CLT_{d\in(300,600]}$					0.0053^{**}	0.0083^{**}	0.0021	0.0005
					(0.0022)	(0.0041)	(0.0082)	(0.0035)
Fixed-effects								
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	916,054	916,054	916,054	916,054	916,054	916,054	916,054	916,054
R^2	0.34116	0.15004	0.18524	0.05748	0.34121	0.15007	0.18527	0.05752

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

Next, we are interested in whether CLTs induce changes in the demographic composition of a neighborhood. Table 10 presents estimates of the effects of CLT activity on the probability that the head of a household belongs to a specific race or ethnicity, included in the Data Axle USA dataset.[19] We include here only the estimates from our main specification, but tables with the progressive addition of fixed effects for each group can be found in Appendix C.

Our extensive margin estimates suggest an increase in the probability that the head of household is Hispanic by 0.75 percentage points for houses within 300m and 0.45 percentage points for houses between 300m and 600m of any CLT property compared to houses located between 600m and 1000m. We also see a decrease in the probability that the household is White within 300m, while

[19] Data Axle USA imputes head-of-household's race and ethnicity based on names and local census data, so the measurement does not come from an administrative source.

we find no detectable effect between 300m and 600m. The extensive margin effect on the probability that a head of household is Asian is not statistically significant from 0 for houses within 300m of a CLT property, while it is slightly positive (+0.47 percentage points) for houses between 300m and 600m.

If we look at the intensive margin results, we can see some more nuance in the results. In particular, we notice that areas experiencing a more intense CLT activity also see an increase in the probability that the head of a household is Black, both within 300m of the CLT home and between 300m and 600m.

Overall results suggest higher neighborhood affordability and ability to retain current neighborhood residents, although this does not translate in an increase in the local homeownership rates. The composition of the neighborhood seem to suggest slight increases in racial and ethnic groups traditionally more affected by displacement, providing some encouragement in the role that CLTs can play to prevent it.

5.2.1 Treatment Effect Heterogeneity

In this subsection we repeat our analysis by market affordability groups. Table 11 shows the extensive and intensive response of the probability of moving to CLT activity within 300m and between 300m and 600m in each market type.

These estimates suggest that the negative effects on the probability of moving found in the full are driven by the not "high cost" sample, especially in the immediate surroundings of a newly purchased CLT property (−1.04 percentage points on the extensive margin and increasing with CLT activity on the intensive margin). The effects on the moving probability in the "high cost" sample are mostly statistically insignificant, suggesting that we do not have enough power to assess whether CLTs are able to slow displacement in areas facing higher prices.

Table 12 shows the extensive and intensive response of the probability that a household is a homeowner to CLT by market type. In this case, the results seem mostly consistent with our full-sample analysis, although it seems noticeable that the negative effects are driven by the not "high cost" market.

Finally, we focus on the effects of CLT activity on demographic composition across different market types. Table 13 shows our estimates for the extensive and intensive response of the probability that the head of a household is Black or Hispanic to CLT activity by market type. We see that, while we lose some power when splitting the sample, the direction and magnitude of the

Table 11: Effect of Nearby CLT Acquisitions on Likelihood of Moving by Market Type

Dependent Variable:	Moved			
Model	Model 1		Model 2	
Sample	High Cost	Rest	High Cost	Rest
Model:	(1)	(2)	(3)	(4)
Variables				
Any $\text{CLT}_{d\in(0,300]}$	-0.0052	-0.0104***		
	(0.0050)	(0.0028)		
First $\text{CLT}_{d\in(0,300]}$			-0.0006	-0.0076***
			(0.0037)	(0.0023)
Second $\text{CLT}_{d\in(0,300]}$			0.0171*	-0.0109
			(0.0104)	(0.0068)
Third+ $\text{CLT}_{d\in(0,300]}$			0.0129	-0.0241***
			(0.0081)	(0.0075)
Any $\text{CLT}_{d\in(300,600]}$	-0.0032	-0.0135***		
	(0.0033)	(0.0020)		
First $\text{CLT}_{d\in(300,600]}$			-0.0051*	-0.0150***
			(0.0030)	(0.0017)
Second $\text{CLT}_{d\in(300,600]}$			0.0029	0.0016
			(0.0070)	(0.0044)
Third+ $\text{CLT}_{d\in(300,600]}$			0.0376***	-0.0061
			(0.0092)	(0.0054)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Census Tract	Yes	Yes	Yes	Yes
Fit statistics				
Observations	226,727	543,237	226,727	543,237
R^2	0.13984	0.17207	0.14060	0.17218

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

effects remains similar to the full-sample analysis. In particular, the positive effects on the probability that the head of a household is Black or Hispanic is higher in the not high cost sample and generally increasing in the intensity of CLT activity in this market group.

Table 14 shows our estimates for the extensive and intensive response of the probability that the head of a household is White or Asian to CLT activity by market type. We see that the direction of the effects of CLTs on the probability that the head of a household is White differs across market types: we observe a negative response in the not high cost market but a mostly positive but statistically insignificant one in the high cost market. Finally, we observe an increase in the probability that the head of a household is Asian in high-cost markets for properties located between 300m and 600m from a CLT property but the effect dissipates as the activity of a CLT intensifies in the area.

Although we do not have enough power to find heterogeneous effects on all outcomes, these results provide suggestive evidence that CLTs may help maintain affordability and prevent dis-

Table 12: Effect of Nearby CLT Acquisitions on Likelihood of Owner-Occupied by Market Type

Dependent Variable:	Owner-Occupied			
Model	Model 1		Model 2	
Sample	High Cost	Rest	High Cost	Rest
Model:	(1)	(2)	(3)	(4)
Variables				
Any $\text{CLT}_{d\in(0,300]}$	0.0242^{***}	-0.0259^{***}		
	(0.0088)	(0.0043)		
First $\text{CLT}_{d\in(0,300]}$			-0.0199^{***}	-0.0106^{***}
			(0.0058)	(0.0030)
Second $\text{CLT}_{d\in(0,300]}$			-0.0237	-0.0781^{***}
			(0.0155)	(0.0110)
Third+ $\text{CLT}_{d\in(0,300]}$			-0.0425^{***}	-0.0923^{***}
			(0.0131)	(0.0131)
Any $\text{CLT}_{d\in(300,600]}$	5.1×10^{-5}	-0.0320^{***}		
	(0.0049)	(0.0029)		
First $\text{CLT}_{d\in(300,600]}$			-0.0034	-0.0209^{***}
			(0.0038)	(0.0022)
Second $\text{CLT}_{d\in(300,600]}$			0.0218^{**}	-0.0365^{***}
			(0.0086)	(0.0055)
Third+ $\text{CLT}_{d\in(300,600]}$			0.0012	-0.0312^{***}
			(0.0112)	(0.0075)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Census Tract	Yes	Yes	Yes	Yes
Fit statistics				
Observations	253,992	620,054	253,992	620,054
R^2	0.50669	0.53900	0.50680	0.53956

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

placement in more affordable areas, but they may not be able to achieve the same results in more high-cost areas. Future research could explore more localized definitions of "high cost" in order to assess heterogeneity within a market. A possibility could be to look at a Census-tract specific measure of housing cost burden, or follow the classification of gentrifying tracts provided by Choi et al., 2018.

6 Conclusion

Community Land Trusts (CLTs) 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 underneath. The governance structure of CLTs ensures that relevant stakeholders, including the surrounding community and local government, participate in the trust's decision-making. Despite widespread concerns about

Table 13: Effect of Nearby CLT Acquisitions on Demographic Composition Market Type (I)

Dependent Variables:	Black		Hispanic		Black		Hispanic	
Model	Model 1		Model 2		Model 1		Model 2	
Sample	High Cost	Rest	High Cost	Rest	High Cost	Rest	High Cost	Rest
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Any $\text{CLT}_{d\in(0,300]}$	-0.0028	0.0001	0.0049	0.0097^{***}				
	(0.0022)	(0.0023)	(0.0049)	(0.0027)				
First $\text{CLT}_{d\in(0,300]}$					0.0025	0.0003	2.42×10^{-5}	0.0068^{***}
					(0.0018)	(0.0016)	(0.0033)	(0.0020)
Second $\text{CLT}_{d\in(0,300]}$					0.0079	0.0172^{***}	0.0033	0.0180^{**}
					(0.0068)	(0.0055)	(0.0081)	(0.0089)
Third+ $\text{CLT}_{d\in(0,300]}$					-0.0010	0.0251^{***}	-0.0035	0.0148
					(0.0034)	(0.0073)	(0.0057)	(0.0121)
Any $\text{CLT}_{d\in(300,600]}$	-0.0006	0.0020	0.0009	0.0079^{***}				
	(0.0015)	(0.0016)	(0.0030)	(0.0019)				
First $\text{CLT}_{d\in(300,600]}$					-0.0002	0.0037^{***}	0.0011	0.0118^{***}
					(0.0012)	(0.0012)	(0.0023)	(0.0014)
Second $\text{CLT}_{d\in(300,600]}$					0.0047	0.0058^{**}	-0.0006	0.0128^{***}
					(0.0032)	(0.0028)	(0.0052)	(0.0042)
Third+ $\text{CLT}_{d\in(300,600]}$					-0.0012	0.0132^{***}	0.0013	0.0148^{**}
					(0.0027)	(0.0034)	(0.0056)	(0.0060)
Fixed-effects								
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	266,424	649,630	266,424	649,630	266,424	649,630	266,424	649,630
R^2	0.01388	0.37050	0.05689	0.17706	0.01407	0.37064	0.05684	0.17716

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

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 230 CLTs have emerged since the first organization was founded in the 1960s, and that 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 trusts remain perpetually affordable, their impact on neighboring properties is less clear.

This paper estimates the effect of CLT activity on neighborhood outcomes. Our results on the impact of CLTs on home sale prices suggest that the effects depend on the intensity of CLT activity in the neighborhood. Initially, a CLT purchase is associated with a decrease in surrounding transaction prices and estimated property value, but this effect is mitigated and even reversed as CLT activity increases. We also find that the effect of CLTs on prices varies depending on the housing market. CLTs in high cost markets may have as their main mission to preserve housing

Table 14: Effect of Nearby CLT Acquisitions on Demographic Composition Market Type (II)

Dependent Variables:	White		Asian		White		Asian	
Model	Model 1		Model 2		Model 1		Model 2	
Sample	High Cost	Rest	High Cost	Rest	High Cost	Rest	High Cost	Rest
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Any $\text{CLT}_{d\in(0,300]}$	-0.0018	-0.0158***	-0.0006	0.0023				
	(0.0103)	(0.0058)	(0.0050)	(0.0021)				
First $\text{CLT}_{d\in(0,300]}$					0.0039	-0.0028	0.0033	-0.0003
					(0.0072)	(0.0042)	(0.0034)	(0.0014)
Second $\text{CLT}_{d\in(0,300]}$					0.0017	-0.0568***	-0.0095	-0.0065*
					(0.0181)	(0.0135)	(0.0070)	(0.0036)
Third+ $\text{CLT}_{d\in(0,300]}$					0.0541***	-0.0225	-0.0062	0.0144**
					(0.0140)	(0.0163)	(0.0065)	(0.0071)
Any $\text{CLT}_{d\in(300,600]}$	0.0046	-0.0073*	0.0116***	-0.0003				
	(0.0066)	(0.0039)	(0.0035)	(0.0013)				
First $\text{CLT}_{d\in(300,600]}$					0.0076	-0.0067**	0.0084***	-0.0022**
					(0.0052)	(0.0031)	(0.0025)	(0.0010)
Second $\text{CLT}_{d\in(300,600]}$					0.0019	-0.0031	0.0217***	0.0002
					(0.0112)	(0.0072)	(0.0058)	(0.0024)
Third+ $\text{CLT}_{d\in(300,600]}$					-0.0031	0.0052	-0.0020	0.0016
					(0.0142)	(0.0089)	(0.0065)	(0.0029)
Fixed-effects								
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	266,424	649,630	266,424	649,630	266,424	649,630	266,424	649,630
R^2	0.13119	0.20947	0.05912	0.04612	0.13144	0.20954	0.05924	0.04623

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

affordability, and therefore, the negative effects on sale prices are larger in these markets. However, in markets that are not facing high housing costs, CLTs have a more positive effect on the sale prices of houses around them, consistent with the idea that their focus in those areas may be to neighborhood revitalization.

We also find that CLT activity reduces the moving probability of households in the surroundings but is also associated with a decrease in the likelihood that households own the home they are living in. This suggests that the increased likelihood of a neighborhood to retain its current residents is accompanied by an influx of renters in the areas around CLTs, likely due to increased affordability. For what concerns the effects of CLTs on the demographic composition of a neighborhood, our results show an increase in the probability that the head of a household near a CLT property is Black or Hispanic, especially outside the areas that are experiencing high housing costs. These effects are also increasing in the intensity of CLT activity in the area. We find opposite effects on the probability that the head of the household is White, with an increase in the immediate surroundings of a CLT property in high-cost markets and a decrease in other markets. The probability that the head of a household is Asian differs across market types is also mostly positive, although with lower magnitudes in areas with higher home prices.

Overall our results suggest that CLTs may yield higher neighborhood affordability and ability to retain current residents, although this does not translate in an increase in the local homeownership rates. The composition of the neighborhood seem to suggest slight increases in racial and ethnic groups traditionally more affected by displacement, providing some encouragement in the role that CLTs can play to prevent it. However, our results also provide suggestive evidence that, while CLTs may help maintain affordability and prevent displacement in more affordable areas, they may not be able to achieve the same results in higher-cost areas.

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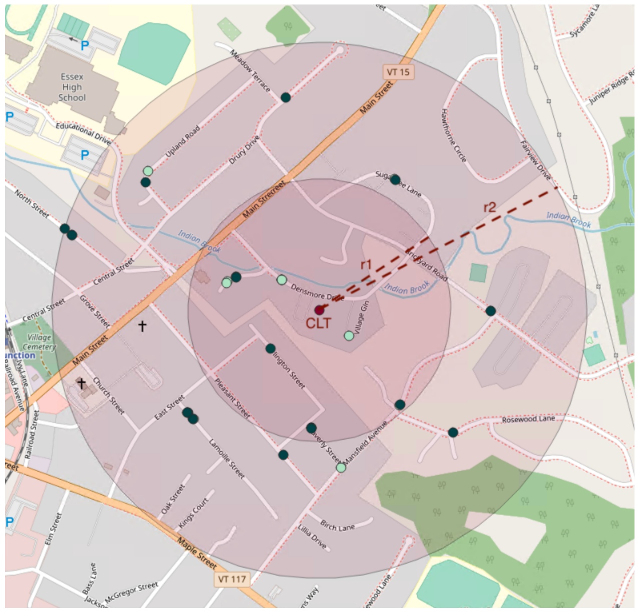
A Additional Figures

Figure 5: Illustration of the ring method using a microneighborhood in Essex Junction, VT



Note: The red dot represents a home purchased by the Champlain CLT in year 2004. 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.

B Tables by 2010 Census Block Group

Table 15: Effect of Nearby CLT Acquisitions on Sale Prices (% change)

Dependent Variable:	log(Transaction Price)					
	Model 1			Model 2		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any $\text{CLT}_{d\in(0,300]}$	-0.1298***	-0.1907***	-0.0286			
	(0.0274)	(0.0263)	(0.0289)			
First $\text{CLT}_{d\in(0,300]}$				0.0407***	-0.0301**	-0.0253**
				(0.0155)	(0.0137)	(0.0115)
Second $\text{CLT}_{d\in(0,300]}$				0.0728*	0.0236	0.0659**
				(0.0426)	(0.0390)	(0.0293)
Third+ $\text{CLT}_{d\in(0,300]}$				-0.0206	-0.0427*	0.0089
				(0.0268)	(0.0249)	(0.0211)
Any $\text{CLT}_{d\in(300,600]}$	-0.1404***	-0.2137***	-0.0381**			
	(0.0133)	(0.0130)	(0.0167)			
First $\text{CLT}_{d\in(300,600]}$				-0.0124**	-0.0872***	-0.0372***
				(0.0054)	(0.0062)	(0.0061)
Second $\text{CLT}_{d\in(300,600]}$				-0.0034	-0.0945***	-0.0288**
				(0.0150)	(0.0144)	(0.0118)
Third+ $\text{CLT}_{d\in(300,600]}$				0.0374*	-0.0516***	0.0117
				(0.0192)	(0.0196)	(0.0123)
Fixed-effects						
Year-Month		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	233,037	233,037	233,037	233,037	233,037	233,037
R^2	0.12786	0.21337	0.39680	0.12914	0.21589	0.39972

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

Table 16: Effect of Nearby CLT Acquisitions on Estimated Home Values (% change)

Dependent Variable:	log(Estimated Home Value)					
	Model 1			Model 2		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any $\text{CLT}_{d\in(0,300]}$	2.63×10^{-5}	0.0136^{***}	-0.0200^{***}			
	(0.0044)	(0.0045)	(0.0036)			
First $\text{CLT}_{d\in(0,300]}$				-0.0087^{***}	-0.0006	-0.0093^{***}
				(0.0033)	(0.0034)	(0.0026)
Second $\text{CLT}_{d\in(0,300]}$				-0.0491^{***}	-0.0470^{***}	-0.0679^{***}
				(0.0123)	(0.0123)	(0.0113)
Third+ $\text{CLT}_{d\in(0,300]}$				0.0712^{***}	0.0763^{***}	0.0143
				(0.0106)	(0.0108)	(0.0100)
Any $\text{CLT}_{d\in(300,600]}$	0.0333^{***}	0.0513^{***}	0.0039			
	(0.0033)	(0.0036)	(0.0025)			
First $\text{CLT}_{d\in(300,600]}$				0.0134^{***}	0.0257^{***}	0.0050^{**}
				(0.0026)	(0.0028)	(0.0020)
Second $\text{CLT}_{d\in(300,600]}$				-0.0530^{***}	-0.0377^{***}	-0.0036
				(0.0070)	(0.0071)	(0.0048)
Third+ $\text{CLT}_{d\in(300,600]}$				0.0311^{***}	0.0548^{***}	0.0094
				(0.0110)	(0.0117)	(0.0069)
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Block Group			Yes			Yes
Fit statistics						
Observations	652,022	652,022	652,022	652,022	652,022	652,022
R^2	0.40565	0.43801	0.70777	0.40689	0.43893	0.70795

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

Table 17: Effect of Nearby CLT Acquisitions on Probability of Moving

Dependent Variable:	Moved					
	Model 1			Model 2		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any $CLT_{d\in(0,300]}$	0.0364***	0.0068***	-0.0124***			
	(0.0023)	(0.0024)	(0.0026)			
First $CLT_{d\in(0,300]}$				0.0352***	0.0073***	-0.0070***
				(0.0018)	(0.0019)	(0.0020)
Second $CLT_{d\in(0,300]}$				0.0284***	0.0040	-0.0055
				(0.0057)	(0.0057)	(0.0059)
Third+ $CLT_{d\in(0,300]}$				0.0289***	-0.0016	-0.0099
				(0.0049)	(0.0049)	(0.0066)
Any $CLT_{d\in(300,600]}$	0.0329***	0.0035**	-0.0129***			
	(0.0016)	(0.0017)	(0.0018)			
First $CLT_{d\in(300,600]}$				0.0275***	-6.44×10^{-5}	-0.0134***
				(0.0013)	(0.0014)	(0.0015)
Second $CLT_{d\in(300,600]}$				0.0583***	0.0275***	0.0032
				(0.0035)	(0.0036)	(0.0038)
Third+ $CLT_{d\in(300,600]}$				0.0501***	0.0192***	0.0094*
				(0.0047)	(0.0048)	(0.0051)
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Block Group			Yes			Yes
Fit statistics						
Observations	769,964	769,964	769,964	769,964	769,964	769,964
R^2	0.13479	0.14279	0.16611	0.13570	0.14317	0.16622

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

Table 18: Effect of Nearby CLT Acquisitions on Probability of Owner-Occupied

Dependent Variable:	Owner-Occupied					
	Model 1			Model 2		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any $\text{CLT}_{d\in(0,300]}$	-0.0679***	-0.0498***	-0.0020			
	(0.0040)	(0.0041)	(0.0039)			
First $\text{CLT}_{d\in(0,300]}$				-0.0416***	-0.0259***	0.0027
				(0.0028)	(0.0029)	(0.0025)
Second $\text{CLT}_{d\in(0,300]}$				-0.1102***	-0.1032***	-0.0589***
				(0.0093)	(0.0093)	(0.0089)
Third+ $\text{CLT}_{d\in(0,300]}$				-0.1800***	-0.1692***	-0.0606***
				(0.0076)	(0.0076)	(0.0104)
Any $\text{CLT}_{d\in(300,600]}$	-0.0820***	-0.0640***	-0.0156***			
	(0.0025)	(0.0028)	(0.0024)			
First $\text{CLT}_{d\in(300,600]}$				-0.0575***	-0.0401***	-0.0139***
				(0.0020)	(0.0022)	(0.0018)
Second $\text{CLT}_{d\in(300,600]}$				-0.1258***	-0.1131***	-0.0113**
				(0.0050)	(0.0052)	(0.0045)
Third+ $\text{CLT}_{d\in(300,600]}$				-0.1605***	-0.1426***	-0.0078
				(0.0066)	(0.0068)	(0.0057)
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Block Group			Yes			Yes
Fit statistics						
Observations	874,046	874,046	874,046	874,046	874,046	874,046
R^2	0.37597	0.38031	0.56401	0.37951	0.38394	0.56425

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

C Tables with Progressive Addition of Fixed Effects

Table 19: Effect of Nearby CLT Acquisitions of Likelihood of Black Head of Household

Dependent Variable:	Black					
	Model 1			Model 2		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any $\text{CLT}_{d\in(0,300]}$	0.0026	-0.0058***	-0.0011			
	(0.0021)	(0.0022)	(0.0018)			
First $\text{CLT}_{d\in(0,300]}$				0.0078***	-0.0001	0.0005
				(0.0014)	(0.0015)	(0.0012)
Second $\text{CLT}_{d\in(0,300]}$				0.0027	-0.0038	0.0133***
				(0.0046)	(0.0047)	(0.0043)
Third+ $\text{CLT}_{d\in(0,300]}$				0.0241***	0.0159***	0.0097**
				(0.0043)	(0.0043)	(0.0039)
Any $\text{CLT}_{d\in(300,600]}$	0.0049***	-0.0034**	4.94×10^{-5}			
	(0.0012)	(0.0013)	(0.0012)			
First $\text{CLT}_{d\in(300,600]}$				0.0079***	0.0001	0.0016*
				(0.0010)	(0.0010)	(0.0009)
Second $\text{CLT}_{d\in(300,600]}$				-0.0006	-0.0094***	0.0041*
				(0.0024)	(0.0025)	(0.0021)
Third+ $\text{CLT}_{d\in(300,600]}$				0.0104***	0.0022	0.0053**
				(0.0028)	(0.0029)	(0.0022)
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	916,054	916,054	916,054	916,054	916,054	916,054
R^2	0.01264	0.01443	0.34116	0.01279	0.01446	0.34121

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

Table 20: Effect of Nearby CLT Acquisitions of Likelihood of Hispanic Head of Household

Dependent Variable:	Hispanic					
		Model 1			Model 2	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any $\text{CLT}_{d\in(0,300]}$	0.0138***	-0.0103***	0.0075***			
	(0.0026)	(0.0026)	(0.0024)			
First $\text{CLT}_{d\in(0,300]}$				0.0153***	-0.0073***	0.0046***
				(0.0018)	(0.0019)	(0.0017)
Second $\text{CLT}_{d\in(0,300]}$				0.0396***	0.0223***	0.0122*
				(0.0082)	(0.0082)	(0.0068)
Third+ $\text{CLT}_{d\in(0,300]}$				0.0193***	-0.0038	0.0048
				(0.0065)	(0.0066)	(0.0063)
Any $\text{CLT}_{d\in(300,600]}$	0.0074***	-0.0163***	0.0045***			
	(0.0015)	(0.0016)	(0.0016)			
First $\text{CLT}_{d\in(300,600]}$				0.0113***	-0.0108***	0.0078***
				(0.0012)	(0.0013)	(0.0012)
Second $\text{CLT}_{d\in(300,600]}$				0.0236***	0.0008	0.0072**
				(0.0034)	(0.0034)	(0.0033)
Third+ $\text{CLT}_{d\in(300,600]}$				0.0288***	0.0041	0.0083**
				(0.0042)	(0.0042)	(0.0041)
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	916,054	916,054	916,054	916,054	916,054	916,054
R^2	0.01673	0.02551	0.15004	0.01786	0.02570	0.15007

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

Table 21: Effect of Nearby CLT Acquisitions of Likelihood of Asian Head of Household

Dependent Variable:	Asian					
		Model 1			Model 2	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any $\text{CLT}_{d\in(0,300]}$	0.0107^{***}	0.0019	0.0022			
	(0.0019)	(0.0019)	(0.0020)			
First $\text{CLT}_{d\in(0,300]}$				0.0069^{***}	-0.0019	0.0008
				(0.0013)	(0.0014)	(0.0014)
Second $\text{CLT}_{d\in(0,300]}$				-0.0078^{**}	-0.0147^{***}	-0.0065^{**}
				(0.0031)	(0.0031)	(0.0032)
Third+ $\text{CLT}_{d\in(0,300]}$				0.0152^{***}	0.0062	0.0047
				(0.0039)	(0.0039)	(0.0048)
Any $\text{CLT}_{d\in(300,600]}$	0.0154^{***}	0.0067^{***}	0.0047^{***}			
	(0.0013)	(0.0014)	(0.0014)			
First $\text{CLT}_{d\in(300,600]}$				0.0109^{***}	0.0022^{**}	0.0016
				(0.0010)	(0.0011)	(0.0010)
Second $\text{CLT}_{d\in(300,600]}$				0.0148^{***}	0.0055^{**}	0.0079^{***}
				(0.0024)	(0.0024)	(0.0025)
Third+ $\text{CLT}_{d\in(300,600]}$				0.0188^{***}	0.0093^{**}	0.0005
				(0.0037)	(0.0037)	(0.0035)
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	916,054	916,054	916,054	916,054	916,054	916,054
R^2	0.00467	0.00675	0.05748	0.00468	0.00679	0.05752

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

Table 22: Effect of Nearby CLT Acquisitions of Likelihood of White Head of Household

Dependent Variable:	White					
		Model 1			Model 2	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Any $\text{CLT}_{d\in(0,300]}$	0.0813^{***}	-0.0078	-0.0126^{**}			
	(0.0051)	(0.0052)	(0.0050)			
First $\text{CLT}_{d\in(0,300]}$				0.0863^{***}	-0.0015	-0.0016
				(0.0038)	(0.0039)	(0.0036)
Second $\text{CLT}_{d\in(0,300]}$				0.0458^{***}	-0.0228^{**}	-0.0397^{***}
				(0.0115)	(0.0114)	(0.0109)
Third+ $\text{CLT}_{d\in(0,300]}$				0.0842^{***}	-0.0069	0.0255^{**}
				(0.0093)	(0.0091)	(0.0107)
Any $\text{CLT}_{d\in(300,600]}$	0.0704^{***}	-0.0177^{***}	-0.0022			
	(0.0032)	(0.0035)	(0.0034)			
First $\text{CLT}_{d\in(300,600]}$				0.0708^{***}	-0.0159^{***}	-0.0012
				(0.0026)	(0.0028)	(0.0027)
Second $\text{CLT}_{d\in(300,600]}$				0.0798^{***}	-0.0120^{**}	-0.0010
				(0.0058)	(0.0059)	(0.0060)
Third+ $\text{CLT}_{d\in(300,600]}$				0.0547^{***}	-0.0410^{***}	0.0021
				(0.0082)	(0.0082)	(0.0082)
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	916,054	916,054	916,054	916,054	916,054	916,054
R^2	0.04015	0.06909	0.18524	0.04067	0.06946	0.18527

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

D Full Coefficients Tables

Table 23: Effect of CLT Acquisitions on Estimated Home Value - Full Coefficients Table

Dependent Variable:	log(Estimated Home Value)					
	Model 1			Model 2		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\text{Pre}_{d\in(0,300]}$	-0.0463***	-0.0552***	-0.0250***	-0.0539***	-0.0591***	-0.0288***
	(0.0032)	(0.0033)	(0.0025)	(0.0033)	(0.0033)	(0.0026)
$\text{Post}_{d\in(0,300]}$	-0.0463***	-0.0417***	-0.0443***			
	(0.0042)	(0.0042)	(0.0032)			
Post first $\text{CLT}_{d\in(0,300]}$				-0.0627***	-0.0598***	-0.0390***
				(0.0031)	(0.0031)	(0.0024)
Post Second $\text{CLT}_{d\in(0,300]}$				-0.0403***	-0.0464***	-0.0555***
				(0.0122)	(0.0122)	(0.0106)
Post Third+ $\text{CLT}_{d\in(0,300]}$				0.1203***	0.1233***	0.0934***
				(0.0151)	(0.0152)	(0.0129)
$\text{Pre}_{d\in(300,600]}$	-0.0107***	-0.0226***	-0.0244***	-0.0258***	-0.0329***	-0.0306***
	(0.0026)	(0.0028)	(0.0020)	(0.0029)	(0.0030)	(0.0022)
$\text{Post}_{d\in(300,600]}$	0.0226***	0.0287***	-0.0177***			
	(0.0034)	(0.0035)	(0.0025)			
Post First $\text{CLT}_{d\in(300,600]}$				-0.0124***	-0.0072***	-0.0254***
				(0.0027)	(0.0028)	(0.0022)
Post Second $\text{CLT}_{d\in(300,600]}$				-0.0664***	-0.0634***	-0.0108**
				(0.0068)	(0.0067)	(0.0046)
Post Third+ $\text{CLT}_{d\in(300,600]}$				0.0840***	0.0925***	0.0248***
				(0.0126)	(0.0129)	(0.0075)
Constant	11.92***			11.94***		
	(0.0030)			(0.0031)		
Length of Residence	0.0010***	0.0009***	0.0006***	0.0010***	0.0009***	0.0006***
	(8.96×10^{-5})	(9.14×10^{-5})	(6×10^{-5})	(8.93×10^{-5})	(9.1×10^{-5})	(5.99×10^{-5})
Income in $	4.89×10^{-6}***	4.89×10^{-6}***	3.04×10^{-6}***	4.86×10^{-6}***	4.87×10^{-6}***	3.03×10^{-6}***
	(1.75×10^{-8})	(1.78×10^{-8})	(2.01×10^{-8})	(1.73×10^{-8})	(1.76×10^{-8})	(2.02×10^{-8})
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	652,022	652,022	652,022	652,022	652,022	652,022
R^2	0.40565	0.43801	0.68569	0.40689	0.43893	0.68605

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

Table 24: Effect of CLT Acquisitions on Likelihood of Moving - Full Coefficients Table

Dependent Variable:	Moved					
	Model 1				Model 2	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\text{Pre}_{d\in(0,300]}$	-0.0221***	-0.0020	0.0035**	-0.0187***	-0.0006	0.0043***
	(0.0015)	(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0016)
$\text{Post}_{d\in(0,300]}$	0.0143***	0.0048**	-0.0050**			
	(0.0021)	(0.0021)	(0.0022)			
Post first $\text{CLT}_{d\in(0,300]}$				0.0164***	0.0067***	-0.0008
				(0.0016)	(0.0016)	(0.0017)
Post Second $\text{CLT}_{d\in(0,300]}$				-0.0067	-0.0034	0.0032
				(0.0057)	(0.0056)	(0.0056)
Post Third+ $\text{CLT}_{d\in(0,300]}$				0.0005	-0.0055	-0.0052
				(0.0070)	(0.0069)	(0.0073)
$\text{Pre}_{d\in(300,600]}$	-0.0211***	0.0007	0.0065***	-0.0158***	0.0024*	0.0064***
	(0.0012)	(0.0013)	(0.0014)	(0.0013)	(0.0013)	(0.0014)
$\text{Post}_{d\in(300,600]}$	0.0117***	0.0042***	-0.0051***			
	(0.0014)	(0.0015)	(0.0016)			
Post First $\text{CLT}_{d\in(300,600]}$				0.0117***	0.0024**	-0.0065***
				(0.0012)	(0.0012)	(0.0013)
Post Second $\text{CLT}_{d\in(300,600]}$				0.0309***	0.0276***	0.0151***
				(0.0035)	(0.0035)	(0.0035)
Post Third+ $\text{CLT}_{d\in(300,600]}$				-0.0083	-0.0084	0.0093*
				(0.0055)	(0.0055)	(0.0056)
Constant	0.2952***			0.2876***		
	(0.0013)			(0.0012)		
Length of Residence	-0.0085***	-0.0085***	-0.0082***	-0.0085***	-0.0085***	-0.0082***
	(4.14×10^{-5})	(4.14×10^{-5})	(4.26×10^{-5})	(4.09×10^{-5})	(4.1×10^{-5})	(4.24×10^{-5})
Income in $	-3.84×10^{-7}***	-3.77×10^{-7}***	-4.33×10^{-7}***	-3.69×10^{-7}***	-3.69×10^{-7}***	-4.33×10^{-7}***
	(6.37×10^{-9})	(6.39×10^{-9})	(8.89×10^{-9})	(6.32×10^{-9})	(6.35×10^{-9})	(8.9×10^{-9})
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	769,964	769,964	769,964	769,964	769,964	769,964
R^2	0.13479	0.14279	0.16247	0.13570	0.14317	0.16262

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

Table 25: Effect of CLT Acquisitions on Likelihood of Owner-Occupied - Full Coefficients Table

Dependent Variable:	Owner-Occupied					
	Model 1			Model 2		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\text{Pre}_{d\in(0,300]}$	0.0863***	0.0751***	0.0284***	0.0828***	0.0724***	0.0299***
	(0.0026)	(0.0027)	(0.0026)	(0.0027)	(0.0027)	(0.0027)
$\text{Post}_{d\in(0,300]}$	0.0184***	0.0253***	0.0191***			
	(0.0039)	(0.0039)	(0.0039)			
Post first $\text{CLT}_{d\in(0,300]}$				0.0412***	0.0465***	0.0211***
				(0.0029)	(0.0029)	(0.0029)
Post Second $\text{CLT}_{d\in(0,300]}$				-0.0686***	-0.0774***	-0.0479***
				(0.0092)	(0.0092)	(0.0089)
Post Third+ $\text{CLT}_{d\in(0,300]}$				-0.0698***	-0.0660***	-0.0146
				(0.0106)	(0.0106)	(0.0114)
$\text{Pre}_{d\in(300,600]}$	0.0573***	0.0458***	0.0164***	0.0536***	0.0442***	0.0197***
	(0.0021)	(0.0022)	(0.0020)	(0.0023)	(0.0024)	(0.0023)
$\text{Post}_{d\in(300,600]}$	-0.0247***	-0.0182***	-0.0026			
	(0.0027)	(0.0027)	(0.0026)			
Post First $\text{CLT}_{d\in(300,600]}$				-0.0038*	0.0041*	0.0063***
				(0.0023)	(0.0023)	(0.0023)
Post Second $\text{CLT}_{d\in(300,600]}$				-0.0683***	-0.0730***	-0.0023
				(0.0048)	(0.0049)	(0.0044)
Post Third+ $\text{CLT}_{d\in(300,600]}$				-0.0347***	-0.0295***	-0.0019
				(0.0075)	(0.0075)	(0.0069)
Constant	0.2706***			0.2776***		
	(0.0023)			(0.0024)		
Length of Residence	0.0143***	0.0144***	0.0106***	0.0142***	0.0142***	0.0105***
	(6.82×10^{-5})	(6.85×10^{-5})	(7.1×10^{-5})	(6.79×10^{-5})	(6.82×10^{-5})	(7.09×10^{-5})
Income in $	2.51×10^{-6}***	2.51×10^{-6}***	2.16×10^{-6}***	2.48×10^{-6}***	2.48×10^{-6}***	2.17×10^{-6}***
	(1.91×10^{-8})	(1.91×10^{-8})	(2.18×10^{-8})	(1.9×10^{-8})	(1.9×10^{-8})	(2.18×10^{-8})
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	874,046	874,046	874,046	874,046	874,046	874,046
R^2	0.37597	0.38031	0.52751	0.37951	0.38394	0.52769

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

Table 26: Effect of Nearby CLT Acquisitions of Likelihood of Black Head of Household - Full Coefficients Table

Dependent Variable:	Black					
		Model 1			Model 2	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\text{Pre}_{d\in(0,300]}$	-0.0054***	-0.0001	-0.0008	-0.0046***	9.75×10^{-5}	-0.0002
	(0.0014)	(0.0014)	(0.0012)	(0.0014)	(0.0015)	(0.0012)
$\text{Post}_{d\in(0,300]}$	-0.0028	-0.0059***	-0.0019			
	(0.0021)	(0.0021)	(0.0017)			
Post first $\text{CLT}_{d\in(0,300]}$				0.0032*	-4.43×10^{-5}	0.0003
				(0.0016)	(0.0016)	(0.0013)
Post Second $\text{CLT}_{d\in(0,300]}$				-0.0050	-0.0037	0.0128***
				(0.0045)	(0.0045)	(0.0042)
Post Third+ $\text{CLT}_{d\in(0,300]}$				0.0214***	0.0197***	-0.0036
				(0.0057)	(0.0057)	(0.0050)
$\text{Pre}_{d\in(300,600]}$	-0.0088***	-0.0030***	-0.0015	-0.0073***	-0.0026**	-0.0005
	(0.0011)	(0.0011)	(0.0009)	(0.0012)	(0.0013)	(0.0011)
$\text{Post}_{d\in(300,600]}$	-0.0039***	-0.0065***	-0.0015			
	(0.0014)	(0.0014)	(0.0011)			
Post First $\text{CLT}_{d\in(300,600]}$				0.0007	-0.0025*	0.0011
				(0.0013)	(0.0013)	(0.0011)
Post Second $\text{CLT}_{d\in(300,600]}$				-0.0086***	-0.0095***	0.0025
				(0.0023)	(0.0023)	(0.0020)
Post Third+ $\text{CLT}_{d\in(300,600]}$				0.0111***	0.0115***	0.0012
				(0.0033)	(0.0033)	(0.0025)
Constant	0.0585***			0.0563***		
	(0.0010)			(0.0011)		
Length of Residence	0.0005***	0.0004***	0.0002***	0.0005***	0.0004***	0.0002***
	(4.61×10^{-5})	(4.64×10^{-5})	(3.57×10^{-5})	(4.61×10^{-5})	(4.64×10^{-5})	(3.57×10^{-5})
Income in $	-3.28×10^{-7}***	-3.3×10^{-7}***	-7.53×10^{-8}***	-3.25×10^{-7}***	-3.29×10^{-7}***	-7.34×10^{-8}***
	(6.5×10^{-9})	(6.53×10^{-9})	(4.78×10^{-9})	(6.49×10^{-9})	(6.53×10^{-9})	(4.78×10^{-9})
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	916,054	916,054	916,054	916,054	916,054	916,054
R^2	0.01264	0.01443	0.34116	0.01279	0.01446	0.34121

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

Table 27: Effect of Nearby CLT Acquisitions of Likelihood of Hispanic Head of Household - Full Coefficients Table

Dependent Variable:	Hispanic					
	Model 1			Model 2		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\text{Pre}_{d\in(0,300]}$	-0.0087***	0.0066***	-0.0002	-0.0059***	0.0076***	0.0004
	(0.0016)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
$\text{Post}_{d\in(0,300]}$	0.0051**	-0.0037	0.0072***			
	(0.0025)	(0.0025)	(0.0023)			
Post first $\text{CLT}_{d\in(0,300]}$				0.0094***	0.0003	0.0051***
				(0.0018)	(0.0019)	(0.0018)
Post Second $\text{CLT}_{d\in(0,300]}$				0.0243***	0.0296***	0.0076
				(0.0082)	(0.0082)	(0.0067)
Post Third+ $\text{CLT}_{d\in(0,300]}$				-0.0203**	-0.0261***	-0.0074
				(0.0099)	(0.0100)	(0.0086)
$\text{Pre}_{d\in(300,600]}$	-0.0082***	0.0084***	-0.0054***	-0.0015	0.0118***	-0.0032**
	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0014)	(0.0014)
$\text{Post}_{d\in(300,600]}$	-0.0007	-0.0079***	-0.0009			
	(0.0016)	(0.0016)	(0.0016)			
Post First $\text{CLT}_{d\in(300,600]}$				0.0098***	0.0010	0.0046***
				(0.0014)	(0.0014)	(0.0014)
Post Second $\text{CLT}_{d\in(300,600]}$				0.0123***	0.0116***	-0.0006
				(0.0033)	(0.0033)	(0.0032)
Post Third+ $\text{CLT}_{d\in(300,600]}$				0.0051	0.0033	0.0010
				(0.0051)	(0.0051)	(0.0046)
Constant	0.1046***			0.0959***		
	(0.0013)			(0.0013)		
Length of Residence	-0.0013***	-0.0014***	-0.0011***	-0.0013***	-0.0014***	-0.0011***
	(3.9×10^{-5})	(3.92×10^{-5})	(4×10^{-5})	(3.92×10^{-5})	(3.95×10^{-5})	(4×10^{-5})
Income in $	-3.2×10^{-7}***	-3.17×10^{-7}***	-5.42×10^{-8}***	-3.07×10^{-7}***	-3.1×10^{-7}***	-5.19×10^{-8}***
	(6.61×10^{-9})	(6.62×10^{-9})	(6.93×10^{-9})	(6.52×10^{-9})	(6.54×10^{-9})	(6.95×10^{-9})
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	916,054	916,054	916,054	916,054	916,054	916,054
R^2	0.01673	0.02551	0.15004	0.01786	0.02570	0.15007

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

Table 28: Effect of Nearby CLT Acquisitions of Likelihood of Asian Head of Household - Full Coefficients Table

Dependent Variable:	Asian					
		Model 1			Model 2	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\text{Pre}_{d\in(0,300]}$	-0.0064***	-0.0009	-6.06×10^{-5}	-0.0062***	-0.0009	-0.0002
	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0014)
$\text{Post}_{d\in(0,300]}$	0.0042**	0.0010	0.0021			
	(0.0019)	(0.0019)	(0.0020)			
Post first $\text{CLT}_{d\in(0,300]}$				0.0007	-0.0028**	0.0006
				(0.0014)	(0.0014)	(0.0015)
Post Second $\text{CLT}_{d\in(0,300]}$				-0.0146***	-0.0129***	-0.0073**
				(0.0031)	(0.0031)	(0.0032)
Post Third+ $\text{CLT}_{d\in(0,300]}$				0.0230***	0.0210***	0.0112**
				(0.0043)	(0.0043)	(0.0049)
$\text{Pre}_{d\in(300,600]}$	-0.0077***	-0.0017*	-0.0022**	-0.0078***	-0.0026**	-0.0033***
	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0012)
$\text{Post}_{d\in(300,600]}$	0.0077***	0.0050***	0.0025*			
	(0.0014)	(0.0014)	(0.0015)			
Post First $\text{CLT}_{d\in(300,600]}$				0.0031***	-0.0004	-0.0016
				(0.0011)	(0.0011)	(0.0012)
Post Second $\text{CLT}_{d\in(300,600]}$				0.0039*	0.0033	0.0063***
				(0.0022)	(0.0022)	(0.0022)
Post Third+ $\text{CLT}_{d\in(300,600]}$				0.0040	0.0038	-0.0074**
				(0.0043)	(0.0043)	(0.0036)
Constant	0.0482***			0.0481***		
	(0.0010)			(0.0010)		
Length of Residence	-0.0006***	-0.0007***	-0.0005***	-0.0006***	-0.0007***	-0.0005***
	(3.16×10^{-5})	(3.19×10^{-5})	(3.46×10^{-5})	(3.13×10^{-5})	(3.16×10^{-5})	(3.45×10^{-5})
Income in $	-7.75×10^{-8}***	-7.82×10^{-8}***	-2.82×10^{-8}***	-7.5×10^{-8}***	-7.79×10^{-8}***	-2.96×10^{-8}***
	(6.63×10^{-9})	(6.69×10^{-9})	(7.89×10^{-9})	(6.5×10^{-9})	(6.55×10^{-9})	(7.89×10^{-9})
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	916,054	916,054	916,054	916,054	916,054	916,054
R^2	0.00467	0.00675	0.05748	0.00468	0.00679	0.05752

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

Table 29: Effect of Nearby CLT Acquisitions of Likelihood of White Head of Household - Full Coefficients Table

Dependent Variable:	White					
	Model 1			Model 2		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\text{Pre}_{d\in(0,300]}$	-0.0532***	0.0031	-0.0052	-0.0504***	0.0023	-0.0052
	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0037)	(0.0037)
$\text{Post}_{d\in(0,300]}$	0.0280***	-0.0047	-0.0178***			
	(0.0047)	(0.0047)	(0.0047)			
Post first $\text{CLT}_{d\in(0,300]}$				0.0359***	0.0008	-0.0068*
				(0.0035)	(0.0035)	(0.0036)
Post Second $\text{CLT}_{d\in(0,300]}$				-0.0406***	-0.0213*	-0.0382***
				(0.0114)	(0.0112)	(0.0107)
Post Third+ $\text{CLT}_{d\in(0,300]}$				0.0384***	0.0159	0.0652***
				(0.0134)	(0.0131)	(0.0135)
$\text{Pre}_{d\in(300,600]}$	-0.0627***	-0.0013	-0.0023	-0.0581***	-0.0060*	-0.0032
	(0.0027)	(0.0029)	(0.0028)	(0.0030)	(0.0031)	(0.0032)
$\text{Post}_{d\in(300,600]}$	0.0077**	-0.0190***	-0.0045			
	(0.0033)	(0.0033)	(0.0034)			
Post First $\text{CLT}_{d\in(300,600]}$				0.0126***	-0.0219***	-0.0044
				(0.0028)	(0.0029)	(0.0030)
Post Second $\text{CLT}_{d\in(300,600]}$				0.0090	0.0039	0.0002
				(0.0056)	(0.0055)	(0.0056)
Post Third+ $\text{CLT}_{d\in(300,600]}$				-0.0251***	-0.0290***	0.0031
				(0.0092)	(0.0090)	(0.0085)
Constant	0.5029***			0.4966***		
	(0.0024)			(0.0025)		
Length of Residence	0.0030***	0.0027***	0.0009***	0.0030***	0.0026***	0.0009***
	(0.0001)	(9.97×10^{-5})	(9.76×10^{-5})	(0.0001)	(9.98×10^{-5})	(9.76×10^{-5})
Income in $	1.09×10^{-6}***	1.09×10^{-6}***	2.47×10^{-7}***	1.1×10^{-6}***	1.08×10^{-6}***	2.48×10^{-7}***
	(1.94×10^{-8})	(1.93×10^{-8})	(2.17×10^{-8})	(1.95×10^{-8})	(1.93×10^{-8})	(2.17×10^{-8})
Fixed-effects						
Year		Yes	Yes		Yes	Yes
Census Tract			Yes			Yes
Fit statistics						
Observations	916,054	916,054	916,054	916,054	916,054	916,054
R^2	0.04015	0.06909	0.18524	0.04067	0.06946	0.18527

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