ABSTRACT

Title of Document:	THE IMPACT OF LOW INCOME HOUSING TAX CREDIT PROJECTS ON NEIGHBORHOOD PROPERTY VALUES: THE CASE OF MONTGOMERY COUNTY, MD
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Previous studies on the impact of the impact of subsidized housing on neighborhood property values have not been able to provide any consensus due to the implementation of estimation strategies that have serious if somewhat different limitations. This study utilizes the difference-in-difference propensity score matching methodology to estimate the impact of Low Income Housing Tax Credit (LIHTC) projects on neighborhood property values in Montgomery County, Maryland by comparing the difference between pretreatment and post-treatment housing prices for neighborhoods that received an LIHTC project with those that did not. Results show that proximity to an LIHTC project has a significant negative impact on neighborhood property values.

THE IMPACT OF LOW INCOME HOUSING TAX CREDIT PROJECTS ON NEIGHBORHOOD PROPERTY VALUES: THE CASE OF MONTGOMERY COUNTY, MD

By

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I: Introduction

The provision of safe, decent and inexpensive housing for the poor is an important policy issue in the United States. Every year, the Congress allocates roughly $26 billion to fund several programs that provide access to housing to the poor (U.S. House of Representatives, 2004). However, the means by which housing assistance should be provided still remains a topic of considerable debate. While supply side approaches to address lack of affordable housing have typically included the direct provision of housing services or subsidies that promote the construction of public housing, demand side approaches have included voucher based programs which pay a portion of the rent of privately provided housing for eligible households. Past research has looked into the merits and demerits of such programs by measuring the benefits received by its residents. However, if economically important externalities are present, a crucial aspect of this debate is to assess the potential spillover effect of such programs on their neighborhood. Of particular relevance to this work is an examination of the impact of subsidized housing projects on neighborhood property values.

Conventionally, subsidized housing has been viewed as having a negative impact on surrounding property values, forming the basis for the not-in-my-backyard (NIMBY) mentality. Common reasons cited for this attitude include increased noise and litter, poorly kept properties, increased criminal activities and traffic. However, subsidized housing projects may have a positive impact on neighborhood property values if they replace blights such as an abandoned buildings or parking lot, if they lead to other new constructions in the neighborhood (unless there is a supply effect) and/or if they are of attractively designed. In any scenario, the loss or gain from locating close to subsidized projects needs to be accounted for while performing a cost benefit analysis of subsidized housing projects.

Unfortunately, previous studies have not been able to provide any consensus on the impact of subsidized housing projects on neighborhood property values due to the implementation of different estimation strategies that have serious if somewhat different limitations. The goal of this paper therefore is to estimate the impact of the Low Income Housing Tax Credit (LIHTC)[1] projects on neighboring single family properties in Montgomery County, Maryland using a difference-indifference propensity score matching approach, a non-parametric approach first suggested by Rubin (1983). This methodology compares the difference between pretreatment and post-treatment housing price for two neighborhoods, one that received a new LIHTC project and another that did not. By taking advantage of a strong predictor of location of LIHTC housing – proximity to a government designated Priority Funding Area, and Qualified Census tract, this specification overcomes the location bias associated with LIHTC developments. Using a dataset of 6756 arms-length repeat sales transactions within 2000 meters of 7 new construction LIHTC sites and 22 developable sites between 2000 and 2007, the impact of proximity to an LIHTC project on neighborhood property values is found to be negative and statistically significant[2]. Likewise, by restricting the repeat sale transactions within 1000 meters of 7 new construction LIHTC sites and 22 developable sites between 2000 and 2007, a similar yet stronger negative impact is obtained.

[1] The Low Income Housing Tax Credit (LIHTC) program is the largest federal subsidized housing

[2] The impact of rehabilitated LIHTC buildings, albeit important is not covered in this paper.

The paper begins with a review of the past literature on the topic. Next a hedonic model of housing market is presented. Then I discuss the LIHTC program and the policy process that influences the location of these projects. Next, the difference-in-difference propensity score matching approach is presented after which the data used in this study is discussed. Finally, I discuss the results and conclude with a section on future directions.

II. Literature Review

There exists a considerable amount of empirical literature investigating the question of whether subsidized housing projects affect neighborhood property values with conflicting results. One of the first studies that looked at the impact of affordable housing sites on neighborhood property values was by Nourse (1963). Using data from 1937-1959, the study implemented a repeat sales technique for neighborhoods with and without affordable housing units in St. Louis, controlling for housing and demographic characteristics. A modest positive impact of affordable housing projects on neighboring property values was found. Another early study commonly mentioned in the literature is by Robert Schafer (1972). Schafer looked at the impact of Below Market Interest Rate (BMIR) housing on neighborhood property values in Los Angeles to find a negative relation. The results however were not statistically significant.

Some of the earlier studies did not have access to arms-length transaction data. For example, DeSalvo (1974) investigated the Mitchell- Lama program in New York City using assessed value for properties to find an appreciation in housing prices in treatment area when compared to the control area. Guy et al. (1985) differ in their approach from previous studies by implementing a hedonic regression. They regress the sale price of property values on housing characteristics and distance from BMIR sites in Fairfax County, Virginia, to find an increase of $1.57 for every additional foot of distance away from the development.

More recently, researchers have exploited the availability of geographically referenced data. Lee et al. (1999) examines several federally assisted housing programs, designs (such as new/rehabilitated, high rise public housing and voucher based programs) between 1989 and 1991. By including dummy variables for units located either in 1/8th or 1/4th of a mile radius of an affordable housing development and controlling for demographic, housing and amenity variables, they find that high rise public housing developments had a small negative effect on property values while the voucher based programs had a positive impact. Galster et al. (1999) look at the effect of Section 8 developments on single family houses in Baltimore County, Maryland .Their results show that while an increase in housing values was observed in higher-valued tracts with greater white population, a decrease in neighborhood house prices was observed in lower valued tracts. These adverse impacts were limited to a small area, beginning to fall off significantly after 500 feet and practically vanishing within 2,000 feet.

Green et al. (2002) present weak evidence that LIHTC projects in Milwaukee decrease property values but show mixed evidence for other areas. Schwartz et al. (2006) study the impact of low income housing developments in New York City using a difference-in-difference approach to find that they have large positive effects on local housing values, due to a positive amenity effect of new construction.

Two recent and more methodologically sophisticated studies have looked at the impact of Low Income Housing Tax Credits units on its surrounding neighborhood. Baum-Snow et al. (2009) evaluates the impacts of all new Low Income Housing Tax Credit (LIHTC) developments in the U.S. on the neighborhoods in which they are built using a regression discontinuity approach. Their results show that tracts where projects are awarded 30 percent higher tax credits receive approximately six more low income housing units on a base of seven units per tract. This increase in low income developments leads to a reduction of incomes in gentrifying areas. They also find that LIHTC units considerably crowd out nearby new rental construction in gentrifying areas but do not shift new construction in stable or declining areas. Finally, they obtain a small positive impact of subsidized housing projects on census tract property values. One perspective worth considering would be the local and narrow focus on Montgomery County compared with the national focus of Baum-Snow et al. (2009). Their effort to estimate a single average treatment effect for all the LIHTC's in the United States makes little sense if the prediction of the direction of these projects is ambiguous. Baum-Snow et al. (2009) counter this by estimating the impacts for different levels of income

Eriksen et al. (2007) examines the crowd out and stigma/amenity effects of LIHTC developments at increasing geographic scales using the instrumental variables technique. They instrument for LIHTC housing between 1987 and 2000 using 1970 housing stock structure types (i.e.multi-family, single family) and the distribution of bedrooms for both owner- and renter-occupied units. Their intuition behind using these instruments is that past willingness to allow high-density development may play a role in explaining the current willingness of local communities to allow further multi-family housing development, including LIHTC projects. Their results suggest that LIHTC developments have a positive amenity effect in low-income areas within one-half mile, but a negative stigma effect in high-income areas at the same scale. These effects however, disappear with distance. Also, in areas within ten miles, one-third of LIHTC development is compensated by crowd out of private unsubsidized rental housing construction.

As a group, this body of research represents a significant attempt to understand the impact of subsidized housing programs on neighborhood property values. However foregoing analysis, which can be classified into three groups of methodologies - control area approach, pre/post approach and difference-in-difference approach have some serious weakness. The control area approach represented by Schafer (1972), DeSalvo (1974) compares property value levels between neighborhoods that have subsidized housing located within them (also referred to as the treatment group) to areas that do not have subsidized housing located within them but are identical in all other respects (control group). A major problem here is to find control areas that are similar in all respects to the treatment areas such that no other forces affect them in a different way after the subsidized housing is placed in service.

The pre/post approach represented by Colewell et al. (1976), Santiago et al. (2001) compares the difference in price of houses sold in a neighborhood before and after the introduction of a subsidized housing development. The difficulty here lies in ensuring that there exist no additional forces concurrent with the placement of subsidized housing that affect neighborhood prices. Also, since the placement of subsidized housing projects is non-random, it becomes difficult to convincingly distinguish the direction of causation between neighborhood property values and location of such projects. In other words, it difficult to establish whether proximity to subsidized housing leads to declining property values or whether subsidized projects are strategically located in areas having low property values. The problem, also known as simultaneity occurs when one or more of the independent variables are jointly determined. In a standard econometric model, the independent variables are exogenous while the dependent variable is endogenous.

However, in the case of simultaneity, the independent variable is also endogenously determined. This is problematic from the econometric standpoint (OLS estimation of such models yield biased estimates) since the endogenous explanatory variable is correlated with the error term in a regression model. This leads to ambiguity in determining causality between the two variables.

Finally, some studies have combined the pre/post approach and the control area approach using the difference in difference approach represented by Schwartz et al (2006), Cummings et al. (2000) etc. However this approach imposes a linear functional form restriction in estimating the conditional expectation of the outcome variable. Also there is no way to ensure that the parcels in the treatment group are comparable to those in the control group.

In this paper, the difference-in-difference propensity score matching approach is implemented by constructing a treatment group consisting of newly LIHTC buildings and a control group where no new LIHTC project was placed in service. This method has several benefits. Firstly, the matching procedure ensures that the parcels in the treatment group will be matched to those parcels in the control group that are most similar in terms of observable characteristics. Thus observations that do not fall into the common support will not have any impact on the price. Secondly it does not presuppose that distance of a house sold from an LIHTC site is exogenous. Finally this approach does not assume a linear functional form for the price equation unlike the standard difference-in-difference approach.

III. Theory

The hedonic pricing method, developed by Rosen (1974) has been widely used to study the housing market. Housing is a differentiated good, which means that although there are apparent differences between each house (number of bathrooms, bedrooms etc.), they are traded in the same market. In Rosen's formulation, a differentiated good is described by a vector of its characteristics $C = (c_1, c_2, \ldots, c_n)$. Thus, differences in housing characteristics lead to a different price in the market even when the market is competitive. That is, the price of a house being sold depends on consumer preferences for the characteristics of the house. Note that for the housing market, these characteristics are broadly classified into three categories – structural attributes, neighborhood public services and local amenities.

Researchers generally assume that the supply of houses is fixed in the short-run. The prices of existing houses are therefore demand determined. For this reason, the model discussed here will concentrate on the consumer side of the market and take the supply of houses to be fixed.

The market price of the ith house can be written as:

$$P_i = P(c_{i1}, c_{i2}, \ldots, c_{in}).$$

where $\partial P/\partial c_j$, the partial derivative of price with respect to the jth characteristic, is the marginal implicit price. It is the marginal price of the jth characteristic implicit in the overall price of the house, holding constant all other characteristics.

In the hedonic model, it is assumed that the markets are competitive and all consumers rent one house at the market price. The utility of the consumer's depends on the consumption of the numeraire good X (with price = 1) and vector of housing characteristics subject to a budget constraint. Mathematically, this can be expressed as

$$u = u(X,\mathbf{C}) \text{ subject to } I - P - X = 0$$

where I is income. Maximization the above problem with respect to the budget constraint gives us

$$(\partial U/\partial c_j) / (\partial U/\partial_x) = \partial P/\partial c_j$$

The economic interpretation of the above equation is that the marginal willingness to pay for the jth characteristic of a house equals the marginal cost of an extra unit of jth characteristic in equilibrium.

Substituting the budget constraint into the utility function gives, $u = u(I- P, c_1, c_2,\ldots, c_n)$. This equation can be inverted (holding all characteristics of the house but j constant) to obtain an expression for the consumer's willingness to pay for cj

$$Bj = Bj\ (I - P, c_j, \mathbf{C}_{-j*}, u^*).$$

Here, u^* is the highest level of utility attainable given the budget constraint and $\mathbf{C}_{-j*}$ is the optimal quantities of other characteristics.

The above equation reveals the maximum amount that an individual would pay for different values of cj, holding utility constant. It is also known as the bid curve.

IV. About the LIHTC Program

The Low Income Housing Tax Credit Program was instituted through the Tax Reform Act of 1986 as a means to promote the development of affordable rental housing units for low-income households. Every year, the Congress assigns federal tax credits to each state. This allocation of federal tax credits is based on state population. Until 2000, each state received a tax credit of $1.25 per person. This amount was increased to $1.75 in 2002 and adjusted for inflation over subsequent years. The allocation in 2007 was $1.95 per person. The tax credits are subsequently paid to developers of LIHTC projects in a competitive allocation process by the state authority handling these credits. In Maryland, the process is overseen by Maryland Department of Housing and Community Development.

Maryland has adopted a “Qualified Allocation Plan” (QAP) to determine whether or not developments should receive federal tax credits. The QAP is consistent with federally mandated restrictions but also includes state priorities. The allocation process is overseen by Maryland’s Department of Housing and Community Development. Following the guidelines of the QAP, points are awarded to project applications. These points are subsequently added up and projects are ranked based on the total number of points received. Tax credits are finally allocated in decreasing order of points until money runs out. Factors affecting allocation of tax credits to projects include size of the project, location, rehabilitation or new construction, amenities, costs and resident characteristics.

In order to be eligible for tax credits, prospective projects must meet one of the two criteria listed below

1) 20 percent or more of the residential units in the project are both rent restricted and occupied by individuals whose income is 50 percent or less of area median gross income. 2) 40 percent or more of the residential units in the project are both rent restricted and occupied by individuals whose income is 60 percent or less of area median gross income. Additionally, the rent condition is applicable for 15 years, after which a less restrictive rent condition is mandated for an additional 15 years.

The actual amount of tax credit allocated to an individual project is obtained from its qualified basis. To compute the qualified basis, non depreciable costs (such as land, rent reserves) are subtracted from total project costs to obtain the eligible basis. Next, projects located in Qualified Census Tracts receive a 130% adjustment on the eligible basis. A Qualified Census Tract is one where at least 50% of its population is eligible to rent LIHTC units (i.e. have incomes below 60% of the area median gross income). Finally, the adjusted eligible basis is multiplied with the percentage of low income units to total units to obtain the qualified basis. The qualified basis is finally multiplied by the federal tax credit rate (obtained from the IRS) to determine the maximum allowable tax credit allocation.

To give an example of how large the subsidies involved can be, if a $15 million project has land and financing costs as $5 million, the "eligible basis" works out to $10 million. The tax credit computation begins from this amount, adjusted for the number of rent restricted units in the project. If only 80% of the projects were devoted to low income residents, then the "qualified basis" is .80 x $10 million or $8 million. If the project is not located in a QCT, then the qualified basis is multiplied by the tax credit rate to determine annual subsidy. Most new construction projects are eligible for 9% tax credit rate which means the developer would receive $720,000 per year for the first ten years after the project is completed. This works out to a total of $7.2 million, almost 50% of the starting cost. A project located in a QCT receives a qualified basis multiplied by a factor of 1.3 which in our case works out to $10.4 million, with an annual subsidy of $1.04 million (roughly 60% of the starting cost). Thus the tax credits incentivize builders to invest in subsidized housing.

As mentioned before, the placement of LIHTC projects is non-random, making it difficult to convincingly distinguish the direction of causation between neighborhood property values and location of such projects. To overcome this difficulty, a plausibly exogenous variation in the location of LIHTC projects generated by the QAP is utilized. Two locational factors play an important role in this matter – Qualified Census Tracts and Priority Funding Area. The role of Qualified Census Tracts in LIHTC building location is already described above. Priority Funding Areas (PFA) are existing communities and places where local governments want state investment to support future growth. Up to 20 points (out of a total of 350) are awarded to projects that plan to locate in a priority funding area. Since profit maximizing builders seek to reduce total costs involved in the creation of an LIHTC unit and the allocation process is competitive, builders have an incentive to locate their project in Priority Funding Areas. This would increase their chances of receiving tax credit. Thus a distance measure from the nearest priority funding area from a residential parcel can be used as a determinant of the location of LIHTC housing projects.

V. Methodological Framework

The main problem with evaluating the impact of subsidized housing on neighborhood property values is that not all neighborhoods are equally likely to receive an affordable housing project for many reasons. The first constraint is the availability of vacant buildable land for new subsidized projects or existing structures for acquisition and rehabilitation. Secondly, builders of subsidized projects are restricted to appropriately zoned parcels for development, which typically includes mixed use or high density zoning areas, which are likely to have lower home values to begin with. Another important factor for builders is minimizing their total costs implying that projects may be concentrated in lower valued neighborhoods. Finally, builders are likely to locate in lower value areas since they expect less opposition from the current residents. All of the above reasons point towards a general bias in the location of subsidized housing projects to lower income areas, implying a non-random treatment assignment. To overcome the problem of non-random treatment assignment, matching methods are implemented.

Let D_{it} be an indicator of value one if an LIHTC project was placed close to a house i to at time period t. Denote y_{it+s}^{1} as the selling price of a house near this subsidized housing project after its placement, i.e. at time $\mathrm{t} + \mathrm{s}$. Also let y_{it+s}^{0} be the price of a house sold at time t+s had the LIHTC project not been built. Then, the causal effect of low income people dwelling in LIHTC housing on the selling price of a house at time period t+s is then defined as

$$y_{it+s}^{1} - y_{it+s}^{0}$$

Since y^0_{it+s} is not observed, following the impact evaluation literature (Heckman et al 1997), the average effect of subsidized housing on selling price of a house (also known as ATT - the Average treatment effect on the treated) is defined as

$$\tau = \mathrm{E}\{ y^1_{it+s} - y^0_{it+s} \mid D_{it} = 1 \} = \mathrm{E}\{ y^1_{it+s} \mid D_{it} = 1 \} - \mathrm{E}\{ y^0_{it+s} \mid D_{it} = 1 \}$$

Causal inference depends on the construction of the counterfactual for the last term. Using $\mathrm{E}\{ y^0_{it+s} \mid D_{it} = 0 \}$ would yield a biased estimate of τ because housing prices of the neighborhoods that did not receive a subsidized housing project would not necessarily be the same as those neighborhoods that did. This can be mathematically represented as

$$\mathrm{E}\{ \mathrm{y}^1_{\mathrm{it+s}} \mid \mathrm{D}_{\mathrm{it}} = 1 \}] - \mathrm{E}\{ \mathrm{y}^0_{\mathrm{it+s}} \mid \mathrm{D}_{\mathrm{it}} = 0 \} = \mathrm{E}[\mathrm{y}^1_{\mathrm{it+s}} - y^0_{it+s} \mid D_{it} = 1] +$$

$$\{\mathrm{E}[y^0_{it+s} \mid D_{it} = 1] - \mathrm{E}[y^0_{it+s} \mid D_{it} = 0] \}$$

$$\tau = \mathrm{E}\{ y^1_{it+s} \mid D_{it} = 1 \} - \mathrm{E}\{ y^0_{it+s} \mid D_{it} = 0 \} - \mathrm{E}\{ y^0_{it+s} \mid D_{it} = 1 \} - \mathrm{E}\{ y^0_{it+s} \mid D_{it} = 0 \}$$

where the term $\mathrm{E}\{ y^0_{it+s} \mid D_{it} = 1 \} - \mathrm{E}\{ y^0_{it+s} \mid D_{it} = 0 \}$ represents the bias.

Since the assignment of treatment is not random, matching techniques are employed by conditioning the assignment on a set of observables. As per the locational guidelines for LIHTC projects governed by federal rules and the Qualified Allocation Plan for Maryland, two variables, one measuring distance to priority funding area and another dummy variable identifying whether or not the house is located in a Qualified Census tract are included as determinants of the treatment. Other variables unaffected by participation are also included in the model such as distance to metro station, distance to bus stop, log of census block median income in 2000, census block percentage minority and distance to downtown Washington D.C. Thus upon conditioning on observables, a counterfactual for houses near subsidized housing is obtained. The matching procedure is favorable to arbitrarily choosing the comparison group, because it is less likely to induce estimation bias by picking houses with markedly different characteristics.

In this study, matching is performed by creating a single index, a propensity score that captures information from all pre-treatment characteristics to reduce the dimensionality problem. It also allows for comparison between the treatment and control groups. The method was first suggested by Rosenbaum and Rubin (1983)**.**

Thus the probability of being close to a subsidized housing project is estimated using a probit model,

$$P(D_{it} = 1) = F(X_{it-1})$$

where X is a vector of covariates observed in the time period before the placement of subsidized housing as mentioned above

Now let p_i be the predicted probability of being close to a subsidized housing project for the treatment group and p_j be the predicted probability of being close to a subsidized housing project for the control group. A difference-in-difference matching estimator to obtain the causal effect of proximity to subsidized housing projects on neighborhood property values is expressed as .

$$\delta = \sum_{i \epsilon A} \left(\Delta y_i - \sum_{j \epsilon A} g(p_i, p_j) \Delta y_i \right)$$

where Δy_i is the difference in housing price before and after a subsidized housing project was placed in service and g is a function assigning weights to the comparison group j while constructing the counterfactual for house i.

The Difference-in-Difference (DID) matching estimator is different from a simple matching estimator because it compares the before-after outcome of the treatment group and the control group, thereby eliminating unobserved temporally invariant differences**.** It requires repeated cross section data on treatment and control groups. To the best of my knowledge, no one has used this methodology to identify the effect of subsidized housing projects on neighborhood property values.

Once the matching exercise is completed, balancing and specification tests are performed to check the quality of the match. Balancing refers to the fact that after conditioning on the propensity score, the conditioning variables should not differ across treatment and control group across the matched subsample. The specification test, as suggested by Ham et al, (2001) involves testing for mean differences in the lagged outcome across the matched treatment and outcome groups. This is useful because if the lagged outcome is significantly different across the treatment and control group, this is a clear indication of the presence of uncontrolled unobservables that may bias the estimated treatment effect.

VI. Data

The primary source of data for this study is MDPropertyView 2002 Database, a GIS database that consists all arm's length transaction prices for single family houses sold between 2000 and 2007[3]. This dataset is published by Maryland Department of Planning. Any property that did not meet the following criterion was dropped from the database:

- within 2000 meters of an LIHTC project or a buildable open space under consideration (as the outer bound of the effect of LIHTC or apartment building on property values)
- sold once at least a year before the placement of a LIHTC housing project and sold again at least after a year after the placement (to obtain a transaction price before and after the placement of treatment)

This resulted in 6756 repeated sales observations for properties within 2000 meters of an LIHTC project or a buildable open space of which 1134 were in the treatment group (i.e. transactions near LIHTC projects). For properties within 1000 meters of an LIHTC building project or a buildable open space, there were a total of 1750 observations of which 340 were within the treatment group.

Some variables representing housing characteristics used in this paper are – Age and Square of Age of the house (Age, age2). These were included to account for the non linearity in relationship. Other variables added were acreage of the house (Acres) and the number of stories (Story).

[3] Prices were adjusted using the Consumer Price Index (CPI) to a base year of 1983 to account for any inflation.

The variable, “log(pricediff)” measures the log difference in prices before and after the placement of an LIHTC project adjusting for the time difference between the first and second sale. The variable, “treatment”=1 indicates the presence of an LIHTC project with 2000 meters of the property while “percmin” is a measure of the percentage of non-whites within a block group and “loginc” represents the median income of households within a block group[4]. The census data was matched with the transaction data by overlapping the census blocks/ census block groups with geographic coordinates for the properties using GIS techniques.

The Department of Housing and Urban Development (HUD) publishes all the tracts that satisfy the requirements for Qualified Census tract on their website. Information on which tracts within Montgomery County satisfy this critera was noted to create the variable “qct”, which is a dummy referring to whether or not a property lies within a Qualified Census Tract.

Using GIS layers on metro stops, bus stops and priority funding area provided by Montogomery County Board of Supervisors and Planning & GIS Service data, various distance measures are computed. The variable “distance_PFA” measures the distance of a property from nearest Priority Funding Area. The variable “dist_metro” measures distance of a parcel from the nearest metro-station while “dist_bus” measures the distance of a parcel from the nearest bus stop. The variable “dist_DC” measures the distance between a residential parcel and downtown Washington D.C.

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[4] Data on MEDIAN_INC and PERC_MINORITY are obtained from the 2000 Census and values are assigned to properties based on the block group that they lie within

VII. Results

Table 1 provides a description of the variables used in this analysis. Table 2 provides the descriptive statistics for the full sample of properties that are within 2000m of an LIHTC building or an open buildable space. Table 3 provides summary statistics for the full sample treatment and control group for properties within the 2000m radius. Table 4 provides the summary statistics for a subsample of treatment and control groups that are matched after treatment for properties within the 2000m radius. The mean distance to the nearest priority funding area (distance_PFA) differs significantly for the treatment and control groups before matching. The same holds true for distance to nearest bus stop, metro station and Washington D.C. (dist_bus, dist_metro, dist_DC). Also, the percentage of minority within a census block (percmin) is higher in treatment areas than control areas. Notice that these differences are minimized in the case of the matched treated and matched untreated. That is the counter factual looks identical to the treated in observable covariates, essentially eliminating outliers from the original dataset. This fact is also observed in the reduction of number of observations between the matched versus the unmatched cases. The reduction occurs because these observations were considered “off support” as there were no untreated observations in the control group with close enough propensity scores to those removed in the treated group. Tables 5, 6 and 7 repeat the same exercise for the case where only properties within 1000m of an LIHTC building or a buildable open space.

The first stage of the difference in difference matching analysis involves estimating a probit model of the propensity for a house to be near a LIHTC project[5]. Two probit models are presented – one for the case where only properties within 2000m of an LIHTC building or an open buildable space are included and another for the case where only properties within 2000m of an LIHTC building or an open buildable space are included. Table 8 shows the result obtained from these models. Most of the variables have the expected signs. An increase in the log median income decreases the probability of locating close to an LIHTC building. An increase in the percentage of minorities has a positive impact on the probability of locating close to LIHTC building. As the distance of a property from state designated PFA increases, the probability of being close to an LIHTC building decreases. The coefficient on distance from the closest metro stop has an unexpected sign but is not statistically significant. As the coefficient on distance of a property to the closest bus stop increases, the probability of locating close to an LIHTC building decreases. Next, as the distance of the parcel from Washington D.C. increases, the probability of locating near an LIHTC building decreases. If a property is located in a Qualified Census tract, it is likely to be closer to an LIHTC building compared to a property not located in a Qualified Census Tract. The age variables have the expected sign, and this accounts for the non linearity in the probability of being close to an LIHTC project. As the number of stories of a house increases, the probability of being close to an LIHTC building increases. This makes intuitive sense because LIHTC buildings are typically high rise and areas with taller residential buildings are more likely to accept an LIHTC building in their neighborhood. Also, as the acreage of the house increases, the probability of locating close to an LIHTC building decreases

[5] The algorithm passed both the balancing and specification test.

Table 9 presents the end results of the difference-in-difference propensity score matching approach for the case where only properties within 1000m of an LIHTC building or an open buildable space are considered. Here, the "average effect of treatment on treated" is calculated as the log difference between the change in housing prices for the treatment group (houses close to an LIHTC housing project) and control group with similar estimated probabilities of being close to a LIHTC project (houses not close to an LIHTC building), adjusting for the time between the two sales. The nearest neighbor approach is implemented, which matches a treatment observation to the single closest control observation. The results from Table 9 show that LIHTC buildings do have a significant negative impact on neighborhood property values. Table 10 repeats the same exercise but this time only utilizing the differences in prices adjusted for time between the sale (as opposed to the log of price difference in Table 9). Again the results are similar and a significant negative impact of an LIHTC building on neighborhood property values is observed. Table 11 and 12 are similar to Tables 9 and 10, but only include properties that are within 1000m of a LIHTC project or an open buildable space. The magnitude of the impact increases in this case and the results are statistically significant.

One important limitation of this study is that we are comparing an LIHTC building to an open buildable space. Thus the value obtained gives us the combined impact of the building itself and all its characteristics (including residents). Future work includes comparing LIHTC buildings to other multi-family housing units to isolate the effect of its characteristics.

VIII. Conclusion

Previous studies on the effect of LIHTC housing projects on neighborhood property values have not been able to arrive at any consensus due to the shortcomings of several different estimation strategies implemented. This study utilizes the difference-in-difference propensity score matching

methodology to estimate the impact of Low Income Housing Tax Credit (LIHTC) projects on neighborhood property values by comparing the difference between pretreatment and post-treatment housing price for neighborhoods that received or did not receive an LIHTC project. With the aid of a scoring procedure for prospective LIHTC projects outlined in the Qualified Allocation Plan for Maryland, a variable measuring distance of a residential parcel to government designated priority funding area (PFA) and another representing whether or not the property is in a Qualified Census Tract (QCT) are used to explain the location of LIHTC projects. This selection is made because LIHTC projects located in PFA's get more points during the selection process and therefore have a higher probability of receiving tax credits. Likewise projects in QCT's get more tax credits than projects not in QCT's. Results show that as the distance of a property from nearest PFA increases, the probability of being close to LIHTC projects decreases. Also, if a property is located within a QCT, it is more likely to be closer to an LIHTC building. Finally, results from the difference-in-difference matching estimator show that proximity to an LIHTC project has a significant negative impact on neighborhood property values with the impact increasing significantly at a distance of 1000m compared to a distance of 2000m.

APPENDIX

TABLE 1: Description of variables

Variable	Description	Unit
Medinc	Median Household Income in Block Group	$
Loginc	Log of Median Household Income in Block Group	
Percmin	Percentage minority population	%
distance_PFA	Distance from nearest Priority Funding Area	meters
dist_bus	Distance from nearest Bus Stop	meters
dist_metro	Distance from nearest Metro Station	meters
dist_DC	Distance from Washington DC	meters
Pricediff	Change in price of a single family house, adjusted for time between two sales	$
Lnpricediff	Log change in price of a single family house, adjusted for time between two sales	$
Qct	Whether a property is located inside a Qualified Census Tract	1= YES
Acres	Acreage of the house	Acres
Age	Age of house	Years
Age2	Square of age of house	
Story	Number of stories	

TABLE 2: Summary Statistics for distance from LIHTC < 2000m

	FULL SAMPLE	
Variable	**Mean**	**Std. Dev.**
Loginc	11.150	0.300
Percmin	30.000	17.660
distance_PFA	191.950	395.240
dist_bus	473.620	660.200
dist_metro	2864.710	2525.480
dist_DC	26556.530	9080.810
Age	29.188	16.634
age2	1128.584	1583.362
Acres	0.273	0.272
Story	1.936	0.355
Qct	0.013	0.116
Number of Observations	**6756**	

TABLE 3: Summary Statistics treated and untreated –
(distance from LIHTC < 2000m)

	TREATED		**UNTREATED**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Loginc	11.110	0.320	11.160	0.290
Percmin	32.000	17.440	29.590	17.680
distance_PFA	230.460	351.200	184.220	403.080
dist_bus	412.680	683.200	485.850	654.900
dist_metro	2257.000	2309.040	2986.670	2549.510
dist_DC	24146.090	10284.190	27040.310	8740.790
Age	35.958	24.233	27.822	14.249
age2	1479.690	2372.768	977.080	1319.553
Acres	0.319	0.305	0.234	0.244
Story	1.879	0.433	1.948	0.336
Qct	0.019	0.137	0.009	0.095
Number of Obs.	**1134**		**5705**	

TABLE 4: Summary Statistics matched treated and matched untreated
(distance from LIHTC < 2000m)

	MATCHED TREATED		**MATCHED UNTREATED**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Loginc	11.13	0.32	11.16	0.29
percmin	29.94	14.89	29.66	17.7
distance_PFA	183.59	282.04	185.3	275.01
dist_bus	472.9	482.2	469.97	491.2
dist_metro	2751.63	2406.92	2786.13	2541.57
dist_DC	26550.38	9794.8	26555.6	9620.05
Age	35.95767	24.23331	34.74059	13.63456
age2	1464.69	2372.768	1852.4082	2282.651
Acres	0.297	0.303	0.2931	0.3098
Story	1.881	0.423	1.894	0.419
Qct	0.012	0.122	0.011	0.127
Number of Obs.	**1134**		**1402**	

TABLE 5: Summary Statistics for distance from LIHTC < 1000m

	FULL SAMPLE	
Variable	**Mean**	**Std. Dev.**
Loginc	11.07122	0.3163367
Percmin	32.77439	19.91858
distance_PFA	171.3894	352.0851
dist_bus	485.054	468.059
dist_metro	2888.958	2636.142
dist_DC	26978.58	9403.403
Age	29.41429	17.83709
age2	1183.18	1790.442
Acres	0.1106269	0.2637272
Story	1.910868	0.3129214
Qct	.012	.123
Number of Observations	**1750**	

TABLE 6: Summary Statistics treated and untreated – (distance from LIHTC < 1000m)

	TREATED		UNTREATED	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Loginc	11.09806	0.2927328	11.06475	0.3215325
Percmin	27.85203	14.44174	33.96134	20.85789
distance_PFA	205.7866	375.8961	163.095	345.7268
dist_bus	431.144	452.877	488.387	470.41
dist_metro	2492.644	2705.573	2984.523	2611.111
dist_DC	25147.98	11076.12	27420	8901.749
Age	36.94412	24.9605	27.59858	15.10157
age2	1286.062	2504.29	989.5773	1509.067
Acres	0.1101735	0.215224	0.1107362	0.287719
Story	1.811765	0.4098814	1.934954	0.2793319
Qct	0.017	0.127	0.010	0.098
Number of Observations	**340**		**1410**	

TABLE 7: Summary Statistics matched treated and matched untreated (distance from LIHTC < 1000m)

	MATCHED TREATED		MATCHED UNTREATED	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Loginc	11.09806	0.2927328	11.03946	0.2923156
Percmin	27.85203	14.44174	27.15898	14.4898
distance_PFA	205.7866	375.8961	209.5362	379.7402
dist_bus	431.144	452.877	439.718	459.735
dist_metro	2492.644	2705.573	2496.525	2706.805
dist_DC	25147.98	11076.12	25139.84	11069.414
Age	36.94412	24.9605	36.8867	25.1679
age2	1286.062	2504.29	1276.014	2503.22
Acres	0.1101735	0.215224	0.116	0.2500073
Story	1.811765	0.4098814	1.825	0.4308077
Qct	0.0132	0.1162	0.0137	0.1134
Number of observations	**340**		**361**	

TABLE 8: Probit Model of location of LIHTC projects (Model I: radius<2000m ; Model II: radius<1000m)

DEPENDENT VARIABLE: treatment		
INDEPENDENT VARIABLES	**Model I**	**Model II**
Loginc	-0.53082	-0.7422
	(-7.7)	(-4.02)
Percmin	0.00275	-0.00378
	(2.42)	(7.46)
dist_pfa	-0.00004	-0.0000324
	(-2.86)	(-6.35)
dist_bus	-0.00049	-0.00063
	(-11.58)	(-14.92)
dist_metro	0.00000264	0.00000393
	(0.18)	(0.97)
dist_DC	-0.00043	-0.000373

	(-10)	(-11.66)
Qct	0.77230	0.6436
	(4.6)	(5.12)
Acres	-0.8345	-0.8774
	(-3.57)	(-3.35)
Story	0.0448	0.6885
	(0.39)	(4.28)
Age	-.0365	-0.01862
	(-4.65)	(-2.55)
age2	.0005306	0.000284
	6.41	(4.63)
Intercept	6.192	12.4052
	(7.63)	(5.63)
Pseudo R2	**0.61**	**0.632**
Log Likelihood	**-2533.84**	**-2592.130**

T-Statistics in parenthesis

TABLE 9: ATT estimation with Kernel Matching method: (radius <1000m)
Dependent variable: Difference in log prices adjusted for time between the two sales
Bootstrapped standard errors (Number of bootstraps = 100)

n. treat.	n. contr.	ATT	Std. Err.	t
1134	1402	-0.191	0.059	-3.258

Note: the numbers of treated and controls refer to actual nearest neighbour matches

TABLE 10: ATT estimation with Kernel Matching method: (radius <1000m)
Dependent variable: Difference in prices adjusted for time between the two sales
Bootstrapped standard errors (Number of bootstraps = 100)

n. treat.	n. contr.	ATT	Std. Err.	t
1134	1402	-43500	20370.713	-2.134

Note: the numbers of treated and controls refer to actual nearest neighbour matches

TABLE 11: ATT estimation with Kernel Matching method (radius <2000m)
Dependent variable: Difference in log prices adjusted for time between the two sales
Bootstrapped standard errors (Number of bootstraps = 100)

n. treat.	n. contr.	ATT	Std. Err.	t
340	361	-0.148	0.075	-2.000

Note: the numbers of treated and controls refer to actual nearest neighbour matches

TABLE 12: ATT estimation with Kernel Matching method (radius <2000m)
Dependent variable: Difference in prices adjusted for time between the two sales
Bootstrapped standard errors (Number of bootstraps = 100)

n. treat.	n. contr.	ATT	Std. Err.	t
340	361	-28500	9589.461	-2.968

Note: the numbers of treated and controls refer to actual nearest neighbour matches

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