Neighborhood Home Price Impacts of Community Development Block Grant Spending: Longitudinal Evidence From Three Jurisdictions

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Abstract

For a half-century, the Community Development Block Grant (CDBG) program has been one of the largest federal programs supporting local economic and community development, although few rigorous evaluations of its impacts have been conducted. This study measures CDBG's local housing market effects using annual data collected over roughly the past 20 years in Jersey City, Los Angeles County, and Washington, D.C., which are analyzed with the adjusted interrupted time series quasi-experimental impact evaluation model. Considerable, non-random selection determines which places receive CDBG-funded investments. Nevertheless, this study finds plausibly causal evidence that these investments produced substantial, persistent changes in the housing price trajectories in low-income neighborhoods. Home prices within 2,000 feet of these investments in Los Angeles County, Jersey City, and Washington, D.C., rose, on average, 5, 16, and 19 percent more than the counterfactual, respectively, although those impacts generally eroded slowly over time. At all sites, effects were measurable up to 2,000 feet in distance but differed in the degree to which they decayed across space. Cross-site differences emerged with respect to when the effects commenced after the CDBG expenditure and how long the effects persisted. Those differences likely reflect cross-site variations in the composition, intensity, and context of CDBG expenditures.

Introduction

Since its passage in 1974, the Community Development Block Grant (CDBG) program has provided billions of dollars in capital investment to local communities through their state and local governments. When it passed, the program replaced several categorical grant programs administered by HUD that sought to improve urban neighborhoods and housing (Rohe and Galster, 2014). Despite a significant decline in real-dollar investment since its peak in the 1970s, the program remains one of the largest federal programs supporting economic and community development (Theodos, Stacy, and Ho, 2017). Over the course of its half-century existence, the program has funded hundreds of thousands of neighborhood enhancements in the form of new community facilities, housing construction and repair, infrastructure improvements, demolition of derelict properties, and business development.

But has the CDBG program improved economic outcomes in low- to moderate-income (LMI) communities? Unfortunately, quasi-experimental statistical analyses of its impacts on neighborhoods have been few, typically considered only a single jurisdiction, and are dated. This limited literature leaves many key aspects of CDBG's area-wide effects unknown or uncertain; those gaps inform the research questions addressed in this paper:

1. Is plausibly causal evidence available that CDBG spending has changed the home price trajectories of LMI neighborhoods?

2. If so, how far, spatially, do those impacts extend?

3. If so, what is the time lag between CDBG spending and this local housing market response, and how long does that response persist?

The research reported here addresses those questions using data collected over roughly the past 20 years in three urban jurisdictions: Jersey City, New Jersey; Los Angeles County, California; and Washington, D.C. (hereafter, DC). The authors selected these jurisdictions because they have high-quality, longitudinal information about their CDBG expenditures and were willing to cooperate in this research. The outcome measure employed is sales transaction prices of individual single-family homes and condominiums. Statistically, the authors model the relationship between individual home sales prices and proximate CDBG-funded investments during previous years at various distances from the sale. Home prices are not only of intrinsic interest, but they also represent an appealing summary indicator because they have long been shown to capitalize many crucial aspects of neighborhood quality of life (Grieson and White, 1989; Palmquist, 1992).

In estimating parameters of those relationships, the authors employ the adjusted interrupted time series (AITS) econometric model, a well-established, quasi-experimental specification for measuring property value impacts of various local investments or land uses. This model assesses impact by comparing levels and trends of home prices before any proximate CDBG-funded investments to those levels and trends after such spending, while controlling for the coinciding price trajectories of other lower-income neighborhoods that do not get such investments during the period. This AITS specification reduces the bias arising from the non-random selection of neighborhoods where CDBG funds are spent. As such, the estimated parameters can be thought of as plausibly causal impact estimates.

The authors find that average home prices within 2,000 feet of CDBG-funded investments in all three study sites rose significantly more than the counterfactual, although those impacts decayed slowly over time. The counterfactual group included sales located between 3,000 and 6,000 feet of a CDBG project and in tracts where the median income was at or below 80 percent of the Area Median Income in 2019. Differences emerged across sites in how long those impacts endured, when they commenced after the CDBG expenditure, and the degree to which the impacts extended across space.

Previous Literature and This Contribution

Despite the program's longevity, size, and importance, limited research exists into the outcomes of CDBG spending. Some studies document how the grants have been spent on specific types of activities (e.g., Rosenfeld et al., 1995; Walker, Abravanel et al., 2002). Others interview local officials to provide qualitative evidence about CDBG's importance for accomplishing community development objectives (Prunella et al., 2012; Prunella, Theodos, and Thackeray, 2014; Walker, Hayes et al., 2002). Yet little quantitative, methodologically rigorous, and recent evidence exists about whether CDBG spending has substantial, measurable impacts on the disadvantaged neighborhoods in which it occurs.

The U.S. Department of Housing and Urban Development (HUD) has commissioned and published two quantitative evaluations of CDBG, which are now dated: Bleakly et al. (1982) and Walker, Hayes et al. (2002). Bleakly et al. analyzed CDBG spending from 1979 to 1981 in 30 Neighborhood Strategy Areas (NSAs) in 20 cities. They observed positive correlations between higher-than-average spending levels on a block and a composite NSA condition index including the percentages of blocks with well-maintained streets, little litter, and landscaping and structures in very good condition. An Urban Institute study (Walker, Hayes et al., 2002; later published as Galster, Walker et al., 2004) examined three summary indicators and found measured multiple dimensions of market activity in census tracts across 17 cities: the median amount of the home purchase loans originated, the home purchase mortgage approval rate, and the number of businesses. They found that cumulative CDBG spending per low-income resident from 1994 to 1996 was positively correlated with 1994-to-1999 changes in those indicators (especially the first, which was highly correlated with home prices) only when tracts received an above-median amount of CDBG investment ($86,737 or more in current dollars). Pooley (2014) compared CDBG spending and changes in mean census tract values of owner-occupied homes in Philadelphia from 1990 to 2009. She found that the percentage growth in mean values was significantly greater than in control tracts only in those tracts receiving at least $964,800 (current dollars) of CDBG spending over 5 years during the 1995-to-2007 period. Overton and Stokan (2023) analyzed the relationship between assessed values of single-family residential properties in Dallas County and the amounts of CDBG spending of various types from 2004 to 2017, using a hedonic regression model with census block group and time fixed effects, 3-year moving average changes in lagged local assessed values, and controls for dwelling and census tract characteristics. They found that more CDBG spending on a parcel for place-based investments—such as housing improvements, demolition, parks and recreation facilities, or water and sewer improvements—were associated contemporaneously, 1 year later, and 2 years later with higher assessed values of single-family residential parcels within 2,000 feet.[1]

Galster, Tatian, and Accordino (2006) is the only study to have used a quasi-experimental design (AITS) to measure CDBG impacts. The authors focused on changes in individual single-family home prices from 1998 to 2004 in the seven Neighborhoods in Bloom (NiB) revitalization target areas in Richmond, Virginia, resulting from a comprehensive set of services and place-based investments jointly funded by HUD's CDBG, HOME, and HOPE VI programs; the Local Initiatives Support Center (LISC); and city general funds. The authors found that during the course of the initiative, the annual growth of home values in the target areas was almost 11 percent greater after controlling for coincident trajectories in lower-income control areas. That positive impact was most strongly observed for blocks exhibiting an above-average concentration of CDBG spending.

Although path-breaking in its efforts to identify plausibly causal impact estimates, the Galster, Tatian, and Accordino (2006) study leaves many questions unanswered. First, given that the NiB initiative involved an unusually well-targeted, long-sustained, wide-ranging amalgam of hard and soft investments and complementary programmatic initiatives that were funded by many city, nonprofit, and federal sources beyond CDBG,[2] how general the findings are for more generic CDBG expenditure patterns exhibited across several jurisdictions is unclear. Second, their study did not investigate the temporal pattern of local housing market responses to the investments or the scale of their spatial externalities. The authors of this article add to those studies with a research design that controls for the likely non-random selection of CDBG spending in neighborhoods based on their preexisting conditions and trajectories. This article builds on their AITS model and employs an updated, long panel of observations in three jurisdictions to address those gaps.

Analytical Approach

Overview

The foremost of several empirical challenges (see Theodos and Firschein, 2015) in obtaining an unbiased estimate of the impacts of place-based investments by public or private entities is that the locations chosen for those investments are typically not representative of all potential places where they might have been made. Some might be selected, for example, because of the expectation that properties there will soon start rapidly inflating in value because the jurisdiction may want to put its resources into places where it perceives the market will respond to those investments. In another case, a place might not yet be on the cusp of revitalizing, but some added public investment might be sufficient to encourage market response. Conversely, jurisdictions might choose the neediest, hardest-to-redevelop places for attention on equity grounds.

[1] Overton and Stokan (2023) employ block-group fixed effects and a 3-year-lagged moving average of land values as controls. Unfortunately, both of those values are endogenous with previous, spatially clustered CDBG expenditures, as is likely given the findings in Figure 3 that display the geographic and temporal patterns of these expenditures. As such, their CDBG impact estimates are likely biased downward.

[2] All the city's CDBG funds for 5 years were targeted to a single area. For more comprehensive descriptions of the NiB Program, see Accordino, Galster, and Tatian (2005) and Rossi-Hansberg, Sarte, and Owens (2010).

Regardless, neighborhoods observed with place-based investments are unlikely to perform in many dimensions in the same way as others, even those that are similar in many observable characteristics. Given those expected idiosyncrasies of targeted neighborhoods, program impact evaluators find it difficult to identify valid counterfactuals against which to compare their performance after intervention. That is, accurately measuring the degree to which changes in targeted neighborhoods post-investment are due to the intervention or would have occurred in any event is problematic.

This article employs the adjusted interrupted time series (AITS) model to meet the challenge of non-random selection of neighborhood investments. AITS represents an amalgam of the well-known interrupted time series (ITS) and difference-in-differences (DiD) approaches to quasi-experimental impact assessment.[3] From ITS, AITS employs the intuition that the impact of a place-based investment ("treatment") will manifest itself as a post-treatment change in the pre-treatment trend or level—or both—of the outcome indicator in question. But the internal validity of ITS is threatened if (1) the sample of treated neighborhoods is not randomly chosen or (2) both treated and non-treated neighborhoods are influenced by some exogenous force coincident with the post-treatment period. The ITS estimator thus requires "adjustment" to address both possibilities, as is at the core of the DiD approach. The standard DiD estimator is the difference between pre-treatment and post-treatment differences between treated and control neighborhoods in the mean *level* of the outcome indicator. Its internal validity is threatened by pre-intervention *trends* in the outcome indicator that differ between control and treatment areas. Instead of assuming those trends are parallel, as in DiD, AITS controls for them explicitly. Thus, its estimate of impact is the difference between pre-treatment and post-treatment differences between treated and control neighborhoods in both the mean *level* and *trends* of the outcome indicator.[4]

AITS Model for Addressing the Research Questions

In this study, the core AITS model of the impacts of CDBG-funded investments on nearby home prices is expressed symbolically:

$$[1]\ P_{it} = c + \alpha_{1d}\, T_{id} + \alpha_2\, TR_t + \alpha_{3d}\, (T_{id} * TR_t) + \delta_{1d}\, PostT_{id} + \delta_{2d}\, (PostT_{id} * TR_t)$$
$$+ [\lambda_s][STRUCT_s] + [\eta_k][JURIS_k] + [\psi_t][CYCLE_t] + \beta SPACET_{it} + [\varphi_L](\mathrm{LAT/LON}_i) + \epsilon_{it}$$

where—

P is the natural logarithm of the sales price of a single-family home or condominium;

i represents the individual home sale;

t represents the year;

[3] For a comparison of the internal validity of the AITS and other quasi-experimental approaches, see Galster, Temkin, et al. (2004).

[4] AITS has already been successfully employed in community development evaluation research appearing in many peer-reviewed articles (e.g., Galster, Tatian, and Accordino, 2006; Galster, Temkin et al., 2004; Nygaard, Galster, and Glackin, 2022; Woo, Joh, and van Zandt, 2016). An independent assessment of the method concluded that "the AITS method can produce compelling evidence on the effects of place-based intervention" (Deng and Freeman, 2011: 310). Colwell, Dehring, and Lash (2000) and Ellen and Voicu (2006) employ models that are intuitively similar to, but operationally somewhat different from, AITS.

c is a constant;

T_{id} is a dummy variable denoting whether the sale i is in the "treatment group," i.e., will receive or has received CDBG investment anytime within distance d (2,000 feet in the core model) during the analysis period;

TR_t is an annual trend variable taking the value one in the first year of the analysis period, two in the second year, and so forth;

$PostT_{id}$ is a dummy variable denoting whether sale i has been "treated", i.e., *has* received CDBG investment within distance d at any time (within the analysis period) prior to the time of sale i;

[$STRUCT_s$] is a set of s structural characteristics for the dwelling sold;

[$JURIS_k$] is a set of dummy variables denoting the political jurisdiction (city or county) where the sale occurred;

[$CYCLE_t$] is a set of dummy variables denoting the expansionary or contractionary stage of the regional housing market cycle during year t;

$SPACET_{it}$ is a spatial lag in the dependent variable (a control for spatial autocorrelation);

LAT/LON_i is the latitude and longitude of the ith sale (a control for spatial heterogeneity of the time-invariant characteristics of the local geography);[5] and

ϵ_{it} is a random error term with the usual assumed statistical properties.

The interpretation of the key impact parameters of (1) follows. Coefficients α_{1d} and α_{3d} measure the degree to which the areas where sales have or will be treated by nearby CDBG-funded investments systematically differ from control areas in their level and/or trend in prices, respectively; they represent the controls for non-random targeting of CDBG. Coefficients δ_{1d} and δ_{2d} measure average treatment effects of nearby CDBG-funded investments on the level or trend in prices, respectively, and represent the answers to the first research question.

For the second research question, about the extent of spatial externalities, T_{id} in (1) is replaced with a set of dummy variables denoting whether CDBG-funded investment was ever within 0 to 250 feet; 251 to 500 feet; 501 to 1,000 feet; or 1,001 to 2,000 feet. Given that little variation in impacts emerged over those ranges, the authors employ for subsequent analysis the simpler specification of a single, 2,000-foot-radius impact area.[6]

The third research question, about the temporal pattern of impacts, is addressed by replacing T_{id} in (1) with time dummy variables denoting the most recent year that any CDBG-funded investment occurred within 2,000 feet: 1 year ago, 2 years ago, and so forth. That specification tests how long impacts take to appear and then (potentially) decay over time after the last investment has been made in the vicinity by the time of sale.

[5] See Can and Megbolugbe (1997).

[6] This approach is comparable to the one in Overton and Stokan (2023).

Data

CDBG Data

The authors gathered annual information about the amounts, types, and locations of CDBG expenditures directly from three local jurisdictions that agreed to collaborate on this research. The Jersey City Division of Community Development supplied that information for 1994 through 2019; the Los Angeles County Development Authority for 2009 through 2021; and the DC Department of Housing and Community Development for 2000 through 2020.[7] Although the sites reflect diversity of region and size, the authors make no claims about the representativeness of the three study sites; descriptive statistics for the demographic, economic, and housing characteristics of those places are provided in appendix exhibit A1.

Because this study focuses on the spatial impact of CDBG-funded investments, the analysis excludes CDBG-funded activities related to the provision of social services, funding of administrative personnel, planning, administration, Section 108 repayments, and other non-place-specific activities. See appendix exhibit A2 for a list of HUD matrix codes for place-based project types included in this study; the authors geocoded those CDBG-funded, place-based investments.

Descriptive statistics for the CDBG (inflation-adjusted) expenditure patterns during the analysis periods of this study are presented in exhibit 1. They show large cross-site variation in total CDBG funding, how those funds were distributed across different parcels, and their spatial concentration. DC received the largest annual average grant during the period ($17.9 million per year), followed by Los Angeles County ($9.9 million) and Jersey City ($5.7 million). DC also devoted by far the largest median amount of CDBG invested in a parcel ($563,730); by contrast, the figures were $74,351 for Jersey City and only $8,725 for Los Angeles County. The spatial concentrations of CDBG-funded investments were extremely different across the sites: annual spending per square mile of the jurisdiction varied from a high of $387,026 in Jersey City to a low of $2,450 in Los Angeles County. Jersey City focused most investments on its Martin Luther King Drive Redevelopment Plan, a 26-block-long (about 1.5 miles) project focused on the comprehensive revitalization of the main retail corridor of the city.

[7] Within Los Angeles County are many other CDBG entitlement jurisdictions whose investments are not considered here, including Compton, Glendale, Inglewood, Long Beach, Los Angeles City, Monterey Park, Palmdale, Pasadena, Pomona, Redondo Beach, and Santa Monica. See https://www.hudexchange.info/grantees/allocations-awards. Many of the CDBG investments analyzed were located in those jurisdictions within Los Angeles County, however. The practical implication of this spatial overlap is that some areas specified in this study as "control" because they had no Los Angeles County-funded CDBG nearby may, in fact, have been the site of investments funded by the smaller jurisdiction's CDBG allocation. To the extent that the control areas were contaminated in that way, the impact estimates will be biased downward.

Exhibit 1

Descriptive Statistics of CDBG Place-Based Investment Expenditures During the Analysis Period, by Site

	Jersey City, NJ	Los Angeles County, CA	Washington, D.C.
CDBG funding years analyzed	1994-2018	2009-2018	2000-2020
Total CDBG-funded projects*	443	436	307
Total CDBG funding*	$142,618,921	$99,422,948	$376,571,809
CDBG funding* per year	$5,704,757	$9,942,295	$17,931,991
CDBG funding* per year per sq. mi.	$387,026	$2,450	$293,726
N of parcel x year observations^	1,919	11,531	668
Average CDBG amount per project	$321,939	$230,746	$1,226,618
Median CDBG amount per project	$76,648	$140,473	$197,587
Average amount per parcel x year	$74,351	$8,725	$563,730
Median amount per parcel x year	$5,140	$1,605	$33,999
Projects by Category:			
Business development	24	26	46
CDBG funding	$51,453,695	$6,897,976	$22,617,855
Share of all CDBG funding	36.1%	6.9%	6.0%
Public facilities	129	32	26
CDBG funding	$35,563,404	$20,667,458	$63,543,390
Share of all CDBG funding	24.9%	20.8%	16.9%
Acquisition	40	4	111
CDBG funding	$21,784,160	$3,128,281	$227,430,730
Share of all CDBG funding	15.3%	3.1%	60.4%
Residential development	203	317	116
CDBG funding	$13,849,880	$52,546,292	$46,554,707
Share of all CDBG funding	9.7%	52.9%	12.4%
Infrastructure	27	55	6
CDBG funding	$11,319,229	$16,182,941	$12,627,842
Share of all CDBG funding	7.9%	16.3%	3.4%
Demolition	20	2	2
CDBG funding	$8,648,553	$1,182,225	$3,797,285
Share of all CDBG funding	6.1%	1.2%	1.0%

** Projects that could be accurately geocoded during analysis period shown.*

^ Observations of Community Development Block Grant (CDBG)-funded investment parcels joined to home sales data for adjusted interrupted time series modeling.

Note: All dollar figures are adjusted to constant 2019 dollars.

Source: Author's analysis of CDBG investment data from Jersey City, Los Angeles County, and Washington, D.C.

Cross-site variations are also apparent in the types of neighborhoods targeted, the types of investments supported, and how investment types were combined in the same project. The 2000 median values of owner-occupied homes within CDBG treatment areas were $127,200 in Jersey City, $137,200 in DC, and $190,800 in Los Angeles County (all expressed in 2000 dollars). The median poverty rates within treatment areas were 10 percent in Los Angeles County, 16 percent in Jersey City, and 20 percent in DC. Within treatment areas, the median percentage non-White population share ranged from 69 percent in Los Angeles County to 95 percent in DC.

How the jurisdictions invested their CDBG funds was also different. DC allocated more than 60 percent of its CDBG funding over the period to property acquisition; Los Angeles County allocated more than 50 percent to residential development (typically, small-scaled home rehabilitation); and Jersey City allocated more than 30 percent to business development and about 25 percent to public facilities. Finally, the jurisdictions bundled various types of investments in distinctive ways within the same target area. Almost 25 percent of the treated home sales were treated with at least five different investment types in Jersey City, whereas only 3 percent of sales in DC and no sales in Los Angeles County were so treated. At the other end of the spectrum, 35 and 95 percent of the treated home sales were treated with only one type of investment in DC and Los Angeles County, respectively, whereas just 16 percent were so treated in Jersey City. The combinations of treatments that were associated most often with bundling also varied across sites. In Jersey City, treated homes were frequently exposed to combined housing/public facilities and acquisition/business development investments; demolition often occurred with acquisition and infrastructure. In DC, acquisition/public facilities (sometimes also with housing) and acquisition/infrastructure/public facilities/business development were oft-observed combinations of treatments. In Los Angeles County, the only noticeable (but rare) pairing was acquisition and business development; the vast majority of investments were solely single-family rehabilitation (see Theodos, Galster, and Hermans, 2024 for additional information).

In sum, the three study sites reflect wide variations in multiple dimensions of how they have employed their CDBG dollars. Unfortunately, that multidimensional variability challenges the ability to interpret cross-site variations. Put differently, the nature of the CDBG "treatment" is different—it is applied with different intensities and in different contexts across the three study sites—so findings are challenging to parse.

Home Sales and Structural Characteristics Data

The authors secured information on single-family (detached, townhouse, cooperative, and condominium) property values from the Zillow transaction and assessment dataset (Z-TRAX). Z-TRAX provides records of individual properties' sales prices, addresses, and limited structural characteristics.[8] Data were available from 2000 to 2019 (2022 in the case of DC). Those home data were employed for the three study jurisdictions and the adjacent counties (cities, in the case of Jersey City) to provide a more expansive set of observations for use as control area sales, as explained below.

The home sales and CDBG information were merged using both time and spatial criteria. For each sale in the jurisdiction (and its associated control areas in adjacent jurisdictions) beginning in 2001 (2010 in the case of Los Angeles County due to its more limited CDBG data), the authors coded the annual amount and types of CDBG expenditures that had occurred (if any) within several, mutually exclusive concentric distance rings centered on the sale, beginning the year before the

[8] Zillow shared Z-TRAX with the Urban Institute through a research partnership.

sale and continuing to the earliest year for which CDBG data were available for that jurisdiction.[9] Those bespoke distance rings were 0 to 250 feet; 251 to 500 feet; 501 to 1,000 feet; 1,001 to 2,000 feet; 2,001 to 3,000 feet; and 3,001 to 6,000 feet.[10]

Variable Specifications

As is conventional in hedonic price models, the dependent variable is the natural logarithm of the home sales price. The CDBG impact variables of primary interest are as specified in equation 1. As controls for property characteristics, dummy variables are employed denoting size (number of bedrooms in Los Angeles County; bathrooms in DC); structure type (single-family detached; townhouse; condominium in multifamily structure; co-op in multifamily structure), year built, and political jurisdiction. Business cycle fixed effects control for cyclical macroeconomic conditions affecting the metropolitan area-wide property market, distinguished by three periods: 2001 through 2007, 2008 through 2013, and 2014 and after.[11] The authors employ the spatial lag of housing prices[12] to control for spatial autocorrelation and the latitude and longitude of the property control for spatial heterogeneity (Can and Megbolugbe, 1997). The latter can be viewed as controls for unmeasured attributes of the local natural and built environment. Descriptive statistics for all those variables are in appendix exhibit A3.

Designation of Treatment and Control Groups

The authors assigned sales observations that had received in the past or would receive in the future any CDBG-funded investments within 2,000 feet of the treatment group. The control group was assigned observations if they (1) were within 3,001 and 6,000 feet of a treatment group sale; (2) were located in an LMI census tract; and (3) did not qualify for the treatment group. The intuition behind the control group selection criteria was that the authors sought sales from places that were eligible for CDBG-funded investments, were relatively near those that did, and did not receive any. The 2,000-foot limit for defining the treatment group was based on preliminary analyses and a

[9] The authors recognize that the analysis period has observations that are left-censored (i.e., missing older data) for CDBG and right-censored (i.e., missing newer, future data) on home sales. Although that censoring likely erodes the statistical power of efforts to identify temporal patterns of responses to CDBG-funded investments, the authors do not believe it to bias. The left-censoring may overstate the impacts of CDBG at the beginning of the panel because other CDBG spending may previously have occurred in those locations. On the other hand, it may understate the impact if the previous spending occurred in places assigned to the control group. Nevertheless, this study has much longer panels of CDBG spending in all of the study sites than the only previous quasi-experimental impact evaluation of CDBG, which was 5 years (Galster, Tatian, and Accordino, 2006).

[10] This specification of bespoke distance rings to measure the extent of externalities is conventional (Baum-Snow and Marion, 2009; Ding and Knaap, 2003; Galster, Tatian, and Smith, 1999; Koschinsky, 2009; Nygaard, Galster, and Glackin, 2022; Overton and Stokan, 2023; Santiago, Galster, and Tatian, 2001; Schwartz et al., 2006). For a critique of this approach, see Diamond and McQuade, 2019.

[11] All three of the study sites exhibited similar metropolitan home price trajectories during the designated periods: expansion—2000 through 2007; contraction—2008 through 2013; expansion thereafter. See https://realestatedecoded.com/case-shiller/.

[12] The authors operationalize this value as the weighted average of sales prices in the same census tract and all adjacent tracts in the previous year.

large body of previous research on place-based investment externalities.[13] To ensure that the control group sales were free from potential contamination, however, the authors mandated an additional 1,000 feet of separation from any CDBG spending. The sample selection processes resulted in the following numbers of home sales observations (treatment group sales shown parenthetically), with full information that meets the selection criteria: Jersey City = 46,872 (45,676); Los Angeles County = 166,036 (136,923); DC = 106,554 (92,354).

In all three study sites, substantial numbers of sales in control areas are in LMI census tracts in adjacent political jurisdictions, which raises the specter of potential unobserved contamination of control areas, whereby, unbeknownst to the authors, the adjacent jurisdictions may have spent CDBG or other funds to revitalize those areas. To the degree that such contamination was present, it would bias downward the impact estimates. Another potential problem arises in Jersey City because its small geographic scale renders few observations of home sales in LMI areas beyond 3,000 feet of treatment areas. As a result, sales in control areas are notably clustered outside the Jersey City jurisdiction, especially in Union City. However, because all those adjacent New Jersey communities can be considered reasonably close-substitute housing markets, the authors anticipate no major bias arising from that circumstance.

Results

Before discussing spatial variation and temporal patterns of CDBG impacts, this paper first presents the core model's CDBG impact. Impacts are evident in all three study sites, though the extent of those impacts vary.

Core Model of CDBG Impacts

The authors estimated the parameters for equation 1 in each of the study sites using ordinary least squares (exhibit 2). Overall, the model performance was acceptable, given the paucity of dwelling characteristics available as covariates. The authors focus on the variables unique to the AITS specification. As predicted, the places where jurisdictions directed CDBG-funded investments were distinctly different in their housing price trajectories from other LMI neighborhoods in the vicinity (see the coefficients for the "CDBG treatment group" in exhibit 2). In Jersey City and DC, the price level in the treatment group was 12 percent and 6 percent lower, respectively, than in the control group.[14] Turning next to trends (see the coefficients for the "CDBG Treatment Group Trend" in exhibit 2), however, the comparative price trends pre-treatment were significantly higher—by 3 percentage points in Jersey City and 2 percentage points in DC. Those sets of findings suggest

[13] Baum-Snow and Marion (2009) observed LIHTC impacts within a single ring of 3,274 feet (1 km). Rossi-Hansberg, Sarte, and Owens (2010) and Diamond and McQuade (2019) observed small effects of place-based developments beyond 2,000 feet, but the vast majority of studies do not (Baird et al., 2020; Colwell, Dehring, and Lash, 2000; Ding and Knaap, 2003; Ding, Simons, and Baku, 2000; Ellen et al., 2001; Ellen and Voicu, 2006; Koschinsky, 2009; Leonard, Jha, and Zhang, 2017; Nygaard, Galster, and Glackin, 2022; Overton and Stokan, 2023; Santiago, Galster, and Tatian, 2001; Schwartz et al., 2006; Simons, Quercia, and Maric, 1998; Wilson and Bin Kashem, 2017). See the review in Thomson (2008).

[14] In a semi-log model such as this study, one cannot interpret coefficients of dummy variables (C) as percentage differences in prices unless one transforms them using the standard formula: 100 [exp(C) – 1] (Halvorsen and Palmquist, 1980). This means that the transformed results discussed in the text will appear slightly different than the non-transformed results for dummy variables shown in the tables.

that in those two jurisdictions, CDBG spending was directed primarily to neighborhoods that were most disinvested but were apparently rebounding. Los Angeles County reflects the opposite pattern: target areas exhibited 19-percent-higher price levels but with slower-growing trends relative to other LMI areas. Results in all three sites also confirm the importance of employing the AITS estimator for impact evaluation because the parallel price trends pre-treatment assumption required for DiD internal validity (Wooldridge, 2002) is violated.

Exhibit 2

Estimated Parameters of AITS Model of Home Price Impacts of CDBG-Funded Investments, by Study Site (1 of 2)

VARIABLES	Jersey City, NJ	Los Angeles County, CA	Washington, D.C.
CDBG Treatment^ Group	– 0.133*** (0.0472)	0.177*** (0.00607)	– 0.0581*** (0.0122)
Time Trend	0.0500*** (0.00352)	0.0495*** (0.00101)	0.0273*** (0.00105)
CDBG Treatment^ Group Time Trend	0.0338*** (0.00715)	– 0.0136*** (0.00125)	0.0191*** (0.00145)
CDBG Treated^ Group (i.e., after treatment)	0.149*** (0.0292)	0.0453*** (0.00495)	0.176*** (0.00855)
CDBG Treated^ Group Time Trend (after treatment)	– 0.0422*** (0.00645)	– 0.0155*** (0.00108)	– 0.0329*** (0.00131)
Contraction Period 2008–13	– 0.336*** (0.0137)	N/A	– 0.0524*** (0.00636)
Expansion Period 2014+	– 0.514*** (0.0212)	0.0481*** (0.00383)	– 0.0196* (0.0107)
Single Family (vs. 2–4 unit)	0.142*** (0.0397)	0.158*** (0.00423)	– 0.220 (0.137)
Condominium (vs. 2–4 unit)	– 0.108*** (0.0390)	– 0.148*** (0.00585)	– 0.413*** (0.137)
Cooperative (vs. 2–4 unit)	0.624 (0.432)	– 0.578*** (0.0953)	N/A
Number of Bathrooms	N/A	N/A	0.201*** (0.00193)
Number of Bedrooms	N/A	0.0961*** (0.000994)	N/A
Jersey City (vs. Secaucus/Weehawken)	0.381*** (0.0852)		
Hoboken (vs. Secaucus/Weehawken)	0.432*** (0.0856)		
Bayonne (vs. Secaucus/Weehawken)	0.460*** (0.0945)		
Union City (vs. Secaucus/Weehawken)	0.128 (0.0866)		

Exhibit 2

Estimated Parameters of AITS Model of Home Price Impacts of CDBG-Funded Investments, by Study Site (2 of 2)

VARIABLES	Jersey City, NJ	Los Angeles County, CA	Washington, D.C.
North Bergen (vs. Secaucus/Weehawken)	0.248*** (0.0958)		
Los Angeles County (vs. Ventura County)		– 0.451*** (0.0223)	
Orange County (vs. Ventura County)		– 0.454*** (0.0285)	
San Bernardino County (vs. Ventura County)		– 0.628*** (0.0483)	
District of Columbia (vs. Prince George's County)			0.503*** (0.00778)
Montgomery County (vs. Prince George's County)			0.426*** (0.0141)
Spatial Lag of Home Prices	2.29e-06*** (3.09e-08)	1.53e-06*** (3.86e-09)	1.64e-06*** (1.50e-08)
Latitude	– 1.691*** (0.275)	– 0.602*** (0.00569)	0.336*** (0.0574)
Longitude	3.517*** (0.293)	0.0672*** (0.00574)	– 3.114*** (0.0674)
Constant	340.5*** (30.44)	40.29*** (0.718)	– 241.6*** (5.040)
Year Built Fixed Effects	YES	YES	YES
Observations	46,872	166,036	106,554
R-Squared	0.354	0.649	0.621
Period of Sales Analyzed	2000–2019	2010–2019	2001–2022 Q1

*** $p<0.01$. ** $p<0.05$. * $p<0.1$.

AITS = adjusted interrupted time series. CDBG = Community Development Block Grant. N/A = not applicable. Q1 = first quarter.

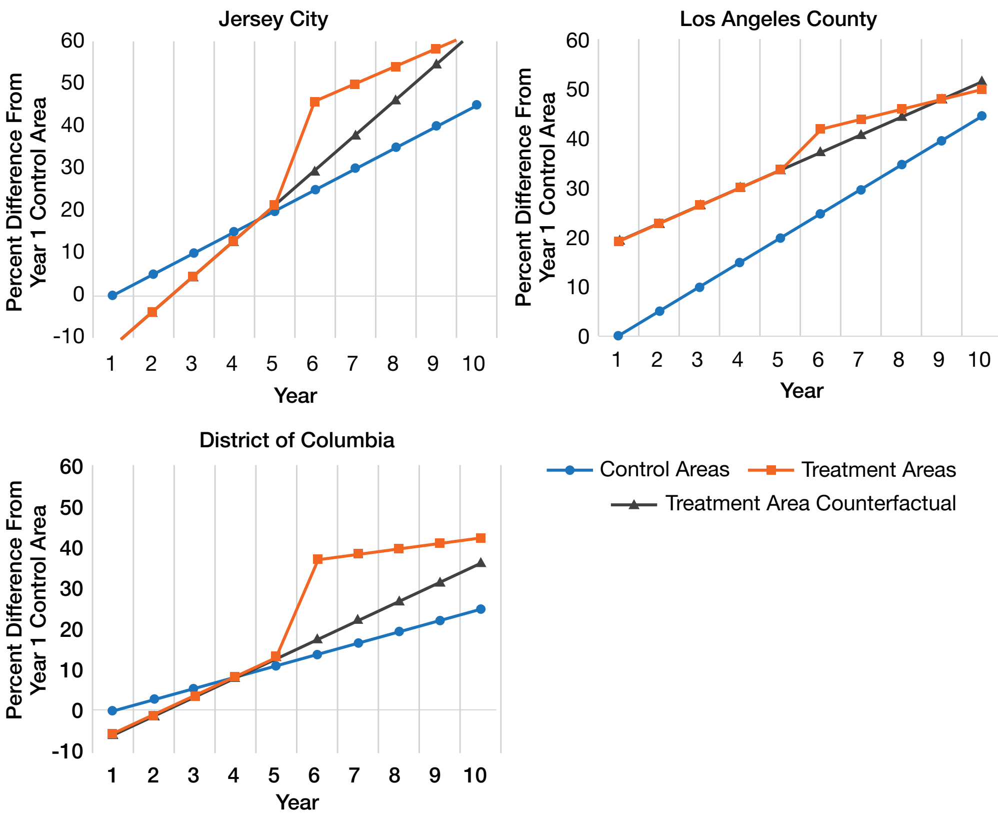
Note: Standard errors in parentheses.

Source: Authors' analysis of CDBG and Z-TRAX data in Jersey City, Los Angeles County, and Washington, D.C.

Looking next at impacts (see the coefficients for the "CDBG treated group" and its time trend in exhibit 2), the clear result across all three jurisdictions was that CDBG-funded investments were associated with a significantly (statistically and substantively) higher level of housing prices within 2,000 feet but a lower subsequent rate of increase (which can be interpreted as temporal erosion in the initial impact) compared with the counterfactual. The initial price level impacts were 16 percent in Jersey City, 5 percent in Los Angeles County, and 19 percent in DC. The reduction in price trend effects was minus 4, minus 2, and minus 3 percentage points in annual growth for Jersey City, Los Angeles County, and DC, respectively. How those two sorts of impacts interact can be most easily portrayed graphically. Exhibit 3 shows (in the line with squares) the predicted home price trajectory for a typical treatment area associated with a typical CDBG-funded investment in (arbitrarily chosen) year 5 during the analysis period in the particular jurisdiction. The counterfactual is the projected pre-treatment home price trend, shown in the line with triangles. The trend for low- to moderate-income control area prices is also portrayed (in the line with diamonds) for comparison. Exhibit 3 shows, first, that the initial positive impacts fade over time; the authors probe this temporal pattern in depth below. It shows, second, that typical impacts are comparatively small and short-lived in Los Angeles County, which is unsurprising given the weak intensity of treatment that the aforementioned small amounts of widely scattered CDBG funds represented there.

Exhibit 3

Graphic Representation of Home Price Trajectories Associated with CDBG-Funded Investment



CDBG = Community Development Block Grant.
Source: Authors' calculations based on parameters in exhibit 2

Although the impacts measured for DC and Jersey City are substantial, they are not out of line with those estimated by Galster, Tatian, and Accordino (2006) for Richmond's aforementioned NiB initiative, using a similar econometric approach. After inflating the dollar amounts invested in this program to be equivalent to the 2019 dollars used here, the NiB invested, on average, about $100,000 per block in the target areas over the course of 5 years, with funding sourced by CDBG (35 percent), other federal programs (42 percent), and the Local Initiatives Support Center (22 percent). At the end of the program, home prices in target areas were almost 55 percent higher than they were a year before the program started, controlling for coincident trends in other LMI neighborhoods and other non-NiB neighborhoods in Richmond. Unfortunately, those researchers did not investigate how the short-term impacts may have eroded over time.

Model of Spatial Variation of CDBG Impacts

The authors of this study explored whether spatial heterogeneity was present in the apparent impacts shown in exhibits 2 and 3 by reestimating equation 1 with the more fine-grained distance rings specified above. The results are in exhibit 4, with parameters for controls omitted for brevity. Exhibit 4 shows, first, that the apparent non-random selection of treatment neighborhoods persists across smaller scales. That is, both the direction and magnitudes of both pre-investment price levels and trends in the treatment group are quite homogenous over a range of 2,000 feet in all three study sites. That finding indicates that the jurisdictions did not seem to be "micro-targeting" specific neighborhood contexts.

Exhibit 4

Estimated Parameters of Core AITS Model of Home Price Impacts of CDBG-Funded Investments, by Study Site, Alternative Impact Distances (1 of 2)

	Jersey City, NJ	Los Angeles County, CA	Washington, D.C.
Treatment Group Within 250’	– 0.236***	– 0.0378***	– 0.195***
	(0.0233)	(0.0101)	(0.0200)
Treatment Group Within 251–500’	– 0.280***	– 0.0542***	– 0.102***
	(0.0188)	(0.00762)	(0.0121)
Treatment Group Within 501–1,000’	– 0.283***	– 0.000137	– 0.133***
	(0.0206)	(0.00584)	(0.00955)
Treatment Group Within 1,001–2,000’	– 0.137***	0.136***	– 0.145***
	(0.0407)	(0.00581)	(0.0104)
Time Trend	0.0413***	0.0434***	0.0215***
	(0.00309)	(0.000936)	(0.000976)
Treatment Group Time Trend Within 250’	0.0171***	0.00598**	0.0177***
	(0.00374)	(0.00247)	(0.00303)
Treatment Group Time Trend Within 251–500’	0.0218***	0.00468**	0.0108***
	(0.00295)	(0.00183)	(0.00168)
Treatment Group Time Trend Within 501–1,000’	0.0242***	-0.000176	0.0124***
	(0.00311)	(0.00137)	(0.00142)
Treatment Group Time Trend Within 1,001–2,000’	0.00964*	– 0.0114***	0.0244***
	(0.00556)	(0.00123)	(0.00137)
Treated Within 250’	0.131***	0.0236	0.160***
	(0.0283)	(0.0168)	(0.0283)
Treated Within 251–500’	0.230***	0.0319***	0.160***
	(0.0216)	(0.0119)	(0.0175)
Treated Within 501–1,000’	0.0628***	0.00345	0.122***
	(0.0190)	(0.00793)	(0.0124)

Exhibit 4

Estimated Parameters of Core AITS Model of Home Price Impacts of CDBG-Funded Investments, by Study Site, Alternative Impact Distances (2 of 2)

	Jersey City, NJ	Los Angeles County, CA	Washington, D.C.
Treated Within 1,001–2,000’	0.0918***	0.0454***	0.179***
	(0.0252)	(0.00563)	(0.00934)
Treated Group Time Trend Within 250’	– 0.0132***	– 0.00723**	– 0.0187***
	(0.00396)	(0.00311)	(0.00331)
Treated Group Time Trend Within 251–500’	– 0.0252***	– 0.00386*	– 0.0164***
	(0.00307)	(0.00225)	(0.00188)
Treated Group Time Trend Within 501–1,000’	– 0.0159***	– 0.00176	– 0.0146***
	(0.00307)	(0.00158)	(0.00153)
Treated Group Time Trend Within 1,001–2,000’	– 0.0215***	– 0.0124***	– 0.0308***
	(0.00488)	(0.00117)	(0.00134)
Observations	46,872	166,036	106,554
R-Squared	0.370	0.648	0.623

**** p<0.01. ** p<0.05. * p<0.1.*

AITS = adjusted interrupted time series. CDBG = Community Development Block Grant.

Notes: Standard errors in parentheses. Models include controls, as in exhibit 2.

Source: Authors’ analysis of CDBG and Z-TRAX data in Jersey City, Los Angeles County, and Washington, D.C.

Of more core interest, exhibit 4 shows that the apparent impacts from CDBG-funded investments (1) are measurable up to a distance of 1,000 to 2,000 feet and (except in Los Angeles County) within all closer distance rings; (2) generally decay with distance (except in Los Angeles County); and (3) do not persist as long past 1,000 feet. The authors hypothesized that the greatest initial impacts would occur closest to the investment, given prior research (Colwell, Dehring, and Lash, 2000; Diamond and McQuade, 2019; Nygaard, Galster, and Glackin, 2022; and Rossi-Hansberg, Sarte, and Owens, 2010).[15] In this study, that conventional pattern was exhibited in DC, where price levels were boosted by 15 to 21 percent within 500 feet but only by 7 to 9 percent from 501 to 2,000 feet. In Jersey City, the impacts were 14 to 26 percent within 500 feet but only 6 to 10 percent from 501 to 2,000 feet. In Los Angeles County, however, distance decay was not apparent within 2,000 feet.

Although the consistently negative post-treatment trend variable coefficients indicate that at all distances, the initial impacts fade over time, the largest amount of such temporal erosion occurred at the farthest distance (except for Jersey City). This new and intriguing finding seems plausible inasmuch as the long-standing physical changes in the neighborhood environment directly funded by CDBG (new construction or rehabilitation of housing and community facilities, infrastructure improvements, etc.) are less visible beyond the immediate environs.

[15] However, Theodos et al. (2021) did not find distance decay effects for the New Markets Tax Credit program.

Model of Temporal Pattern of CDBG Impacts

Results for the variation on equation 1 employing dummy variables denoting the most recent year that any CDBG-funded investment occurred within 2,000 feet are in exhibit 5. On overview, two points stand out. First, the linear post-treatment trend estimated in the basic AITS model (exhibit 2) oversimplifies the temporal pattern of impacts. Second, the temporal patterns of home price level impacts were very different across sites.

Exhibit 5

Estimated Parameters of AITS Model of Home Price Impacts of CDBG-Funded Investments, by Site and Timing of Most Recent Investment

	Jersey City, NJ	Los Angeles County, CA	Washington, D.C.
CDBG Treatment^ Group	– 0.124***	0.177***	– 0.0557***
	(0.0443)	(0.00607)	(0.0122)
Time Trend	0.0526***	0.0493***	0.0283***
	(0.00350)	(0.00101)	(0.00107)
CDBG Treatment^ Group Time Trend	0.0191***	– 0.0136***	0.0192***
	(0.00655)	(0.00125)	(0.00145)
CDBG Treated^ Group Time Trend	– 0.0271***	– 0.0181***	– 0.0312***
	(0.00575)	(0.00109)	(0.00133)
Last Treated^ 9+ Years Ago	0.200***	0.0692***	0.118***
	(0.0262)	(0.0227)	(0.0117)
Last Treated^ 8 Years Ago	0.0872***	0.136***	0.146***
	(0.0287)	(0.0147)	(0.0127)
Last Treated^ 7 Years Ago	0.185***	0.121***	0.141***
	(0.0287)	(0.0114)	(0.0123)
Last Treated^ 6 Years Ago	0.132***	0.0949***	0.122***
	(0.0277)	(0.00953)	(0.0116)
Last Treated^ 5 Years Ago	0.173***	0.0767***	0.129***
	(0.0274)	(0.00804)	(0.0111)
Last Treated^ 4 Years Ago	0.0920***	0.0763***	0.179***
	(0.0270)	(0.00708)	(0.0107)
Last Treated^ 3 Years Ago	0.0251	0.0787***	0.181***
	(0.0263)	(0.00631)	(0.00995)
Last Treated^ 2 Years Ago	0.0424*	0.0754***	0.177***
	(0.0257)	(0.00566)	(0.00971)
Last Treated^ 1 Year Ago	– 0.00588	0.0427***	0.157***
	(0.0253)	(0.00501)	(0.00889)
Observations	46,872	166,036	106,554
R-Squared	0.360	0.649	0.621

*** $p<0.01$. ** $p<0.05$. * $p<0.1$.

^ within 2,000 feet.

AITS = adjusted interrupted time series. CDBG = Community Development Block Grant.

Notes: Standard errors in parentheses. Models include controls, as in exhibit 2.

Source: Authors' analysis of CDBG and Z-TRAX data in Jersey City, Los Angeles County, and Washington, D.C.

In Jersey City, the expenditure of CDBG funds did not have an impact (9 percent) for 3 years, rising to 10 percent after 4 years and 18 percent after 5 years. Those impacts persisted (with some year-to-year variation) at roughly the same magnitude (if not larger, i.e., 22 percent) after 9 years, if not longer. By contrast, in DC, the impacts arose at almost full magnitude the year after the CDBG expenditure (i.e., 17 percent, rising to 20 percent) but began tapering off after 4 years while still remaining significant after 9 years (13 percent). The temporal patterns were different in Los Angeles County yet again. Impacts registered after 1 year (4 percent), remained roughly constant (7 to 8 percent) for the next 4 years, rose from 10 to 14 percent over the next 3 years, and finally diminished thereafter (to 7 percent). The authors attribute those differences in temporal patterns to systematically different types and intensities of investments funded by CDBG and to different neighborhood and market contexts.

The results in this study mirror the similarly disparate findings of previous studies of the temporal pattern of place-based investment impacts. Ellen and Voicu (2006) find that the positive price spillovers in New York City from publicly funded, rehabilitated subsidized multifamily units did not decline over time, whereas those generated by private, unsubsidized infill construction did decline. Koster and van Ommeren (2019) found that the home price increases in distressed Dutch neighborhoods (0.9 square mile in size) resulting from the rehabilitation of large public housing estates emerged within 2.5 years of project completion and grew steadily up to 7.5 years after the investment (the end of their analysis window). Diamond and McQuade (2019) found considerable differences in temporal patterns depending on neighborhood context. The positive price impacts of LIHTC developments in the lowest-income-quartile of U.S. neighborhoods began immediately after funding for the project was announced and rose steadily for the next 10 years. By contrast, negative impacts after project announcement continued to accumulate slowly over 10 years in third-income-quartile neighborhoods, whereas they registered immediately in the highest-quartile neighborhoods. Overton and Stokan (2023) found for most categories of place-based CDBG expenditures in Dallas County that impacts were higher after a 1-year lag than they were when measured either contemporaneously or with a 2-year lag; longer lags were not investigated.

Discussion and Conclusion

The CDBG program is one of the largest community/economic development tools available to states and local governments. More than 5 decades old, it is also one of the longest standing. Its ability to fund a variety of projects and its structure of giving control over many decisions to states and local governments pose challenges for understanding the impacts. For example, Jersey City spent a plurality of its CDBG funds on business development but also combined that investment with sustained redevelopment of a main retail corridor. Los Angeles County's CDBG-funded investments emphasized small-scale residential development projects scattered across the jurisdiction. And DC invested the most CDBG funds per project, particularly for property acquisition but often combined with other investment types.

The authors observed that in all three study sites, the places where CDBG-funded investments were targeted did not represent a random sample of the jurisdiction's LMI neighborhoods. Whether by accident, policymakers' strategic designs, or particular neighborhood groups' effective advocacy, in Jersey City and DC, those selections built on preexisting positive trends in the neighborhood property market. The authors also observed impacts of a substantial boost in home prices within 2,000 feet of CDBG-funded investments. By contrast, in Los Angeles County, CDBG-funded investments were targeted to less-disadvantaged places, but their trends were underperforming those in other LMI neighborhoods. That targeting (coupled with a much less intense treatment) yielded weaker and short-lived changes in local market trajectories in Los Angeles County. If those results may be generalized, they imply that local planners will likely gain more traction from their CDBG-funded investments if they build on existing momentum in localized property markets with a substantial concentration of resources. That statement echoes a long-standing conclusion about targeting in the CDBG and place-based program evaluation literature (Bleakly et al., 1982; Galster, 2019: ch. 11; Galster, Walker et al., 2004; Pooley, 2014; Rohe and Galster, 2014; Theodos, 2022a,b,c; Thomson, 2008).

Although the authors observed positive externalities as far as 1,000 to 2,000 feet from CDBG-funded investments, the distance decay patterns were different across sites. Previous research indicates that impact spatial decay patterns likely depend on the type of place-based investment generating the property value externalities; see Baird et al. (2020); Baum-Snow and Marion (2009); Colwell, Dehring, and Lash (2000); Ding, Simons, and Baku (2000); Diamond and McQuade (2019); Nygaard, Galster, and Glackin (2022); Overton and Stokan (2023); Rossi-Hansberg, Sarte, and Owens (2010); Santiago, Galster, and Tatian (2001); Schwartz et al. (2006); Simons, Quercia, and Maric (1998); Theodos et al. (2021). The authors therefore suspect that much of the cross-site heterogeneity in the spatial patterns of price impacts observed can be traced to their different compositions of the CDBG-funded investments and perhaps their intensity, concentration, and neighborhoods targeted, suggesting an important topic for future research.

The authors also observed heterogeneity in the timing of impacts across sites, which may be explained by variable completion periods for different place-based investments. Moreover, in the period before completion, the area may undergo temporary disruptions, depending on the investment—for example, the exterior rehabilitation of several single-family homes, a major sewer replacement, or the construction of a new community center. Finally, timing of observed impacts may be complicated by anticipation effects. If the planned investment is highly visible, large scale, and well publicized in advance, the property market may well register price gains before construction begins, as speculators perceive future arbitrage opportunities (as observed by Baum-Snow and Marion, 2009; Colwell, Dehring, and Lash, 2000). Nevertheless, the findings from this study indicate that local policymakers should not expect long lags between when they spend their CDBG funds and resulting property market impacts.

The authors employed quasi-experimental econometric methods to investigate whether CDBG-funded investments can change the home price trajectories of LMI neighborhoods. This research study, although a meaningful contribution to the understanding of the program, should not be the final word. Spatial spillovers from certain types of CDBG-funded investments may be greatest within line-of-sight, so future studies might explore impacts using block-face geographies. Even longer panels of CDBG spending and home price data will be required to probe further the provocative finding that impacts decay over time. This study examined outcomes for only three entitlement communities, and, given their idiosyncratic CDBG spending patterns, how well those outcomes can be generalized to other jurisdictions is unclear. Only one outcome is examined in this study, and although a parsimonious measure of community impacts, other measures are also worthy of investigation.

From this analysis of longitudinal data from the past 2 decades in Jersey City, Los Angeles County, and DC, the authors conclude that CDBG-funded, place-based investments (especially in Jersey City and DC, where they were applied more intensely) plausibly caused substantial and long-lived boosts to the local home sales market, indicating that their positive externalities were being capitalized within a range of 2,000 feet. A notable observation is that statistically significant impacts occurred in all three study sites, in light of the large variation in the amounts, types, and bundling of CDBG-funded investments that these jurisdictions exhibited. Given that evidence of the CDBG program's widespread efficacy, Congress would do well to reevaluate the wisdom of allowing the budget for this program to continually decline in inflation-adjusted terms.

Appendix

Exhibit A1

Characteristics of the Study Sites

	Jersey City, NJ			Los Angeles County, CA			Washington, D.C.		
	Non-White (%)	Poverty (%)	Price ($2,000)	Non-White (%)	Poverty (%)	Price ($2,000)	Non-White (%)	Poverty (%)	Price ($2,000)
Mean	68.7%	16.4%	$173,889	66.8%	13.4%	$228,687	82.6%	20.9%	$178,447
Minimum	22.1%	0.0%	$0	8.6%	0.0%	$0	10.0%	1.2%	$0
1st Quartile	60.4%	9.7%	$113,900	48.5%	6.3%	$157,700	74.0%	13.1%	$108,800
Median	72.7%	16.0%	$127,200	68.9%	10.1%	$190,800	94.8%	19.6%	$137,200
3rd Quartile	81.7%	21.1%	$157,400	90.1%	18.3%	$269,300	98.5%	27.3%	$183,400
Maximum	99.5%	49.3%	$625,000	99.8%	67.1%	$1,000,001	100.0%	63.4%	$1,000,001
N Treated Sales	45,676	45,676	45,676	136,923	136,923	136,923	92,354	92,354	92,354

Non-White = those who are not Non-Hispanic White. Price = median value of specified owner-occupied dwellings ($0 = insufficient N to estimate).
Note: Poverty based on all persons for whom poverty status is determined.
Source: 2000 U.S. Decennial Census

Exhibit A2

HUD Matrix Codes in This Study, Grouped by Spending Category (1 of 2)

Acquisition projects include HUD Codes 1 (Acquisition of Real Property); 14G (Rehab: Acquisition)

Business development projects include HUD Codes 14E (Rehab: Publicly or Privately Owned Commercial/Industrial); 17A (Commercial/Industrial: Acquisition/Disposition); 17C (Commercial/Industrial: Building Acquisition, Construction, Rehabilitation); 17D (Commercial/Industrial: Other Improvements)

Demolition projects include HUD Codes 04 (Clearance and Demolition); 07 (Urban Renewal Completion)

Infrastructure projects include HUD Codes 03H (Solid Waste Disposal Improvements); 03I (Flood Drainage Improvements); 03J (Water/Sewer Improvements); 03K (Street Improvements); 03L (Sidewalks); 04A (Cleanup of Contaminated Sites); 05V (Neighborhood Cleanups); 11 (Privately Owned Utilities); 17B (Commercial/Industrial: Infrastructure Development)

Exhibit A2

HUD Matrix Codes in This Study, Grouped by Spending Category (2 of 2)

Public facility projects include HUD Codes 03A (Senior Centers); 03B (Handicapped Centers); 03C (Homeless Facilities [not operating costs]); 03D (Youth Centers); 03E (Neighborhood Facilities); 03F (Parks, Recreational Facilities); 03G (Parking Facilities); 03M (Child Care Centers); 03N (Tree Planting); 03O (Fire Stations/ Equipment); 03P (Health Facilities); 03Q (Facilities for Abused and Neglected Children); 03S (Facilities for AIDS Patients [not operating costs]); 16B (Non-Residential Historic Preservation); and 23 (Tornado Shelters Serving Private Mobile Home Parks)

Residential development projects include HUD Codes 12 (Construction of Housing); 13 (Direct Homeownership Assistance); 14A (Rehab: Single-Unit Residential); 14B (Rehab: Multi-Unit Residential); 14C (Rehab: Public Housing Modernization); 14D (Rehab: Other Publicly Owned Residential Buildings); 14H (Rehab: Administration); 16A (Residential Historic Preservation)

108 loan projects included HUD Codes 19F (Planned Repayments of Section 108 Loans) and 19G (Unplanned Repayments of Section 108 Loans). 108 loan projects were recategorized into whichever of the previous six categories best fit the funded activity for the purpose of analysis.

Exhibit A3

Descriptive Statistics of Variables in AITS Model, by Site (1 of 3)

Jersey City, NJ					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Ln (home sales price)	46,872	12.49992	0.754267	9.21034	15.42495
CDBG Treatment group^	46,872	0.974484	0.157689	0	1
Time Trend	46,872	9.269052	5.599561	1	19
CDBG Treatment^ Group Time Trend	46,872	9.023788	5.711419	0	19
CDBG Treated^ Group	46,872	0.932284	0.251261	0	1
CDBG Treated^ Group Time Trend	46,872	8.859575	5.892199	0	19
Contraction Period 2008–2013	46,872	0.176438	0.381196	0	1
Expansion Period 2014+	46,872	0.317439	0.465485	0	1
Single-Family Unit	46,872	0.473332	0.499294	0	1
Condominium	46,872	0.520823	0.499572	0	1
Cooperative	46,872	4.27E-05	0.006532	0	1
Duplex or Quad	46,872	0.005803	0.075957	0	1
Jersey City	46,872	0.805044	0.396171	0	1
Hoboken	46,872	0.116658	0.321016	0	1
Bayonne	46,872	0.006934	0.082981	0	1
Secaucus	46,872	0	0	0	0
Union City	46,872	0.060932	0.239208	0	1
North Bergen	46,872	0.009302	0.095998	0	1
Weehawken	46,872	0.001131	0.033608	0	1
Spatial Lag	46,872	339896.9	163464	70830.4	967118
Latitude	46,872	40.72681	0.019118	40.67615	40.77395
Longitude	46,872	– 74.0608	0.021218	– 74.1075	– 74.0239
Year Built	46,872	1950.147	40.48773	1714	2021

AITS = adjusted interrupted time series. CDBG = Community Development Block Grant. Max = maximum. Min = minimum. Obs = observations. Std. Dev. = standard deviation.

Note: ^ within 2,000 feet.

Source: Authors' analysis of CDBG and Z-TRAX data in Jersey City, Los Angeles County, and Washington, D.C.

Exhibit A3

Descriptive Statistics of Variables in AITS Model, by Site (2 of 3)

Los Angeles County, CA					
Variable	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Ln (home sales price)	166,036	12.90941	0.659977	9.21034	15.42495
CDBG Treatment Group^	166,036	0.824659	0.38026	0	1
Time Trend	166,036	5.317666	2.802759	1	10
CDBG Treatment^ Group Time Trend	166,036	4.410429	3.25244	0	10
CDBG Treated^ Group	166,036	0.579055	0.493712	0	1
CDBG Treated^ Group Time Trend	166,036	3.635802	3.650298	0	10
Contraction Period 2008–2013	166,036	0.422932	0.494026	0	1
Expansion Period 2014+	166,036	0.577068	0.494026	0	1
Single-Family Unit	166,036	0.711412	0.453107	0	1
Condominium	166,036	0.203022	0.40225	0	1
Cooperative	166,036	0.000102	0.010118	0	1
Duplex or Quad	166,036	0.085463	0.279571	0	1
Number of Bedrooms	166,036	3.208828	1.300619	0	32
Los Angeles County	166,036	0.994459	0.074231	0	1
Orange County	166,036	0.003005	0.054739	0	1
San Bernardino County	166,036	0.000512	0.02262	0	1
Ventura County	166,036	0.002024	0.04494	0	1
Spatial Lag	166,036	504962.1	293549.8	66661.18	1999775
Latitude	166,036	34.05701	0.18665	33.74588	34.80317
Longitude	166,036	– 118.135	0.191621	– 118.833	– 117.699
Year Built	166,036	1961.855	26.51551	1821	2021

CDBG = Community Development Block Grant. Max = maximum. Min = minimum. Obs = observations. Std. Dev. = standard deviation.

Note: ^ within 2,000 feet.

Source: Authors' analysis of CDBG and Z-TRAX data in Jersey City, Los Angeles County, and Washington, D.C.

Washington, D.C.					
Variable	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Ln (home sales price)	106,554	12.69391	0.771108	9.21034	15.42295
CDBG Treatment Group^	106,554	0.866734	0.339863	0	1
Time Trend	106,554	11.389	6.243762	1	22
CDBG Treatment^ Group Time Trend	106,554	10.07577	7.046699	0	22
CDBG Treated^ Group	106,554	0.681223	0.466005	0	1
CDBG Treated^ Group Time Trend	106,554	9.21941	7.789721	0	22
Contraction Period 2008–2013	106,554	0.212259	0.408909	0	1
Expansion Period 2014+	106,554	0.434296	0.495667	0	1
Single-Family Unit	106,554	0.604576	0.488944	0	1
Condominium	106,554	0.395311	0.48892	0	1
Cooperative	106,554	0.000113	0.010612	0	1
Number of Bathrooms	106,554	1.951184	0.881727	0.5	10.5
District of Columbia	106,554	0.873285	0.332655	0	1

Exhibit A3

Descriptive Statistics of Variables in AITS Model, by Site (3 of 3)

Washington, D.C.					
Variable	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Montgomery County	106,554	0.015438	0.123288	0	1
Prince George's County	106,554	0.111277	0.314476	0	1
Spatial Lag	106,554	407134.9	192781.4	56973.22	1602267
Latitude	106,554	38.9096	0.033035	38.80901	38.99792
Longitude	106,554	– 76.9982	0.03689	– 77.0638	– 76.8894
Year Built	106,554	1945.097	37.00281	1780	2020

CDBG = Community Development Block Grant. Max = maximum. Min = minimum. Obs = observations. Std. Dev. = standard deviation.
Note: ^ within 2,000 feet.
Source: Authors' analysis of CDBG and Z-TRAX data in Jersey City, Los Angeles County, and Washington, D.C.

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