The Positive Spillovers to Risky Investments in Vacant, Abandoned, and Disinvested Properties

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1 Overview

Disadvantaged and underserved communities are disproportionately vulnerable to the effects of climate risks on property values (Clayton et al. (2021); Bunten and Kahn (2014)). Infill development is a growing strategy to redevelop vacant, abandoned, and disinvested (VAD) land in urbanized areas (McConnell and Wiley (2011)). In the 209 largest U.S. metropolitan areas, infill was estimated to comprise of 21% of new housing development (U.S. Environmental Protection Agency (2014)). These policies offer important environmental and social benefits by mitigating urban sprawl and promoting economic stabilization (U.S. Environmental Protection Agency (2014, 2007)). In addition to direct benefits of infill development, scholars have argued that these policies generate positive housing externalities to nearby communities (Rossi-Hansberg and Sarte (2012); Schwartz et al. (2006); Bourassa, Hoesli and Sun (2005)). Housing externalities are often debated in the context of government revitalization projects, in which public funds can stimulate private housing investment in neighboring areas (Rossi-Hansberg and Sarte (2012); Rossi-Hansberg, Sarte and Owens III (2010)). If nearby housing investments are compliments, then prior theory predicts neighborhood revitalization. In contrast, if private investors view revitalization as a substitute for their own investment and instead benefiting from the total nearby investment, then theory predicts no significant neighborhood revitalization.

However, the spillover benefits of infill development on nearby properties have been hard to measure. This is because impact evaluation is not only information intensive, but also the civic data necessary for evaluation is often siloed in city information systems and other public data sources (Glaeser and Poterba (2020, 2021)). These issues make it difficult to quantify social benefits, which remain uncertain. This leads to potential investors and lenders to view infill development, particularly in climate-disadvantaged areas, as risky (U.S. Environmental Protection Agency (2015)).

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In this study, we evaluate the long-run impact of infill development in Savannah, Georgia, a major port city in the US. The city boasts significant economic activity, but its various neighborhoods have struggled with climate-related issues, leading to blighted properties that incur an estimated $ 5.6 million per year (i.e. $1300 per property) in costs that is used to address overgrown grass, litter, illegal dumping, securing open structures and demolishing properties, and lost property tax revenue (City of Savannah (2020)). In response, the city has been implementing infill development interventions targeted towards income-qualified and distressed city blocks with the goal of neighborhood revitalization. In this paper, we studied the extent to which government-funded revitalization stimulates spillover gains in appraised property values. We used web scraping and record linkage procedures to analyze the spillover effects of infill development with large scale civic data, which includes 2.43 million yearly records for 104,836 parcels covering the years 2001-2022. Given higher resolution data, we address issues related to observational bias and other empirical challenges common in many evaluation studies. Our analysis revealed that next door neighbors of infill development experienced the highest increase in appraised value for several years following the initial intervention. We show that infill policies led to substantial market value (i.e. an estimated $1.8 million) which largely stay within in climate-disadvantaged communities at the block scale rather than neighborhood boundaries as often theorized. We also test theories of agglomeration economies and find that these benefits tend to be concentrated in blocks where infill developments are more densely located. We quantify social benefits that might otherwise remain hidden from policymakers and investors.

2 Research Question

Do urban infill developments stimulate amenity effects in low-moderate income communities?

Hypothesis 1: *Infill development strategies on VAD properties increase nearby appraised property values through an amenity effect.*

Hypothesis 1a: *Infill development on VAD properties increase nearby appraised property values through an amenity effect, especially for properties in closest range to the infill site.*

Hypothesis 1b: *Infill development on VAD properties increase nearby appraised property values through an amenity effect, especially for properties in areas with high concentration of infill development.*

3 Related Literature

Prior evidence and results of the spillover effects of infill development have been relatively mixed. Some studies have shown that nearby houses experience positive housing externalities and improved perception through the "amenity" effect (Ooi and Le (2013); Ellen et al. (2001); Brunes et al. (2020); Ding, Simons and Baku (2000); Zheng, Li and Lv (2020); Kurvinen and Vihola (2020); Nordahl and Sommervoll (2020); Ellen and Voicu (2006, 2014)). For example,

Ooi and Le find that in Singapore, sales prices of properties within 500 meters from an infill site increased by 1.22% (Ooi and Le (2013)). On the contrary, other studies have suggested that infill development can lead to adverse effects such as increased traffic/congestion and loss of green space that result in nearby resident resistance (Funderberg and MacDonald (2010); Newell (2010); Malpezzi (1996); Preez (2013)). Funderberg and MacDonald conducted a study in Polk County, Iowa and found that low-rise construction projects were associated with a 2-4% decrease in valuation for nearby single-family houses (Funderberg and MacDonald (2010)). Furthermore, others have found that infill development produces negligible impacts on surrounding properties, suggesting that positive spillovers due to the amenity effect and negative externalities may balance out (Ahvenniemi et al. (2018); Blanchard, Clegg and Martin (2008)).

4 Data

4.1 Data Sources

To evaluate program spillovers including economic returns and selection criteria, we obtained historical data for all 396 publicly-funded infill projects in Savannah, GA, from 2004-2019. These projects are independently managed by the City of Savannah Housing and Neighborhood Services, which administers housing repair, construction, and development projects, targeted to qualified households with modest and limited income. The program data includes the service address, parcel ID, the year receiving infill assistance, and direct total program expenditures as tracked and provided to us by city administrators.

To obtain detailed housing characteristics such as the square footage, year built, number of rooms, and yearly appraised building property values, we compiled data from the Chatham County Tax Assessor Database for the period 2001-2022. We accessed geospatial data from the Savannah Area Geographic Information System (SAGIS) to identify the location of target and surrounding properties. SAGIS maintains parcel and neighborhood-level geocoding and shape files (e.g. converting location descriptions into latitude and longitude) for all residential parcels in Chatham County. We also obtained socioeconomic characteristics at the Census block group level including income, population density, educational attainment, age, etc. from the 2019-2023 5-year American Community Survey. In the next section, we describe protocols for record linkage and automated data collection.

4.2 Record Linkage and Automated Data Collection

The City of Savannah leverages open data platforms to make property and neighborhood-level information publicly available. Through a collaborative partnership with the city, we obtained parcel and address-level records on 104,836 residential properties in Chatham County. This includes 78,864 residential properties within the city limits. For program evaluation, we performed record linkage using the 10-digit numeric parcel ID as the primary linking variable. We match records across the various information sources by parcel ID because it is a unique and complete identifier that avoids common errors in string matching by address. We note that the vast majority of parcels only contain a single property, so

we use the terms parcel and property interchangeably. During the period of study, an infill project can only receive funding once. We successfully merged all 396 documented infill projects with 104,836 residential parcels. Of these 104,440 parcels available for counterfactual analysis, approximately 5% (5,223 parcels) were not usable due to missing geocoded fields. We confirmed that the missing data did not statistically change the distribution of our key performance outcomes (KS test p-value = 0.999). This yielded an unbalanced panel of 2.43 million observations of record-linked, housing performance data. We provide further details on the variables and their data sources in Table A1.

As part of our collaboration with the City of Savannah Housing and Neighborhood Services, we developed a custom web scraping tool to automatically query and download all relevant civic data from the Chatham County assessor database. This allowed us to mitigate search costs and time associated with large-scale data collection from separate city departments. To do this, we deployed two open-source Python libraries, namely Beautiful Soup and Selenium, to automatically read, click through and store structured data from webpages inside the Chatham County Tax Assessor database. To disseminate the use of these automated data collection tools, we open source a user-friendly implementation. In an ongoing collaboration with city officials, we held a workshop to test and pilot its use in data science workforce training and development. This allowed city managers to query custom parcels as part of their workflow. We note that such strategies are becoming increasingly important given that small to medium sized cities do not necessarily have in-house data science teams (materials here).

5 Empirical Strategy

To estimate the spillover effects of infill developments, we use a propensity score weighted difference-in-differences (DiD) design that compares properties within a certain distance from an infill site to properties outside the distance. We expect there to be covariate imbalance between properties neighboring infill developments and other properties, which can lead to violations of the parallel trends assumption, particularly if observable characteristics are correlated with outcome dynamics. Under the conditional parallel trends assumption discussed in Abadie (2005), we incorporate propensity score weighting and other matching procedures with staggered DiD estimators to more credibly identify the spillover effects of infill development (Abadie (2005)). We found that, without covariate balance, there are severe pre-trend violations that resulted in negatively biased treatment effect estimates (see Figure A3). We also implement alternative counterfactuals with synthetic controls to quantitatively validate our program evaluation.

5.1 Spatial Identification and Statistical Matching

To precisely identify properties that are close to infill developments, we create a variable, $Dist_i$, as the distance (in meters) between property i and the nearest infill project. We define an infill zone as a perimeter area k meters from the centroid of an infill site. We consider properties within an infill zone to be treated, and those outside an infill zone to be non-treated. To identify spillover effects as opposed to direct intervention effects, infill zones

include neighboring parcels but exclude infill sites where $Dist_i = 0$. We express parcels that are within k meters from an infill site as a binary indicator:

$$Near_i^k = \mathbb{1}_{0<Dist_i \leq k} \tag{1}$$

In this study, we test for potential spillovers at distances of $k = 25, 50, 75, 100$. Increments of 25 meters are chosen since this is approximately equal to the average parcel length in Chatham County. This spatial cutoff allows us to identify granular treatment effects at the city block level and down to the nearest neighbor.

Prior infill studies have often constructed counterfactual zones by selecting adjacent reference properties or setting a broad geographic boundary such as neighborhoods (Rossi-Hansberg and Sarte (2012); Ooi and Le (2013); Brunes et al. (2020)). This is usually under the assumption that properties closer together might be similar on observable characteristics. However, this choice of using adjacent properties as counterfactual is somewhat arbitrary and its validity depends critically on housing stock characteristics. To define more precise statistical comparison groups, we employ data-driven matching procedures that leverage any available parcels in Chatham County to ensure pre-treatment covariate balance between the infill zone (where we test for potential spillovers) and weighted counterfactual areas.

We evaluated propensity score matching (PSM) and genetic matching procedures to achieve covariate balance between infill zone properties and our reference properties (Diamond and Sekhon (2013); Rosenbaum and Rubin (1983); Stuart et al. (2011)). Given substantial median bias across variables known to impact property values, we matched on property characteristics (i.e., year built, number of stories, quality, distance to nearest green space, type of building) and socioeconomic characteristics at the block group level (i.e., population density, income level, % black population, % single female household). We included those variables for matching through a process of feature selection for overt bias (see Table A2). Given recent insights from the statistical literature, we did not match on pre-treatment outcomes due to the known regression-to-the-mean effect, which can inject bias (Ham and Miratrix (2024)). We derived optimal matching parameters such as the caliper and ratio for at each infill zone to ensure covariate balance. For comparative evaluation of matching effectiveness, we report standardized & median bias reduction across all matched covariates in Table A4. We chose genetic matching as our preferred procedure, as we found that genetic matching consistently achieves better bias reduction with a 98-99% bias reduction across all infill zone distances from 25-100 (see Table A4).

5.2 Treatment Effects Under Staggered Adoption

To estimate the spillover benefits of neighborhood improvements on surrounding properties, we employ a DiD approach to compare changes in appraised values of properties near an infill project before and after the development relative to changes in values of other properties within the same time period. Infill projects were administered at yearly budget cycles from 2004-2019 with an average of 26.4 projects administered every year. Our baseline model uses a two-way fixed effects (TWFE) specification including unit and year fixed effects:

$$y_{i,t} = \alpha_i + \lambda_t + \beta \cdot Near_i^k \cdot Post_{i,t} + \epsilon_{i,t} \tag{2}$$

where $y_{i,t}$ is the normalized appraised parcel value ($) divided by living area (in sqft) for property i at year t; α_i represents unit fixed effects; λ_t represents yearly fixed effects; $Post_{i,t}$ is a binary indicator that is encoded as 1 when a property i's closest infill was built prior to or at year t; β is the estimated coefficient that represents the spillover effect; and $\epsilon_{i,t}$ is an error term. Under the parallel trend assumption and simultaneous adoption, we can interpret β as the average causal effect of a property being within k meters from an infill development.

There is a large literature on the consistent estimation of TWFE in the presence of heterogeneous effects over time, particularly when there are multiple dates of treatment (Sun and Abraham (2021); Goodman-Bacon (2021); Callaway and Sant'Anna (2021); Athey and Imbens (2022); de Chaisemartin and D'Haultfœuille (2020)). Given the staggered implementation of infill projects, one potential concern is that treatment effects estimated in a given year could be contaminated by cohort effects in previous years. To address this issue, we implement the staggered DiD estimator proposed by Sun & Abraham (Sun and Abraham (2021)). In Figure A3, we show that TWFE exhibits a downward bias in treatment effect estimates when compared with the preferred staggered DiD estimator.

To understand how treatment effects may vary with years of exposure, we also estimated an extension of our baseline model that includes leads and lags of the treatment. The dynamic model is estimated as follows:

$$y_{i,t} = \alpha_i + \lambda_t + \sum_{l=-18}^{-2} \beta_l \cdot Near_i^k \cdot D_{i,t}^l + \sum_{l=0}^{19} \beta_l \cdot Near_i^k \cdot D_{i,t}^l + \epsilon_{i,t} \tag{3}$$

where l is relative year of the infill construction, $D_{i,t}^l$ is a dummy variable for whether property i is l years away from an infill's year of construction at year t. Given the annual time series of normalized property values, we use the year preceding the intervention as the reference year ($l = -1$). Our stacked regression includes all available years prior to the intervention (2-18 lags) years and all years post intervention (0-19 leads). To estimate Equation 3, we implement the dynamic model extension of the Sun & Abraham estimator Sun and Abraham (2021). The estimator ensures that the β_l coefficients for leads and lags are not contaminated by heterogeneous treatment effects in other periods by estimating cohort average effects relative to never treated units. The dynamic specification also allowed us to visually assess the plausibility of the parallel trend assumption by checking for pre-trends in years prior to treatment (see Figure A2). In pre-trends test, we found that parallel trends does not hold in staggered DiD models without matching as described in section 3.1.

5.3 Aggregating to Blocks

Infill developments are dispersed unevenly across Savannah, where some city blocks receive heavier investment than others. To analyze how the effect of the infill policy varies by infill density, we perform an aggregate analysis that uses parcel data aggregated at the block level. We adopt an identification strategy based on the infill density of a block, which we define as follows for a city block j:

$$density_j = \frac{\text{\# of infill properties in block } j}{\text{\# of properties in block } j} \tag{4}$$

To test for treatment effects that vary with infill density, we consider blocks that contain at least one infill development and rank them by infill density as defined in (4), splitting them into quintiles. We then perform an aggregate analysis by taking averages of parcel-level appraised values and pre-treatment covariates at the city block level. We do not include infill properties in the aggregate outcome. For each quintile of treated blocks, we employ the same empirical strategy used for the parcel-level analysis. Therefore for each block, we use genetic matching to construct a group of counterfactual blocks similar in observable characteristics aggregated to the block level, and then estimate staggered DiD treatment effects with the Sun & Abraham estimator (Sun and Abraham (2021)).

5.3.1 Alternative Counterfactuals with Synthetic Controls

In settings where panel data is reported at aggregate levels such as countries, cities, or other jurisdictions, researchers will often use the synthetic control method (SCM) as an alternative to difference-in-differences (Abadie, Diamond and Hainmueller (2010)). The synthetic control method constructs a counterfactual by taking a weighted average of control units to minimize imbalance in pre-treatment outcomes between the treated and control unit. For alternative counterfactuals, we implement the partially pooled SCM (Ben-Michael, Feller and Rothstein (2021)). Partially pooled SCM is a generalization of SCM that allows for analysis in the staggered adoption setting by finding a weighted average of control units that minimize pre-treatment imbalance for individual treated units and average pre-treatment imbalance across all treated units. We find a separate set of weights to construct counterfactuals for each quintile of blocks, and estimate quintile treatment effects.

5.4 Placebo/Falsification Tests

To validate the robustness of our results, we conducted falsification tests by restricting the analysis period to observations prior to an intervention year. In this way, we were able to test for treatment effects versus our matched reference group where none are logically possible. We did this placebo test by restricting our observations of treated parcels to those that occurred prior to the nearest infill construction. We then set a new "treatment" year to be the mid-point between that property's earliest year and newly assigned latest year. For example, if a property is within 25 meters from an infill property that was constructed in 2009, we only considered observations from 2001-2008 and reassign its year of treatment to be 2005. Next, to ensure that the matched observations coincide with those in the treated group, we only considered observations that occurred prior to the last year of an infill construction. We then implemented the staggered DiD estimator proposed by Sun and Abraham and used the same specifications in our main results to calculate treatment effects. We provide a summary of these results in Table A8 at multiple distances between 25-100 meters. As expected, we recovered effects not statistically different from zero for all distances at the 5% level.

6 Results

6.1 Spatial Distribution of Infill Development

To assess the spillover impacts of housing policies, we first explored the spatial and individual characteristics of properties in proximity to parcels targeted for infill development within the last 20 years. Targeted blocks occur most commonly in neighborhoods surrounding the central business district and in northwest Savannah within the city limits. We focused on distances of 100 meters (approx. 330 ft) or less to isolate approximately one block length away. In this way, our analysis is given at a finer spatial scale than typical studies that focus on neighborhood level changes. In Figure A1, we visualize the spatial distribution of infill developments and their nearby properties over Census tracts. Given our interest in the effects of infill development in climate-disadvantaged communities, we merged the federally recognized tracts provided by the Climate and Economic Justice Screening Tool (CEJST). A tract is defined to be climate disadvantaged if it meets both a climate burden (climate change, energy, health, housing, legacy pollution, transportation, water and wastewater, workforce development) threshold and a economic burden (income less than or equal to twice the federal poverty level, not including students enrolled in higher education) threshold (on Environmental Quality (2022)). Interestingly, we found that despite climate resilience not being an explicit consideration for public administrator program selection, 95% of infill projects and 90% of properties within 100 m are highly concentrated in climate disadvantaged tracts (Figure A1). This suggests that infill strategies managed by the Savannah Housing and Neighborhood Services are highly synergistic co-policies for community revitalization in response to the growing impacts of climate change such as economic loss to building value resulting from natural hazards or projected flood risk.

6.2 Block Level Effects

Prior theories of agglomeration economies have suggested that economic benefits in cities and industries tend to rise with density (Glaeser and Gottlieb (2009)). We test the hypothesis that spillover effects may be heterogeneous across blocks, where blocks receiving higher investment may experience more positive externalities. In Table A5, we report treatments effects by quintiles that are ordered by infill density. We found that effects are highest within blocks with the highest infill density. At the top quintile, which includes blocks with an infill density ranging from 16.667%-76.923%, we report a long-run increase in 11.046 $/sqft. For the other quintiles with lower infill density, we recover treatment effects not statistically different from zero. For the alternative analysis, we estimate quintile treatment effects using partially pooled SCM. Consistent with the DiD analysis, we found that only the highest infill density quintile produced statistically significant premium.

6.3 Spatial Decay of Spillover Effects

In Table A6 we report estimates for the effects of infill development on appraised building values for properties that were within 25, 50, 75, and 100 meters from the infill site. Consistent with prior theory and evidence, we found that effects are highest for properties closest

to the intervention. Within approximately one parcel length from an infill development at 25 meters, we report a long-run increase in 3.610 $/sqft, which translates to a 11% increase in appraised value versus the matched statistical control group. At a distance of 50 and 75 meters, which is about two or three parcel lengths away, we found that spillover effects begin decaying at a premium of 1.961 $/sqft and 1.632 $/sqft respectively, or a 4-5% increase. At 100 meters, or approximately one block length away, the effect begins tapering towards zero, as we estimate an average effect of 0.635 $/sqft, or a 2% increase. Our results provide empirical evidence that block level boundaries may be the more appropriate scale for public investment projects, as opposed to larger scales such as the neighborhood boundary as previously suggested (Rossi-Hansberg and Sarte (2012); Rossi-Hansberg, Sarte and Owens III (2010); Ooi and Le (2013); Ellen and Voicu (2006)). Further work to understand the relative reach of building as opposed to land or sales premiums, particularly with updated econometric methodologies, is needed.

To understand how effects vary over time, we employed an event study analysis to estimate yearly effects. We present dynamic effects for properties within 25 meters from an infill development in Figure 2. Notably, we found that there is an immediate positive effect on neighboring properties that lasts up to 6 years. Over the period of study, these treatment effects amount to statistically significant increases of $\$4,696.40$ per building and approximately $1.8 million in additional market value overall for the city. This suggests that government-invested projects that particularly focus on climate distressed areas may yet see multi-year benefits for up to 6 years or more despite the perceived investment risks. This is important because policymakers and practitioners have argued that even if investors are willing to take the risk, they often have trouble securing financing as lenders view investments in climate disadvantaged communities as risky (U.S. Environmental Protection Agency (2015)). In addition, we note that public investments yield returns not only for neighboring parcels, but also to private citizens under both amenity effects and induced innovation effects.

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8 Appendix

Figure A1: Spatial distribution of infill development in climate disadvantaged communities



Table A1: Data dictionary

	Data Type	Description	Source
Property Variables			
Address	String	Full address for a property	City
PARID	String	Parcel ID for a property	City
Type	String	Type of residential property (for example single family residence, town house, etc.)	City
Stories	Float	Number of stories	City
Grade	Float	Discrete value reflecting the condition of the property. Values range from 1, 1.5, 2, 2.5,. . . , 6	Chatham Tax Assessor Database
Year Built	Int	Year the property was built	Chatham Tax Assessor Database
Living Area	Float	Building area of the property (sqft)	Chatham Tax Assessor Database
Land Area	Float	Land area of the parcel (sqft)	Chatham Tax Assessor Database
Bedrooms	Int	Number of bedrooms	Chatham Tax Assessor Database
Bathrooms	Int	Number of bathrooms	Chatham Tax Assessor Database
Longitude	Float	Longitude value of the parcel's centroid	Savannah Area Geographic Information System
Latitude	Float	Latitude value of the parcel's centroid	Savannah Area Geographic Information System
Nearest Park	String	Name of the nearest park	Savannah Area Geographic Information System
Park Distance	Float	Distance to the nearest park	Author derived

INFILL	Int	Binary indicator for receiving infill assistance	City
Closest Infill	String	Parcel ID of the closest property that received infill assistance	Author derived
Closest Infill Distance	Int	Straight line distance to the closest infill property	Author derived
Census Variables			
Blockgroup	String	Blockgroup a property is in	Census Reporter
Total Pop	Int	Total population of the blockgroup	Census Reporter
Male Pct	Float	Male %	Census Reporter
Female Pct	Float	Female %	Census Reporter
Pop Density	Int		Census Reporter
Median Age	Float	Median age	Census Reporter
Income Pcp	Float	Average income	Census Reporter
White Pct	Float	White %	Census Reporter
Black Pct	Float	Black %	Census Reporter
Native Pct	Float	Native %	Census Reporter
AAPI Pct	Float	AAPI %	Census Reporter
Hispanic Pct	Float	Hispanic %	Census Reporter
Other Pct	Float	Other ethnicity %	Census Reporter
Married	Float	Married household %	Census Reporter
Single Female	Float	Single female household %	Census Reporter
Single Male	Float	Single male household %	Census Reporter

Non-Family	Float	Non-family household %	Census Reporter
Total Units	Float	Total units in the block group	Census Reporter
Occupied	Float	Occupied units %	Census Reporter
Vacant	Float	Vacant units %	Census Reporter
Owner	Float	Owned units %	Census Reporter
Renter	Float	Rented units %	Census Reporter
High School	Float	High school educated %	Census Reporter
Bachelors	Float	Bachelors educated %	Census Reporter
Time Variant Variables			
Year	Int	Year of an observation	Chatham Tax Assessor Database/Savannah Area Geographic Information System
Appraised Building	Int	Appraised building value of a property	Chatham Tax Assessor Database/Savannah Area Geographic Information System
Appraised Land	Int	Appraised land value of a parcel	Chatham Tax Assessor Database/ Savannah Area Geographic Information System
Infill Year	Int	Year of receiving infill assistance (N/A if never received)	City

Table A2: Covariate balance before matching

Variable	**Treated Mean**	**Control Mean**	**Mean Difference**	**t-Statistic**
Grade	2.548	3.380	-0.832	-81.398
Income	20294.81	36606.26	-16.411.45	-84.182
Dist. nearest park	371.920	1663.697	-1291.777	-180.34
Year built	1950.411	1976.667	-26.256	-55.458
No. bath	1.374	1.923	-0.549	-55.461
No. bedrooms	2.669	2.940	-0.271	-13.495
No. stories	1.161	1.253	-0.092	-15.379
Population density	5495.39	2453.05	3042.34	72.736
% single female	47.616	20.146	27.470	103.97
% black	84.515	32.554	51.961	174.05

Table A3: Covariate balance after matching

Variable	**Treated Mean**	**Control Mean**	**Mean Difference**	**t-Statistic**
Grade	2.548	2.539	0.009	0.590
Income	20294.81	20653.80	69.740	-0.244
Dist. nearest park	371.920	378.570	-6.650	-1.112
Year built	1950.411	1950.539	-0.128	-0.185
No. bath	1.374	1.372	0.002	0.117
No. bedrooms	2.669	2.680	-0.011	-0.398
No. stories	1.161	1.160	0.001	-0.039
Population density	5495.39	5503.692	-8.302	-0.129
% single female	47.616	47.540	0.127	-0.189
% black	84.515	84.389	0.076	-0.288

Table A4: Median bias reductions for PSM versus genetic matching

Distance	**PSM**	**Gen Match**
25	94.390%	99.310 %
50	95.717%	98.699%
75	93.150%	99.190%
100	91.217%	99.115%

Table A5: Spillover treatment effects of infill development at increasing infill density

	Infill density %				
	(0.395, 4.545)	(4.545, 6.250)	(6.250, 8.333)	(8.333 16.667)	(16.667, 76.923)
Diff-in-diff	2.852	2.779	4.691	0.223	11.046***
	(2.331)	(2.779)	(4.691)	(1.661)	(1.438)
Diff-in-diff placebo	1.967	1.403	-1.243	-0.154	0.520
	(1.345)	(0.889)	(0.884)	(0.650)	(0.986)
Synthetic controls	0.816	2.510	0.175	-0.464	6.980**
	(2.215)	(2.436)	(3.607)	(1.706)	(3.099)
Synthetic controls	-1.882	-2.832	1.544	-1.885	-2.604
placebo	(3.489)	(3.840)	(4.681)	(2.559)	(3.258)
No. of observations	3,473	4,941	4,674	3,492	2,155

Note: Significant to p < *0.1, **0.05, ***0.01. The dependent variable is the block-level average appraised building value divided by the block-level average living area square footage of residential properties. Treated blocks include any blocks that contained at least one infill development, and quintiles are created by ranking treated blocks by infill density. Treatment effects are estimated using the Sun & Abraham staggered difference-in-differences estimator and the synthetic control method with staggered adoption proposed by Ben-Michael et al. (Sun and Abraham (2021); Ben-Michael, Feller and Rothstein (2021)). Standard errors are clustered by block ID.

Table A6: Spillover treatment effects of infill development on nearby residential parcel values (2004-2019)

	Distance to nearest infill			
	25 meters Approx. 1 parcel	50 meters Approx. 2 parcels	75 meters Approx. 3 parcels	100 meters Approx. 4 parcels
Mean spillover effect	3.610**	1.961***	1.632***	0.635
($/sqft)	(1.440)	(0.680)	(0.512)	(0.511)
Percent increase	11.266%	5.696 %	4.625 %	1.733 %
Parcel fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
No. of observations	57,464	112,995	197,00	149,211
No. of treated parcels	389	1,440	2,587	3,980

Note: Significant to p < *0.1, **0.05, ***0.01. The dependent variable is the appraised building value divided by the living area square footage of residential properties as reported by the Chatham County Tax Assessors Database (2001-2022). Spillover areas include all parcels that are within a circular boundary. Spillover effects are estimated using the Sun and Abraham staggered difference-in-difference estimator versus a matched counterfactual of statistically similar parcels (Sun and Abraham (2021)). Standard errors are clustered by parcel ID.

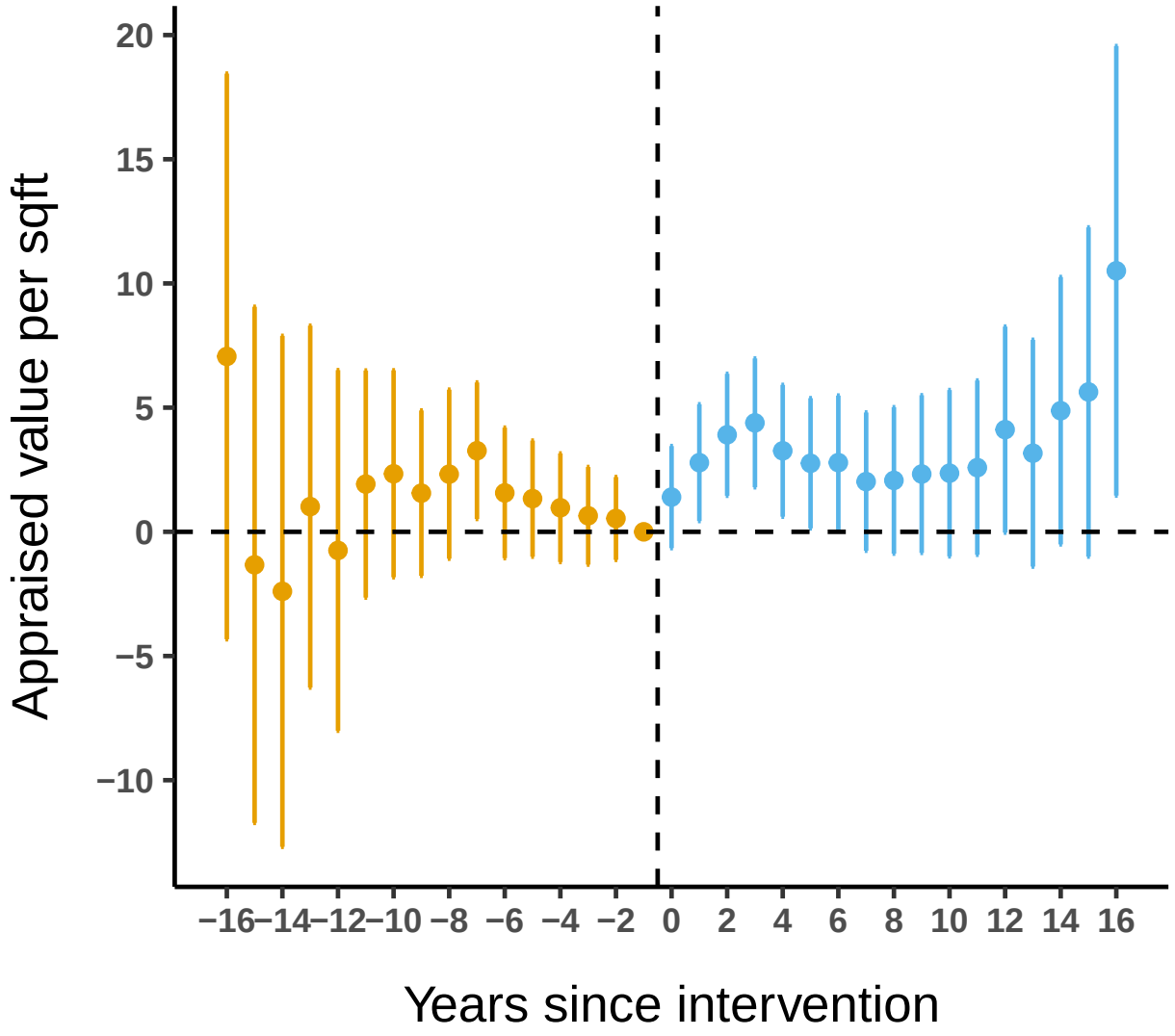


Figure A2: Dynamic treatment effects of infill development on neighboring residential parcels. The figure shows dynamic treatment effects of neighboring infill development in the county assessed appraised values ($/sqft) relative to the intervention year. The analysis is based on a stacked regression where 0 is defined as the intervention year relative to a matched reference set that includes statistical adjustment for observable property and socioeconomic characteristics. To control for potential biases due to staggered program participation, we use the staggered DiD estimator proposed by (Sun and Abraham (2021)). The standard errors are clustered by the parcel ID and the vertical lines in the figure represent the upper and lower 95% confidence intervals. We find evidence of positive treatment effects which persist for approximately 6 years after the initial investment with a peak return between year 2 and 3. The maximum return is in year 3 with a 2.01-7.18 $/sqft which corresponds to a 4.81-17.17% premium. Given the quality of the high resolution data and technical approach, we are able to measure significant yearly treatment effects and do not rely on cross-sectional results for inference.

Figure A3: Event study without matching

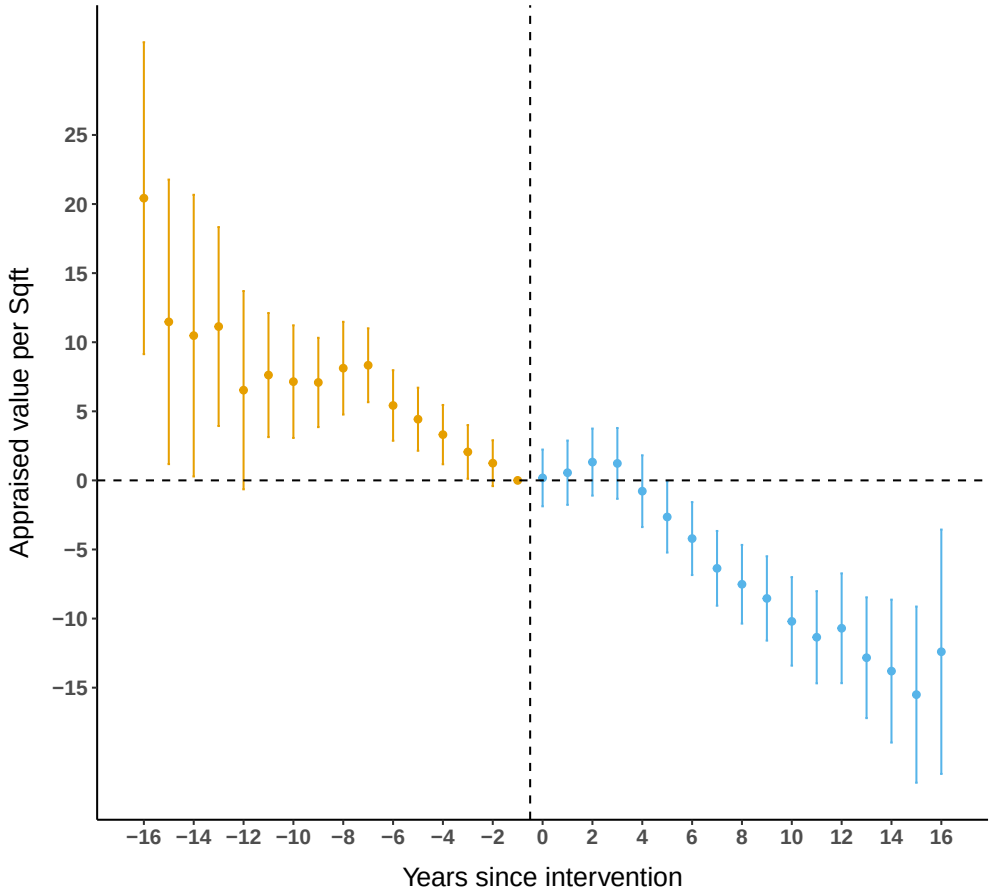


Table A7: TWFE versus Sun & Abraham spillover effects

Distance	**TWFE**	**SunAb**
25	0.762	3.610**
	(1.215)	(1.440)
50	0.013	1.961***
	(0.572)	(0.680)
75	-0.228	1.632***
	(0.416)	(0.512)
100	-0.795*	0.635
	(0.408)	(0.511)

Table A8: Falsification tests for parcel-level effects

Distance	**Spillover effect**
25	-0.178
	(0.659)
50	0.013
	(0.640)
75	0.326
	(0.634)
100	0.138
	(0.634)