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Placemaking and Segregation: Built Environment Impacts on Community in Philadelphia

1. Introduction and Context

Overview

The ultimate goal of this thesis is to measure the impact of street-level features (as a means of placemaking) on house prices and extrapolate the results to examine subsequent socio-economic and racial segregation patterns in the city of Philadelphia. I chose five placemaking elemental features to analyze; road classification, litter, public art, sidewalks, and shade (detailed in the Data section below). I selected these features for three main reasons: 1) data availability (e.g., accuracy of machine learning), 2) they draw on Jane Jacobs and William Holley Whytes' definitions of good public spaces (i.e., placemaking, which I further discuss in the Literature Review subsection below), and 3) they reflect culturally significant urban community built environment features of Philadelphia (detailed in the 'Significance of Place in Philadelphia' subsection below).

I ultimately use hedonic pricing (a revealed preference method for determining values of characteristics of a good, in my case, housing) to measure the impact of these placemaking-related features. Although hedonic pricing is a relatively straightforward method for this type of analysis, my study also contributes to the ongoing literature by:

a) Attempting to bridge the gap between current anthropological/ethnographic theories and economic theories regarding hyperlocal built environment features. I go an extra step beyond typical hedonic pricing literature by considering the impact on sorting and segregation.
b) Exploring potential uses of fairly novel, fine-grained, machine-learning generated datasets, extracted from Google Street View.
c) Using the Unconditional Quantile Regression method to explore ties between income, race, and ability or willingness to pay for certain street-level characteristics.

The rest of Section 1 introduces the local context of place in Philadelphia and reviews relevant literature. In Section 2, I review my data sources and describe how I constructed the dataset I used for my analysis. In Section 3, I explain the econometric and statistical methods I used for my analysis. I describe the results and discuss their implications in the context of Philadelphia in Section 4. Lastly, Section 5 concludes my thesis with overall policy implications for placemaking and directions for future empirical research.

Of the placemaking-related features included, I find the most impact on home prices in Philadelphia from road classification and amount of litter. Smaller placemaking efforts, like the presence of murals, showed little impact when considering the study areas in aggregate. There is also evidence of socio-economic (and therefore racial) segregation among most of my chosen characteristics, with wealthier, Whiter residents likely crowding out other groups for homes with better amenities.

The Significance of Place in Philadelphia

Philadelphia, Pennyslvania, the 6th most populous city in the United States in 2022, yet one of the poorest with the highest poverty and homicide rates, is a self-proclaimed "gritty" city, rich in history and culture (Rhynhart, 2020). The City of Brotherly Love is also the City of Firsts; the States' first capital; the city with the first library, hospital, and university; the nation's first "planned" city; the location where the Declaration of Independence was signed and the Constitution was ratified.

Once a booming production metropolis following the industrial revolution, Philadelphia faced population, and subsequently economic, decline beginning in the 1950s. A loss of tax base and job opportunities were results of the dual forces of white flight (the mass exodus of white families to suburban areas) and the fall of the manufacturing industry. White flight, the Great Migration (of African Americans out of the South and into Northern, Midwest, and Western cities), and historical, de jure discrimination (e.g., redlining, the practice of bank lenders to color code neighborhoods based on their 'ethnic desirability,') have contributed to Philadelphia becoming one of the most diverse but most segregated cities in the U.S. today (Otterbein, 2015).

Sandwiched between New York City and Washington D.C. by a two-hour drive or train ride north or south, Philadelphia is often overlooked by tourists and millennial job-seekers. For a time, the city was once dismissed as the 'next Detroit'. However, the city has seen a transformational comeback since the turn of the 21st century. Inga Saffron, the *Philadelphia Inquirer'*s 20-year veteran architecture critic, cites a large part of the city's salvation to its urban form: that, "threadbare as [the city] was [after decades of decline], the existence of [a] basic urban fabric meant [Philadelphia] didn't have to be reconstructed from scratch when people began trickling back] (Saffron, 2020).

The basic urban fabric Saffron alludes to is the result of Pennsylvania's namesake's greatest accomplishment: the birth of the American planned city and the invention of the 'grid system'. William Penn's ideas were grand and novel for their time, reserving green space for residents, allocating blocks for open public squares, and designing street widths appropriate to the desired function. Many credit his planning for making Philadelphia a city flexible for development, easy for visitors to understand, and "great for walking, working and living" (American Society of Civil Engineers; Mann, 2016).

Likely a result of its city planning model, Philly prides itself on being "*The* City of Neighborhoods," with well-defined areas of residential character, often separated by those streets classified (e.g., as a main arterial or neighborhood side street), by Penn himself. South Philadelphia has long been known for its colorful Italian and Irish communities, and more recently, Mexican and Vietnamese immigrants, as well as younger, wealthy White residents seeking a sense of community in its cozy, rowhome streets. Center City is known for its iconic and ritzy buildings (the Philadelphia Art Museum, Rittenhouse Square, and Constitution Hall) and residents. However, within walking distance lie North and West Philadelphia, known as the most segregated (both racially and socio-economically) areas in the city, with high concentrations of poverty, vacant homes, and crime (excluding the University City area, dominated mostly by students and academics).

Although the demographics and features of the neighborhoods continue to change as gentrification (i.e., the process of an area improving, prices rising, and poorer residents, typically people of color, being displaced, typically by White people) sweeps through some communities while others continue to grapple with crime and poverty, "the pride in being a part of a neighborhood remains resilient" (Washington Jr., 2012). One example of this resilience and community connection is the city's unique and culturally significant to the Block Party Program—walking through residential areas on a summer weekend, you're bound to come across at least one, in any part of town. After getting 75% approval from the street's occupants and paying a $25 fee, residents can "close their streets for a weekend day of community fun" (Geeting, 2016). Barbecues and inflatable pools are brought into the streets, and neighbors have a chance to commune and chat over drinks while their kids have free roam on territory usually overtaken by vehicles.

The urban design and cultural factors in Philadelphia have emphasized hyper-local pride and identity around 'place'. In a city that faces increasingly concerning socioeconomic and racial segregation, with many neighborhoods deep in crime and poverty crises, perhaps there is a way to capitalize on cherished spaces and places. Can the city influence built environment nuances on its blocks and streets to create better outcomes for its residents? Or will these improvements, enacted independently (e.g., without anti-displacement measures), just continue to push out poorer residents?

Literature Review

Historical Theory

Urban scholars have long debated the impact of human-scale street characteristics on community outcomes and makeup. Most famously, Jane Jacobs promoted the concept of 'eyes on the street,' the idea that active, lively, and diverse public spaces help a city flourish socially and economically (Jacobs, 1961). Jacobs, an ardent New Yorker at the time she wrote her seminal book *The Death and Life of Great American Cities,* was notably an enthusiast of Philadelphia's Rittenhouse Square, which she considered a textbook case of a welcoming, intricate public space, lively with residents from all backgrounds at every hour of the day.

William Holley Whyte, a contemporary and mentor of Jacobs came to similar conclusions during his in-depth, direct observation projects. His sociological, field-based approach was novel to urban planning: using film cameras and notebooks, Whyte developed an objective way to measure city dynamics, which many modern businesses and academics have since adapted to more easily capture with new technologies like artificial intelligence. He praised small, interesting spaces, and pointed out that 'failing' streets were often lined with blank walls and empty shops. Whyte's ultimate contribution to the field was convince planners "to leave assumptions behind and to go down at the street level" (Riou, 2022). This bottom-up approach to street design, he believed, would facilitate the positive social encounters essential to a healthy, happy city.

Jacob's and Whyte's works have since morphed into 'placemaking', the people-centered "process of creating quality places that people want to live, work, play and learn," which includes community buy-in and collaboration (Wyckoff, 2014). The community-based aspect of placemaking is crucial—projects should capitalize on existing community assets and potential to help ensure long-term success. Placemaking has since given birth to movements like New Urbanism (which calls for restoring urban physical environments into places where communities thrive) and smart growth (development that makes "communities more attractive, economically stronger, more socially diverse" and combats sprawl) (U.S. Environmental Protection Agency, 2021). Methods such as pedestrian-oriented design are often means to accomplish such goals. All of these movements and methods rely –at least partially– on creating livable streets through design and policy practices under the purview of engineers, architects, planners, and economists. Although these ideas are well over a half-century old, practical approaches to measuring built environment aspects of street design have only recently become available.

Modern Advancements and Thoughts

Because placemaking focuses on the unique bottom-up, community-influenced built environment microcosms of neighborhoods, measuring and analyzing its effects was time-consuming and unreliable until the advent and continuing development of automated data collection. Advancements in GIS, LIDAR, VR Photography (services like Google Street View), machine learning, and artificial intelligence now allow us to track subtleties more easily in urban environments. These subtleties encourage the "sidewalk ballet"—i.e., the benches, trees, public art, etc. that facilitate (or deter) human interaction— that Jacobs proposed promotes economic health and diversity (Jacobs, 1961).

Inclusivity and universal design are also important developments in recent placemaking movements and research. Whyte and Jacobs were proponents of urban demographic diversity and opponents of mid-century discriminatory practices such as the urban renewal projects that intentionally razed Black and Brown neighborhoods throughout U.S. cities. However, modern thinkers are now more heavily focused on the inclusion of race, gender, disability, and class considerations into urban planning and development.

Racial minorities have long been excluded from and even violently punished for "intruding" in American public spaces. After slavery was outlawed, the cruel treatment of Black Americans lived on through legal segregation and discrimination. In the built environment and on public streets, this took the form of separate schools, subway cars, and even building entrances for Black people. Although water fountains are no longer labeled 'Coloured' and 'White,' Black Americans are still overpoliced in public spaces (e.g., for jaywalking or social distancing violations during COVID) and are more likely to feel less safe in their communities (Riveron, 2020). Richard Rothstein's 2017 *The Color of Law: A Forgotten History of How Our Government Segregated America* chronicles the de jure racism minorities have faced in trying to find 'place' throughout America's past such as covenants that explicitly blocked non-Whites from buying properties in certain neighborhoods (Rothstein, 2017). The critically acclaimed bestseller recently renewed urban planning interest in disentangling systematic racism from city streets. Philadelphia is just one of many American cities that faces this challenge.

By adjusting street features through placemaking programs, cities may be able to facilitate more inclusive communities and foster better social, economic, and health outcomes. Noting how spaces and streets affect historically oppressed peoples' perception of place and safety is important in moving forward. This can look like cleaner, graffiti-free streets; public spaces that do not enable illicit activities but that also engage residents needs and desires so that they are encouraged to use them.

Empirical Research on the Outcomes of Place

One of the motivations behind this study is that location is a hugely important component of ensuring that people have access to opportunity; i.e., the sorting effects of placemaking may be harmful if they price people out of places with opportunity (or helpful if they generate benefits when implemented). The notion that "zip code matters" first captured the attention of public health experts, who were generally interested in addressing the negative health outcomes from environmental exposures (e.g., heat islands, higher-than-average traffic or industrial pollution) in (typically Black and Brown) impoverished neighborhoods (Frumkin, 2005).

Economists have since followed suite. The groundbreaking Moving to Opportunity research led by Raj Chetty in 2015 found that moving households out of segregation-induced high-poverty and high-crime neighborhoods "reduces the intergenerational persistence of poverty" (Chetty et al., 2015). Many point to social connectedness differences between neighborhoods as the causal root of the improved outcomes. That "unique, spatial conditions that can undermine" a child's chance at mobility opens the door for placemaking policies. Perhaps encouraging more, safer 'sidewalk ballets' in communities can induce the connections and sense of ownership that leads to happier, healthier lives.

Although Chetty's work underscores the importance of the spatial location where you are raised, empirical studies on the human-scaled built environment elements influencing such outcomes are scarce. However, one of the only rigorous longitudinal randomly controlled trials using placemaking concepts took place in Philadelphia itself. After getting city buy-in and working with hundreds of local residents across the city, researchers assigned over 500 vacant lots across the city to treatment and control groups—the treated group was 'cleaned' and 'greened' using inexpensive, scalable, and sustainable methods (Branas et al., 2018). Over 38 months, the team found that near the improved lots, there was a significant decrease in crime and fear. Although beautified lots won't eradicate poverty and crime in Philadelphia, placemaking projects like this with strong policy backing could give communities sustainable, engaging ways towards safer, productive public spaces.

Much of the economic hedonic literature on 'place-based' (*not* placemade) policy tends to interpret rising house prices as a positive outcome (Rossi-Hansberg et al., 2010); however, this may not be the case for tenants who are subsequently displaced (or, sorted out) as their rents go up. Cities could consider more holistic community development and housing policies to protect the most vulnerable communities against displacement. Koster & van Ommeren's recent study showed that improvements to *social* housing (which is not as widely available in the U.S.) in the Netherlands raised surrounding neighborhoods' market rate rents, but impoverished tenants in the publicly-owned, rent-stabilized housing were protected against rising costs (Koster & Ommeren, 2019).

Economic Methodology and Related Research

The economic literature concerning place-based policies often seeks to measure the impact of public investments on affected areas—and hedonic pricing is typically the standard method for this. Hedonic pricing is a method of measuring the marginal value of various "utility-bearing" characteristics of multidimensional goods, evaluated at a market and spatial equilibrium (Rosen, 1974). Hedonic pricing ultimately attempts to identify the marginal household's willingness to pay for a good's characteristics and explains that these differences are how buyers and sellers on the market are able to match, given that the good is so multifaceted. For example, house prices are a complex combination of the built form of the house (e.g., square footage, number of rooms, building materials) and locational factors (e.g., proximity to jobs). Holding these factors constant, hedonic pricing models allow us to observe how property prices vary on streets with different placemaking design elements and therefore draw inferences about households' willingness to pay for these features (Kuminoff et al., 2013).

House prices can sometimes provide a good proxy for the willingness to pay for neighborhood characteristics at the margin. If two homes are identical (both physically and in their surroundings) except for the quality of street design, we should theoretically be able to observe how much more or less a household values that street design through the price. For the context of this research, if we see more demand for housing with 'livable' street design in my hedonic pricing analyses, it is likely to see sorting across the wealth distribution and, subsequently, across racial lines as the two are heavily correlated in the U.S. (Bhutta et al., 2020). Conversely, if the demand is insignificant, 'livable, place-made' streets may be present in communities of many different income levels and races.

Most of the hedonic literature regarding livability through built environment quality has looked at street characteristics, similar to the 'road classification' variable that I include in my analysis. Regarding street layout, Matthews and Turnbull's 2007 paper uses hedonic pricing to find that house prices are higher on grid streets than cul-de-sacs (Matthews & Turnbull, 2007). Their hedonic price model considers many variables other than street layout, including basic structural elements such as the number of bedrooms and square footage, land use and density measures, and distances to amenities such as schools and cultural centers. However, the non-experimental nature of the analysis (i.e., street layouts aren't randomly assigned across locations; newer suburbs are more likely to be cul-de-sacs which may induce endogeneity) makes it nearly impossible to determine the causal effects of street networks.

Ossokina and Verweij are able to exploit quasi-experimental variation to try to overcome the endogeneity just discussed (the opening of a new bypass that halved daily traffic density in several neighborhoods in the Hague) and use hedonic pricing to examine the effects of traffic nuisance on housing prices in the Dutch context (Ossokina & Verweij, 2015). They found that for a 50% decrease in traffic volume, there is a subsequent 1.4% increase in house prices; this may suggest that if we intentionally design our residential streets to be safer and amenable to human-scaled activity, our homes could be more desirable (i.e., more 'livable').

In 2017, Polloni was also able to exploit quasi-experimental variation in his hedonic analysis of a traffic-calmed streets in Portland, Oregon (Polloni, 2017). At the time of his study, the city had built approximately 1600 speed bumps, 70 traffic circles, 300 curb extensions, 26 raised crosswalks, and 30 cul-de-sacs or semi-diverters to make neighborhoods safer and encourage more active transportation, like biking and walking. He found that for every 16% decrease in automobile volume, housing prices rose by 1%. The impact of more livable design on housing prices seems to be much more significant in the U.S. context than the Dutch: perhaps because they are less common and, therefore, there is more demand for calm streets than supply in the car-centric country.

As our cities become more interconnected and new data sources and computing methods become more available, there is more opportunity to use hedonic pricing for a more holistic look at the impact of placemaking elements. Rather than focus solely on roads or road networks, a recent 2022 paper looks at the impact of streetscape design (namely enclosure, greenery, and walkability) on Airbnb prices in Amsterdam (Wang & Rasouli, 2022). In addition to controlling for structural (season, age) and reputational (review ratings) characteristics, the authors include locational attributes of distance (to central station and other attractions) and density (to competitors). To quantify the locational attribute of streetscape design, they apply a neural network analysis to publicly available Google Street View data (e.g., to count green pixels of vegetation towards greenery) up to 100m away from each Airbnb location. Wang and Rasouli's results show significant spatial heterogeneity; the effects of streetscape vary widely depending on the neighborhood. They find largely positive effects, particularly around central neighborhoods, and conclude that "streetscape features… are in fact influential in travelers' decision to book and pay a certain price for their stays”. Although tourists and short-stay travelers may have different criteria in choosing a location than residents buying or renting a home, their methodology and findings are important and relevant in determining the value of place-made or human-scaled spaces.

2. Data

State of Place (SoP), a U.S. based “Smart and Equitable City Planning Software” company provided the main variables of interest for this study. The team seeks to “harness the power of data” to help create “more livable, equitable, resilient, and sustainable places that make communities happier, safer, and healthier.” They have worked with city governments across the world on projects that strategize neighborhood investment plans, maximize walkability, and enable better public spaces (Alfonzo, 2022).

SoP’s data collection methodology was originally a field checklist—staff would use paper forms with almost 300 questions to evaluate the walkability and quality of life of a single city block. They have since developed a visual machine learning (VML) algorithm that uses imagery from Google Street View to measure hundreds of ‘micro-built environment features’ on a block level (i.e., the street between two intersections), similar to Wang & Rosouli’s analysis on Airbnb prices. State of Place is essentially modernizing Whyte’s early ethnographic work. Examples of features measured include the amount of graffiti, the presence and type of bicycle lanes, and the general maintenance of buildings on a block. They then weight and aggregate these features into 10 different “urban design dimension” indices: density, aesthetics, traffic safety, connectivity, parks and public spaces, personal safety, form, recreational facilities, pedestrian and bike amenities, and proximity. These indices are then re-aggregated together to create the ‘State of Place Index,’ “a walkability and quality of place score from 0-100.”

The four variables I used in my final model as proxies for ‘placemaking elements’ can be found in Table 1. In addition to the SoP generated variables, I also included Road Classification as a variable of interest, taken from the City of Philadelphia’s Open Data portal. I ultimately did not use State of Place’s Public Art variable due to accuracy and measurement issues. The variable I used to replace Public Art, Mural Density, is discussed further below.

Table 1: State of Place Variables of Interest Used in Final Model

State of Place Variable	Description	Numeric Definition	Accuracy*
Litter	How much litter is apparent on this segment?	2.0: 'Some/A lot', 1.0: 'Few', 0.0: 'None'	High
Public Art**	Is there public art that is visible on this segment?	1.0: 'Yes', 0.0: 'No'	Low
Sidewalk	Does this street have sidewalks on either side of the street?	1.0: 'Yes', 0.0: 'No'	High
Sidewalk Shade**	Is the sidewalk shaded by trees?	1.0: ‘25%-50%’, 0.0: ‘<25%’	High
Road Classification****	What is the function and capacity of the street?	0 – Major Arterial 1 – Minor Arterial 2 – Collector 3 – Local	N/A

*Accuracy (High: >85%; Medium: 70% - 85%; Low: <70%)
**This variable was not used for the final regression due to its low accuracy.
***This variable was modified for this study. The original SoP variable was described as “How many sides of the street have sidewalks?” with numeric values between 0 and 2.

****This variable of interest was taken from the City of Philadelphia's Open Data website, not State of Place's dataset.

The dataset I used for this research comes from State of Place's 2020 pilot project with the City of Philadelphia. The State of Place team told me that the project was "mostly a mapping exercise" in which they worked with the city to show that disproportionate health outcomes across race and income (particularly regarding COVID) are tied to disinvestment in the built environment. The city of Philadelphia wanted a broad range of neighborhoods captured but could not survey the whole city due to budget constraints. The city chose 17 zip codes (out of the 48 total in Philadelphia, Figure 1) a priori to represent neighborhoods of different economic and racial demographics. Details on each of the 17 zip codes included in the SoP's Philadelphia project data and this study can be found in Table 2.

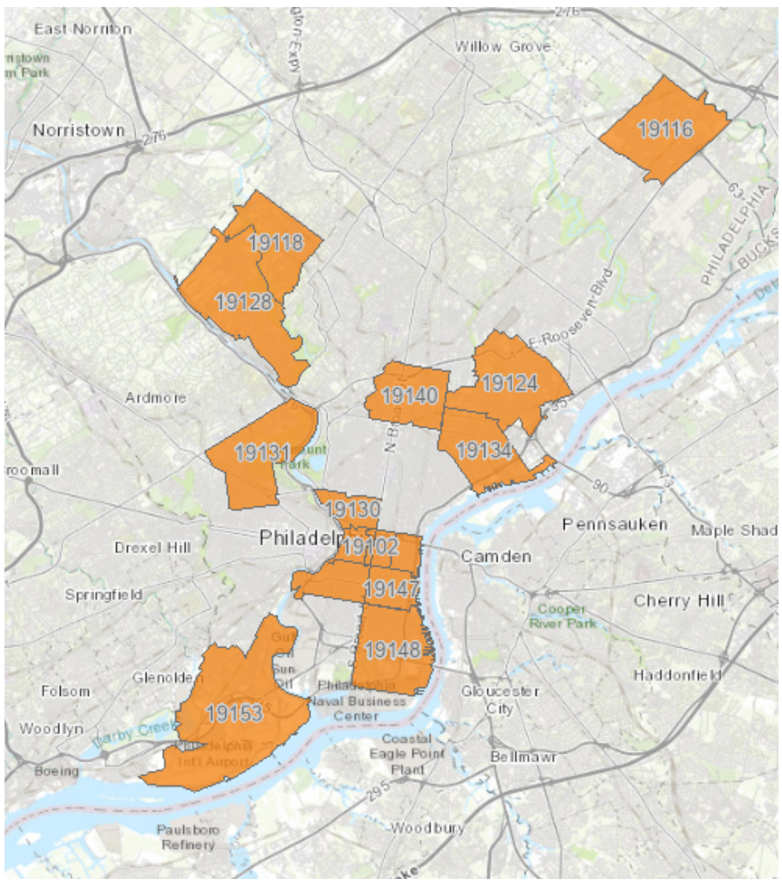

Figure 1: Study Area Zip Codes

Figure 2 shows SoP's results for their Aesthetics (urban design features that make places dynamic and thriving"), Connectivity ("ease of access; lack of pedestrian barriers"), Pedestrian & Bike Amenities ("features that make it comfortable for pedestrians and bicyclists"), Personal Safety ("factors that influence perception of safety"), and full State of Place Index for each of the Block Groups within the 17 zip codes (Alfonzo, 2022). Although there are dozens of features incorporated into these indices other than those I consider in my analysis, these most closely represent the street characteristics included in my analysis.

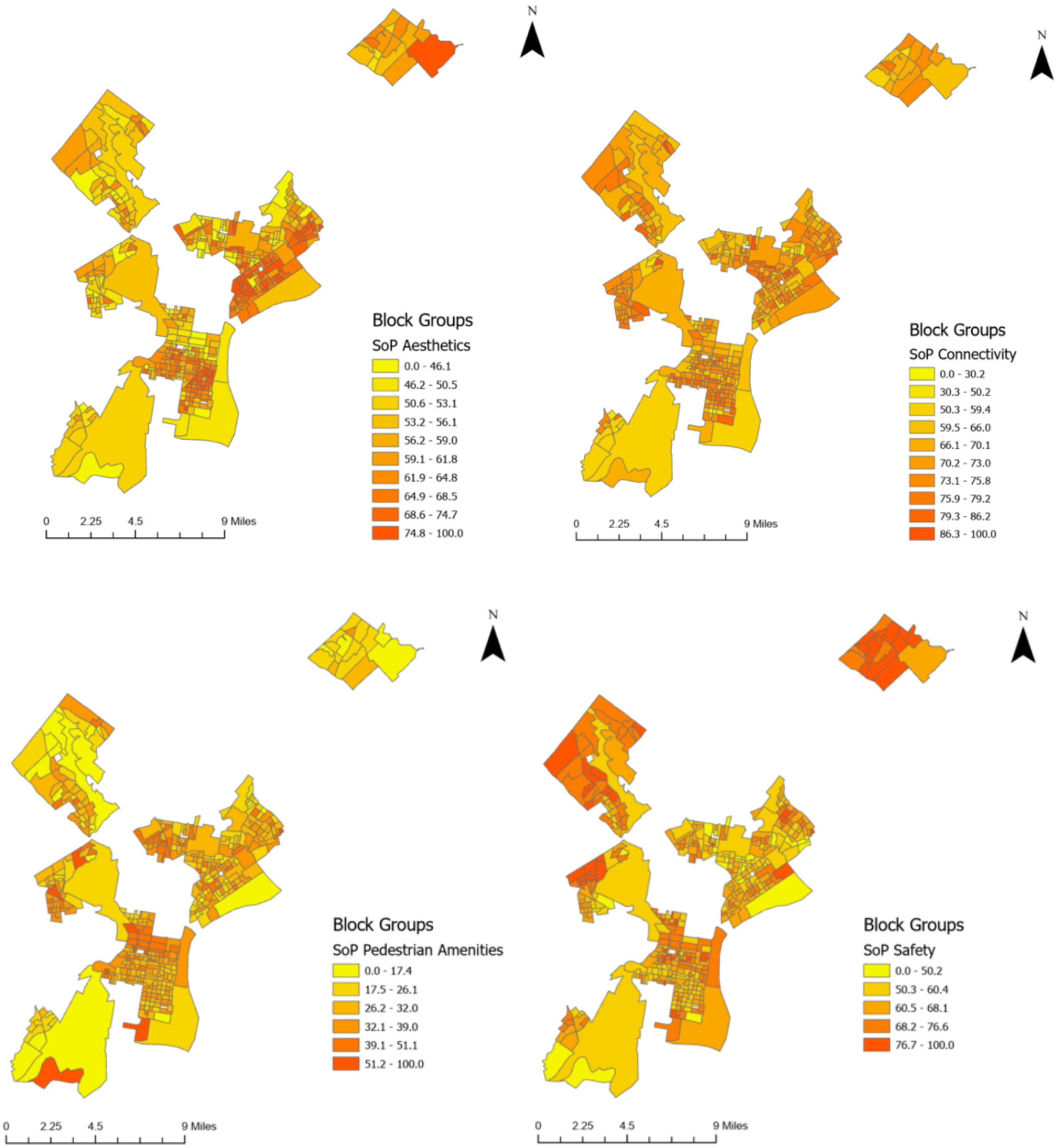
N
Block Groups
SoP Aesthetics
0.0 - 46.1
46.2 - 50.5
50.6 - 53.1
53.2 - 56.1
56.2 - 59.0
59.1 - 61.8
61.9 - 64.8
64.9 - 68.5
68.6 - 74.7
74.8 - 100.0
0 2.25 4.5 9 Miles
N
Block Groups
SoP Connectivity
0.0 - 30.2
30.3 - 50.2
50.3 - 59.4
59.5 - 66.0
66.1 - 70.1
70.2 - 73.0
73.1 - 75.8
75.9 - 79.2
79.3 - 86.2
86.3 - 100.0
0 2.25 4.5 9 Miles
N
Block Groups
SoP Pedestrian Amenities
0.0 - 17.4
17.5 - 26.1
26.2 - 32.0
32.1 - 39.0
39.1 - 51.1
51.2 - 100.0
0 2.25 4.5 9 Miles
N
Block Groups
SoP Safety
0.0 - 50.2
50.3 - 60.4
60.5 - 68.1
68.2 - 76.6
76.7 - 100.0
0 2.25 4.5 9 Miles

Figure 2: State of Place Philadelphia Indices Maps

The SoP team determined the accuracy of the features by comparing ±40 blocks of VML data to a dataset collected using the original field method in Austin, Texas. One of the limitations to SoP's VML is that it may not have the granularity required to predict or measure every detail of a feature in the built environment. One example an SoP employee gave is that their VML may be able to measure that there is or is not a crosswalk at an intersection, but it may not be able to count how many or which street it is crossing. Another important limitation is that the accuracy is biased towards a negative detection rate— i.e., it is rare that the VML will measure something that is not there, but it may have a harder time detecting things that are present.

State of Place also incorporated the City of Philadelphia's '2017-2018 Litter Index' into its Litter variable. The sidewalk shade variable is heavily influenced by the presence of awnings—this is particularly relevant in Philadelphia, where awnings are a signature architectural feature in the west and south (See Figure 3, (Bixler, 2016)). Public Art is currently one of SoP's lowest accuracy features—it can include structures (e.g., sculptures, fountains), murals, or other features that the field team, and subsequently the VML, deemed as art. The determination of what is "public art" is a fine line, even to those who work in the field; unsanctioned graffiti may be considered art in some instances but not others (by a human and SoP's algorithm). For this reason, I replaced their variable for my analysis with the manually generated 'Mural Density' variable. Mural Arts Philadelphia, "the nation's largest public arts program… that engages communities in 50-100 projects each year" provided me with a list of all of the public outdoor murals and their addresses. I created 500-foot buffers around each mural and created three categories for each property in my database: "No Mural within 500 Feet (of the property)," "1 Mural within 500 Feet," and ">1 Mural within 500 Feet," under the assumption that there are diminishing marginal returns (on utility, happiness, value, etc.) for each additional mural near your home.

Figure 3: "Old and New Collide on Chadwick Street" Photo by Michael Bixler. Source: Bixler (2016)

Table 2: Demographics for Zip Codes Included in Study

	Region	Neighborhood	Population	Median Income (USD)	Median Home Value (USD)	% Black	% with College Degree
United States			*331,893,745*	*64,994*	*229,800*	*13.6*	*32.9*
Philadelphia			*1,576,251*	*49,127*	*171,000*	*43.6*	*31.2*
All Study Zip Codes			*33,211*	*64,286*	*280,776*	*23*	*44.7*
19102	Center City	Middle City East	5,147	96,953	-----	5	86.2
19103	Center City	Rittenhouse Square	24,214	76,103	503,061	6.6	81.7
19106	Center City	Society Hill	12,592	107,388	521,548	8.2	77.8
19107	Center City	Washington Square West	14,526	57,735	384,831	9.8	66.6
19116	Northeast	Somerton	34,747	57,126	240,658	4.8	32.3
19118	Northwest	Chestnut Hill	10,884	89,422	540,918	18.6	66.9
19124	North	Frankford/Juanita	70,304	33,611	103,782	41	10.6
19125	North	East Kensington	25,850	72,990	241,850	4.5	46.3
19128	Northwest	Roxborough	37,644	74,564	250,082	14.2	51.4
19130	North	Spring Garden	27,093	84,308	379,834	17.4	73.5
19131	West	Fairmount Park	44,723	37,345	124,277	80.7	27.5
19134	North	Kensington	62,087	31,533	92,210	16.7	10.2
19140	North	North Philadelphia	51,766	22,790	64,245	56.7	8.6
19146	South	Southwest/Graduate Hospital	39,282	69,305	329,485	37.4	53.5
19147	South	Passyunk	38,472	81,519	380,863	9.1	61.7
19148	South	South Philadelphia	52,259	52,001	194,616	6.3	26.5
19153	South	Eastwick/Airport	13,006	48,177	140,159	71.5	19.8

*Source: SimpleMaps.com (2022)

I used the City of Philadelphia's Office of Property Assessment's (OPA) Properties datasets to create my independent and control variables (City of Philadelphia, 2022). OPA's Properties data contains dozens of characteristics of properties sold in Philadelphia, such as the type of basement, number of fireplaces, and the type of view from the home. The dependent variable I used was the natural logarithm of the most recent sales price (the price paid by a buyer to purchase the given property). A description of other OPA housing characteristics I used as control variables can be found in Table 3.

I excluded all properties that were sold for less than $10,000 or more than $5,000,000; I also dropped all observations that were categorized as anything other than residential (e.g., industrial, commercial). I consolidated the OPA's 'Building Code' variable, which described each property in detail (e.g., 3-Story Loft Condo or 2-Story Mason Rowhome) into five categories of building type-- Rowhomes (the "base case", typical home in Philadelphia), Condominiums, Apartments, Semi-Detached, and Detached.

Table 3: Property Characteristics Summary

Property Characteristic	Numeric Value	Transformation	Mean/ Percent (for Categorical)	Std. Dev.
Sales Price (USD)	Natural logarithm of sales price in USD	Natural Logarithm	$291,248	$335,849
Livable Area (Sq. Ft)	Natural logarithm of square footage	Natural Logarithm	1,387 sq ft	1112 sq ft
Central Air	0 – No air conditioning present 1 – Air conditioning present	Dummy Variable	.539	.498
Building Type	0 – Rowhome 1 – Condo 2 – Apartment 3 – Semi-Detached 4 – Detached	Categories created from 'Building Code'	71.8% 9.6% 4.9% 9.1% 4.4%	
Interior Condition	0 – Newly Constructed 1 – Newly Rehabbed 2 – Above Average 3 – Average 4 – Below Average 6 – Structurally Deficient		8.12% 11.17% 18.23% 58.57% 2.28% 1.64%	
Exterior Condition	0 – Newly Constructed 1 – Newly Rehabbed 2 – Above Average 3 – Average 4 – Below Average 6 – Structurally Deficient		8.30% 9.70% 16.02% 61.51% 2.65% 1.83%	
Period Built	0 – Before 1880 1 – 1880 to 1930 2 – 1930 to 1945 3 – 1945 to 1960 4 – 1960 to 1970 5 – 1970 to 1990 6 – 1990 – 2010 7 – After 2010	Categories created from values given for 'Year Built'	4.63% 61.48% 9.01% 5.44% 4.24% 2.89% 3.71% 8.59%	
Number of Bathrooms			1.14	.78
Number of Stories			1.96	2.01
Number of Garage Spaces			.24	.57

I joined all properties (point data) sold after 2016 to the closest State of Place block (line data) within 500 feet. I then ensured that each property was joined to the correct block by matching the street name from the SoP data with that in the OPA data, resulting in 27,904 observations for my dataset (approximately 64% of properties were correctly matched).

3. Methods and Analysis

Regression Equation

I am interested in establish a causal effect of the placemaking elements I defined on house prices—particularly within and between low, medium, and high-value neighborhoods (which can be tied to stratifications in race and income). I began my analysis with a simple ordinary least squares (OLS) regression with no controls or fixed effects; the only variables included were variables of interest (Equation 1). I then added property characteristics as controls, then time fixed effects (Equations 2 and 3). Equation 2 builds on the first by trying to hold constant house characteristics. Equation 3 attempts to remove the effect of price fluctuations across the city over time.

$$\ln(price)_{it} = \beta_1 Road_{it} + \beta_2 Litter_{it} + \beta_3 Art_{it} + \beta_4 Sidewalk_{it} + \beta_5 Shade_{it} + \varepsilon_{it} \quad (1)$$

$$\ln(price)_{it} = \beta_1 Road_{it} + \beta_2 Litter_{it} + \beta_3 Art_{it} + \beta_4 Sidewalk_{it} + \beta_5 Shade_{it} + \beta_6 X_{it} + \varepsilon_{it} \quad (2)$$

$$\ln(price)_{it} = \beta_1 Road_{it} + \beta_2 Litter_{it} + \beta_3 Art_{it} + \beta_4 Sidewalk_{it} + \beta_5 Shade_{it} + \beta_6 X_{it} + \mu_i + \varepsilon_{it} \quad (3)$$

My final model (Equation 4) is a spatial fixed effects model, evaluated at different quantiles of house prices (discussed further in the 'Unconditional Quantile Regression' subsection below).

$$\ln(price_{it}) = \beta_1 Road_{it} + \beta_2 Litter_{it} + \beta_3 Art_{it} + \beta_4 Sidewalk_{it} + \beta_5 Shade_{it} + \beta_6 X_{it} + \mu_j + \mu_t + \varepsilon_{it} \quad (4)$$

$price$ is the sale price of the property, i is the notation for location, t is the notation for time, $Road$ is Road Classification (see Table 1), $Litter$ is amount of litter (see Table 1), Art is mural density, $Sidewalk$ is presence of sidewalk (see Table 1), $Shade$ is amount of shade on sidewalk (see Table 1), and X represents the control variables (home property characteristics, see Table 3). μ_t is the time fixed effects; μ_j is the spatial fixed effects (defined below). ε is the error term, which captures variation between the model and actual dataset. The regression ultimately allows us to observe how much Philadelphia residents "value" (price) street characteristics ($Road, Litter, Art, Sidewalk, Shade$) while controlling for the traditional features they consider when purchasing a home (square footage, bathrooms, condition).

Besides misspecification (that the equation does not accurately reflect the relationships I'm attempting to recreate), the main threat to my model is endogeneity, i.e., that there are influences (observed or unobserved) affecting the variables of interest that are also correlated with the error term. Endogeneity can be present under a host of conditions but is primarily persistent through the omitted variable bias. One potential example of an omitted variables includes the social atmosphere or culture of a neighborhood; adding the spatial fixed effects at a street or block level allows for us to control for such differences that may arise across communities. But even finely-aggregated spatial fixed effects will likely never model the complex decisions and tradeoffs a household considers when choosing where to live. Preferences such as sense of community or proximity to family can be hard or even impossible to determine. However, my model does include an idiosyncratic error term that captures unobserved variation in locational preferences.

I set time fixed effects as an interaction between sale year and sale month to account for variation in seasonal and annual price trends. For the final regressions, I observed two levels of spatial fixed effects. The first was Block Group—the lowest level of spatial aggregation for which detailed demographic data is typically available from the U.S. Census. Block Groups generally "contain between 600 and 3,000 people;" Figure 4 shows an illustration of where block groups are in the spatial aggregation hierarchy for typical U.S. census data (U. S. Census Bureau, 2022). The second was the 'lowest' spatial level possible with my available data—the interaction of street and block group (e.g. the entirety of a street throughout a given block group). For this level of aggregation, there were 2,238 'categories' (i.e., streets with a block group); with 19,449 observations, this averages out to approximately 8.7 homes sold on a street within a block group during my data's timeframe. Comparatively, there are 408 Block Groups in my study dataset, with approximately 49 homes per block group.

In Equation 4, my chosen model, what I'm essentially trying to do is remove the bias induced by unobserved differences between blocks that are correlated with both price and each of the placemaking elements. For example, central locations might be high-value because of their proximity to jobs, but also have excessive litter due to high density. Failure to account for location would bias my litter variable. Controlling for location fixed-effects removes this potential source of bias by comparing house prices within a block group by essentially holding location constant.

Data aggregation levels can be critical in hedonic pricing models. The impact of many micro-level street changes may only be measurable on a larger network scale rather than per block (. Two of the most influential urban scholars, Jane Jacobs and Edward Glaeser, are at two ends of the spectrum in this regard, with Jacobs often focused on individual addresses and Glaeser on entire metropolitan areas. Perhaps strategically aggregating placemaking efforts is somewhere between (as Polloni found in his study of traffic-calming infrastructure).

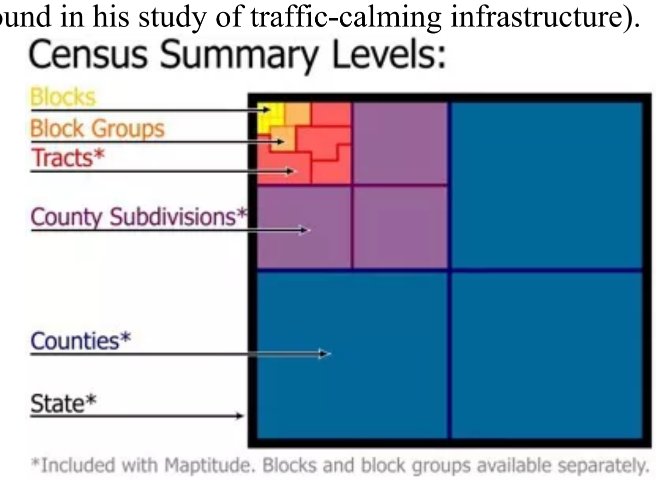

Figure 4: U.S. Census Summary Levels. Source: Caliper (2022)

Unconditional Quantile Regression

The goal of this study was to measure effects on house prices due to differences in small-scale street characteristics that fall in line with what Jacobs and Whyte would consider 'livable', or what modern disciples might call placemaking. From there, I hoped to draw conclusions about these effects' relationship to any sorting or segregation effects across racial or socioeconomic lines. Although I cannot measure this directly with my available data, I can observe differences in preferences across socioeconomic and racial groups that may lead to subsequent sorting. Using Firpo et al.'s Unconditional Quantile Regression (UQR) method, we can observe the "value" of each street characteristics (independent variables) across different quantiles of sales price (the dependent variable) (Firpo et al., 2009). For example, we can see how much the willingness-to-pay is for sidewalks for residents in homes in the bottom 10% and top 90% of the sales price distribution (i.e., Philadelphia's poorest and richest residents).

Prior to Firpo's UQR, *conditional* regressions could not answer questions we asking for this study. Such a regression would condition the variables—e.g., instead of looking at solely the impact of street characteristics on sales price (unconditional distribution), we would observe street characteristics *conditional on* income or race. A person could be on the high side of an unconditional distribution but on the low end of a conditional distribution—conditioning is indeed useful when observing trends in the data, but "conditional *quantiles* do not average up to their unconditional population counterparts." Therefore, when looking for marginal effects (e.g., does the presence of sidewalks affect house prices more in rich or poor neighborhoods?) to consider policy implementation, we must leave out conditioning variables.

Central to explaining the independent variables' (street characteristic) partial effects on our dependent variable (sale price) in the UQR is the recentered influence function (RIF). An influence function measures the dependence of the estimators (β) on the value of our dependent variable (sale price)—e.g., how would the estimators change if our distribution of home sale prices in Philadelphia shifted up or down? Or if the sample was much larger? The 'recentered' portion of RIF uses further statistical tools to account for the influence that each observation of the dependent variable ($sale\_price_i$) has on the function. Ultimately, the RIF a transformation of the dependent variable within UQR (the statistical tool) that allows us to observe the how changes in our explanatory variables (street characteristics), have on the unconditional distribution of Y (sale price) (Rios-Avila, 2020).

Since I hope to uncover patterns that suggest placemaking could help bolster opportunities in the communities most in need, I decided to focus my UQR on the 10th (sale price below \$45,00) 20th (\$45,000 to \$90,000), 80th (\$440,000 to \$621,000) and 90th (above \$621,000) percentiles. I also include the 50th percentile (\$244,000 to \$290,000) to show the effects of each of the placemaking elements for the median resident.

The UQR method should be used with some reservation when extrapolating sorting and segregation effects. Concerning race, my use of Unconditional Quantile Regression assumes that there is a heavy correlation between race and income, where residents of color are much more likely to be in the lower quantiles of income and therefore home sales price. Given the United States' history of enslavement, de jure segregation, and innumerous civil and human rights violations against people of color (particularly Black and Indigenous Americans), this is not hard to explain qualitatively or quantitatively. Systemic inequalities have created vast racial wealth and income gaps across the U.S. (Figure 5) and this pattern is also apparent in the city of Philadelphia (Figure 6).

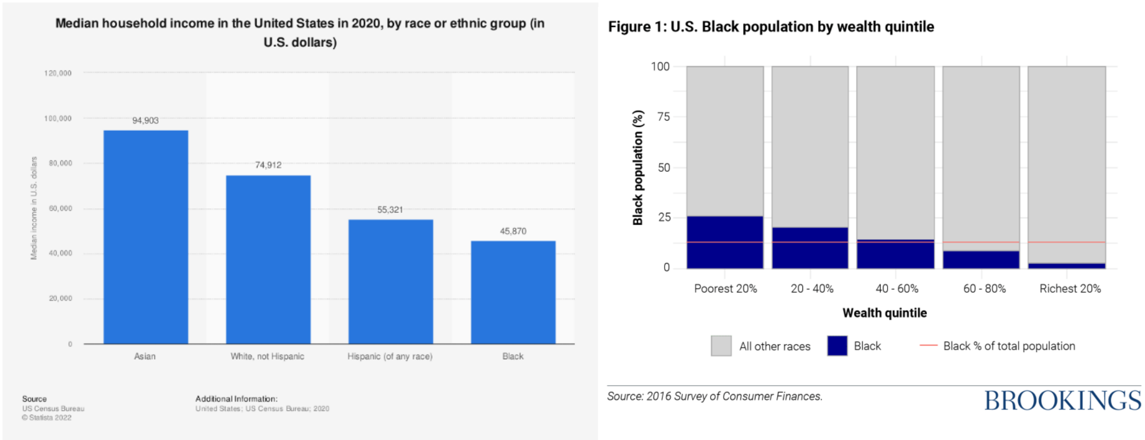

Figure 5: Income and Wealth Inequality in the U.S.

Sources: (Left): Statista Research Department (2021) Source (Right): Williamson (2020)

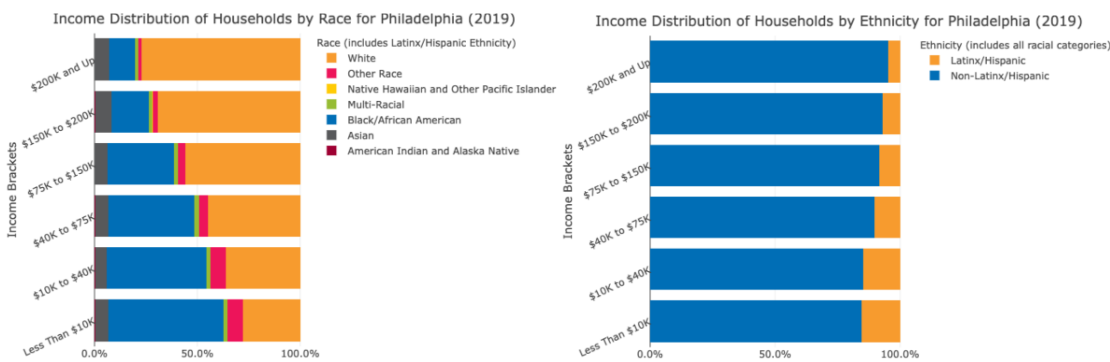

Figure 6: Income Distribution and Inequality in Philadelphia. Source: Shields (2019)

4. Results and Discussion

Regression Progression

I start by showing the effects of adding controls and fixed effects an OLS regression with my variables of interest in

Table 4—I provide interpretations of these in the 'Variables of Interest' subsection below. Property characteristics are clearly important to housing prices, increasing my R^2 (the proportion of variation in the dependent variable, sale_price that can be contributed my independent variables) more than threefold. Time fixed effects do not seem to add much explanatory power to the model, likely because there were not vast changes to the housing market in Philadelphia during the short study period (2016 – 2022). Spatial fixed effects add another 20 to 30

percentage points of explanatory power to my model, where Model 5 with street level fixed effects is able to account for almost 82% of variation in home sales prices.

Table 4: Regression Progression

	(1)	(2)	(3)	(4)	(5)
Minor Arterial[1]	0.244^{***}	0.0564^{**}	0.0670^{***}	0.0486^{**}	0.0237
	(0.0312)	(0.0275)	(0.0253)	(0.0232)	(0.0417)
Collector	0.161^{***}	0.0464^{**}	0.0486^{**}	0.0331^{*}	0.0279
	(0.0262)	(0.0226)	(0.0222)	(0.0199)	(0.0345)
Local	0.0468^{*}	-0.0103	-0.0122	0.0159	0.0268
	(0.0265)	(0.0227)	(0.0225)	(0.0200)	(0.0350)
A Little Litter[2]	-0.597^{***}	-0.287^{***}	-0.283^{***}	-0.0230^{***}	-0.0304^{**}
	(0.0117)	(0.0101)	(0.0104)	(0.00864)	(0.0152)
A Lot of Litter	-1.055^{***}	-0.587^{***}	-0.573^{***}	-0.0867^{***}	-0.0428
	(0.0264)	(0.0246)	(0.0204)	(0.0169)	(0.0327)
1 Mural within 500 feet[3]	0.159^{***}	0.0649^{***}	0.0615^{***}	-0.0139	-0.000249
	(0.0155)	(0.0134)	(0.0122)	(0.0105)	(0.0143)
>1 Mural within 500 feet	0.337^{***}	0.156^{***}	0.159^{***}	0.00883	0.00753
	(0.0141)	(0.0130)	(0.0121)	(0.0121)	(0.0170)
Sidewalk	0.131^{***}	0.0436^{**}	0.0506^{**}	0.0190	0.0446
	(0.0220)	(0.0198)	(0.0213)	(0.0173)	(0.0292)
Sidewalk Shade	-0.277^{***}	-0.0108	-0.00984	0.00452	0.0203
	(0.0126)	(0.0111)	(0.0102)	(0.00832)	(0.0139)
Controls	N	Y	Y	Y	Y
Time FE	N	N	Y	Y	Y
Spatial FE	N	N	N	Y – BG	Y – Street#BG
Observations	27904	19943	19939	19933	19449
R^2	0.153	0.521	0.551	0.786	0.818

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
(1) – Excluded reference category is 'Major Arterial' Road Classification
(2) – Excluded reference category is 'No Litter'
(3) – Excluded reference category is 'No Murals within 500 Feet'

Table 5 shows the UQR Regression at the 10th, 20th, 50th, 80th, and 90th percentiles for my two levels of spatial fixed effects: block group and street within block group (interpretations of variables of interest in the following subsection). The explanatory power for my model is much lower within each of the percentile groups than when looking at the average effect. The R^2 ranges from .493 to .633 for the block group fixed effects and from .566 to .688 for the street within block group fixed effects. The lowest R^2 values are the 10th percentile of homes—perhaps revealing that poorer Philadelphia residents are unable to be selective about characteristics that typically raise home prices (e.g., a low-income buyer can only focus on meeting size criteria rather than considering garage spaces or home condition). The highest R^2 are, unsurprisingly, found at the 50th percentile, reflecting that the variables, controls, and fixed effects in my general model is applicable and relevant to the median home buyer in Philly.

Table 5: Unconditional Quantile Regression

	(1) Q10	(2) Q20	(3) Q50	(4) Q80	(5) Q90	(6) Q10	(7) Q20	(8) Q50	(9) Q80	(10) Q90
Minor Arterial[1]	-0.224** (0.101)	-0.0671 (0.0664)	0.0710** (0.0281)	0.0812*** (0.0301)	0.115*** (0.0421)	0.0106 (0.182)	-0.0221 (0.121)	0.0757 (0.0508)	-0.0821 (0.0526)	0.0261 (0.0720)
Collector	-0.0588 (0.0865)	-0.0326 (0.0568)	0.0906*** (0.0241)	0.0993*** (0.0257)	0.0321 (0.0360)	0.103 (0.151)	0.0209 (0.0997)	0.0834** (0.0420)	0.00291 (0.0435)	-0.0782 (0.0596)
Local	-0.155* (0.0871)	-0.0764 (0.0572)	0.0885*** (0.0242)	0.105*** (0.0259)	0.0491 (0.0362)	0.110 (0.153)	-0.0218 (0.101)	0.0737* (0.0425)	-0.000511 (0.0441)	-0.0531 (0.0603)
A Little Litter[2]	-0.0168 (0.0376)	-0.0455* (0.0247)	-0.0275*** (0.0105)	0.00132 (0.0112)	-0.0477*** (0.0156)	-0.0776 (0.0663)	-0.0866** (0.0438)	-0.0462** (0.0185)	0.0717*** (0.0191)	-0.0344 (0.0262)
A Lot of Litter	-0.328*** (0.0734)	-0.152*** (0.0482)	-0.00526 (0.0204)	-0.00729 (0.0218)	-0.123*** (0.0305)	-0.00985 (0.143)	-0.153 (0.0945)	0.0600 (0.0398)	0.101** (0.0413)	-0.158*** (0.0565)
1 Mural within 500 Feet[3]	-0.00122 (0.0459)	-0.0118 (0.0301)	0.00465 (0.0127)	-0.0239* (0.0136)	-0.00566 (0.0191)	-0.0158 (0.0625)	0.00186 (0.0413)	0.00221 (0.0174)	-0.0296 (0.0180)	0.0345 (0.0247)
>1 Mural within 500 Feet	0.0860 (0.0527)	0.0389 (0.0346)	0.00129 (0.0146)	-0.0379** (0.0157)	-0.00532 (0.0219)	0.0658 (0.0743)	0.00776 (0.0492)	-0.00303 (0.0207)	-0.0400* (0.0215)	0.0138 (0.0294)
Sidewalk	0.0586 (0.0754)	0.0503 (0.0495)	0.00534 (0.0210)	-0.0470** (0.0224)	-0.0289 (0.0314)	0.283** (0.128)	0.178** (0.0844)	-0.0188 (0.0355)	-0.0378 (0.0369)	-0.0171 (0.0504)
Sidewalk Shade	-0.0383 (0.0362)	0.0216 (0.0238)	-0.0178* (0.0101)	0.00316 (0.0108)	0.0322** (0.0151)	0.120** (0.0606)	0.0337 (0.0401)	0.0192 (0.0169)	-0.00607 (0.0175)	0.00248 (0.0240)
Controls			Yes					Yes		
Time FE			Yes					Yes		
Spatial FE			Yes – Block Group					Yes – Street # Block Group		
Observations R^2	19933 0.493	19933 .610	19933 .633	19933 .591	19933 .515	19449 .566	19449 .662	19449 .688	19449 .672	19449 .626

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
(1) – Excluded reference category is 'Major Arterial' Road Classification
(2) – Excluded reference category is 'No Litter'
(3) – Excluded reference category is 'No Murals within 500 Feet'

Variables of Interest

Looking at my variables of interest across the different models, my two key objectives are to a) identify the effect of each (Road Classification, Litter, Public Art, Sidewalks, and Shade) on housing prices, and b) observe how these differ across the distribution of housing prices (i.e., the different socio-economic and racial groups in Philadelphia).

Road Classification

For the Road variable, I focus on Regression 4 from Table 4 and Regressions 1-5 from Table 5. The regressions run with street level fixed effects are not relevant for Road since all homes on the same street will have the same classification.

Table 4 shows that there is an economically and statistically significant effect in home prices when moving away from a major arterial road—a move from a major to minor road sees a 4%increase in sales price. There is less of an effect the 'smaller' the road gets, perhaps reflecting indifference of home buyers as long as the home is not on a major road or a desire to have a balance between access and mobility. This finding is in line with other hedonic studies that have found, noise and air pollution, as well as traffic intensity levels result in a decrease in prices and that (Bajari et al., 2012; Levkovich et al., 2016).

The UQR shows that this effect is much stronger for homes with higher sales prices (i.e., higher-income/wealth residents)—to the tune of a 8-12% price increase when moving from a major to minor arterial for the city's top quintile of homes. The trend for the lowest 10% of homes is notably the opposite— residents in this percentile pay 25% *less* for homes on a minor vs. major arterial. The trend holds for the 20th percentile, but the results are not statistically significant. These trends probably reflect two forces: crowding out and the need for accessibility. Because more affluent households can pay more to live away from polluting major arterials, the housing stock along them becomes more affordable. However, the poorest households may prefer these homes rather than those they can afford 'deeper in' neighborhoods since they are more accessible to amenities like public transit and grocery stores. These households are less likely than their wealthier, Whiter counterparts to have access to a private vehicle and thus rely more on other transportation modes (Anderson, 2016). However, living next to a major arterial is not only bad for public health, but they often remove the ability for a street to become a public space. These streets are prioritized for cars often travelling at fatal speeds to a pedestrian, and thus unwelcoming to "eyes on the street" or the "sidewalk ballet". Although they may help lower income residents of color have better access to jobs and daily life, studies have shown that crime is more likely to occur on these major roads (Wuschke et al., 2021).

Litter

On the block group (neighborhood) level, there is an associated 2.2% decrease in sales price when moving from a neighborhood with no litter to one with a little bit of litter. This effect is more pronounced for those with a lot of litter, with an 8.3% difference with the base case of no litter. When looking at streets within a block group, this trend continues, with 3-4% price decreases for those streets with a little and a lot of litter, although the statistical significance fades for 'a lot of litter'.

There are strange, unintuitive results for the 80th percentile when using the street level fixed effects—apparently, for wealthier households in this percentile, 'A Lot of Litter' can raise house prices by a whopping 10.6% compared to homes with no litter on the street. This may be the result of select streets within high-income block groups have amenities that attract high-income residents but also produce litter (e.g., Farmer's Markets, such as the Italian Market, pictured in Figure 1).

Although litter is not a strange sight to most city-dwellers across the world, Philadelphia has long struggled with keeping its streets clean, even earning the nickname "Filthadelphia" over 100 years ago. A combination of poor administrative sanitation practices (e.g., a lack of public trash bins and curbside garbage pickup without receptacles), high prices for disposing waste (which encourages illegal dumping), and societal factors (attitudes, behavior, and context) has recently landed Philly on the top of Forbes' 'dirtiest cities in America' list (Nickels, 2021)

In 2021, Lockwood et al. Explored the spatial patterns of litter in Philadelphia using the 2018-2019 litter index that the City put together (and was ultimately incorporated into SoP's dataset) (Lockwood et al., 2021). The authors find that disadvantaged and poor communities are likely to have more litter. They posit that, rather than many past theories that this is solely the consequence of individual-level decisions to litter, it may also be a reflection of 1) an unequal distribution of city services and 2) poor planning of receptacle locations and sanitation maintenance schedules.

Lockwood et al.'s findings alongside Branas et al.'s vacant lot experiment and my results suggest an important policy implication regarding place quality and segregation—that some investments in improving small-scale built environment qualities may be able to uplift a community's sense of place, safety, and ultimately, home values. Perhaps a cleaner Philadelphia would allow for better mobility and opportunities of those who need it most.

Mural Art

The results concerning Mural Density and sales price are, on average, economically and statistically insignificant. There is one percentile, the 80th, within the UQR that is statistically significant on the 10% level, showing a 2-4% decrease for home sales around public art murals. The slight negative trend on these and the other results could be a reflection more of home type than presence of art—murals are much more likely to be found on the side of rowhomes than on the side of detached homes, which have average sales prices of $262,021 and $473,298, respectively, in my sample.

Another potential explanation for a negative trend could be that in the case of murals and public art, 'beauty is in the eye of the beholder'. Anecdotally, I was once told by a tour guide and curator at Philadelphia's Magic Gardens (a non-profit gallery space) that they often get calls from new homeowners asking them to remove historic installments of renowned mosaic artist Isaiah Zagar. Zagar mosaicked hundreds of vacant homes around South Philadelphia before the neighborhood began its transformation in the new millennium. Although the Magic Gardens attract thousands of tourists and locals alike, like the many other art museums around the city, the popularity does not seem to translate into home prices.

My findings seemingly contradict former studies. In 2016, University of Warwick researchers found that the presence of public art is correlated with "improving economic conditions of urban neighbourhoods" (Seresinhe et al., 2016). This evidence is consistent with Dutch research findings that 'cultural heritage' (an expression of a community's way of life, like a mural) increases real estate prices (Lazrak et al., 2014).

As Inga Saffron bluntly put it in her 2012 Philadelphia Inquirer column aptly titled 'Murals Will Not Save the City,' "maybe it's time for city officials to acknowledge that it's just not possible to paint your way out of blight" (Saffron, 2020). Although the current data may support her position, Mural Arts Philadelphia may (obviously) disagree. In a prime example of placemaking, their programs work to connect with the surrounding communities to reflect their voices in the art. They also work with prisoners and people with substance abuse issues to create the murals, helping them develop marketable skills (e.g., carpentry, digital literacy) for the workforce and break cycles of poverty and crime. Perhaps murals will not cure blight, but seeing the commitment and passion of non-profits, community organizers, and residents (hundreds of communities are currently on the wait list in Philly) alike have for public art, it may hold the kind of societal value important to placemaking.

Sidewalk

For the average regression, the presence of sidewalks do not seem to add any statistically significant value to home prices across the city of Philadelphia. However, the association is positive. Interestingly, the UQR shows that sidewalks seem to be highly valuable for the two poorest percentiles (an increase of 32% for the 10th percentile from the baseline of 'no sidewalk' and 19% for the 20th). These results are only evident when looking at streets *within* a block group, not between block groups. One potential explanation for this trend could be exactly that of Jane Jacobs hypothesis—poorer residents that are segregated into neighborhoods with higher crime rates would rather be located on streets where there are more "eyes on the street," deterring crime. It could also signal that poorer households have greater needs for multi-modal, accessible neighborhoods, as low-income and people of color are much more likely to rely on walking and public transit for mobility than their higher-income and White counterparts (Anderson, 2016).

The trend for sidewalks in the UQR is opposite, though mostly statistically insignificant, for wealthier homes. For the 80th percentile using block group fixed effects, there is an associated 4% decrease in home value for the presence of sidewalks. One possible cause for this (and the general negative trend) is that many of the highest valued homes in the study area are either in a) historical, sidewalk-less alleyways (which are often already archetypes of human-scaled, place-made spaces), or b) leafy sidewalk-less suburban-esque neighborhoods.

Shade

The average effects of sidewalk shade are also statistically insignificant, but positive. The UQR results show a mixed and unconvincing argument on both levels of fixed effects. At the 50th percentile, homes in more shaded neighborhoods (block groups) are apparently lower in value, but only by about 1.7%. For wealthier households, shadier neighborhoods add about 3% to home value. Within a block group, on the street level, only the 10th percentile returned statistically significant results, but to the tune of an associated increase of almost 13% in value.

I ultimately chose sidewalk shade as a variable of interest because, especially in a city where the summers can be sweltering, being able to sit under a tree or awning on a city block can be a determining factor for attracting the people necessary for a "sidewalk ballet". A large part of SoP's calculation of shade in their data is awnings. While an important built environment factor for summer stoop-sitting, trees, when incorporated thoughtfully and well maintained, often function as a better deterrents for heat islands, which disproportionally affect people of color and those living below the poverty line (Hsu et al., 2021).

Such greenery is also associated with benefits for physical and mental health, contributing to better-quality places as a shading device than awnings. In 2009, the city of Philadelphia set a goal to bring tree canopy cover up to 30% in all neighborhoods by 2025 (unfortunately, there has been a 6% *decrease* since the plan was released). One group of researchers found that 403 premature deaths could be prevented in Philly annually should the city meet that goal (Kondo et al., 2020). There is also some evidence from Portland of tree canopy cover increasing home prices (Netusil et al., 2010). However, better data and further analysis could help to explore its relationships and value to placemaking.

Limitations

As mentioned throughout the review of the independent variable interpretation, the UQR for the 80th percentile produced somewhat inexplicable outliers for my results. This could perhaps be a reflection of the sample size and selection. In the current analysis, there are less than 2,000 homes in each percentile, likely with abundant variability. If the SoP sample size was expanded to all zip codes in Philadelphia and a more accurate method was used to match homes to blocks, I could increase the sample by at least three-fold.

As discussed in the Data section, State of Place's machine learning has a negative detection bias. This measurement biases my SoP independent variables downward and could bias the effect of my estimators $\beta_{2,4,and\ 5}$ towards zero.

Another limitation is that my analysis only uses one point-in-time observation for the State of Place variables. A more causal study could look at how these built environment features change over time alongside subsequent changes in house prices.

Robustness

I did not incorporate the State of Place indices into my main analysis as they are created using the intellectual property of the company (i.e., I do not have insight into the weighting or variables included in each index). However, I ran Regression 4 with the overall State of Place Index at both levels of my fixed effects to find no significant prediction power (i.e. insignificant t-values and unchanging R^2). I also ran the sub-indices (density, safety, etc.)—the only one that was statistically significant for home values was 'Safety,' with an associated .12% increase in price for every 1-point increase in the safety index.

I originally considered including additional housing characteristics (e.g., heater type, basement type, view type, and topography) but decided to drop them because of either lack of significance, overcomplication of model, or potential absorption by fixed effects.

Other control variables I considered including were the number and type of neighborhood associations a given home or block belongs to and the historic Home Owner's Loan Corporation (HOLC) designation of a given block. Neighborhood associations are important in giving communities power and voice for the resources they would need for placemaking initiatives. However, the data does not currently exist to measure the power of these associations, i.e., some of those registered with the city may be defunct or not hold the political sway that others do.

Esri recently made public and usable the historic HOLC data (commonly referred to as 'redlining') publicly available for hundreds of cities across the U.S (Lavery, 2020). Redlining legally ended under the Fair Housing Act of 1968, but racially biased home sales practices are still implicit in the U.S. today (Korver-Glenn, 2018). This made it impossible for many people of color to buy homes and, ultimately build wealth through property as many White families did. My incorporation of the HOLC designation into Regression 4 did not find statistically significant association with recent home prices in Philadelphia, likely due to gentrification and displacement during the resurgence of the city center at the turn of the century. However, there is evidence that the practice of redlining has perpetuated the poverty and segregation of communities of color (An et al., 2019).

It could be useful in the future to observe different characteristics' impacts by location— e.g., the spatial heterogeneity of road classification by neighborhood. Wang and Rasouli do this by mapping each of their Airbnb's as point data and color-coding it red/blue for positive/negative price impact. This could help policymakers in choosing which neighborhoods receive different built environment investments.

5. Conclusion

Summary and Closing Thoughts

The most impactful built environment elements to home prices in Philadelphia from my analysis were the type of road the home is located on and the amount of litter on their street. Smaller placemaking efforts, like the presence of murals, showed little impact. This makes sense: these "one and done" projects are not comprehensive investment that affect residents' daily life. Projects that induce positive, consistent interaction with their community (through the type of street they live on), and the comfort level of doing so (in a neighborhood free of crime and garbage), however, are. That these two aspects seem the most promising ways to positively influence communities' built environments would come as no surprise to placemaking proponents like Jacobs and Whyte.

That higher-income and Whiter residents can (and do) pay more for placemade spaces is also not a shocking conclusion. Investments in shrinking urban roads and vacant lot cleanups are not silver bullets— policies that increase amenity levels and have the potential for better economic, social, and health outcomes often attract wealthier, Whiter residents, perpetuating the cycle of gentrification many cities are facing today. But, as speakers from a recent Smart Growth Equity Summit noted, "the opposite of gentrification is economic segregation... [and] failing to invest is not support." (Hope, 2022) The community collaboration aspect of placemaking could potentially help boost existing residents' ownership of neighborhoods, through coalitions like community land trusts, with the benefit of protecting against displacement when the area improves (usually through increases in rent or property). As the grandmother of placemaking herself put it, "cities have the capability of providing something for everybody, only because, and only when, they are created by everybody" (Jacobs, 1961). Investments must come hand-in-hand with displacement prevention policies (e.g., subsidized units and inclusionary zoning) to fully take advantage of the integration potential seen in Chetty et al.'s Moving to Opportunity work.

Residents of Philadelphia deserve to live in safe places that give them the opportunity to lead healthy, happy lives. Some of my data shows that many of the city's most disadvantaged people are being crowded out of neighborhoods and streets with the built environment aspects that could foster these outcomes. Through equitable provision of resources towards placemaking investments and inclusion of those who could benefit the most, Philadelphia has the potential to transform its promising "urban fabric" into a vibrant, diverse ballet.

Future Research

To understand exactly how strong segregation is along the lines of the presence of 'quality place' elements, demographic information at a household level would be necessary. With such data, one could create a sorting model to "infer structural parameters that characterize preference heterogeneity" (Kuminoff et al., 2013). This could potentially reveal the point at which neighborhood investments or existing placemaking potential begins to induce gentrification. It could also build on Bayer et al.'s earlier sorting work that found that much of segregation can be attributed to the quality of neighborhoods (Bayer et al., 2007). Understanding this could allow policymakers to protect current tenants from displacement while concurrently using development and investment to bring better opportunities and outcomes to neighborhoods with needs. Privacy laws currently prevent household demographic data from being publicly available. However, the data is available for purchase, so such an exercise could be explored by larger research institutions in partnership with geographic data providers.

Advancements in machine learning and neural networks could also vastly help with the accuracy and precision issues faced by the 2020 version of State of Place's algorithms and AI. Recent neurocomputing work from the University of British Columbia used Philadelphia as a case study to "fuse urban data, i.e., metadata and imagery data, with house attributes" to predict property market values. As the capabilities of such models and methods grow, so can sample sizes, and with that, greater certainty and precision in analyses such as mine. With an abundance of data and tools that are making it easier to collect and analyze at different aggregation levels across an entire metropolitan area, there is plenty of room for novel research involving placemaking-related and human-scaled built environment features.

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