A Comparison of the Impacts of Alternative Walkability Measures on House Values

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Executive Summary

Most recent research on the relationship between walkability and housing value has employed Walk Score as their primary measure of walkability. Despite its benefits, Walk Score has several limitations, namely that it is a proprietary measure whose calculation is not entirely transparent and that it must be purchased when analyzing large sets of data. Here we test a variety of alternative measures of walkability and compare how well they explain housing value in comparison with Walk Score.

We hypothesize that the value of walkability may vary across space. For this reason, we here analyze two distinct urban areas, Seattle, and Miami. We also examine how poverty levels act as a mediator on the value of walkability, potentially increasing or decreasing its value.

We gather or create 18 walkability variables, including eight variables related to local street networks, six variables related to activity mix, three variables related to access to destinations, and a nationally available walkability index from the US Environmental Protection Agency. We created walkability variables for 400, 800, and 1600-meter radii, but ultimately conducted our analyses using 400-meter radius data. We also collected a variety of control variables related to residential transactions that have been shown to influence house values. Our samples consist of 29,942 housing transactions in urban Miami-Dade and 5,434 single-family housing transactions in Seattle. Control variables include living area, age of structure, condition of structure, land area, distance to CBD, and view and location amenities. Then we run a variety of hedonic regressions testing various walkability variables. To aid in variable selection, we first correlate walkability variables with Walk Score and select variables with the highest correlations. As a robustness check, we also run regressions with neighborhood dummies, which have been demonstrated in the past to effectively predict housing values.

We find that the marginal effect of walkability varies from -$16,574 (-5.3%) to +40,142 (8.7%) in Miami-Dade and from +$27,189 (3.8%) to +$76,983 (6.3%) in Seattle. Several walkability variables demonstrate similarly sized marginal effects with Walk Score. In Miami-Dade, the EPA Index and Mix3 (3-category land use mix between residential, consumer services, and public services) show a similar performance with Walk Score, while in Seattle, the EPA Index, Mix3, and Street Density show a similar performance with Walk Score. In most cases, the EPA Index demonstrates a larger marginal effect than Walk Scores do. This suggests that there are several freely available walkability variables that may adequately substitute for Walk Score in hedonic analyses.

We also find significant spatial variation in the effect of walkability variables. Firstly, the percentage increase on housing prices of walkability variables appears to be larger in Seattle than in Miami. Secondly, we found evidence that the walkability variables have negative correlations in non-urban areas, which resulted in our restricting our analyses to urban areas (results not shown). And thirdly, we found that poverty level interacts with walkability in the Miami-Dade area, with higher levels of poverty showing a decreased or even negative walkability premium.

Areas for future research would include further investigations into the variability of walkability's effect on property values across space and especially differences across varying city forms. Another potential area of interest would be to construct a new walkability index specifically designed to capture walkability's influence on housing or property values.

Introduction

The convenience of walkability and its influence on house values has been a topic of interest for many years among urban planners, real estate developers, and property appraisers. Walkability refers to how friendly a neighborhood is for pedestrians, encompassing sidewalk availability and condition, street connectivity, accessibility to amenities, safety, and overall pedestrian experience (Talen & Koschinsky, 2014). Many residents view walkable neighborhoods as an amenity, potentially offering residents access to goods, services, jobs, entertainment, recreation, and regional transit connectivity. Walkable communities can also reduce transportation costs and improve health benefits (T. A. Litman, 2003).

Walkability has emerged as an important attribute influencing property values (Cortright, 2009), and research shows a positive relationship between walkability and residential property values (Choi et al., 2021; Zolnik, 2021). Health and well-being are factors that can drive real estate premiums. Homebuyers increasingly prioritize access to parks, recreational facilities, and walking or biking trails (Leyden, 2003). Walkable neighborhoods often feature a mix of land uses, providing residents easy access to shops, restaurants, schools, and public transportation (Cervero & Kockelman, 1997b). This convenience can reduce travel times, lower transportation costs, and enhance the overall quality of life. Walkable neighborhoods can foster social interaction, creating a sense of community and belonging (Leyden, 2003). This social aspect appeals to many homebuyers and renters, enhancing the desirability of a neighborhood.

This study examines the impact of walkability on home values with an in-depth survey and analysis of alternative measures. Many studies use Walk Score as a predictor of residential property values. Walk Score has some distinctive strengths. Walk Score accounts for proximity to a variety of useful destinations for residents, and integrates this information into an easy-to-interpret 0-100 score (Walk Score, 2021). Because the website allows users to quickly test the Walk Score of different places they have visited or known, people can quickly get a feel for the meaning of different levels of Walk Score. However, the use of Walk Score is problematic for several reasons. First, the methodology underlying the calculation of Walk Score values for each address is a black box. The company keeps this information confidential because of proprietary commercial considerations. Not knowing the underlying factors is problematic for researchers and professionals, including planners and developers interested in maximizing the value of real estate when developing walkable communities. Second, although Walk Score is free on an individual address level, the company does not allow bulk downloads to study how walkability and real estate values interact. Purchasing the data from the firm is expensive and can be cost-prohibitive for researchers interested in exploring how walkability and property values interact.

Fortunately for scholars and those interested in examining bulk datasets connecting walkability to property values, the study finds that several other freely available metrics, such as the EPA's National Walkability Index (a.k.a., "EPA Index"), are available for analysis. The study concludes that such alternatives could be a free or low-cost alternative to Walk Score in modeling the connections between walkability and property values.

Specifically, this study examines the following questions:

1. Which measures of walkability are highly correlated with Walk Score?

2. How do the different measures compare to Walk Score as a predictor?

This study examines data from Miami-Dade County in Florida and King County (Seattle) in Washington. Both counties are somewhat typical of core American cities in that they include both walkable and non-walkable areas. The results of this study aim to contribute to real estate valuation research by providing an analysis and comparison of different measures of walkability, how effective they are at predicting residential property values, and how freely available data compare to Walk Score.

Literature Review

This section focuses on literature that urban designers utilize to measure walking quality. This includes built environment metrics, such as block size and street network design, land use diversity, and computed measures, such as Walk Score (Walk Score, 2021) and the EPA's National Walkability Index (Environmental Protection Agency, 2021).

Several methods are utilized for measuring walkability based on block size. These are typically calculated using TIGER (topologically integrated geographic encoding and referencing) data (Schlossberg, 2006). Smaller blocks tend to promote walkability as they create a more diverse, permeable, and interconnected street network (Ewing & Handy, 2009). Methods for measuring walkability based on block size include block area and perimeter. Smaller block areas typically indicate more walkable environments (Ewing & Cervero, 2001). Renne and Ewing (Hamidi et al., 2020; 2013) used an average block size of 6.5 acres or less as a threshold for defining walkable transit-oriented developments. Similarly block perimeter has been used to quantify walkability, with smaller perimeters indicating higher levels of walkability (Frank et al., 2010b; Pafka & Dovey, 2017).

Street network design indicators, including intersection density (including the percentage of four-way or three-way intersections), and the link-to-node ratio of intersection to street segments, have been used as walkability proxies to measure travel behavior (Marshall & Garrick, 2012). Others have utilized a pedestrian shed (also called "ped shed") approach which is the share of the area that can be covered by walking along the street network in comparison with the area encompassed by the crow flies distance. More fine-grained street networks yield a higher ped shed percentage compared to auto-oriented suburban settings (Ellis et al., 2016; Porta & Renne, 2005).

Walking metrics summarized above, including Walk Score and the EPA National Walkability Index have been widely used in research and urban planning, especially with respect to exploring the connections between neighborhood design and travel behavior. Walkability and transit use are increasingly recognized as vital components of sustainable urban development, with numerous studies demonstrating their interrelated effects on health, social equity, and environmental outcomes (Ewing & Cervero, 2010; Saelens & Handy, 2008). High levels of walkability can promote increased transit use by providing a more inviting and accessible pedestrian environment (Frank & Pivo, 1994; Rodríguez & Joo, 2004), while well-connected transit systems can encourage walking by offering a reliable alternative to private automobiles (Lee & Moudon, 2006; Manaugh & El-Geneidy, 2011a). Mixed land-use, density, and street connectivity are key factors contributing to walkability, which in turn affects transit use (Cervero & Kockelman, 1997a; Ewing et al., 2015). The association between walkability and transit use has significant implications for urban planning and policy, emphasizing the need to prioritize walkability and public transit access to foster sustainable, livable communities (T. M. Litman, 2022; Newman & Kenworthy, 1999).

One of the important reasons walkability and travel behavior are connected to home values is due to the concept of location efficiency. The Housing + Transportation (H+T) Affordability Index is a widely recognized tool that examines the combined cost of housing and transportation based on an inputted address, providing a more comprehensive understanding of location affordability (Center for Neighborhood Technology, 2021). Housing guidelines suggest that housing costs should not exceed 30% of household income whereas a combined H + T budget should be limited to 45%. However, if neighborhoods facilitate walking and transit use, thus reducing transportation costs, people could shift those savings into higher housing costs, thus driving up the price of homes without changing overall affordability of the area (Haas et al., 2016). In fact, a study of transit-oriented developments found that on average, households living in such stations spent an average of 5% less of their household budget on transportation compared to average households living near rail stations with auto-oriented urban form. Given the median household income of $55,000, this translates into an extra $230 per month that such residents save in transportation costs, which could be used to offset higher housing costs (J. L. Renne et al., 2016).

Some studies have examined the phenomenon of self-selection in walkable communities. This means people with a desire to in walkable communities will seek out housing and often pay a premium for this amenity (Cao et al., 2009). However, research also shows an unmet demand for housing in such communities, thus putting upward pricing pressure on housing in walkable communities due to limited supply (Frank et al., 2015; J. L. Renne, 2013).

Other research on walkability and its connection to home values that is less explored relate to the design quality of the streetscape, including the urban-design qualities of imageability, enclosure, human scale, transparency, and complexity (Ewing & Handy, 2009).

In summary, streets contain many factors that influence walkability. A number of these factors influence the walkability and desirability of neighborhoods. These amenities may have a direct influence on home values or an indirect effect via the mechanisms of decreased transportation costs. Moreover, the literature indicates that walkable neighborhoods themselves may be an amenity that is in high demand and short supply, resulting in upward pressure on home values, and even result in longer-term gentrification (Knight et al., 2018; Levine et al., 2005).

Study Area

We aimed to select urban counties with considerable variability across walkability metrics, on the hypothesis that we would find greater effects if there were more variation in the independent walkability variables. We also endeavored to choose study areas that were different in terms of climate, mobility culture, and transit provision, hypothesizing that the value of walkability might vary significantly across differentiated metropolitan regions.

Miami-Dade is considerably more auto-dependent than King County. According to 2021 1-year ACS data, 77.7% percent of commuters drove to work, 2.7% took public transit, and 1.9% walked, as compared with 51.7% drivers, 4.0% public transportation users, and 2.0% walking in King County (US Census Bureau, 2020). We also referenced *Foot Traffic Ahead*'s (Loh et al., 2019) ranking of metro areas by walkability, in which Seattle ranks #8 and Miami ranks #24. *Foot Traffic Ahead*'s ranking may be more appropriate because they identify pockets of walkability within largely suburban metropolitan areas and analyze the increase in property values associated with these walkable areas. Metropolitan areas with pockets of high-value walkability, as well as locations of poor walkability, are in theory ideal for an analysis of the association of walkability with housing value.

Miami and Seattle also vary significantly on the level of public transit provision, with metro Seattle offering 34.7 vehicle revenue miles per capita and metro Miami offering 18.1 vehicle revenue miles per capita in 2017 (authors' calculations, using data from Merlin et al., 2021). Furthermore, differing climatic conditions may make walking more attractive in some regions than in others; Miami is known for its hot and humid climate that can serve as a deterrent to walking, which possibly could reduce the value of walkability within that region.

Data Sources for Walkability Metrics

At the beginning of the project, we reviewed the walkability metrics that have been used in previous work. These metrics are summarized in Table 1. In this table, we record the name of the metric, whether it is an original source or secondary source, the website where it is provided, a brief description of the walkability factors considered, the geographic unit of analysis, whether or not the data source is free, and how recently it was last updated as of the beginning of our study (January 2021).

It is notable that there is an increasing number of proprietary walk accessibility tools available that integrate multiple data sources to calculate walk accessibility metrics, including Conveyal, Cube Access, and Goat. We decided to focus on the leading proprietary measure, Walk Score, in comparison with a number of freely available metrics with national coverage. Our aim is in part to determine whether any of the latter are good alternatives to Walk Score.

There is a great deal of heterogeneity in how walkability variables are calculated. Some of the more complex metrics are conventional accessibility measures that account for proximity of different destinations (Merlin & Jehle, 2023). Other walkability variables are measurements of street and block structure others are measures of land use characteristics or mixes, or indexes that combine multiple types of such information into a standardized single measurement. We make no claim that Table 1 is comprehensive, given that researchers continue to develop new walkability metrics (see for example (2020)). We review several of the different walkability metrics more thoroughly in later sections of the report.

Walk Score

Walk Score is a proprietary measure of walkability created by the company Walk Score Management, LLC. A Walk Score in the range of 0-100 can be requested for any individual address, neighborhood, or city through their website, www.walkscore.com. Walk Score considers the proximity of a variety of destination types from a given address, including restaurants, coffee shops, bars, grocery stores, parks, schools, shopping, entertainment, and errands. It also accounts for block length and intersection density, both measures of the street network as discussed in more detail below. The various proximity and street connectivity measures are aggregated in a proprietary formula into a single score in the range from 0-100, with 0 representing the least possible walkability and 100 representing the best. According to the official Walk Score guidelines, scores of 90-100 represent a "Walker's Paradise", while 70-89 is "Very Walkable", 50-69 being "Somewhat Walkable," and 0-49 being "Car-Dependent.[1]". Researchers have used Walk Score for a variety of academic research, including studies of housing and property values[2].

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[1] https://www.walkscore.com/methodology.shtml

[2] https://www.walkscore.com/professional/walkability-research.php

Table 1. Selected Walkability Metrics

Metric Name	Original Source?	Website/Source	Factors Considered	Unit of Analysis	Cost	Recency
AARP	No	https://livabilityindex.aarp.org/data-sources	Based on predicted walk trips from EPA's Smart Location Database	Address	Free	2013
Access Across America	Yes	http://access.umn.edu/research/america/walking/2014/	Walk access to jobs (Destinations, distance)	Census Block	Free	2014
Block Length	Yes	Any street shapefile	Street geometry	Census Block	Free	
Conveyal	Yes	https://www.conveyal.com/	Walk access to destinations	250 m grid cell	~$10,000	Current
Cube Access	Yes	Bentley	Destinations, distance, route directness	Census Block	~$10,000	2017
Goat	Yes	https://www.open-accessibility.org/versions/	Destinations, distance. Customizable	Hexagonal grid cell	~$10,000	Current
HUD Location Affordability Index	No	https://www.hudexchange.info/programs/location-affordability-index/documentation/#data-and-methodology	Average block density (street geometry)	Census Block Group		
Intersection Density	Yes	Any street shapefile	Street geometry	Census Block	Free	
Land Use Mix	Yes	https://lehd.ces.census.gov/data/	Diversity of jobs and workers	Census Block	Free	2015
National Walkability Index	Yes	https://www.epa.gov/smartgrowth/smart-location-mapping#walkability	Land use mix, street geometry, model of walk commute mode share	Census Block Group	Free	2010-2012
Urban Footprint	No	https://urbanfootprint.com/whitepaper/urbanfootprint-tech-guide/				
Walk Commute Mode Share	Yes	https://data.census.gov/cedsci/	Reported walk commute mode share	Census Block Group	Free	Annual
Walk Score	Yes	https://www.walkscore.com/methodology.shtml	Distance to destinations, street geometry	Address	Cost per Address	Annual

Other Walkability Metrics

In addition to Walk Score®, we attempted to create and collect as many walkability metrics as possible that were freely available at the Census Block or Block Group level of geography. Roughly, the walkability metrics can be categorized into four groups: street network measures, mixed-land use measures, walk accessibility measures, and indices. For each of these, we calculated the measure based on 400-meter, 800-meter, and 1600-meter radii from Census Block centroids.

Street network measures are based solely on the physical nature of streets and their connectivity. These measures include the number of intersections, the number of 3+ way intersections, connected node ratio, street miles, mean and median block perimeter, and mean and median block area. For each of these measures, we included all intersections, streets, or blocks that intersected with the chosen radius of analysis (400, 800, or 1600 meters). Therefore, the measures are not influenced by differences in Census Block shapes or sizes. All such data can be constructed based on a comprehensive street network through tools available in ArcGIS. Note that such measures do not account for the location of land uses, nor for other factors that may affect walkability such as street crossing features or obstacles.

Mixed-use measures, on the other hand, focus on the variety and balance of activities present within the given radius (Song et al., 2013). Activities are measured via job counts from the LODES database, which provide worker and job counts for each of the 20 NAICS codes at the Census Block level for every year, thereby providing very detailed data on the spatial location of job-related activities (US Census Bureau, 2021). LODES data is aggregated by the US Census from state reported unemployment insurance and other administrative records, so it may not include all types of jobs; for example, self-employment would not be captured. Most mixed-use measures are based on the entropy formula which accounts for the balance between various activities present within the same area. If equal amounts of every activity are present across the categories considered, the entropy formula yields a 1; if any of the activities is absent, the entropy score yields a 0; and, generally, the more balanced the activities present are, the higher the entropy score. Therefore, the set of activities considered in the balance formula is important and varies across studies. Here, we attempted to be inclusive of a range of alternative methods for calculating land-use entropy and examine five different mixed-use entropy measures, including one of our own devising (Ewing et al., 2013; Hamidi et al., 2020; Tian et al., 2020). Our proposed mixed-use measure attempts to define three categories of activity: the presence of residences; the presence of commercial services of any kind; and the presence of public services of any kind. By using three broad categories, we hope to avoid having many zero or near-zero values, since the entropy formula yields a zero value if any of the subcategories have a value of zero.

$$Entropy = -\sum_i \frac{p_i ln(p_i)}{\ln(k)}$$

Where *k* is the number of categories, *i* is an index of the categories, and p_i is the percentage of activity or land use within each category in a given analysis area.

Table 2: Description of Mixed-Use Measures

Mixed Use Measure Name	Categories Considered
Mix3 (Created by authors)	3 categories: Workers, Consumer Services, and Public Services.
Emp5	5 categories: Office, Retail, Industrial, Services and Entertainment
Ewing5 (Hamidi & Ewing, 2014)	5 categories: Retail, Entertainment, Health, Education, and Personal Services
Mix5	5 categories: Workers, Retail, Arts and Entertainment, Health Care and Education, and All Other
Mix9 (Greenwald, 2006)	9 categories: Workers, Retail, Manufacturing, Transportation, Arts and Entertainment, Health Care and Education, Construction, Mining, and Agriculture.

Accessibility measures take into account both the walking distance to destinations and the number of destinations nearby (Committee of the Transport Access Manual, 2020). One example is the job accessibility measure created by Access Across America in 2014 (Owen et al., 2015). The Accessibility Observatory provides detailed information on how this walk to jobs accessibility measure is calculated (Owen et al., 2015). Also, unlike Walk Score, the data from the Accessibility Observatory explicitly assumes that distance is based upon the street network rather than straight-line distance from origins to destinations. The other major accessibility measures include the number and acres of parks within the walkshed of either 400, 800, or 1600 meters. These distances are commonly used in the walkability literature (Manaugh & El-Geneidy, 2011b; Semler et al., 2016). It is also worth noting that Walk Score is an accessibility measure, as it indicates the relative proximity of a variety of destination types, although how Walk Score discounts for distance is not made explicit in its documentation.

The National Walkability Index was created by the U.S. Environmental Protection Agency (EPA) in 2015. The EPA National Walkability Index is calculated using publicly available data from the EPA Smart Location Database, which includes data from a variety of federal agencies. The EPA Walkability Index includes two entropy measures, street intersection density, and walk commuter mode split. Each variable is then turned into a ranking variable on a scale from 1-20, with 20 representing the highest-ranking walkability across block groups within a given metropolitan area. Then the various rankings are averaged together into an index (Ramsey & Bell, 2014). The index ranges from 0 to 20, with higher scores indicating greater walkability. Scores of 15.26 – 20 indicate the most walkable areas, 10.51 – 15.25 indicate above average walkability, 5.76 – 10.5 indicate below average walkability, and the least walkable areas include scores below 5.75 (Environmental Protection Agency, 2021).

In some cases, computation of walkability measure may result in missing values. For example, if there are no blocks fully contained within a 400-meter radius, block-based measures have no applicable value. Likewise, for job-worker balance, if the denominator (workers) is missing, then the ratio is undefined so missing values should occur.

Comparison of Walkability in Miami and Seattle

One of the most commonly used measures of walkability is block perimeter, or distance around the block. Smaller blocks are considered to be more pedestrian friendly, and in fact many jurisdictions create regulations around maximum block sizes. Figure 1 illustrates a measure of block size: median block perimeter of all blocks that intersect within 400 meters of each block centroid. The maps are at the same scale for King and Miami-Dade counties. The maps illustrate that the entirety of downtown Seattle and a good distance to the north and east are comprised of small, pedestrian-friendly blocks. In Miami-Dade, on the other hand, small blocks are only in the immediate downtown and cluster along a corridor running north and west, with substantial gaps between the small-block areas. This means that the area of contiguous walkability is lesser around the Miami-Dade downtown area.

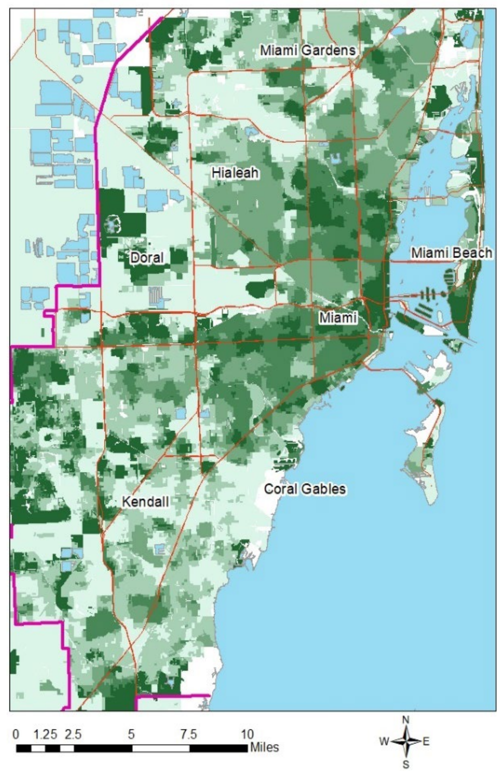

Figure 1: Block Perimeter in Seattle (left) and Miami (right) (quantiles)

The pattern of mixed use is displayed in Figure 2 below. We show three-category mixed-use, as it displays the highest variation across the two study areas. In King County, the areas of greatest mixed use are the town centers, such as Redmond, Bellevue, and Renton. In Miami-Dade, the mixed-use areas are arrayed linearly along major corridors. This linear pattern is less conducive to compact walkable areas, as these corridors are primarily major roadways.

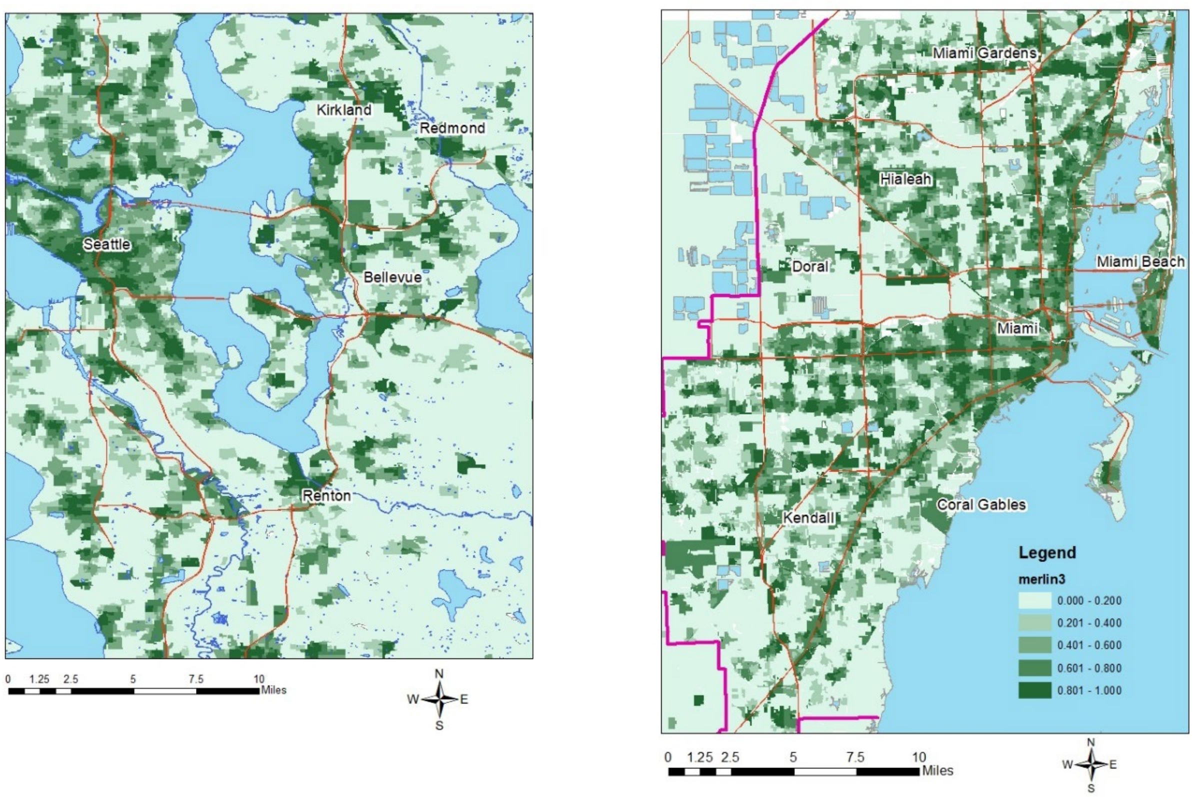

Figure 2: Three-Category Activity Entropy, Seattle (left) and Miami (right) (equal interval)

Lastly, we compare the EPA Index across the two study areas. In King County, much of central and northern Seattle is highly walkable, as are pockets in suburban cities to the east. In Miami-Dade, again the areas of walkability are more scattered and less clustered. The southern part of Miami Beach and the areas around downtown Miami are walkable, but these areas do not extend as much into adjoining neighborhoods. There is a band of high walkability to the west of Miami, but it is interrupted and not contiguous.

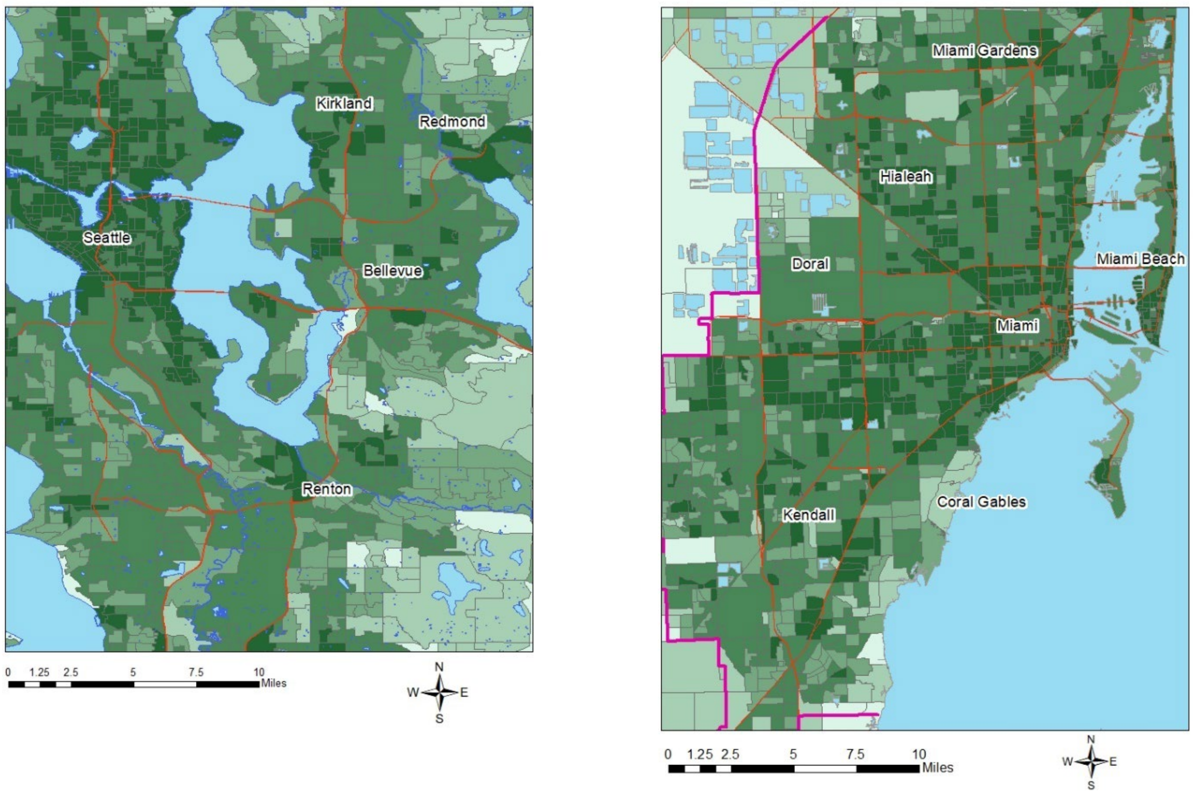

Figure 3: EPA Walkability Index, Seattle (left) and Miami (right) (Block Groups, equal interval)

Other Data

We use residential transactions data from Miami-Dade County, Florida, for 2017 and King County, Washington, for 2021. The data are from the Florida Department of Revenue and the King County Property Appraiser's Office, respectively.[3] We focus on the more walkable parts of each county: the urban area (as defined by the U.S. Census Bureau) in Miami-Dade County and the City of Seattle in King County. The Miami-Dade data include both single-family houses and condominiums, while the Seattle data are limited to single-family houses due to incompatibilities between the sets of characteristics

[3] For information about Florida property tax data, see https://floridarevenue.com/property/Pages/Home.aspx; the King County property data are available at https://kingcounty.gov/depts/assessor.aspx.

available for two types of dwellings.[4] The sample sizes are approximately 29,900 for Miami-Dade County and 5,400 for Seattle.

The poverty rate data are the American Community Survey 5-year estimates for Block Groups for 2017 (Miami-Dade) or 2021 (Seattle).[5] We calculated the distance to the CBD and ocean measures and introduced Zip codes as controls for small areas in the Miami-Dade analysis. Census Tracts were used as locational controls in the Seattle analysis in lieu of zip codes because the latter were missing in many cases. Because Census Tracts are relatively small areas, this involved combining adjacent tracts so that each neighborhood contained at least 50 transactions.

The Miami-Dade and Seattle data differ in some key respects (see Table 3 and Table 4). One striking difference is the higher average property value in Seattle (which as noted above includes only single-family houses). The mean Walk Score for Seattle is 67.3, compared with 56.3 for Miami-Dade. The mean EPA Index for Seattle is slightly higher than that for Miami-Dade, while the mean values for Mix3 are virtually the same. The mean poverty rate (for Block Groups) in Seattle is about half that in Miami-Dade. Another notable difference is the much younger average age of properties in Miami-Dade.

The walkability measures are standardized (mean = 0 and standard deviation = 1) so that the results are comparable across measures. This leads us to report property value impacts for one standard deviation changes in the relevant walkability measure.

[4] We plan to add a separate analysis of Seattle condominiums at a later date.
[5] The ACS data are available at https://data.census.gov.

Table 3. Sample statistics for Miami-Dade County urban area

Variable	Mean	Standard Deviation	Minimum	Maximum
Sale price ($)	423,375	364,375	115,000	3,379,900
Walkability measures				
Walk Score	56.3	28.7	0	99
EPA Index	13.3	3.7	3	20
Mix3	0.382	0.322	0.000	1.000
Poverty rate	0.144	0.103	0.000	0.775
Living area (square feet)	1,627	749	442	4,914
Age of structure	25.5	20.6	0	108
Condo	0.536	—	0	1
Value of distinctive features ($)	4,448	10,416	0	113,960
Land area (square feet)	4,212	6,597	0	219,107
Distance to CBD (feet)	58,138	35,232	689	158,755
Distance to ocean (feet)	7,549	6,362	14	23,111
Sale quarter				
1	0.219	—	0	1
2	0.293	—	0	1
3	0.243	—	0	1
4	0.245	—	0	1

Notes: The sample size is 29,942 except for Mix3, which has a sample size of 29,916. The sample includes both single-family houses and condominiums.

Table 4. Sample statistics for Seattle

Variable	Mean	Standard Deviation	Minimum	Maximum
Sale price ($)	1,032,958	464,632	294,074	3,000,000
Walkability measures				
Walk Score	67.3	19.1	0	98
EPA Index	15.5	2.1	9.5	19.5
Street density	25.7	5.8	0.8	43.9
Mix3	0.388	0.262	0.000	0.999
Poverty rate	0.070	0.069	0.000	0.604
Living area (square feet)	1,874	757	740	4,750
Age of structure	60.5	38.7	0	121
Condition				
Poor or fair	0.004	—	0	1
Average	0.592	—	0	1
Good	0.258	—	0	1
Very good	0.146	—	0	1
Land area (square feet)	4,643	2,724	378	32,153
Distance to CBD (miles)	5.16	1.69	0.95	10.05
Views				
Puget Sound	0.040	—	0	1
Lake Washington	0.025	—	0	1
Cascade Mountains	0.039	—	0	1
Olympic Mountains	0.031	—	0	1
Other	0.008	—	0	1
Waterfront location	0.003	—	0	1
Sale quarter				
1	0.191	—	0	1
2	0.313	—	0	1
3	0.275	—	0	1
4	0.221	—	0	1

Notes: The sample size is 5,434 except for street density and Mix3, which have a sample size of 5,406. The sample includes single-family houses only.

Methods

We focus on Walk Score and other walkability measures that are highly correlated with Walk Score (Table 5). Our aim was to choose at least one measure from each of the street network and land use mix categories; however, none of the street network measures for Miami-Dade was highly correlated with Walk Score. Although Job Access is highly correlated with Walk Score in the Miami-Dade data, it consistently had the wrong (negative) sign in estimations, so we excluded that variable from the analysis presented here. We present results for analyses using Walk Score, EPA Index, and three-category mixed use for both Miami-Dade and Seattle; we also include Street Density for Seattle.

Table 5. Correlations of Walk Score with other walkability measures

Walkability measure	Miami-Dade County urban area	Seattle
EPA Index	0.651	0.535
Walk commute	0.518	0.285
Parks	0.473	0.083
Park acres	0.413	-0.204
Job access	0.627	0.336
Intersection density	0.023	0.537
Street density	0.146	0.544
Connected node ratio	0.200	0.511
Block perimeter median (feet)	-0.084	-0.344
Block area median (acres)	-0.062	-0.150
Job-work balance	0.561	0.389
Mix3	0.654	0.496
Emp5	0.447	0.260
Ewing5	0.572	0.325
Mix5	0.561	0.362
Mix9	0.083	—

Note: The Miami-Dade sample size varies from 29,464 to 29,942 and the Seattle sample size varies from 5,406 to 5,434, depending on the measure. All correlations are statistically significant at the 0.0001 level.

Our estimation method is the conventional hedonic approach, which explains property value using a set of property characteristics. These characteristics refer to the structure and lot, neighborhood, and location. We experimented with different specifications of certain variables and decided to use a natural logarithmic transformation in some cases. The dependent variable is always the natural logarithm of sale price. We also deleted observations in the top and bottom one percent of the distribution for the sale price and floor area variables; this excluded unusually large or small properties which may, in some cases, have been due to data entry errors.

We include the poverty rate as a neighborhood characteristic, partly because we hypothesize that the impacts of walkability vary with the poverty level. To capture this, we interact the poverty rate with each walkability measure. It turned out that this relationship exists in Miami-Dade, but not in Seattle, so we report results containing the interacted term only for Miami-Dade.

We estimate models for each walkability measure both with and without controls (dummy variables) for small areas. Such controls have been shown in previous studies to greatly improve the explanatory power of hedonic models (e.g., Bourassa et al., 2021) However, they are often collinear with other location-related variables (which would include walkability measures) and can wash out the effects of such variables; hence the models without the location controls are likely to give a better indication of the impact of walkability on property values.

Results

We first examined how a number of walkability variables correlate with Walk Score, shown in Table 5. In Miami-Dade, we found high correlations between Walk Score and the EPA Index, Job accessibility, Job-worker balance, and most of the land-use mix variables. In Seattle, variables that correlated moderately with Walk Score included the EPA Index, Intersection and Street Density, Connected-node ratio, and the Mix3 variable. It is interesting that the correlations between Walk Score and various other walkability variables were not consistent across the two study areas, with Job accessibility more highly correlated in the Miami-Dade area and various street network variables more highly correlated in Seattle.

The hedonic regression results are summarized in Table 6. Control variables behave as expected in the model. For example, floor and land area are positively correlated with housing value, while poverty rate, and distance to the CBD and the ocean are negatively related.

We found that walkability measures had a positive and statistically significant relationship with housing value although different walkability measures were significant in the two study areas. Walk Score, EPA Index, and Mix3 were statistically significant in urban Miami-Dade County, while Street Density was also significant in Seattle. In Miami-Dade County, property values decline with age, but increase for the oldest age group (56 to 108). In Seattle, the oldest decile (93 to 121) is the most valuable age group. Building condition has a positive relationship with value in Seattle but was omitted from the Miami-Dade analysis as it did not appear to be measured in a consistent manner. The inclusion of building condition in the Seattle model but not in the Miami-Dade model may help to explain the contrasting results with respect to age.

We also found an interaction effect of poverty levels with walkability variables in Miami but not in Seattle. As expected, we found that the value of several walkability variables decreased as the level of poverty increased. We looked for a similar relationship in Seattle but did not find it.

When we add neighborhood dummy variables, the effect of walkability variables drops or even reverses sign. For example, in Miami, we found that the coefficient on Walk Score, the EPA Index, and Mix3 all dropped by about 50% when Zip code dummies were added to the model. In Seattle, on the other hand, all four walkability variables became either insignificant or negatively signed with the introduction of census-tract related neighborhood dummy variables.

Comparison of Walk Score and Freely Available Walkability Measures

For each study area, we examine the marginal effect on housing price of a one standard deviation increase in a set of walkability measurements (Table 7). For both study areas, we find a number of alternative walkability variables whose controlled marginal effect is similar in magnitude to Walk Score. These variables include the EPA Index and the Mix3 in both locations, and also Street Density in Seattle.

For example, at the median value of housing and the median poverty level in urban Miami-Dade, a one standard deviation increase in Walk Score displays a marginal effect of $8,456 (2.7%), in comparison to $10,864 (3.4%) for the EPA Index and $9,175 (2.9%) for Mix3. For the median-priced residence in Seattle, we find marginal effects of $34,034 (3.8%) for Walk Score, $51,335 (5.7%) for the EPA Index, $56,708 (6.3%) for Street Density, and $37,781 (4.2%) for Mix3.

These relative effects extrapolate to other assumptions about house prices: the EPA Index correlates with a larger increase in value across a range of house prices (we report results for the 25^{th}, 50^{th}, and 75^{th} percentiles in each location) for areas with median poverty rate or lower in Miami and for all three benchmark prices in Seattle. Walk Score displays a higher marginal influence than Mix3 for all categories in Miami but is lower in Seattle, however the effects of Walk Score and Mix3 are quite similar in magnitude and sign across all settings.

Context Sensitivity of Walkability's Value

Walkability variables demonstrated considerable context sensitivity in terms of their correlation with housing value. Unexpectedly, we found that the controlled correlation with walkability variables were often negative when we enlarged our study area to the entire county; this result occurred in both Miami-Dade and King Counties.

Furthermore, we found strong interaction effects of most walkability variables with percentile of poverty in the Census block in the Miami-Dade urban area. Several walkability variables indicated greater value premiums in low-poverty areas than in high-poverty areas. Moreover, we even found some evidence of a negative effect of walkability in very high-poverty areas, for example in the 95^{th} percentile of poverty in urban Miami-Dade.

Table 6. Hedonic regression results

A. Miami-Dade County Urban Area (2017)

	Without Zip code dummies			With Zip code dummies (not shown)		
Parameter	Walk Score	EPA Index	Mix3	Walk Score	EPA Index	Mix3
Intercept	13.133***	13.147***	13.153***	13.383***	13.341***	13.351***
Walkability measure	0.053***	0.083***	0.043***	0.023***	0.049***	0.010***
Walkability interacted with						
poverty rate	-0.214***	-0.395***	-0.203***	-0.195***	-0.182***	-0.123***
Poverty rate	-0.711***	-0.664***	-0.716***	-0.411***	-0.429***	-0.430***
Age of structure (deciles)						
<1 year	0.401***	0.400***	0.402***	0.592***	0.589***	0.587***
1 to 5 years	0.313***	0.319***	0.315***	0.453***	0.458***	0.452***
6 to 11	0.085***	0.090***	0.088***	0.260***	0.261***	0.261***
12 to 15	0.133***	0.136***	0.133***	0.247***	0.249***	0.248***
16 to 22	0.190***	0.186***	0.190***	0.227***	0.225***	0.227***
23 to 29	0.092***	0.087***	0.091***	0.134***	0.134***	0.134***
30 to 36	0.031***	0.026***	0.033***	0.083***	0.083***	0.085***
37 to 44	-0.020**	-0.023***	-0.019**	$-0.121\text{x}10^{-3}$	$-0.877\text{x}10^{-3}$	$-0.353\text{x}10^{-3}$
45 to 55	-0.069***	-0.071***	-0.070***	-0.109***	-0.106***	-0.108***
56 to 108 (default)	—	—	—	—	—	—
Floor area (square feet)	0.001***	0.001***	0.001***	$0.433\text{x}10^{-3}$***	$0.437\text{x}10^{-3}$***	$0.433\text{x}10^{-3}$***
Distinctive features value (ln[$])	0.009***	0.008***	0.009***	0.008***	0.007***	0.007***
Land area (square feet)	$0.313\text{x}10^{-5}$***	$0.287\text{x}10^{-5}$***	$0.298\text{x}10^{-5}$***	$0.666\text{x}10^{-5}$***	$0.672\text{x}10^{-5}$***	$0.651\text{x}10^{-5}$***
Condo	0.059***	0.059***	0.057***	-0.120***	-0.115***	-0.120***
Distance to CBD (feet)	$-0.600\text{x}10^{-5}$***	$-0.589\text{x}10^{-5}$***	$-0.622\text{x}10^{-5}$***	$-0.249\text{x}10^{-5}$***	$-0.185\text{x}10^{-5}$***	$-0.246\text{x}10^{-5}$***
Distance to ocean (ln[feet])	-0.121***	-0.123***	-0.120***	-0.162***	-0.164***	-0.159***
Sale quarter						
1	0.025***	0.024***	0.024***	0.004	0.003	0.004
2	0.021***	0.021***	0.021***	0.002	0.001	0.003
3	0.002	0.002	0.002	-0.001	-0.002	-0.001
4 (default)	—	—	—	—	—	—
Zip code dummies	No	No	No	Yes	Yes	Yes
R-squared	*0.729*	*0.731*	*0.728*	*0.822*	*0.823*	*0.822*
Sample size	*29,942*	*29,942*	*29,916*	*29,942*	*29,942*	*29,916*

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

B. Seattle (2021)

Parameter	Without Census Tract dummies Walk Score	EPA Index	Street density	Mix3	With Census Tract dummies (not shown) Walk Score	EPA Index	Street density	Mix3
Intercept	13.403***	13.439***	13.371***	13.440***	13.247***	13.186***	13.230***	13.219***
Walkability measure	0.037***	0.056***	0.061***	0.041***	-0.027***	-0.003	-0.008**	-0.009***
Poverty rate	-0.677***	-0.612***	-0.626***	-0.707***	-0.158***	-0.169***	-0.163***	-0.154***
Age of structure (deciles)								
0 to 8 years	-0.005	0.005	0.014	-0.016	0.120***	0.123***	0.122***	0.124***
9 to 18	-0.104***	-0.097***	-0.077***	-0.110***	0.022**	0.027***	0.026**	0.028***
19 to 28	-0.103***	-0.096***	-0.096***	-0.116***	-0.010	-0.004	-0.004	-0.003
29 to 38	-0.067***	-0.060***	-0.061***	-0.072***	-0.009	-0.003	-0.006	-0.005
39 to 47	-0.125***	-0.128***	-0.110***	-0.141***	-0.032*	-0.025	-0.026	-0.023
48 to 56	-0.095***	-0.093***	-0.086***	-0.099***	-0.012	-0.006	-0.005	-0.005
57 to 64	-0.083***	-0.080***	-0.083***	-0.092***	-0.040***	-0.032**	-0.032**	-0.033**
65 to 74	-0.049***	-0.052***	-0.045***	-0.055***	-0.019**	-0.012	-0.012	-0.013
75 to 92	-0.028***	-0.033***	-0.030***	-0.029***	-0.011	-0.010	-0.010	-0.011
…93 to 121 (default)	—	—	—	—	—	—	—	—
Condition of structure								
Poor or fair	-0.470***	-0.472***	-0.459***	-0.468***	-0.458***	-0.462***	-0.462***	-0.461***
Average	-0.110***	-0.115***	-0.112***	-0.112***	-0.130***	-0.130***	-0.130***	-0.130***
Good	-0.057***	-0.059***	-0.058***	-0.059***	-0.066***	-0.065***	-0.065***	-0.065***
Very good (default)	—	—	—	—	—	—	—	—
Floor area (square feet)	0.363×10^{-3}***	0.354×10^{-3}***	0.351×10^{-3}***	0.358×10^{-3}***	0.283×10^{-3}***	0.285×10^{-3}***	0.285×10^{-3}***	0.285×10^{-3}***
Land area (square feet)	0.676×10^{-5}***	0.840×10^{-5}***	0.848×10^{-5}***	0.440×10^{-5}***	2.288×10^{-5}***	2.451×10^{-5}***	2.445×10^{-5}***	2.461×10^{-5}***
Distance to CBD (ln miles)	-0.121***	-0.137***	-0.097***	-0.123***	-0.142***	-0.102***	-0.127***	-0.123***
Views								
Puget Sound	0.109***	0.083***	0.106***	0.091***	0.098***	0.113***	0.109***	0.111***
Lake Washington	0.233***	0.218***	0.221***	0.229**9	0.138***	0.154***	0.155***	0.155***
Cascade Mountains	-0.013	-0.017	-0.010	-0.018	0.029**	0.030**	0.028*	0.027*
Olympic Mountains	0.065***	0.069***	0.075***	0.074***	0.066***	0.071***	0.070***	0.069***
Other view	0.045	0.022	0.032	0.034	-0.007	-0.001	0.170×10^{-3}	0.169×10^{-3}
Waterfront location	0.444***	0.412***	0.519***	0.473***	0.394***	0.410***	0.434***	0.440***
Sale quarter								
1	-0.059***	-0.059***	-0.060***	-0.060***	-0.066***	-0.066***	-0.065***	-0.065***
2	0.005	0.003	0.004	0.002	-0.007	-0.007	-0.007	-0.006
3	0.011	0.010	0.008	0.007	-0.002	-0.001	-0.002	-0.001
4 (default)	—	—	—	—	—	—	—	—
Census Tract dummies	No	No	No	No	Yes	Yes	Yes	Yes
R-squared	*0.676*	*0.688*	*0.688*	*0.679*	*0.809*	*0.808*	*0.808*	*0.808*
Sample size	*5,434*	*5,434*	*5,406*	*5,406*	*5,434*	*5,434*	*5,406*	*5,406*

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Controlling for Neighborhoods

We also ran a series of hedonic regressions while controlling for geographic zone (either Zip code or Census Tract clusters). Theoretically, Zip codes are large enough that walkability measures could vary significantly across this scale; however, we found that adding Zip code dummies as controls significantly reduced the marginal impacts of all the walkability variables in the case of Miami-Dade. For Seattle, incorporation of Census Tract dummies caused the marginal impacts of the walkability measures to change sign. Because these neighborhood dummies are not theoretically meaningful, these results do not invalidate our findings regarding the impacts of walkability. But they do suggest that walkability variables may not be useful for predicting housing values when neighborhood-related variables such as Zip codes or Census Tracts are readily available. The change in marginal effects of various walkability variables with the introduction of geographic zone controls also suggests that walkability may occur in a clustered fashion at larger-than-neighborhood scales.

Discussion and Conclusion

We found three alternative walkability variables that displayed similar marginal effects on housing value as Walk Score across the two urbanized regions of Miami-Dade and Seattle: the EPA Index, Mix3, and street density. Of these, the EPA index, displayed a higher marginal effect than Walk Score in nearly all contexts – that is, both in Seattle and in Miami-Dade for all low and moderate poverty areas. Mix3 performed similarly to Walk Score in both cities. Street density had a larger effect than Walk Score in Seattle but did not have a positive effect on housing value within urban Miami-Dade.

Although the EPA Index is becoming a bit dated (from 2012) and runs at a coarser geography than Walk Score (census block groups), we found it to be an adequate substitute when predicting walkability's impact on housing value. Considering the potential value of this free, standardized, and nationwide metric for the study of walkability and its impacts, we strongly recommend that the EPA continue to develop, update, and publish this metric on a regular basis. In fact, it appears that the EPA just recently updated the National Walkability Index in 2021 (Thomas & Reyes, 2021).

Mix3 is a standard activity entropy measure of mixed use that incorporates three broadly construed categories of activities: residential, consumer services, and public services. We found it to be the most effective of the mixed-use measures in comparison with Walk Score. This three-category mixed-use measure also has theoretical benefits as compared with other mixed-use measures with more categories. Because the entropy measure returns a value of zero if any of the categories are absent from the analysis area, mixed-use variables with fewer (three, as opposed to five or nine) and broader activity categories (i.e., combining many NAICS codes together within each category) are more likely to have non-zero values and to display a larger amount of variation. Mixed-use measures can be calculated at a fine scale due to block-level residential and employment data from LEHD Origin-Destination Employment Statistics (LODES) datasets from the US Census[6] .

[6] Longitudinal Employer-Household Dynamics, https://lehd.ces.census.gov/data/

Table 7. Effect of a one standard deviation increase in the walkability measures

A. Miami-Dade County Urban Area (2017)

Without Zip code dummies

		25th percentile price ($230,000)			Median price ($315,000)			75th percentile price ($463,000)		
Poverty rate percentile	Poverty rate	Walk Score	EPA Index	Mix3	Walk Score	EPA Index	Mix3	Walk Score	EPA Index	Mix3
5%	0.0%	$12,558	$19,941	$10,143	$17,198	$27,311	$13,891	$25,279	$40,142	$20,418
25%	7.1%	$8,881	$12,992	$6,699	$12,163	$17,793	$9,175	$17,878	$26,153	$13,486
50%	12.5%	$6,174	$7,933	$4,162	$8,456	$10,864	$5,700	$12,429	$15,968	$8,379
75%	19.3%	$2,749	$1,601	$949	$3,765	$2,192	$1,300	$5,534	$3,222	$1,911
95%	34.7%	-$4,813	-$12,101	-$6,153	-$6,592	-$16,574	-$8,427	-$9,689	-$24,360	-$12,386

With Zip code dummies

		25th percentile price ($230,000)			Median price ($315,000)			75th percentile price ($463,000)		
Poverty rate percentile	Poverty rate	Walk Score	EPA Index	Mix3	Walk Score	EPA Index	Mix3	Walk Score	EPA Index	Mix3
5%	0.0%	$5,248	$11,650	$2,382	$7,187	$15,956	$3,263	$10,564	$23,453	$4,796
25%	7.1%	$1,992	$8,533	$349	$2,728	$11,686	$478	$4,010	$17,177	$702
50%	12.5%	-$408	$6,233	-$1,157	-$559	$8,537	-$1,584	-$821	$12,548	-$2,328
75%	19.3%	-$3,448	$3,317	-$3,072	-$4,723	$4,543	-$4,208	-$6,942	$6,678	-$6,185
95%	34.7%	-$10,175	-$3,143	-$7,345	-$13,935	-$4,305	-$10,060	-$20,482	-$6,327	-$14,786

B. Seattle (2021)

Without Census Tracts

25th percentile price ($715,000)				Median price ($895,000)				75th percentile price ($1,215,000)			
Walk Score	EPA Index	Street Density	Mix3	Walk Score	EPA Index	Street Density	Mix3	Walk Score	EPA Index	Street Density	Mix3
$27,189	$41,011	$45,303	$30,183	$34,034	$51,335	$56,708	$37,781	$46,203	$69,690	$76,983	$51,289

With Census Tracts

25th percentile price ($715,000)				Median price ($895,000)				75th percentile price ($1,215,000)			
Walk Score	EPA Index	Street Density	Mix3	Walk Score	EPA Index	Street Density	Mix3	Walk Score	EPA Index	Street Density	Mix3
-$18,747	-$1,846	-$5,785	-$6,401	-$23,466	-$2,311	-$7,242	-$8,012	-$31,856	-$3,138	-$9,831	-$10,876

Because we found that both simple mixed-use measures and street network measures are useful in predicting housing value, this suggests that there is potential for a newly constructed index incorporating both types of variables, as well as perhaps some others. The key challenge would seem to be creating an index that is nationally relevant and correlated with important walkability outcomes, such as walk trips or mode share. Frank et al. and others (Frank et al., 2010a; Manaugh & El-Geneidy, 2011b) have developed such walkability indices, but the authors are not aware of these being freely available for download across the US.

One of our most interesting results was unexpected – the value of walkability is highly context dependent. That is, the value of walkability appears to depend upon the socioeconomic characteristics of the area, with greater walkability premiums in lower poverty areas in urban Miami-Dade County (but not Seattle), and with the level of urban development generally; we found that the value of walkability could even possibly be negative in areas that are not urban, suggesting that it may be a proxy for something else in such contexts. An interesting research question not addressed here is how to define and identify which contexts are "urban" enough that walkability has a positive rather than negative or neutral value. Chernobai and Ma (2022) found that the value of walkability varied systematically with the number of parking spaces available, with a positive value for walkability for properties with zero or one parking space, a negligible value for properties with two parking spaces, and a negative value for properties with three parking spaces.

We also found that although the same set of walkability measures worked across both Miami-Dade and Seattle, the walkability premium appears to be higher in Seattle than in Miami-Dade, even when controlling for differences in house prices across the two locations. Is this evidence that walkability creates a positive feedback loop for itself, i.e., cities with more walkable areas have a greater walkability premium? Research into a greater number of metro areas might help address this question.

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