Does Walkability Influence Housing Prices?*

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Objective. We examine the effects of neighborhood walkability on house values. Recent research claims that walkability makes homes more valuable, ceteris paribus. We contend that some studies report a spurious effect of walkability because of differences between areas with high and low walkability. *Methods.* We replicate the positive effect of walkability on prices for single-family homes and condominiums in Miami, Florida, using a unique data set of house values and characteristics. We employ a fixed effects regression model instead of a traditional ordinary least squares regression model to account for the unobserved heterogeneity of neighborhoods. *Results.* We find that walkability's impact on housing value becomes statistically insignificant at the margin after controlling for heteroscedasticity and neighborhood fixed effects. *Conclusions.* The significant impact of the fixed effects suggests that something other than walkability is affecting prices and that better specified models are needed to discern the real price effects of walkability.

This research asks whether walkability is rewarded with higher house prices. A recent study of housing in the suburban Washington, D.C. DC, area concludes that walkability provides significant benefits in those communities, including better economic performance, than nonwalkable areas, lower transportation but higher housing costs than less walkable areas, more affluent citizens, and, most relevant for our purposes, walkable areas "exhibit higher rents and home values" than less densely populated walkable areas (Leinberger and Alfonso, 2012:1). Proponents of the New Urbanism movement place high value on neighborhoods that are walkable. The emphasis on walkability is prominent among critics of urban sprawl. Recent empirical research shows walkability to be associated with higher commercial real estate prices in some areas (Pivo and Fisher, 2010), higher land prices in some cases (Rauterkus and Miller, 2011), and higher housing prices in some Metropolitan Statistical

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Areas (MSAs) (Cortright, 2009). We construct a model of housing prices in which we control for fixed effects of area characteristics and heteroscedasticity, thus providing better-specified models that enable us to question whether the effects of walkability noted in existing studies are genuine.

We analyze house values in Miami, Florida, which is listed in July 2013 as the eighth most walkable city in the United States (Walk Score, 2013). The Walk Score®, which is constructed by a Seattle-based group of planners and other urbanists and made available in its simplest form for no charge, measures the extent to which people are car-dependent in residential areas. Walk Scores are based on a number of factors that measure proximity to amenities within an urban area. Miami's Walk Score is 73. The most walkable U.S. cities, in ascending order, are New York; San Francisco; Boston; Chicago; Philadelphia; Seattle; and Washington, D.C. DC (Walk Score, 2013). Minneapolis ranks ninth, and the tenth most walkable U.S. city is Oakland, California. Miami is the southernmost city to be ranked among the top 10. Miami is uniquely walkable among Florida cities; the next highest ranking city in the national listing is Jacksonville, ranked at 50. The combination of Miami's high walkability and the presence of a unique collection of housing sales data makes it an ideal locale to address the question of whether more walkable houses are rewarded with higher values.

This research is organized in four sections following this introduction. In the next section, we discuss the prior research on walkability's effects on housing prices and the logic of an expectation that walkable neighborhoods should result in higher house prices. In the third section, we introduce the model of house prices to be estimated as well as the estimation methods we will use', describe the independent variable of primary interest, the Walk Score, and describe its distribution in the Miami, Florida, area; and also describe the other measures used in the article. The fourth section includes the estimation, including both an ordinary least squares (OLS) estimation, as is consistent with existing models, and a fixed effects model, which is a departure from previously published estimates of the effects of walkability. That section also includes robustness checks. The fifth section includes a brief discussion, and the final section concludes by placing these findings in the broader context of walkability research.

Do Walkable Neighborhoods Add Value?

Previous research indicates numerous positive effects of living in a more walkable area. The built environment of cities influences local transportation patterns (Handy, 1996, 2005).[1] Urban forms and land-use patterns that encourage walkability are expected to decrease reliance on the automobile,

[1]Ewing and Cervero (2010) provide a meta-analysis of urban form and transportation patterns.

improving local environmental conditions (Frank and Engelke, 2005; Frank, Stone, and Bachman, 2000). A neighborhood's built environment and walkability have implications for public health, especially physical activity (Doyle et al., 2007; Ewing and Cervero, 2010). Recent research indicates that walkable neighborhoods may lead to lower resident weight and obesity (Brown et al., 2009; Zick et al., 2009; Papas et al., 2007) and lower residential body mass index (Brown et al., 2009; Smith et al., 2008; Zick et al., 2009).

Walkable neighborhoods may also improve neighborhood social conditions. A study of Australian neighborhoods indicates that walkability decreases incidences of neighborhood incivilities like vandalism (Foster, Giles-Corti, and Knuiman, 2011). A built environment that encourages walking improves the probability that residents interact with each other, and leads to a greater sense of community among residents (Lund, 2002; Talen, 1999; Wood, Frank, and Giles-Corti, 2010). Residents of walkable neighborhoods report more instances of neighborly behavior and sociability occurring in their neighborhoods compared to residents of less walkable neighborhoods (Du Toit et al., 2007; Lund, 2002). These instances of increased sociability and neighborly behavior promote the growth of social capital (Leyden, 2003). Leyden's (2003) research defines social capital in the same manner as Putnam (2000) and Coleman (1990), which includes instances of networking and mutual interactions among citizens that build norms of trust and reciprocity of behavior. Putnam's (2000) seminal work on social capital promotes the idea that social capital increases resident participation in neighborhood affairs and politics. Leyden's (2003) study provides evidence for this effect at the neighborhood level.

Some evidence for walkability's value is indirect. Tu and Eppli (1999) report that New Urbanism is responsible for a 12 percent increase in property values in the Kentlands neighborhood in Gaithersburg, Maryland. One crucial aspect of New Urbanism is creating a walkable community where people have more interactions. The effect of walkability is not separated from that of other New Urbanist dimensions, but is specifically mentioned in their research: "[p]roviding a walkable environment is a key element of TNDs" (traditional neighborhood designs), (1999:248). These results show a positive effect of walkability are problematic because the researchers indicate walkability by using a dummy variable to indicate whether a property is part of the Kentlands neighborhood. The study does not compare more walkable homes to less walkable homes inside the Kentlands neighborhood or in the surrounding areas. The claim is that Kentlands is more walkable than the surrounding area and it also has higher housing prices after controlling for structural characteristics, so New Urbanism features of the area (including walkability) are driving the result.

Cortright (2009) studies 15 large cities/metropolitan areas, but reports regressions for 14. He reports one city with a negative effect of walkability on housing value and one with a statistically insignificant relationship. The other 12 had a positive relationship between walkability and housing value. Cortright (2009) introduces statistical controls for houses' structural characteristics, for median household income in the census block group that contains the house, for the number of jobs within three miles of the property, and the distance to the central business district (CBD). Cortright's models may be poorly specified; he pooled all the homes in the city, ignoring spatial differences in housing value, and did not use heteroscedasticity-robust standard errors. Pooling data for all the homes in the city after controlling for distance to the CBD effectively assumes that the city's neighborhoods are arranged in concentric circles with downtown as the center. Walkability may have different effects on housing value some distance north of the CBD versus an area equidistantly south of the CBD. The t-statistics obtained for Walk Score in most cities in Cortright's study are very high (up to $t = 25$), so while robust standard errors would probably not eliminate significance, they would make the results more credible.

Predictors of House Prices and Description of Data

Consistent with existing research, we estimate a hedonic price model as developed by Rosen (1974) to examine the price premium for more walkable versus less walkable homes. This method treats properties as a bundle of house- and property-specific characteristics that affect the value of the property (Sirmans, Macpherson, and Zietz, 2005). Sirmans, Macpherson, and Zietz (2005) identify square footage, lot size, age, bedrooms, bathrooms, the presence of a garage, a swimming pool, fireplace, and air conditioning as the most frequent predictors to appear in hedonic models of single-family homes. We amend this list slightly in our estimates to reflect the conditions in the Miami, Florida, area. This is crucial, as Sirmans, Macpherson, and Zietz (2005) note, "[in] hedonic pricing models . . . results are location-specific and are difficult to generalize across different geographic locations . . . [but] comparing studies across areas may at least establish those characteristics that are consistently valued (either positively or negatively) by homebuyers" (2005:4). Jud and Winkler (2002) include a fixed effects measure to MSA-level data to control for variations in local conditions that are not amenable to change; we measure neighborhood fixed effects to account for specific conditions, for example, differing zoning regulations that are distinct from our explanatory variables. Given these problems of model specification and measurement, we are careful to specify our models consistently with those we critique insofar as predictors are considered, as our criticism focuses on method of estimation rather than the estimators used. Table 1 describes the variables used in this study.

The dependent variable is the natural logarithm of each home's market value, as determined by its 2012 appraisal on the property tax rolls. Predictors include the home's age (age), which is calculated as the difference from the mean age in the sample, and its square (age^2). Age is squared to account for nonlinear effects of age. Centering ages helps reduce multicollinearity between the untransformed age and its square. Other predictors include the number

TABLE 1

Variable Descriptions

Variable	Obs.	Mean	*SD*	Min.	Max.
Age[a]	3,423	0	20.09	−37.62	63.4
Age^2	3,423	403.4	414.5	0.14	4,017.1
Baths	3,423	1.93	0.69	1	6
Bedrooms	3,423	3.11	0.77	1	6
Condo	3,423	0.11	0.31	0	1
Dist to CBD	3,423	13.29	5.41	0	29.8
Income	3,423	49,237	21,230	7,387	200,001
ln mkt value	3,423	12	0.53	9.51	15.4677
Lot size	3,423	9,338	18,147	752	618,552
Mkt value	3,423	192,656	167,486	13,455	5,218,357
Sq ft	3,423	1,810	730	350	7,515
Pool	3,423	0.17	0.37	0	1
Walk Score	3,423	48	17.8	0	95

[a]Age is centered. The mean age of a home is 38.6 years. The variable "*age*" represents the deviation from the mean, and ranges between −37.62 and 63.4.

of bathrooms (baths), the number of bedrooms (beds), the median income by block group in each neighborhood (income), and whether or not a residence is a condominium (condo = 1, otherwise 0). We also measure the distance to the CBD, the size of the lot (lot size), square footage of the home (sq ft), whether there is a pool (pool = 1, otherwise 0), and Walk Score, which ranges from 0 to 100.

Walkability, the crucial independent variable in the analysis, is measured using Walk Scores for each property in our analysis to score the extent to "which it is easy to live a car-lite lifestyle" in each area (Walk Score, 2013). The Walk Score rates areas according to the straight-line distance from the home to the closest amenity in each category. Amenity categories include restaurants, schools, parks, shopping, coffee shops, grocery stores, bookstores, banks, and entertainment. Amenities are weighted equally and the distance is multiplied by a nonlinear distance decay function. This function equals 1 for amenities within 0.2 miles, then decays at a constant rate out to 1 mile and decays more slowly between 1 and 1.5 miles, where the function equals zero.[2] For practical purposes, any amenity that requires more than a 30-minute walk (using the assumption of a three miles per hour walk speed) is less desirable than those with lesser walk times. Walk Scores are scaled between 0 and 100. Scores of 0–49 are described as "car-dependent," scores from 50–69 "somewhat walkable," and scores greater than 70 and less than 90 are "very walkable," and those over 90 are a "walker's paradise" (Walk Score, 2013).

[2]Walk Score distance decay function is updated now and equals 1 for distances under 0.25 mile and 0 for distances over 1 mile.

Previous research demonstrates Walk Score to be a valid and reliable indicator of access to amenities. Carr, Dunsiger, and Marcus (2010) use geographic information systems (GIS) software to count the number of amenities in a certain category within a one-mile radius of homes. They report high correlations between Walk Score and the number of amenities in each category, leading them to claim Walk Scores to be valid and reliable. Building on the Carr, Dunsiger, and Marcus article, Duncan et al. (2011) use GIS to create a series of spatial walkability measures and compare them to the Walk Score measure. They test their measures in four cities, one in the northeast, one in the south, one in the northwest, and one in the midwest, in an attempt to make more generalizable statements. They report significant correlations between Walk Score and their spatial measures, concluding that Walk Score is a valid measure of walkability. Other independent assessments of Walk Score validity and reliability report similar findings (Manaugh and El-Geneidy, 2011; Weinberger and Sweet, 2013).

Our model is estimated as a cross-section using data from 2011 and 2012. The market value is drawn from the 2011 Dade County property appraiser tax rolls, the most current rolls available at the time of data collection. The distance to CBD is calculated as the walking distance to downtown (the point where longitude equals 80.187039°W and latitude equals 25.774454°N) using Google Maps instead of the usual "as the crow flies" method. There is a correlation of 0.97 between the two methods. Data sources for the property information in this study include Data Quick, walkscore.com, and Google Maps. There are 228,251 Data Quick records with Miami as the city name in the mailing address. Of those, 160,565 were single-family homes or condominiums. Due to the time required to collect some variables and generate others through geocoding, these observations were randomly sampled to produce roughly 3,500 observations with unique addresses. There were instances where random sampling produced observations that were at the same address, such as condominiums with different unit numbers. The walkability of these addresses would be identical and the other housing characteristics very similar, so only one observation was taken from each group of "same address" observations. Other instances with anomalous data were dropped, such as a home reported as having zero bedrooms, lot size equal to zero or one, or a block group where median income was reported as zero.

We estimate an OLS model in Table 2, which replicates the approach used in existing literature (see, e.g., Cortright, 2009), and a fixed effects model in Table 3. We contend that the fixed effects model is the preferred way to handle unobserved heterogeneity in the data because the unobserved effects are correlated with the independent variables. For instance, many subdivisions are full of homes that are built within a year of each other. Homes in certain neighborhoods are closer to downtown than homes in other areas. For these reasons, a random effects model is inappropriate because a random effects model assumes that the unobserved heterogeneity is not correlated with the independent variables.

TABLE 2

OLS Replications of Prior Research

Std. Errors Clustered by Variables	Subdivision ln_mkt_value	Section ln_mkt_value	Zip Code ln_mkt_value
Age	−0.003***	−.003***	−0.003***
	(0.001)	(0.001)	(0.001)
Age^2	−7.54e-05***	−7.54e-05***	−7.54e-05**
	(1.85E-05)	(2.54E-05)	(3.34E-05)
Baths	0.04***	0.04***	0.04**
	(0.01)	(0.01)	(0.02)
Bedrooms	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)
Condo	−0.08***	−0.08***	−0.08**
	(0.02)	(0.03)	(0.03)
Distance to CBD	−0.02***	−0.02***	−0.02***
	(0.003)	(0.004)	(0.01)
Income ($1,000)	0.01***	0.01***	0.01***
	(0.001)	(0.001)	(0.001)
Lot size	4.80e-06***	4.80e-06***	4.80e-06***
	(9.71E-07)	(1.15E-06)	(1.14E-06)
Pool	0.14***	0.14***	0.14***
	(0.01)	(0.02)	(0.02)
Sq ft	0.0003***	0.0003***	0.0003***
	(1.56E-05)	(1.87E-05)	(2.49E-05)
Walk Score	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Constant	10.86***	10.86***	10.86***
	(0.06)	(0.09)	(0.16)
Observations	3,353	3,353	3,353
Adj. R^2	0.75	0.75	0.75

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

All observations were included in every regression regardless of how many homes from an observation's neighborhood are in the sample. This allows the same homes to be compared in all three regressions, because some homes are the only observation in a subdivision but not the only home in the section or zip code. We cannot use the fixed effects model to estimate the unique value of the neighborhood's effect on price when only one house from the neighborhood is represented in the sample, as there is no variation.

We employ three definitions of a neighborhood: subdivision, township range sections (TRS), and zip code. There are a total of 1,708 subdivisions represented in the sample. The first definition of neighborhood as subdivision works well because subdivisions are fairly homogeneous relative to the rest of a city and some are larger than others. If there is a sense of community, it stands to reason that the subdivision is a good level to see it, especially for subdivisions that have their own park, gym, or other such amenities.

TABLE 3

Fixed Effects by Neighborhood

Std. Errors Clustered by Variables	Subdivision ln_mkt_value	Section ln_mkt_value	Zip Code ln_mkt_value
Age	−0.003***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)
Age^2	5.59E-06	−7.57E-06	−4.56E-06
	(3.68E-05)	(2.01E-05)	(2.34E-05)
Baths	0.03	0.02*	0.03**
	(0.02)	(0.01)	(0.01)
Bedrooms	0.02	0.03***	0.03**
	(0.01)	(0.01)	(0.01)
Condo	−0.24***	−0.16***	−0.17***
	(0.04)	(0.03)	(0.03)
Distance to CBD	−0.02***	−0.01	−0.04***
	(0.01)	(0.01)	(0.01)
Income ($1,000)	0.002**	0.003***	0.01***
	(0.0001)	(0.001)	(0.001)
Lot size	3.00e-06***	6.79e-06***	4.90e-06***
	(7.89E-07)	(1.20E-06)	(1.22E-06)
Pool	0.09***	0.12***	0.14***
	(0.01)	(0.01)	(0.01)
Sq ft	0.0003***	0.0003***	0.0003***
	(2.20E-05)	(1.28E-05)	(2.01E-05)
Walk Score	−0.001	−0.0001	0.0003
	(0.001)	(0.0003)	(0.0005)
Constant	11.63***	11.30***	11.47***
	(0.09)	(0.17)	(0.14)
Observations	3,353	3,353	3,353
Adj. R^2	0.68	0.71	0.73
Number of neighborhoods	1,688	261	52
Min. observations/neighborhood	1	1	1
Mean observations/neighborhood	2	12.8	64.5
Max observations/neighborhood	54	45	245

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Instead of defining a neighborhood as a subdivision, it is possible to classify them as one-square-mile plots of land called sections. Sections are contained within ranges, which are in turn, parts of townships. This classification system is abbreviated TRS and is a grid covering the state where the dimensions of a section are one mile by one mile, but not all of that is necessarily on land. Since many subdivisions are smaller than one square mile, this approach increases the size of the defined neighborhood, which allows for more observations in each. This approach brings the average number of observations per neighborhood up to 12.8 compared to 2.0 when using subdivisions. There are 261 sections in the sample.

Fifty-two zip codes are present in the sample.[3] The size of zip codes in the Miami area ranges from under one-half square mile to over 10 square miles with an average around seven square miles. Using zip code as a neighborhood identifier gives another way to isolate spatially part of the sample from the rest of the sample. Zip codes in the sample span from areas such as North Miami Beach, Opa-Locka, Hialeah, Hialeah Gardens, Miami Beach, Key Biscayne, West Perrine, Princeton, Naranja, University Park, The Hammock, South Miami, Coral Terrace, West Miami, Kendale, Kendall, Sweetwater, and others.

OLS Estimates Versus Fixed Effects

Three papers use OLS estimates of cross-sectional data that show the positive effects of walkability on land prices (Rauterkus and Miller, 2011), housing values (Cortright, 2009), and commercial real estate values (Pivo and Fisher, 2010). The OLS output in Table 2 replicates the commonly reported result of a positive and statistically significant effect of Walk Score on the natural log of housing value ($t = 10.55$). When the standard errors are clustered by subdivision, TRS section, or zip code, the corresponding t-statistics are 7.19, 5.34, and 3.50, respectively, for the coefficient on Walk Score, thus showing substantial statistical and substantive effects of walkability on house prices.

OLS estimates of each of the control variables also perform as expected. Condominiums are worth less than otherwise equal single-family homes. Homes closer to the CBD, with bigger lots, more square footage, more bedrooms, more bathrooms, a pool, and in a neighborhood with higher block group median income all tend to be worth more. Walk Score performs as expected in three definitions of neighborhood, with the regression coefficients in each being identical (0.004, $p < 0.001$).

Cross-sectional data often violate the regression assumption that their error terms have a constant variance. Violation of that assumption results in data being distributed heteroscedastically. With heteroscedasticity, coefficients are unbiased, but standard errors are smaller than they would be were the errors distributed homoscedastically. The practical effect is that there is a tendency to judge things to be statistically significant because t-statistics are inflated. We calculated a White (1980) test for heteroscedasticity, which uses a null hypothesis of homoscedasticity and an alternative hypothesis of heteroscedasticity. Our sample yields a chi-square value of 961 with a corresponding p value <0.0001, leading us to reject the null hypothesis of homoscedasticity, which indicates the errors are distributed heteroscedastically. We use heteroscedasticity-robust standard errors, which generally increase the size of standard errors (King and Roberts, 2012) to mitigate the problem. The heteroscedasticity is a function of the variation of the price per square foot for

[3]Information on zip codes may be found at <http://maps.huge.info/zip.htm>.

homes: the range of values for small homes tends to be larger than for large homes. This is a common problem in hedonic price models, as the value of land close to the CBD is consistently high, increasing the variance in land prices within short distances. Other factors such as the quality of schools, distance to other amenities like restaurants, parks, theaters, and the like are also captured in the fixed effect.

When the unobserved heterogeneity of neighborhoods is accounted for with fixed effects, Walk Score effects are no longer statistically significant (Table 3). There are other changes as well: block group median income, distance to CBD, lot size, the homes' square footage, whether the home has a swimming pool, and whether the home is a condominium are statistically significant at the subdivision level. Those measures plus the number of baths and the number of bedrooms are significant at the zip-code level, and the same measures minus distance to the CBD are significant at the section level. The magnitude of effects changes across specifications, as well, which is also due to the inclusion of the additional control for fixed effects. This is consistent with results reported by Jud and Winkler (2002), who note that fixed effects in their models capture "the residuals of housing price appreciation attributable to location" (2002:40). They showed the influence of fixed effects across MSAs, while we demonstrate the effects across subdivisions, zip codes, and block groups.

Table 3 shows that defining neighborhoods by their zip codes or TRS sections yields similar qualitative results when compared with defining neighborhoods as subdivisions. The insignificance of Walk Score in the above regressions (Table 3) implies that a one-unit change in Walk Score is not associated with a percentage change in housing value. One may expect that the value of walkability is independent of the value of the home. That is, a unit of walkability may be worth a constant dollar value, no matter the home it is attached to. In order to allow for this possibility, regressions are run in Table 4 with market value as the dependent variable.

A comparison of adjusted *R*-square values from Table 3 and Table 4 shows that the model better explains the natural log of house prices measure than the untransformed house prices measure. Regardless of whether the dependent variable is measured as a natural log or is untransformed, the effect of walkability on housing values disappears when neighborhood effects are controlled.

Readers may be concerned that including neighborhood effects may reduce much of the variation in Walk Score, and that this reduction of variance in walkability explains the insignificance of the coefficient. Table 5 shows that there is substantial variation in Walk Score among houses in the same neighborhood, especially when neighborhood is defined as zip code. In the sample, the standard deviation of Walk Score is 17.8. In order to see if there is much difference in Walk Score at the neighborhood level, the standard deviation of Walk Scores within neighborhoods can be compared using all three definitions of neighborhood boundary. If there is only one observation

TABLE 4

Fixed Effects by Neighborhood Using Market Value as Dependent Variable

Std. Errors Clustered by Variables	Subdivision mkt_value	Section mkt_value	Zip Code mkt_value
Age	−1,444***	−915.3***	−127.4
	(501.2)	(245.3)	(427.2)
Age^2	26.65	22.93**	32.26
	(17.61)	(10.17)	(19.5)
Baths	12,712	6,475	15,251***
	(8,369)	(5,335)	(4,477)
Bedrooms	−6,770	−3,567	−7,312**
	(5,308)	(2,804)	(3,033)
Condo	−30,935***	499.3	−2,283
	(9,658)	(6,529)	(13,094)
Distance to CBD	−17,560***	−1,978	−11,185***
	(5,437)	(4,190)	(3,808)
Income ($1,000)	612.3**	936.4***	2,162**
	(277)	(356)	(881)
Lot size	1.790***	4.336***	2.385***
	(0.668)	(1.216)	(0.784)
Pool	26,496***	15,103	20,418***
	(4,945)	(11,465)	(6,962)
Sq ft	70.46***	88.26***	92.41***
	(12.18)	(7.519)	(9.267)
Walk Score	−235.1	−95.31	76.83
	(193.9)	(76.51)	(200.1)
Constant	247,054***	−36,616	18,340
	(65,593)	(62,499)	(102,677)
Observations	3,353	3,353	3,353
Adj. R^2	0.61	0.49	0.52
Number of neighborhoods	1,688	261	52
Min. observations/neighborhood	1	1	1
Mean observations/neighborhood	2	12.8	64.5
Max observations/neighborhood	54	45	245

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

in a neighborhood, then a standard deviation cannot be calculated for that neighborhood.

Discussion

One possible explanation for the elimination of Walk Score's significance is that there is not much variation in Walk Score within neighborhoods. Table 4 shows that while there is a large reduction in the variation in Walk Score within subdivisions, there is plenty of variation when looking at the section

TABLE 5

Neighborhood and Sample Standard Deviation of Selected Variables

		Min.	Mean	Max.
Age	Full sample	–	38.62	–
	Subdivision	0	4.05	61.52
	TRS section	0	8.86	38.29
	Zip code	1.37	11.69	28.11
Beds	Full sample	–	0.77	–
	Subdivision	0	0.47	2.83
	TRS section	0	0.65	3.53
	Zip code	0	0.70	1.31
Baths	Full sample	–	0.69	–
	Subdivision	0	0.34	2.21
	TRS section	0	0.53	2.12
	Zip code	0	0.59	1.24
Walk Score	Full sample	–	17.83	–
	Subdivision	0	5.76	52.33
	TRS section	0	10.41	46.67
	Zip code	0	12.35	25.07

or zip code definition of a neighborhood.[4] Substantial variation remains in Walk Score if one compares the ratio of the mean standard deviation of Walk Score at each neighborhood definition to its value in the overall sample and then compares the respective numbers for age. The sample standard deviation for age is 38.62 years, but the average subdivision has a standard deviation of only 4.05 years. Even in the fixed effects models in Table 3, age of home has a statistically significant effect despite its reduced variation. Thus the reduction in variation from the definition of neighborhoods is not driving the result because the standard deviation of Walk Score at each neighborhood definition is higher in terms of its absolute value and its relative value to the sample standard deviation.

One possible reason that other studies have found a relationship between housing value and walkability is that more walkable areas tend to be more developed. By definition, they are closer to many amenities. Amenities will only arise in areas where they are valued. These areas with high value have higher Walk Scores, but the Walk Score relationship with prices is probably not causal. This is a factor that caused some walkability studies such as Tu and Eppli (1999), Rauterkus and Miller (2011), and Cortright (2009) to pick up

[4]Although the mean standard deviation for neighborhoods defined as subdivisions is roughly one-third of the overall sample standard deviation for Walk Score, the mean standard deviation when grouped by zip codes is close to the standard deviation in the overall sample. Therefore, the reduction in variation argument may hold for subdivisions, but it does not when neighborhoods are defined as zip codes. Similar trends can be seen with some of the control variables. There are only three observations in the zip code where the standard deviation of Walk Score equals zero. All three homes have a Walk Score of 86.

a spurious relationship between walkability and value. In essence, these early studies might as well have said that properties downtown are more valuable because they are more walkable. It seems unlikely that walkability drives that result.

In the next round of studies, distance to downtown was included as a control variable to help correct for the relationship mentioned above. Controlling for distance to downtown effectively compares a home that is x miles from downtown to all other homes on the perimeter of a circle centered on downtown with a radius of x miles. In reality, a home two miles east of downtown may be in a very different neighborhood than a home two miles north or two miles west of downtown. Imagine if the area two miles north of downtown is very walkable and the area two miles south is not. In this case, a neighborhood may be both highly walkable and highly valued in the north, but not in the south. Controlling for neighborhood is important because it separates the effect of walkability from the effect of living in a better neighborhood. The approach used in this study comes closer to holding all else equal when making the comparison between homes with different walkabilities.

The same sort of methodology could be used to reexamine results of walkability studies in other fields. The results of this study show that previous housing value research has overlooked important neighborhood effects. This finding may have implications for walkability studies on topics other than housing value; namely, that there might be a selection bias of people who live in walkable communities. Selection bias could explain why residents of those areas are found to be healthier, more interactive, and less prone to incivilities. The authors would hazard to say that people living in the more walkable homes within a community may not on average be healthier or more interactive than their neighbors; however, maybe it is the case that healthier and more active people value walkable neighborhoods more than average, which is why walkable communities are comprised of these types of people.

Reconciling Findings with Previous Research

Previous research claims that the value of living in a home with high walkability gets capitalized into the value of that property. This research demonstrates that walkability is no longer associated with higher property values after controlling for unobserved heterogeneity in neighborhoods. This means that homes that are more walkable are not worth more than homes that are less walkable as long as they are in the same neighborhood. This study controlled for one more factor than previous studies and found that this additional control eliminates the spurious effect that Walk Score was previously shown to have on housing value.

Readers may question whether these findings drawn from a cross-section of data from Miami are generalizable to prior walkability models or to other hedonic price models. The regression results of models based on the Miami data, specified in exactly the manner of the earlier studies, yield similar results: walkability matters, as do the other measures in the model. The similarity of the earlier results to these suggests that the Miami results are generalizable.

The substantive results are consequential. Our findings clearly show that walkability is statistically significant at the $\alpha = 0.01$ level when using an OLS regression as was done in previous research, but then is not significant even at the $\alpha = 0.10$ level after controlling for neighborhood fixed effects. These results are robust to three different types of neighborhood specification and the conclusion is the same whether using market value of the home or its natural log as the dependent variable. Given this, claims of the value of walkability should be viewed cautiously; our data reveal no independent effect of walkability on values.

The results presented above should not be interpreted to mean that more walkable neighborhoods are not more valuable, on average, than less walkable ones. Walk Score's developers desire to have the walkability of areas included, for example, or real estate listings. That is a good idea to the extent that the scores summarize accessibility, but there is error in the measurement. Access to more local amenities should allow for a higher average price in more walkable neighborhoods, all else equal. In the terms of this article, that value is captured in the neighborhood-specific fixed effect and not the marginal improvement in Walk Score.

While the results of this article may be counterintuitive, we believe that future research may show that average neighborhood walkability has a strong and direct relationship with the value of the neighborhood-specific fixed effect. The difficulty in obtaining this relationship lies in collecting values for items that vary at the neighborhood level. For instance, block group median income is readily available from the U.S. Census, but is not very useful in determining neighborhood effects of walkability unless the neighborhood is defined as a block group. Zip code median income is not available and would pose a challenge to studying neighborhoods defined as zip codes. The best approach would be to have micro-level data that could be aggregated to different neighborhood definitions. Then, measures like the neighborhood's median Walk Score could be calculated by using all homes in the neighborhood and not just those in the sample. Without sufficient neighborhood control variables, the effect that more walkable neighborhoods have on price will remain unmeasured.

More walkable homes within a neighborhood should be valued more highly than less walkable homes in the neighborhood if Walk Score is a reliable measure of walkability and if homebuyers value walkability. Previous literature shows Walk Score to be a reliable and valid measure of access to amenities, so this leads to the conclusion that the marginal homebuyer does not value better walkability at the margin. This may be the case if the homebuyer does not plan on walking much in order to take advantage of the amenities afforded him by living in a highly walkable area. Once the homebuyer is in a car, a coffee shop a few blocks (or even a mile) away becomes nearly as accessible as the local one. Leininger and Alfonso (2012) describe numerous benefits of walkability, and also note that the price value of walkability depends largely on the relative density of walkable neighborhoods. We do not disagree that walkable neighborhoods are desirable in some cases, and that neighborhoods that are more proximate to amenities may demand greater house prices. The results of this research suggest that walkability of an individual home should not be examined without accounting for other neighborhood attributes.

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