Analysis of Walkability Estimates and Hotel Real Estate Values in New York City

by

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This thesis is dedicated to my family for their support and to my friends at Cornell for all the great memories I have made during the past four years.

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Abstract: This study examines the relationship between walkability estimates including Walkscore and a 10-year sample of hotel transactions in New York City. Using a Hedonic pricing model, ordinary least squares (OLS) regression applied citywide initially produced significant positive relationships between walkability estimates and transaction value. However, the associations became more obscure once submarket fixed effects were introduced to control for unobserved differences between neighborhoods. More granular analysis of walking accessible destinations revealed that accessibility to certain destination categories like entertainment can have a negative impact on hotel value. The results suggest that built-environment pedestrian friendliness more consistently benefits hotel value compared to accessibility-based walking potential. This study also finds that while high value hotels are often found in areas with high walkability, hotel value premiums in these areas may not be attributable to walkability and can arise from other unobserved neighborhood characteristics. The study concludes by questioning the ability of current walkability estimates to accurately measure walking behavior of travelers.

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AUTHOR'S BACKGROUND

Hyun Ho Lee is a senior at the School of Hotel Administration at Cornell University. He is originally from Seoul, South Korea but grew up in Boulder, Colorado; Montgomery, New Jersey; and Cincinnati, Ohio. In high school, Hyun Ho worked for two years in the kitchen of the Hilton Netherland Plaza in downtown Cincinnati peeling cases of potatoes and manning the fry station during service. Hyun Ho's experience at the Hilton sparked an interest in studying hospitality at Cornell University in order to eventually become a professional chef.

After his freshman year at Cornell, Hyun Ho spent a summer selling ice-cream and donuts from a coconut-themed food cart beneath the Highline in the Meatpacking neighborhood of New York City. During long periods of slow sales when the only respite from boredom was the occasional tourist asking for directions, Hyun Ho observed the busy pedestrian activity of the Highline and wondered how to convert pedestrians into customers.

After taking courses such as Hospitality Development and Planning with Professor Robson and Principles of Hospitality Real Estate with Professor Corgel, Hyun Ho's professional interests shifted to real estate. Hyun Ho has subsequently spent the past two summers completing internships in hospitality real estate development and investment with Aju Hotels and Resorts in Seoul, South Korea and Davidson Hotels and Resorts in Atlanta, Georgia. This thesis has given Hyun Ho the opportunity to combine many of his past experiences and interests into a capstone project.

Hyun Ho looks forward to life after graduating from Cornell in a few weeks and plans to work full-time at KHP Capital Partners in San Francisco, California.

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INTRODUCTION

Overview

This paper is organized into four sections:

I. Introduction to walking, walkable places, and walkability

II. Literature review of walkability and real estate values

III. Data and methodology: Hedonic pricing model

IV. Results and discussion of key findings

Purpose

Walkability, defined for this purpose as spatially bound walking potential and pedestrian friendliness, has recently become a topic of considerable research interest. Previous literature has established that walkability has the potential to improve public health, sustainability and community cohesion (Forsyth et al., 2008; Ewing and Cervero, 2010; Du Toit et al., 2007). There are currently conflicting narratives, however, on whether the benefits of walkability are capitalized into real estate value premiums. Studies have found that walkability can both positively and negatively impact real estate value depending on property type and walkability measure (Cortright, 2009; Guo, Peeta and Somenahalli, 2017). Most studies have examined the relationship between walkability and real estate value in residential property types and there is limited research to date with commercial property types. A review of literature found no previous study on the relationship between walkability and hotel value. This study, therefore, examines the potential impact of multiple estimates of walkability on hotel values in New York City. Significant findings may show that the walkability of a hotel should be considered in hotel underwriting and development decisions.

Where people walk: The growth of walkable space

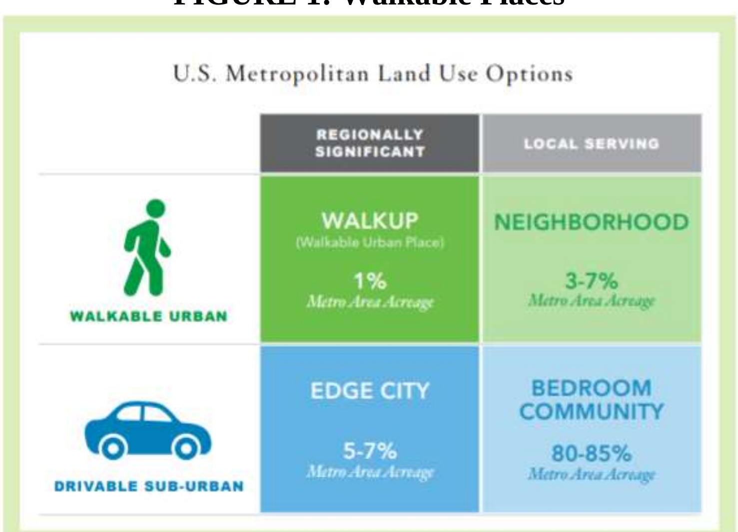
Urbanization has been one of the largest demographics shifts globally over the past century. The United Nations (UN) estimates that urban populations surpassed rural populations globally in 2007 and the gap between urban and rural populations has continued to widen during the subsequent decade. In a 2018 report on urbanization, the UN projected that the percentage of people in the world who live in urban areas will increase from 55% in 2018 to 68% by 2050. In more developed regions of the world such as North America, more than 8 in 10 people already live in urban areas (United Nations Department of Economic and Social Affairs, 2018).

In the US, recent trends point towards not only a shift from rural to urban places but further agglomeration of populations within urban spaces. Historically, sprawl and the development of drivable suburban communities characterized the rapid growth of many US metropolitan areas post World War II. While cities grew geographically, population density in many US cities dropped during the 20th century with land use consumption growing 3 to 8 times faster than metropolitan population growth. This trend appears to be reversing. A 2016 study of the 30 largest metropolitan statistical areas (MSAs) in the US by George Washington University and non-profit organization Smart Growth America, revealed that for the first time in 60 years, development in urban areas that are dense and walkable gained market share over drivable suburban development (Leinberger and Rodriguez, 2016).

As the composition of urban areas change, walkable places have become a focus of new urban development (Wey and Chiu, 2013). Both indirect factors and deliberate measures have promoted the growth of walkable space. Changes in urban demographics and the quality of cities have organically made spaces more walkable. Indirect drivers of walkable growth include an aging population that values walking, falling urban crime rates, increased traffic congestion which acts as a deterrent of individual auto use, urban job growth and the growing popularity of ethnic enclave neighborhoods (Myers and Gearin, 2001; Pivo and Fisher, 2014).

Deliberate legislative measures have also contributed to the growth of walkable space. Studies over the past decade have suggested that walkable communities benefit from healthier residents, reduced pollution, increased community cohesion and higher property values (Forsythe et al., 2008; Ewing et al., 2010; Du Toit et al., 2007; Cortright, 2009; Pivo and Fisher, 2014). Walking has subsequently become an important aspect of urban planning. Motivated to bring these potential benefits into their communities, governments have embraced walkable development. Projects such as the Highline in New York City and the Beltline in Atlanta demonstrate municipal efforts to repurpose public spaces into pedestrian friendly parks. In California, a recently proposed bill would have eased height-based zoning restrictions near major suburban transit hubs. While defeated in committee hearings, SB 827 was intended to create dense, mixed-use communities within walking distance of public transport hubs (California, 2018).

FIGURE 1: Walkable Places



Source: Leinberger and Rodriguez (2016)

Figure 1 shows a summary of land use in the 30 largest US MSAs (Leinberger and Rodriguez, 2016). Walkable and drivable space is further divided into regionally significant areas traditionally characterized as the city center and local serving areas found in towns and suburbs. The figure shows that walkable space can be found in different locations within an MSA. Walkable space in Washington DC, for example, can be found in both the central city and dense, mixed-use suburban centers and satellite cities like Crystal City and Bethesda (Leinberger and Alfonso, 2012). While a large majority of metropolitan land is still not walkable, the growing prevalence of walkable space can be observed in cities around the US. Leinberger and Rodriguez (2016) identifies 54 walkable urban places (WalkUPs) in Boston that together account for 1.2% of the MSA's total acreage. This small proportion of the metro by acreage reportedly absorbed 93% of the MSA's new office and rental multifamily square footage during the most recent real estate development boom from 2010-2014. Even in Atlanta, a city known for sprawl, Leinberger and Rodriguez (2016) found that 49% of new office and rental multifamily development in terms of square feet occurred in walkable urban places from 2010-2013. Since evidence seems to demonstrate that walkable places are on the rise, the next section will describe different factors that influence walking behavior and what makes a space walkable.

Why people walk: Factors that influence walking behavior

Walking is fundamentally a mode of transportation, but the significance of walking extends beyond getting from one point to another. In her book, *A History of Walking*, social historian Rebecca Solnit even argues that the two-legged gait, and not consciousness, is the most distinguishing feature separating the human species from other organisms (Lucas, 2001). What makes pedestrian activity unique to other forms of transport is the embodiment of walking. Activists such as Mahatma Gandhi, for example, have used the embodiment of walking as a tool to organize and protest for change (Lucas, 2001). As an embodied activity, walking is one of the most common forms of exercise and leisure (Giles-Corti and Donovan, 2003).

Because people walk for different reasons, various factors and conditions can influence a decision to walk. Untangling the many factors that influence walking behavior has been a topic of considerable research. In a cross-sectional survey of 1,803 respondents, Giles-Corti and Donovan (2003) organized potential factors that influence walking behavior into individual, social environmental and physical environmental components. Individual factors included attitudes towards walking and intention to engage in physical activity; social environmental factors included the number of others the participant knew engaged in walking behavior; while physical environmental factors included sidewalk conditions, presence of traffic and access to open spaces. Overall, Giles-Corti and Donovan (2003) concluded that individual, social environmental and physical environmental factors all had a significant and equally important influence on walking behavior.

Digging further into individual factors, Watson et al. (2015) investigated walking behavior exhibited by different demographics of US adults. Using a cross-sectional survey of 3,653 individuals, the study found that 90% of respondents believed walking was a reasonable form of transportation, but only a third of respondents reported walking regularly. The results differed depending on the characteristics of respondents. College students, for example, believed that walking was a reasonable form of transport at a higher rate than high school students. There were also more nuanced differences. Individuals over 50 walked most frequently but their perception of a reasonably walkable distance was shorter than the rest of the population (Giles-Corti and Donovan, 2003; Watson et al., 2015). As illustrated by these studies, there seems to be many diverse individual influences on walking behavior.

Socioeconomic factors can also impact walking behavior. Adkins et al. (2017) found that socially disadvantaged groups such as low-income individuals and racial minorities walk significantly less than advantaged groups under similar physical environment settings. Researchers have hypothesized that potential constraints of walking behavior for disadvantaged groups include available time, physically demanding professions, having children and age (Adkins, et al., 2017; Neckerman et al., 2009)

In a discussion of nine different focal points of research on walkable space, Hall and Ram (2019) identified two areas of study that further explains how social environmental factors can impact walking behavior. The first area of study focuses on the governance of pedestrian activity, accessibility and walkable space. Municipal attitudes towards walking are likely demonstrated through laws and programs. Strict, pedestrian-oriented traffic laws, as an example, should make walking behavior more attractive. The second area of study is somewhat more abstract. Hall and Ram (2019) describes it as the collective benefits of walking that "serve as a personal and community behavioral feedback". Many benefits associated with walking are shared by a community. Reducing carbon emissions by walking rather than driving leads to cleaner air that will be enjoyed collectively. Hall and Ram (2019) posits that the potential collective benefits tied to walking can create strong social rewards for walking behavior.

The physical environmental component is the final bucket of factors that Giles-Corti and Donovan (2003) identified as important to walking behavior. The bundle of physical environmental factors that influence walking behavior is often referred to as walkability. Because walkability is the focus of this study, the next two sections will provide a more detailed overview of the characteristics of walkability and how walkability can be measured.

How space informs walking behavior: Walkability correlates

Walkability is a multi-dimensional construct that space can possess. This study defines walkability as spatially bound walking potential and pedestrian friendliness. Walkability includes the availability of walkable destinations (walking potential) and the attractiveness and suitability of the built environment for pedestrian activity (pedestrian friendliness). Walkability is always contained within a space and includes only physical environmental characteristics. A space has high walkability if its physical environmental attributes facilitate walking behavior while a space has low walkability if its physical environmental attributes diminish walking behavior.

In relation to studies on individual and social environmental factors that impact pedestrian activity, research on physical environmental walking correlates is much more comprehensive. Walkability as a research topic is directly relevant to areas of study such as urban planning and real estate. The potential benefits associated with walkability including pollution reduction and physical exercise mean the implications of walkability research extends into topics like sustainable development and public health (Ewing and Cervero, 2010; Forsyth et al., 2008). Additionally, spatial attributes are often much easier to quantify and track than individual or social environmental attributes which makes walkability research more practical (Tribby et al., 2016).

The 3 Ds: Density, Diversity and Design, provide a traditional framework for examining walkability (Cervero and Kockelman, 1997). Density refers to the number of items contained within a space. The items measured can include people, buildings or businesses. Increasing the number of items in an area reduces the distance between items. Reducing distance is especially significant to walkability because walking is only practical as a short-distance mode of transportation (Watson et al., 2015). Density can also lead to high instances of traffic and auto-congestion which may decrease the attractiveness of individual auto use and incentivize people to adopt more active transport modes like walking (Forsyth et al., 2008).

Floor area ratio (FAR) is one way to quantify the density of the built environment and is calculated by dividing total building floor area by the area of the lot the building occupies. Studies have found that drivable suburban neighborhoods are characterized by low-density development with FAR between .05-.4 while highly walkable urban areas were characterized by high-density development with FAR between 1-40 (Leinberger and Rodriguez, 2016).

Diversity refers to the mix of different property types. Walking as functional transportation requires a destination; heterogeneous property types within a walkable space increases the number of potential destinations that can be reached on foot. The diversity of real estate product types can therefore facilitate walking behavior. By analyzing the zoning laws in 22 California cities, Carol et al. (2010) found that mixed use zoning regulations are positively related to increased potential for walking behavior. Leinberger and Rodriguez (2016) further found that diversity of transportation options had positive correlations with walkability. Accordingly, areas where individuals can bike, ride scooters and had access to public transportation options like subway and bus were found to be correlated with higher walkability (Leinberger and Rodriguez, 2016).

The final D is the design of the built environment. This category is the most subjective and refers to both the quantity of amenities that encourage walking such as sidewalks and street trees as well as the quality of a space, including perceived safety and attractiveness of views. To assess how form attributes affect walkability perceptions, Oreskovic et al. (2014) labeled and categorized built environment features in 424 photos depicting different streets. Research participants were then asked to rate their perception of the walkability of each street. Oreskovic et al. (2014) found that variation in building plane parallel to a street was inversely related with perceived walkability while the presence of ground floor windows and street focal points were positively related with perceived walkability. Unsurprising, the study also found that the presence of cars reduced perceived walkability, while the presence of people increased perceived walkability (Oreskovic et al., 2014). Density, Diversity and pedestrian friendly design provide a well-researched framework for organizing the many characteristics of walkability.

How to measure walkability: Accessibility and built-environment methods

The previous section described how walkability is a multidimensional construct that can encompass many correlates of walking behavior like density, diversity and design. It should therefore be no surprise that measuring walkability is a challenging task. The first challenge to measuring walkability is finding data that accurately describes land use and built environment attributes. Walking is a short-distance mode of transportation that is performed within relatively small geographic areas so spatial attributes are often only relevant at the micro-level (Lee and Moudon, 2006; Watson et al., 2016). The second challenge to measuring walkability is identifying specific variables that reliably capture correlates of walkability (Lee and Moudon, 2006). Because walkability encompasses multiple correlates researchers must also determine which correlates of walkability they will attempt to capture. A final challenge to measuring walkability arises from the many fields of study that research walkability. Walkability is studied for different objectives which introduces implicit bias into measurements. Studies interested in public health will likely place emphasis on measuring spatial correlates that promote walking for exercise. Similarly, research on sustainability will likely measure walkability with a focus on walking as functional transportation.

To better understand how walkability is measured, Vale and Pereira (2016) conducted a systematic review of literature and concluded that the methodologies that attempt to measure walkability are “as varied as the number of scholars who study it”. However, the many methodologies used to measure walkability can be broadly grouped into accessibility-based methods and built-environment methods. Accessibility-based methods evaluate an area’s walking potential while built-environment methods evaluate an area’s pedestrian friendliness. Another way to characterize these two methods are measurements of destinations (accessibility-based) and design (built-environment) (Forsyth et al., 2008).

Accessibility-based methods focus on capturing density and diversity related correlates of walkability. Accessibility-based methods are based on the assertion that distance to desired types of destinations is the most important dimension of walkability (Lee and Moudon, 2006). Accessibility-based methods can be further divided into distance-based methods, gravity-based methods and Walkscore type methods. Distance-based methods assume that walkability is simply a function of the spatial separation between places and can be calculated using relatively straightforward approaches. The closer a desired destination is, the greater the potential for walking behavior. Separation to destinations can be measured using Euclidean distance, shortest network distance or travel time distance (Vale and Pereira, 2016). Gravity-based methods build on distance-based methods and add extra complexity. Based on the tradeoff between the opportunity at a destination and the time it takes to get there, gravity-based methods weigh destinations based on distance from origin and type. Destinations that are N units from the origin may receive x weight while destinations N+1 units from the origin may receive y weight with generally x>y. Grocery stores, for example, may also receive higher weight than public libraries if accessibility to grocery stores is found to provide greater benefits than accessibility to libraries.

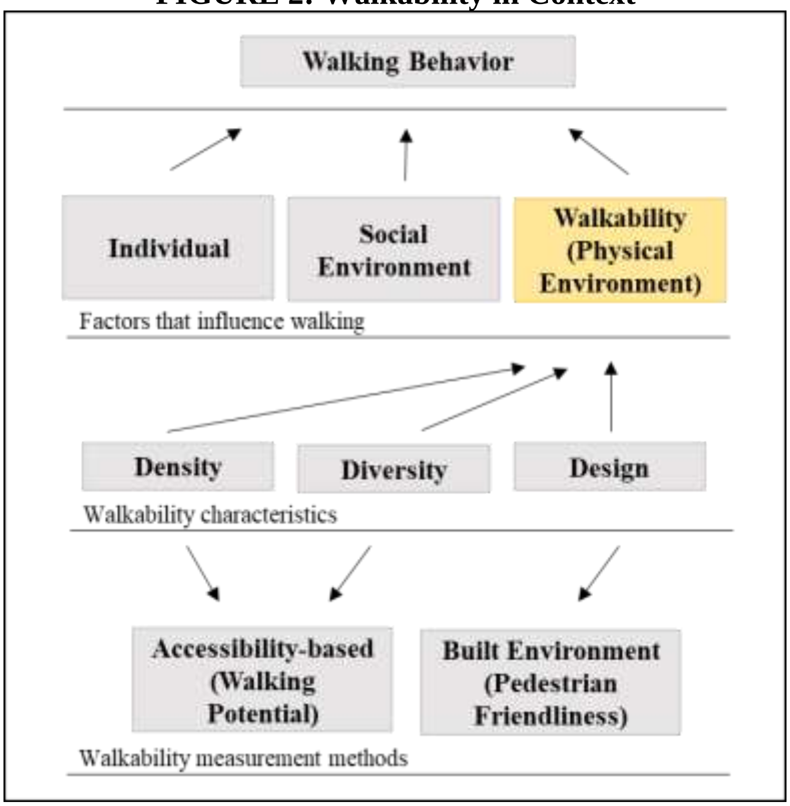
Finally, Walkscore type methods use complex algorithms to create proprietary scoring systems based on aspects of the gravity and distance-based methods discussed above. While this type of method typically evaluates accessibility-based correlates of walkability, it can potentially incorporate aspects of built-environment correlates as well (Vale and Pereira, 2016).

Built-environment methods focus on capturing the design related correlates of walkability. Variables that capture correlates of walkability in the built environment include street connectivity, sidewalk width and continuity, topographical slope, street benches, street trees and vegetation buffers, and signage that provides directions (Pivo and Fisher, 2014; Al-Hagla, 2009). Built-environment characteristics related to safety from both crime and traffic accidents have also been used as correlates of walking behavior to measure walkability (Forsyth, 2015). While accessibility-based methods are focused on origin and potential destinations, built-environment methods focus on the walking route. Therefore, attributes such as network connectivity and route directness have also been used to measure walkability.

There are a few significant drawbacks to using built-environment methods to measure walkability. A primary concern is that built-environment methods are difficult to standardize. The range of variables and methodologies used to measure built-environment walkability is large. Vale and Pereira (2016) were perhaps correct regarding built-environment walkability; studies that measure walkability using built environment correlates typically do so using tailor-made methods. Guo, Peeta and Somenahalli (2017) studied the impact of walkability on residential real estate values using a customized walkability index that combined a property dissimilarity index with built-environment correlates including neighborhood topography, physical barriers and street patterns. In another study, Leinberger and Alfonzo (2012) studied the same relationship between walkability and residential real estate values but used Walkscore and the Irvine-Minnesota Inventory (IMI) to measure walkability. While the results were significant for both studies, it is difficult to compare the findings of the two studies because walkability was measured differently.

Another area of concern is that built-environment methods often require significant time and resources to measure. Take the Irvine-Minnesota Inventory (IMI) for example. Extensive field work is required in order to fill out the 162 items of the inventory (Day et al., 2006). The necessity for in-person observation makes many built-environment methods tedious and difficult to scale. The walkability related factors discussed up to this point are broadly summarized in **Figure 2.**

FIGURE 2: Walkability in Context



A fundamentally different approach to measuring walkability focuses on outcomes. These studies measure walkability through the outcomes fostered by environments that support pedestrian behavior (Forsyth, 2015). Walkability in this case is “a means as well as an end and a measure” (Speck, 2012). It is argued that exercise inducing areas or lively and social space is an outcome of high walkability. This method of measuring walkability however, highlights endogeneity issues and ignores the individual and social environment influences of walking behavior.

LITERATURE REVIEW

Interactions between walkability and real estate values

The seminal paper in walkability is a 2006 study by Lee and Moudon that first quantified physical environmental correlates of walking. Numerous subsequent studies have established that walkability can have a significant impact on the individual, environment and community (Forsythe et al., 2008; Ewing et al., 2010; Du Toit et al., 2007). Most recently, a fourth body of research has emerged to examine the potential impacts of walkability on economic value. Based on existing literature, this section provides a conceptual framework for understanding the interactions between walkability and real estate values.

There are two conflicting narratives that describe how walkability theoretically interacts with real estate value. Landis, Guhathakurta and Zhang (1994) characterizes the correlates of walkability including high density and mixed-use development as a double-edged sword that can have both positive and negative impacts on real estate value. One narrative argues that the benefits associated with walkability increase property value. Accessibility, for example, has been shown to positively impact real estate values. A study on light rail in San Diego found that access to public transportation was positively associated with home values. In this study, the benefits of accessibility outweighed the negative impacts of being near light rail like increased noise and vibration. While dependent on the quality and popularity of the transit options, these findings show that accessibility can be a determinant of real estate value. If increased accessibility is an important outcome of walkability and urban economists generally agree that accessibility can be capitalized into higher property values, real estate in high walkability areas should theoretically realize price premiums (Landis, Guhathakurta and Zhang, 1994).

A second group of benefits with potential for increasing real estate value can be characterized as the proximity effects of walkability. It is argued that walkability has intrinsic economic value because characteristics such as high density can facilitate economic transactions and social exchange (Leinberger and Alfonzo, 2012; Gilderbloom et al., 2015). The assumption is that an area with many individuals and high levels of movement will lead to numerous interactions that create economic value. Litman (2006) further argues that walkability can induce individuals to spend more within their own communities. Correlates of walkability such as street level retail means individuals in high walkability areas will likely interact with local businesses at a higher rate than individuals in low walkability areas (Leinberger and Rodriguez, 2016). It can be expected that these businesses are within close proximity due to the short-distance nature of walking (Watson et al., 2015).

By containing an area's wealth, walkability may make neighborhoods more economically resilient (Litman, 2006). Although more research must be conducted to better understand this hypothesis, a study on walkability and residential real estate foreclosure rates in Louisville, KY showed promising results. Conducted at the census tract level, it was found that neighborhoods with high walkability (top 33% average Walkscore) had significantly lower foreclosure rates compared to the remaining balance of neighborhoods (Gilderbloom et al., 2015). Similarly, a study of 37,000 Fannie Mae multi-family housing loans and Walkscore found that walkability significantly reduced mortgage default risk (Pivo, 2014). Additionally, it has been argued that the collective benefits associated with walkability such as healthier residents and pollution reduction, can create economic benefits within a neighborhood by decreasing the costs of healthcare and infrastructure (Sohn, Moudon and Lee, 2012).

On the other hand, walkability may decrease real estate values. Correlates of high walkability are also associated with potential detriments to convenience and safety. Previous studies have found that density can lead to traffic congestion while heterogenous land use including the increasing presence of retail can attract crime (Watson et al., 2015; Bowes, 2007). There are also clear benefits to locating real estate in low walkability areas such as more space, privacy and quiet (Sohn, Moudon and Lee, 2012). Evidence for the economic benefits of locating real estate in low walkability areas can be found in how cities developed during the 20th century. In many US cities, high value residential real estate is found in drivable suburban communities with quiet enjoyment of a backyard and privacy from neighbors (Li et al., 2015; Leinberger and Rodriguez, 2016). Finally, it can be argued that individuals do not care enough about the potential collective benefits of walkability to pay a premium for it (Sohn, Moudon and Lee, 2012).

Regardless of the actual effect walkability has on economic values, evidence suggests that consumer demand for walkability has grown during the past couple decades. In a cross-sectional and longitudinal survey of American households, Handy et al. (2008) determined that more than half of respondents supported development of communities that exhibit a mix of commercial and residential land uses connected through walkable paths. Support for high walkability development grew over the two years the study was conducted. Demand for walkability was especially high for older respondents who identified that walkable communities could allow them to live independently longer. Younger generations can also value walkability as more recent research suggests that young, higher income individuals select into walkable neighborhoods in San Francisco, Oakland and Berkeley, CA (Foti, 2014). Accordingly, while the impact of walkability on economic value has not yet been fully quantified, it appears that demand for walkability is increasing.

Concurring with Handy et al. (2008) and Foti (2014), Frank (2011) argues that unmet demand for walkability is an underrepresented determinant of the price gap between real estate in urban cores and surrounding suburbs. The latent supply-demand mismatch in high walkability real estate can be attributed to supply and demand constraints. On the supply-side, policy issues like land segregating zoning laws, high parking ratio requirements and low building height restrictions prohibit high walkability development (Washington, 2013). On the demand-side, the high price premium of areas where a majority of walkable real estate is located makes walkability inaccessible for many individuals who would otherwise demand it (Leinberger and Alfonso, 2012). Foti (2014) suggests that developing high walkability real estate in more affordable areas, not unlike what was proposed in SB 827 in California, will help re-balance the market (California, 2018).

Clearly, walkability and real estate values can interact in significant ways. The next two sections summarize studies that attempt to quantify this interaction in residential and commercial property types.

Quantifying the impact of walkability on real estate values

Using Google Scholar and research databases provided by the Nestle Library at Cornell University including ABI/INFORM and Business Source Complete, 12 studies that quantify the relationship between walkability and real estate values were identified. A summary of the 12 studies is provided in **Table 1**. Studies that focused on residential real estate were included in the literature review due to the lack of studies on commercial property types.

TABLE 1: Literature on Walkability and Real Estate Value

	Location	Independent Variable	Dependent Variable	Model
Property level units				
(Cortright, 2009)	15 large US MSAs	Walkscore (1-100 scale)	Housing transaction prices (log)	Hedonic OLS
(Rauterkus and Miller, 2011)	Jefferson County, AL	Walkscore (1-100 scale)	Land transaction prices	Hedonic OLS
(Pivo and Fisher, 2011)	USA	Walkscore (1-100)	NCREIF market value and investment returns for office, industrial, retail and apartment properties	Hedonic OLS
(Li et al., 2015)	Austin, TX	Street Smart Walkscore (1-100), Sidewalk density	Single-family residential transaction prices (log)	Cliff-Ord spatial hedonic model
(Li et al., 2014)	Austin, TX	Street Smart Walkscore (1-100)	Condominium transaction prices	Cliff-Ord spatial hedonic model
(Boyle et al., 2014)	Miami, FL	Walkscore (1-100)	Single-family and condominium residential appraised values (log)	Fixed effects model
(Song and Knaap, 2004)	Washington County, OR	Distance to nearest destination types, Proportion of commercial, residential, public park and industrial land use, Building use entropy index	Housing transaction prices (log)	Hedonic OLS
Census tract level units				
(Gilderbloom et al., 2015)	Louisville, KY	Walkscore (1-100 scale and dummy variable for high walkability (walkscore>66) and not high walkability (walkscore<66))	Median assessed home value, foreclosure rates, crime	Hedonic OLS
(Guo et al., 2017)	Eastern Adelaide, Australia	Generalized dissimiliary index and walkability correlates that capture neighborhood topography, physical barriers and street patterns	Single family residential assessed values per square meter	Hedonic OLS
Neighborhood level units				
(Sohn et al., 2012)	King County, WA	Development density (FAR), Land use mix (ratio of multifamily residential, retail, office), Public open space (distance to public open space), Pedestrian infrastructure (Sidewalk density, distance to nearest bus stop)	Single-family residential, Multi-family residential rental, Office and Retail assessed values (log)	Hedonic OLS
(Leinberger and Alfonso, 2012)	Washington, DC	Walkscore, Irvine-Minnesota Inventory (IMI)	Office, residential and retail rents, Residential transaction prices	Hedonic OLS
City level units				
(Washington, 2013)	US MSAs with population>100,000	Walkscore (at city level)	Median assessed home values (log)	Hedonic OLS

Table 1 is organized by the unit of measurement for the independent variable. As discussed previously, walkability is spatially bound. The space that possesses walkability can be measured at a granular or broad level depending on the purpose of the study. The units used to measure walkability include property level, census tract level, neighborhood level and city level. While property, census tract and city all have objective parameters, neighborhood units of walkability require a subjective definition for each study. To define neighborhood units, Leinberger and Alfonso (2012) catalogued over 400 different neighborhoods in Washington DC using a collection of building plans, specially funded areas, regional and local business activity centers and socially defined neighborhoods. While this method can create units that conceptually contain walkability more homogeneously, the method is time-consuming and susceptible to bias. In addition to property level Walkscore, real estate company Redfin provides city level Walkscore which is the independent variable used in one of the studies (Washington, 2013). While city level units can be used at a national level, it is difficult to match such a broad walkability measure with individual walking behavior. Research on the validity of city level Walkscore as an estimate of walkability was not found. Census tract and property units of walkability can be used to measure different things. Census tract units are relevant to studies that compare areas while property units are tied to specific points.

Walkability and real estate values have been studied in many locations. However, 11 out of 12 of the studies reviewed examined areas in the US. It is unclear whether other parts of the world exhibit different relationships between walkability and real estate values. Important to this paper, none of the reviewed studies were focused on New York City. The geographic scope of studies ranged from being limited to a single city (Gilderbloom et al., 2015; Leinberger and Alfonso, 2012) to nationwide (Washington, 2013; Pivo and Fisher, 2011).

Reflecting discussion in the section on how to measure walkability, studies used different independent variables to measure walkability. Walkscore, used to some extent in 75% of the studies, was by far the most popular way to measure walkability, however. Other walkability correlates used as independent variables included accessibility to destinations (Song and Knaap, 2004; Sohn, Moudon and Lee, 2012) and a generalized property use dissimilarity index (Guo, Peeta and Somenahalli, 2017). While only a few studies used built-environment walkability measures (Li et al., 2015; Guo, Peeta and Somenahalli, 2017; Sohn, Moudon and Lee, 2012; Leinberger and Alfonso, 2012), all 12 studies included an accessibility-based walkability measure as an independent variable.

Real estate values were largely examined using residential property types. Residential real estate has research related advantages like large datasets of transaction prices and assessed values. Residential real estate values are also more transparent than commercial property prices. Valuating hotel real estate, for example, is difficult because a hotel's price is impacted by the complex operating business within the property. Although a few other studies included aspects of commercial property use in their analysis (Leinberger and Alfonso, 2012; Sohn, Moudon and Lee, 2012), only one study focused on the relationship between walkability and commercial land use as the dependent variable (Pivo and Fisher, 2011). Realizing that land improvements can create confounding noise in real estate valuations, one study focused on land transaction prices (Rauterkus and Miller, 2011). This study argues that land value is a more appropriate variable for measuring the potential impact of walkability on real estate values. Finally, many studies found that log transformations of assessed values and transaction prices yielded better model results.

For all studies, a hedonic pricing model was the fundamental tool used to quantify the relationship between walkability and real estate values. Hedonic pricing models can be used to isolate and implicitly quantify attributes that impact price by examining the variation of attributes and price (Rosen, 1974). Applied to real estate prices, hedonic models are used to untangle the bundle of physical, socioeconomic and idiosyncratic attributes that impact real estate value. The use of hedonic pricing models in real estate is established and has also been used to measure environmental features like crime (Lebret and Valentin, 2019). While most studies used ordinary least squares (OLS) regressions, two studies by Li et al. (2014 and 2015) used a modified hedonic pricing model first proposed in Cliff and Ord (1981) to mitigate the risk of "omitted neighborhood variables" (Li et al., 2014, Li et al., 2015). Only one study incorporated neighborhood fixed effects into the regression model (Boyle, Barrilleaux and Scheller, 2014). This study argued neighborhood fixed effects should be incorporated into regression models to account for unobservable differences between neighborhoods. Boyle, Barrilleaux and Scheller (2014)'s motive for including neighborhood fixed effects is the same reason Li et al. (2014 and 2015) uses a modified hedonic model and is corroborated by the heteroskedasticity of error terms in their models.

The relationship between walkability and real estate values has been measured using different property types, units, locations, variables and models. The results of many studies however, as shown in **Table 2**, generally point towards a positive relationship between walkability and real estate values. Positive relationships have been found at different property types and locations using different units, variables and models.

However, studies also found walkability has heterogeneous interactions with real estate and not all correlates of walkability had a positive impact on value. Two studies found that highly mixed property use has a negative impact on single-family housing value (Song and Knaap, 2004; Guo, Peeta and Somenahalli, 2017). These studies contend that the negative elements associated with mixed use such as elevated noise, traffic and pollution outweigh the benefits of walkability for single-family houses. Under different conditions, however, land use mix was found to increase real estate values. Specifically, mixing rental apartment with retail was found to have a positive impact on rental apartment values (Sohn, Moudon and Lee, 2012).

Boyle, Barrilleaux and Scheller (2014) is the only study reviewed that found no significant relationships between walkability and real estate values. It is important to remember, however, that this paper was the only study that included submarket fixed effects in its regression model.

TABLE 2: Summary of Previous Findings

	KEY FINDINGS
(Cortright, 2009)	Walkscore has a positive impact on housing value in 13/15 MSAs 1-point increase in Walkscore = $500-$3,000 increase in housing value in typical markets
(Rauterkus and Miller, 2011)	Walkscore associated with higher land prices
(Pivo and Fisher, 2011)	10-point increase in Walkscore = 1-9% increase in retail, apartment, and office real estate value Walkscore has no impact on NCREIF investment returns Walkscore has no impact on industrial property values
(Li et al., 2015)	Walkscore positive impacts single-family housing values in high walkability areas Sidewalk density positive impactly single-family housing values in high walkability areas
(Li et al., 2014)	Walkscore can positive impact condominium real estate value
(Boyle et al., 2014)	No significance associations between Walkscore and housing values
(Song and Knaap, 2004)	Proximity to public parks and service-based businesses positively impacts single-family housing values Mixing industrial and residential land uses decreases single-family housing value
(Gilderbloom et al., 2015)	Walkscore positively impacts housing values Walkable neighborhoods have lower levels of housing foreclosure Walkscore has no significant impact on crime
(Guo et al., 2017)	Accessibility to education, retail and social destinations positive impacts single-family housing values High mix of property types has the potential to decrease single-family housing values
(Sohn et al., 2012)	High density development positively impacts single-family housing, retail and office real estate values Pedestrian infrastructure positively impacts rental apartment values Land use mix positively impacts rental apartment values Mixing rental rental apartment and retail makes rental apartment more valuable
(Leinberger and Alfonso, 2012)	Walkability positively impacts office rent, housing rent, retail rent and retail revenue Walkability positively impacts housing values Cap rates are lower in high walkability neighborhoods
(Washington, 2013)	City Walkscore and median home value are positively related

DATA AND METHODOLOGY

Study location: New York City

New York City was selected as the location for this study due to availability of data, active hotel real estate market and high walkability. This largest US MSA hosted over 65 million visitors in 2018 and has a current hotel inventory of nearly 120,000 rooms across its 5 boroughs (NYC and Company, 2019). Not surprisingly, New York City has one of the most active hotel real estate markets in the world which means there is a relatively large sample of transactions to be studied. New York City is also a very walkable city. Leinberger and Rodriguez (2016) ranks New York City as the second most walkable MSA in the US after only Washington, DC. A city with high walkability was of interest to this study because previous research has shown that the relationship between walkability and real estate values is more significant in high walkability areas (Cortright, 2009; Li et al, 2015). Finally, New York City is an interesting location for conducting a new study on the relationship between walkability and real estate value because no previous study on the topic in this MSA was found while conducting literature review.

Data sources

The data used in this study was collected from a variety of online repositories. Hotel transaction and property characteristics were obtained from Real Capital Analytics (RCA). RCA is a private real estate analytics provider that collects and distributes property and market data for commercial transactions. According to the RCA website, every RCA transaction record is authenticated using two or more sources and is continually reviewed and updated by active real estate brokers and investors. The sample of transactions consists of 462 hotel transactions in New York City during a 11-year period from 2006-2016. The transaction variables used in this study that were obtained from RCA are: natural log of price per unit, transaction year, property submarket, number of units, number of floors, property age, and dummy variables for refinance or transaction, full-service or limited service, and presence of on-site retail. Transaction values for all years are adjusted to 2016 US dollars.

Crime data was obtained at the point-specific level from the New York City Police Department (NYCPD). A variable to measure the crime level of a hotel was found by aggregating the instances of assault, murder, rape and robbery that occurred from 2006-2016 within a quarter-mile radius of each hotel transaction. Violent crime was then instrumented using precinct level of crime, count of liquor stores within a quarter-mile radius and census tract unemployment consistent with the methodology used in Lebret and Valentin (2019) to control for endogeneity issues between crime and hotel value. Precinct level of crime was collected from NYCPD, liquor store data was collected from the New York State Liquor Authority and census tract unemployment was collected from the US census.

The following variables were used to estimate walkability: Walkscore, Streetscore, Citi Bike count, and count of establishments within a quarter-mile radius. Walkscore was collected from Walkscore.com by Tate Twinam at the University of Washington. Streetscore was obtained as Q-values from the Streetscore Database found at streetscore.media.mit.edu. The Q-values were converted to ScaledQ Streetscore values on a 10-point scale by dividing each Q-value by the maximum Q-value in New York City and multiplying by 10. Streetscores were matched to hotel transactions by calculating the average of all Streetscores within a quarter-mile radius of a property. Citi Bike count was obtained from Citi Bike Systems Data found at citibikenyc.com/system-data. Count of establishments within a quarter-mile radius was obtained from ESRI's Business Location Database using ArcGIS Business Analyst.

Variables used to estimate walkability

Walkscore

As discussed previously, one of the most widely studied proxies for walkability is Walkscore. Built on a patented algorithm, Walkscore estimates walkability on a 100-point scale and is available for any address in the US, Canada and Australia without the need for primary data collection. The algorithm calculating Walkscore is primarily an accessibility-based method that measures the walking potential of a physical environment.

> *The Walk Score algorithm looks at destinations in 13 categories and awards points for each destination that is between one-quarter mile and one mile of the […] property. Destinations get maximum points if they are one quarter mile or less from the residence and no points if they are more than one-mile away (Cortright, 2009).*

Destination categories include banks, restaurants, libraries, entertainment, shopping and parks (Cortright, 2009). A gravity-based approach allows Walkscore to capture the diminishing relevance of destinations as they become farther from an origin. Separation is measured using Euclidean distance, however, which ignores network connectivity (Weinberger and Sweet, 2012). Destination categories are also weighted to account for the varying significance each destination category has on walkability. Grocery stores and restaurants, for example, are weighted more significantly than entertainment destinations and parks. A second version of Walkscore called Street Smart Walkscore incorporates intersection density and blockface length into the algorithm and was used in Li et al. (2014 and 2015). High intersection density and short blockface length increases the directness and diversity of the potential routes between two points (Forsyth et al., 2008).

Traditional Walkscore found on Walkscore.com and available to this study, however, focuses only on availability of destinations. Other limitations of Walkscore include that it does not account for the quality or intensity of individual destination.

Despite its limitations, which are present in all walkability measures, multiple studies have validated Walkscore's ability to broadly describe walkability. Carr et al. (2010) found the Walkscore algorithm to be a reliable indicator of access to walkable amenities. Similarly, Duncan et al. (2013) found that Walkscore was correlated with many walkability characteristics like population density, intersection density and access to public transportation. Weinberger and Sweet (2012) further found evidence that Walkscore is a strong predictor of actual walking behavior. Using Walkscore and walking behavior data from household travel surveys, Weinberger found positive associations in all four US MSAs studied.

Streetscore

Walkscore uses an accessibility-based method and is primarily an estimate of walking potential. The pedestrian friendliness of an area's design and infrastructure is the other major component of walkability. As discussed previously, built-environment correlates of walkability are difficult to identify and measure. Instead of using a walkability index that requires primary data collection or narrowly delimited variables like sidewalk width and street tree count, this study proposes a novel way to measure built-environment walkability using Streetscore. Benefits of using Streetscore as a potential proxy for pedestrian friendliness include ease of use and potential for scale.

Streetscore is built on a recently developed algorithm at MIT Media Lab that uses machine learning to quantify the perceived condition of a space. It is important to note that Streetscore is not an outcomes-based measure of walkability. Rather than directly measuring perception, Streetscore is calculated by measuring specific built-environment features in millions of Google Maps images that a machine learning algorithm determined was relevant to how an area is perceived. Although primarily focused on perceived safety, Streetscore's evaluation of streetscapes extends into perceptions of a place's liveliness and character (Naik et al., 2014). Safety is also loosely defined and can include safety from crime and safety from traffic. This study assumes that built-environment attributes that improve the perception of an area's safety from traffic, safety from crime, liveliness and character also increases an area's walkability.

CitiBike Trips

A third independent variable used to in this study is CitiBike Trips. According to the Citibike website, there are over 12,000 bikes and 750 stations in the CitiBike network which makes it the largest bike sharing program in the US. Previous studies have found that high walkability areas have high diversity of transport options (Leinberger and Rodriguez, 2016) and support other active transport modes like biking and riding a scooter (Tribby et al., 2016). CitiBike Trips was calculated by counting the number of trips that either originated or terminated within a quarter mile radius of each hotel transaction during May 2018. Collecting transportation data in May is recommended by the Institute of Transportation Engineers (ITE) because this time period is generally free of irregular traffic patterns like winter holidays and summer vacations (Turner et al., 1998).

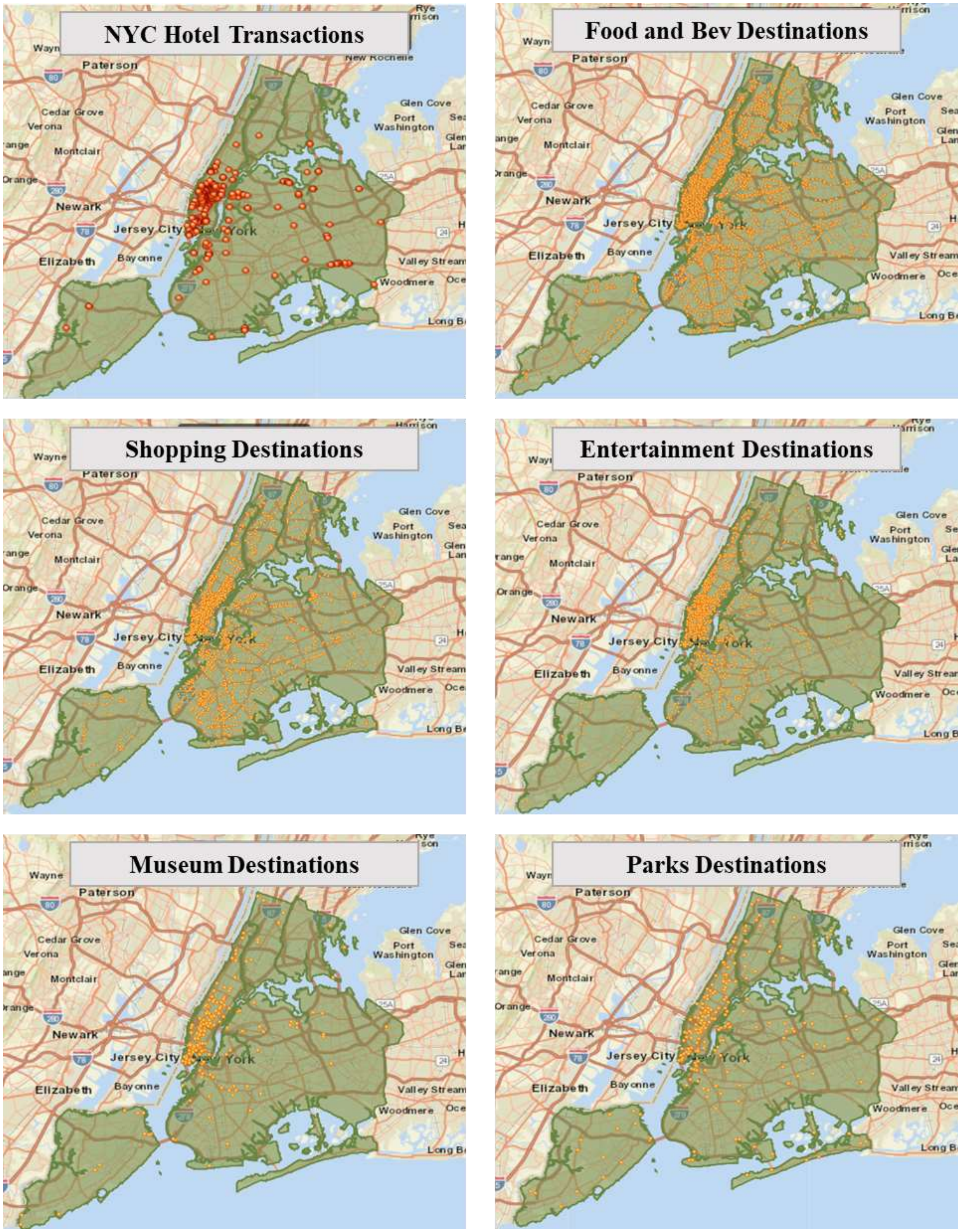
Destinations data

As explored above, individuals walk for many reasons including recreation and exercise but walking as transportion requires a destination. Connected to both density and diversity, Lee and Moudon (2006) found accessible destinations to be the most significant determinant of an area's potential for walking. Variables such as Walkscore quantify an area's walking potential by aggregating destinations into a single score based on distance and destination type. Not all destinations are created equal, however, and destination types can heterogeneously impact walking behavior. After analyzing 24 destination categories, one study found that only grocery, education, bank, restaurant and bar destinations were significantly associated with home-based walking (Lee and Moudon, 2006). Walking accessible destinations also appear to have complicated interactions with real estate value. A study on walking destinations and residential real estate found that accessibility to coffee shops and cafes was associated with higher real estate values but insignificant for other destination types (Foti, 2014). Other studies found walking accessible industrial destinations decreased single-family housing values (Song and Knaap, 2004) while walking accessible education, retail and social destinations raised single-family housing values (Guo, Peeta and Somenahalli, 2017).

Aggregating all walkable destinations into a single score can potentially mask more intricate relationships. This assertion is consistent with Tribby et al. (2016) which found correlates of walkability such as diverse destinations should be measured more granularly. To understand how walking accessible destinations might affect hotel real estate value individually, business establishment data was obtained from ESRI's Business Location Database. ESRI's Business Location Database lists 12.5 million US businesses and includes business name, location at the address level, industry classification code, number of employees and annual sales volume. The dataset is compiled by Infogroup using Yellow Pages, business white pages, annual reports, 10-K and other SEC filings, government data, business magazines, newsletters, and the US Postal Service, (ESRI, 2018).

Using ArcGIS Business Analyst, data was obtained for five destination categories in New York City. The destination categories were chosen based on potential significance to hotel guests and were organized using North American Industry Classification System (NAICS) codes. The destination categories and corresponding NAICS codes analyzed in this study are: Food and Beverage (72251117–sit down restaurants, 72241–drinking places, 72251505–coffee shops, 72251402–cafes); Shopping (448–clothing and clothing accessory stores); Parks (71219004–parks), Entertainment (71111007–theatres, 71113002–orchestras, 71119007–entertainment, 71112002–dance companies, 71111010–performing arts); and Museums (71211001-museums). For each destination category, the count of establishments within a quarter-mile Euclidean distance was calculated for every hotel transaction using ArcMap. The quarter-mile distance was selected to represent destinations that would receive full points in the Walkscore algorithm and is within a 5-minute walk at a reasonable pace. This distance was also chosen to be consistent with a finding by Giles-Corti and Donovan (2003) that people generally drive to destinations farther than a quarter-mile away. The intensity of destinations was accounted for by counting the number of establishments within a walkable area. Maps showing the arrangement of destinations in New York City is summarized in **Figure 3**. Individual maps can be found in **Appendix A-F**.

FIGURE 3: New York City Maps



Control variables

Real estate transaction prices are influenced by a bundle of physical, socioeconomic and idiosyncratic factors of which walkability is just one potential determinant. Various control variables were therefore introduced in order to better isolate the impact of walkability on hotel values. Stull (1975) identifies four fundamental dimensions of real estate value: accessibility, physical site characteristics, environmental features and public sector factors. Building on the four dimensions of real estate value identified in Stull (1975), Pivo and Fisher (2011) reviewed 32 previous studies and categorizes control variables for walkability studies into five groups: market conditions, physical building conditions, neighborhood characteristics, accessibility controls and taxes and government services. The five categories of control variables identified in Pivo and Fisher (2011) were also used to study the effect of walkability on value in a commercial real estate setting.

This study, therefore, considered control variables in each of category identified in Pivo and Fisher (2011). Market conditions were controlled for using a year fixed effect and a dummy variable for whether the hotel "transaction" was a from a sale or refinancing. Physical building conditions were controlled by using number of floors, number of units, age of the property and a dummy variable that captured the presence of on-site retail. Neighborhood characteristics were controlled by using instances of violent crime within a quarter mile radius of the property and was instrumented as previously described. A neighborhood's rate of violent crime was previously found to be a significant determinant of hotel real estate transaction prices in New York City (Lebret and Valentin, 2019). Several accessibility controls such as distance to the nearest airport, distance to Times Square (identified as the city center) and distance to nearest subway were considered. However, these variables were ultimately omitted from final model results due to high multicollinearity issues between walkability and distance to nearest subway and distance to Times Square. Distance to nearest airport was found to be insignificant across various model specifications. Therefore, this study does not isolate walking accessibility from other forms of accessibility. The impact of walkability on hotel value reported in the regressions may, therefore, also encompass accessibility with other transport modes. This assertion is unsurprising and consistent with previous research that found that walkability and accessibility to diverse transportation modes are highly connected qualities (Leinberger and Rodriguez, 2016). It was determined that public sector factors were mostly homogenous for the dataset. Controlling for taxes and government services was important in Pivo and Fisher (2011) because the study was conducted using a cross-sectional sample of properties nationwide. Because all the transactions in this study are in the same municipality, however, it was assumed that taxes and government services would have a homogenous impact on hotel values.

Table 3 provides a summary of all the variables included in this study. It is evident that New York City has high overall walkability and the median Walkscore for hotel transactions was over 99. The median of the dummy variables shows that there are more sale transactions than refinancing transactions and more full-service hotels than limited-service hotels in the dataset. Most hotels in the dataset also do not have on-site retail. Violent crime was highly variable from property to property. Additionally, the data showed variables had different characteristics in different submarkets. The averages for walkability estimates like Walkscore, Streetscore and CitiBike Trips was found to be consistently higher in submarkets of Manhattan compared to submarkets outside of Manhattan. The averages of all variables organized by submarket is available in **Appendix H**.

TABLE 3: Descriptive Statistics for All Variables

	Mean	Median	Std. Err.	Std. Dev.	Min	Max	Range
ln (Ppunit)	12.82	12.93	0.03	0.72	9.23	14.73	5.50
Walkscore	95.3	99.1	0.5	10.3	38.4	100.0	61.6
Streetscore	8.01	8.16	0.03	0.69	5.56	10.00	4.44
CitiBike_Trips	22,550	25,217	651	13,994	0	54,564	54,564
Food_and_Bev_Destinations	62	68	2	38	0	124	124
Entertainment_Destinations	27	14	1	30	0	122	122
Parks_Destinations	1.8	2.0	0.1	1.5	0	6.0	6.0
Museum_Destinations	3.0	2.0	0.1	2.6	0	10.0	10.0
Shopping_Destinations	121	38	8	181	0	780	780
Refinance	0.31	0	0.02	0.46	0	1.00	1.00
Units	257	182	13	271	13	1980	1967
Floors	18	16	1	13	1	73	72
Full_Service	0.64	1.00	0.02	0.48	0.00	1.00	1.00
Onsite_Retail	0.15	0.00	0.02	0.36	0.00	1.00	1.00
Age	45	30	2	42	0	133	137
Violent_Crime	2,849	641	383	8,226	0	66,043	66,043

Model specifications

Regression analysis was conducted on two datasets: one with all hotel transactions in New York City and another with only hotel transactions in Manhattan. Manhattan contained the majority of hotel transactions and the borough had significantly higher walkability overall across different estimates compared to Brooklyn, Queens, Staten Island and the Bronx as shown in **Appendix H**. Transactions in Manhattan were studied to examine if the relationship between walkability and hotel real estate values changed in high walkability areas. After removing transactions with missing data, the number of transactions used for the regression model contained 450 cases in New York City and 360 cases in Manhattan.

Consistent with previous research, this study employed a hedonic pricing model to determine the potential impact of walkability on hotel real estate values using the following form (Rosen, 1974):

$$\ln (\mathbf{Ppunit})_t = f\,(\mathbf{m, p, n, w}) + \mathbf{yfe}_t + \mathbf{e}$$

where **Ppunit** is the transaction price per unit, **t** is the year of the transaction, **m** is market conditions, **p** is physical characteristics, **n** is neighborhood characteristics, **w** is walkability estimates, **yfe** is year fixed effects and **e** is the error term. Consistent with prior studies, price per unit was modeled with a log transformation to diminish the impact of skewed upper values and yielded better results than using raw price per unit values.

The traditional method of modeling walkability and real estate values uses ordinary least squares (OLS) regression and was the base model for this study. The relationship between walkability and hotel real estate value was also examined using a modified OLS model that includes submarket fixed effects of the following form:

$$\ln (\mathbf{Ppunit})_{t,g} = f\,(\mathbf{m, p, n, w}) + \mathbf{yfe}_t + \mathbf{sfe}_g + \mathbf{e}$$

where **g** is the property submarket and **sfe** is a submarket fixed effect. Boyle, Barrilleaux and Scheller (2014) presented the need for neighborhood fixed effects to control for the unobserved differences in areas. While evaluating potential controls for this study, it was difficult to find variables for neighborhood characteristics and accessibility that were both significant and avoided multicollinearity issues. Walkability is a quality influenced by many factors of a space which made it highly connected to many control variables for neighborhood characteristics and accessibility. A model with submarket fixed effects allows this study to examine walkability and real estate values without identifying specific characteristics of a neighborhood. Due to the number of transactions available, census tract level neighborhood fixed effects were not feasible.

Several measures were taken to improve the robustness of the models. First, all models include heteroskedasticity-robust standard errors to account for unequal variance. Second, control variables were chosen to minimize multicollinearity issues with the independent variables. As shown in **Appendix G**, the correlations between control variables and independent variables are generally low. The independent variables showed greater correlations between each other, however. This is unsurprising and likely unavoidable considering the independent variables represent different methods of estimating walkability. The relationship between walkability and real estate value was therefore also regressed using each independent variable individually and the results are available in **Appendix I-P**. Finally, as has been previously discussed violent crime was instrumented using census tract unemployment rate, all precinct crime and number of liquor stores within a quarter mile. An instrumented variables approach was adopted to account for endogeneity issues between crime and real estate value identified in Lebret and Valentin (2019).

All models were run on an open-source statistical software developed by the R Project. Code for conducting regression analysis on R was provided by Daniel Lebret at Cornell University. Regression tables were generated and formatted using the stargazer package on R (Hlavac, 2018).

RESULTS AND DISCUSSION

Walkability and hotel real estate value

The results across the four regression models suggest walkability and hotel real estate values have complicated relationships. Generally, the control variable regressors were significant and had directions that are conceptually consistent with prior understanding of real estate value. Refinancing transactions resulted in higher value compared to sale transactions which may reflect that hotels refinance under favorable economic conditions. Hotel properties with more floors, the presence of on-site retail and full-service operations were associated with higher value in all models. Age was also positively associated with value which perhaps reflects how older hotels in New York City have historic significance and locate in higher value areas. Number of units had a negative impact on value which may be attributed to the decreasing marginal benefit of a hotel room. The incidences of instrumented violent crime within a quarter-mile radius generally decreased hotel value. Although not displayed in **Table 4** for clarity reasons, nearly all submarket fixed effects and many year fixed effects were significant. Both R^2 and adjusted R^2 values for the models were in the range of those found in previous studies on walkability and real estate value although the Manhattan only models had significantly lower values compared to city wide models. This perhaps reflects strong idiosyncratic determinants of real estate value in Manhattan.

Without including submarket fixed effects, the initial base model applied to a city-wide sample of transactions showed significant positive associations between all three estimates of walkability and hotel value. This initial model suggests that walking potential (Walkscore), pedestrian friendliness (Streetscore) and active transportation accessibility (CitiBike Trips) are all capitalized into hotel value premiums. During literature review, 9 out of 12 studies used a

TABLE 4: Walkability Estimates and Hotel Value

Walkscore and other Walkability with Heteroskedasticity-robust Standard Errors

	Dependent Variable: Log of Price per Unit			
	(NYC)	(NYC w Submarket FE)	(Manhattan)	(Manhattan w Submarket FE)
	(1)	(2)	(3)	(4)
Constant	10.345***	11.348***	16.005***	17.083***
	(.377)	(.301)	(2.308)	(2.861)
Walkscore	.011***	-.001	-.047*	-.062**
	(.003)	(.003)	(.024)	(.031)
Streetscore	.079*	.083*	.117*	.187***
	(.046)	(.047)	(.062)	(.072)
CitiBike_Trips	.00001***	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Refinance	.298***	.291***	.224***	.227***
	(.055)	(.054)	(.061)	(.062)
Units	-.001***	-.001***	-.001***	-.001***
	(.0003)	(.0003)	(.0003)	(.0003)
Floors	.022***	.020***	.018***	.020***
	(.003)	(.003)	(.003)	(.003)
Full_Service	.305***	.260***	.382***	.304***
	(.058)	(.056)	(.067)	(.067)
Onsite_Retail	.146*	.123*	.133*	.127*
	(.078)	(.074)	(.077)	(.076)
Age	.002***	.001	.002**	.002**
	(.001)	(.001)	(.001)	(.001)
Violent_Crime	-.00001*	.00001	0.00000	.00001
	(.00001)	(.00001)	(.00001)	(.00001)
Observations	450	450	360	360
R^2	.449	.501	.242	.250
Adjusted R^2	.424	.465	.197	.191
Residual Std. Error	.541	.521	.532	.534

Note: *p<0.1; **p<0.05; ***p<0.01

All Models Include: Year FE

similar OLS approach and found similarly positive associations between walkability estimates and real estate value.

However, as problematized in Boyle, Barrilleaux and Scheller (2014), these approaches do not account for the unobserved differences between neighborhoods. Once submarket fixed effects were included, the relationships between walkability estimates and hotel value became inconsistent. For example, Walkscore and CitiBike Trips were insignificant in the submarket fixed effects model. This finding is similar to what Boyle, Barrilleaux and Scheller (2014) found in the residential real estate market in Miami which showed that positive relationships between Walkscore and value became insignificant after adding neighborhood fixed effects. The results in the New York City regression models and Boyle, Barrilleaux and Scheller (2014) provide evidence that positive associations found in previous studies between walkability estimates like Walkscore and real estate value may not be attributable to walkability but is rather a result of other unobserved neighborhood characteristics that are positively related with Walkscore.

Limiting the sample of transactions to properties in Manhattan further complicated matters. The regression models for Manhattan hotel transactions had significantly lower explanatory power, but still had significant impacts for nearly all regressors. In Manhattan hotel transactions, Walkscore had a negative impact on value both with and without submarket fixed effects. These results suggest that in high walkability areas, the negative consequences of high accessibility-based walkability, including noise and traffic, outweigh the benefits of accessible destinations (Song and Knaap, 2004; Guo, Peeta and Somenahalli, 2017). Ram and Hall (2018) found similar results in their study of Walkscore and hotel room rates in Tel Aviv, Israel. Like New York City, Tel Aviv is a popular travel destination with high walkability. This study found that the highest value hotel rooms were found on the fringes of highly walkable areas. The “sweet spot” was a Walkscore of 93-96 with hotel room prices decreasing with further movement from this range on both sides. Manhattan submarkets in this study had Walkscores above this range with average Walkscores around 99 and standard deviation near one as shown in **Appendix H**.

Streetscore was the only walkability estimate that had a significant positive impact across all four models. It can be inferred that built-environment walkability features like those measured by Streetscore more consistently benefit hotel values compared to accessibility-based walkability characteristics like those captured by Walkscore and increasing walking potential may even negatively impact values in high walkability areas like Manhattan.

If the base OLS model indeed fails to capture relevant neighborhood characteristics, another method that can improve the model’s specification without using submarket fixed effects is introducing better neighborhood controls. This approach was tested using neighborhood wealth. To account for differences in neighborhood wealth, per capita income was introduced as a control variable. Per capita income data was obtained at the census tract level from the US census. Introducing per capita income as a neighborhood control variable had a similar impact on walkability estimates as using a submarket fixed effects model did. The impact of per capita income on hotel values was significant and resulted in all three walkability estimates becoming insignificant in the city-wide OLS model as shown in the **Appendix Q**. The concerns of using per capita income as a control variable in this study should, however, be discussed. Walkability and economic value are connected concepts with potential for multicollinearity issues. Walkability can have intrinsic value by facilitating transactions (Leinberger and Alfonzo, 2012; Gilderbloom et al., 2015) and increasing economic resiliency (Litman, 2006). Further, studies have found that higher income individuals select into areas with high walkability (Foti, 2014).

Accordingly, the correlation between Walkscore and per capita income (.45), for example, was much higher than the correlation between Walkscore and quarter-mile violent crime (.11). Due to these potential endogeneity and multicollinearity issues, it was determined that instrumented violent crime was a better control for neighborhood characteristics and per capita income was therefore not included in the base models.

Overall, a major issue appears to be scale. While property level Walkscore may be unimportant with regard to hotel value, the general walkability level of a neighborhood is likely correlated with other neighborhood characteristics that are associated with higher hotel values. Boyle, Barrilleaux and Scheller (2014) hypothesized that future studies will find positive associations between the strength of neighborhood fixed effect values and walkability measures. Because measures of walkability like Walkscore and Streetscore are imperfect estimates, neighborhood fixed effects may even be capturing unmeasured characteristics of walkability.

Destinations and hotel real estate value

A second set of independent variables were regressed to understand if walking accessibility to specific destinations impacted hotel real estate values differently. The results are displayed in **Table 5**. Using the base OLS model specification, the results show that food and beverage destinations positively impact hotel values. For the sample of all hotel transactions in New York City, the sign and significance of food and beverage destinations remained stable even after submarket fixed effects were introduced. The results suggest that the accessibility benefits of nearby food and beverage destinations are capitalized into higher hotel values. It is conceptually comprehensible that walkable food and beverage destinations provide economic benefits for hotels. This assertion is consistent with previous literature on other property types. In residential real estate, walking accessibility to restaurant, bars, cafes and coffee shops

TABLE 5: Walking Accessible Destinations and Hotel Value

Destinations with Heteroskedasticity-robust Standard Errors

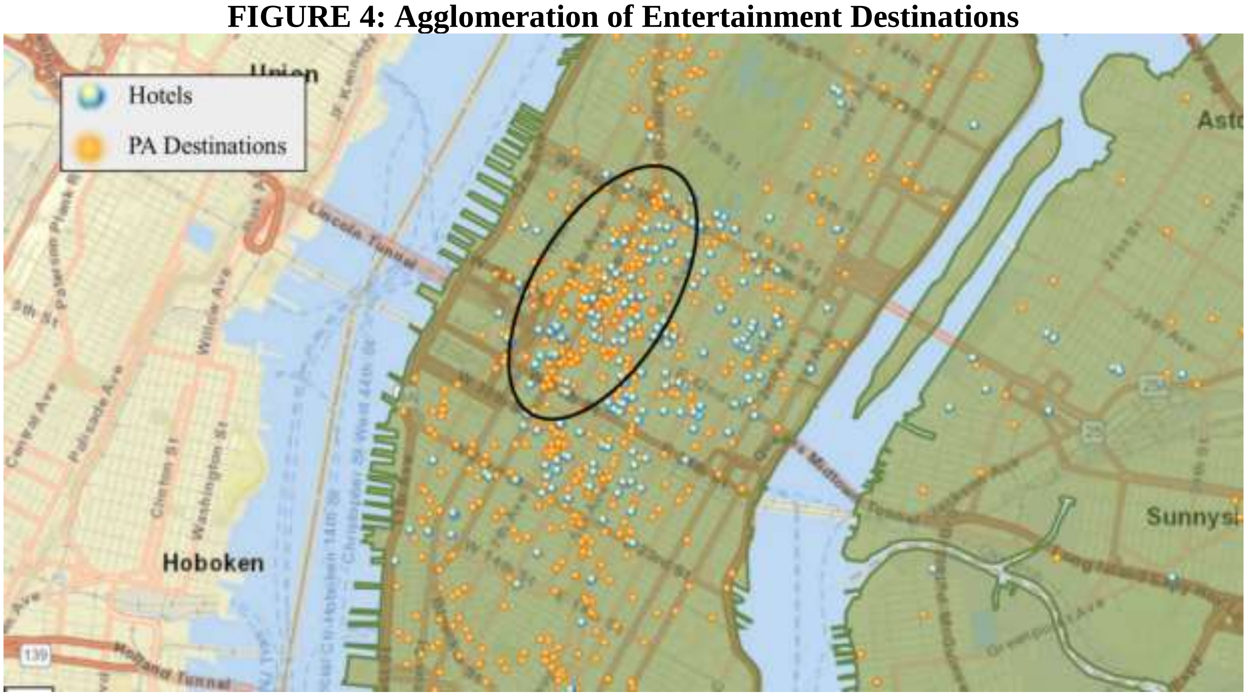
	Dependent Variable: Log of Price per Unit			
	(NYC)	(NYC w Submarket FE)	(Manhattan)	(Manhattan w Submarket FE)
	(1)	(2)	(3)	(4)
Constant	11.932***	11.773***	12.397***	12.326***
	(.164)	(.145)	(.145)	(.219)
Food_Bev_Destinations	.006***	.003*	.002	.003
	(.001)	(.002)	(.002)	(.002)
Entertainment_Destinations	-.004***	-.006***	-.006***	-.007***
	(.002)	(.002)	(.002)	(.002)
Parks_Destinations	.013	-.010	-.012	-.013
	(.025)	(.024)	(.024)	(.026)
Museum_Destinations	.011	-.005	-.002	.001
	(.014)	(.013)	(.013)	(.015)
Shopping_Destinations	.0003	-.001	-.001	-.001
	(.001)	(.001)	(.001)	(.001)
Refinance	.309***	.294***	.229***	.230***
	(.061)	(.052)	(.052)	(.066)
Units	-.001**	-.001**	-.001***	-.001***
	(.0004)	(.0003)	(.0003)	(.0003)
Floors	.025***	.020***	.021***	.020***
	(.004)	(.003)	(.003)	(.004)
Full_Service	.269***	.253***	.336***	.297***
	(.061)	(.056)	(.056)	(.069)
Onsite_Retail	.176**	.138*	.158**	.138*
	(.084)	(.076)	(.076)	(.083)
Age	.003***	.001	.002*	.002**
	(.001)	(.001)	(.001)	(.001)
Violent_Crime	-.00002	.00001	.00003	.00003
	(.00003)	(.00002)	(.00002)	(.00003)
Observations	450	450	360	360
R^2	.387	.522	.151	.194
Adjusted R^2	.356	.485	.095	.126
Residual Std. Error	.572	.511	.565	.555

Note: *p<0.1; **p<0.05; ***p<0.01
All Models Include: Year FE

has been found to positively impact value (Foti, 2014; Lee and Moudon, 2006). In high walkability areas such as Manhattan, however, the benefits of walking accessible food and beverage destinations appear to diminish. The relationship between food and beverage destinations and value became insignificant for both models after the number of samples was limited to transactions in Manhattan. The results suggest that a saturation point exists with food and beverage destinations where perhaps the detriments of noise and traffic start to balance out marginal decreasing benefits.

Conversely, the detriments of more walking accessible entertainment destinations like noise and traffic diminished hotel value across all four models. It is conceivable that entertainment destinations may attract more noise and traffic than the other destination types. ArcGIS maps of destinations categories also show especially high agglomeration among entertainment destinations like theatres, performing arts and dance companies. As shown in **Figure 4**, many entertainment destinations are concentrated along 8th Avenue between 34th and

FIGURE 4: Agglomeration of Entertainment Destinations



56th Street. The tendency for agglomeration and high potential for noise and traffic may explain the particularly negative impact this destination category has on hotel values.

The different destination categories were highly correlated, so each destination category was also regressed individually and is shown in **Appendix L-P**. Regressing destinations individually largely did not show any new consistent trends.

Utility of current walkability estimates for traveler walking behavior

A gap in literature that limits the capacity of this paper is how relevant the walkability estimates and destinations analyzed in this study are to the actual walking behavior of travelers. Discussed briefly up to this point, travel type can add further complicity to walkability estimates. One study found that walking for transport was positively correlated with physical environment characteristics like sidewalks, transit and graffiti while walking for leisure was negatively correlated with these same features (Forsyth and Southworth, 2008). Generally, the literature suggests accessibility-based methods are better suited for measuring travel walking while built-environment features are better proxies for leisure walking. The walking behavior and potential walkability correlates for travelers is much less studied. This is surprising considering travelers engage in walking at a high rate. A study of travelers in the UK found that 60-70% of travelers used walking as transport (Hall and Ram, 2019).

Most walkability estimates like Walkscore have been developed with a resident in mind and the unique characteristics of travelers as walkers may make them weak correlates of actual walking behavior. A recent study by Mansouri and Ujang (2017) on environmental attributes and the walking behavior of travelers in Kuala Lumpur, Malaysia found that features of walking potential (connectivity), pedestrian friendliness (benches and shade) and a unique third dimension of walkability (cultural heritage) were all related to pedestrian movement and count.

There is therefore a need for additional research that connects current walkability estimates like Walkscore to the actual walking behavior of travelers stay at hotels. The positive associations between Streetscore and hotel values suggests that the perceived characteristics of a space may be most relevant to traveler walking behavior.

Conclusion

There are five overall takeaways from this study; (1) high walkability areas have high hotel values; (2) however, because walkability is multi-dimensional and closely connected with many other neighborhood characteristics, it is difficult to isolate and quantify the individual impact of walkability on hotel values; (3) built-environment pedestrian friendliness may have greater benefits on hotel value than accessibility-based walking potential because (4) increasing walking accessible to some destinations like entertainment within high walkability areas hurt hotel values; and finally, (5) there is a need for further research on how walkability estimates such as Walkscore impact the actual walking behavior of travelers.

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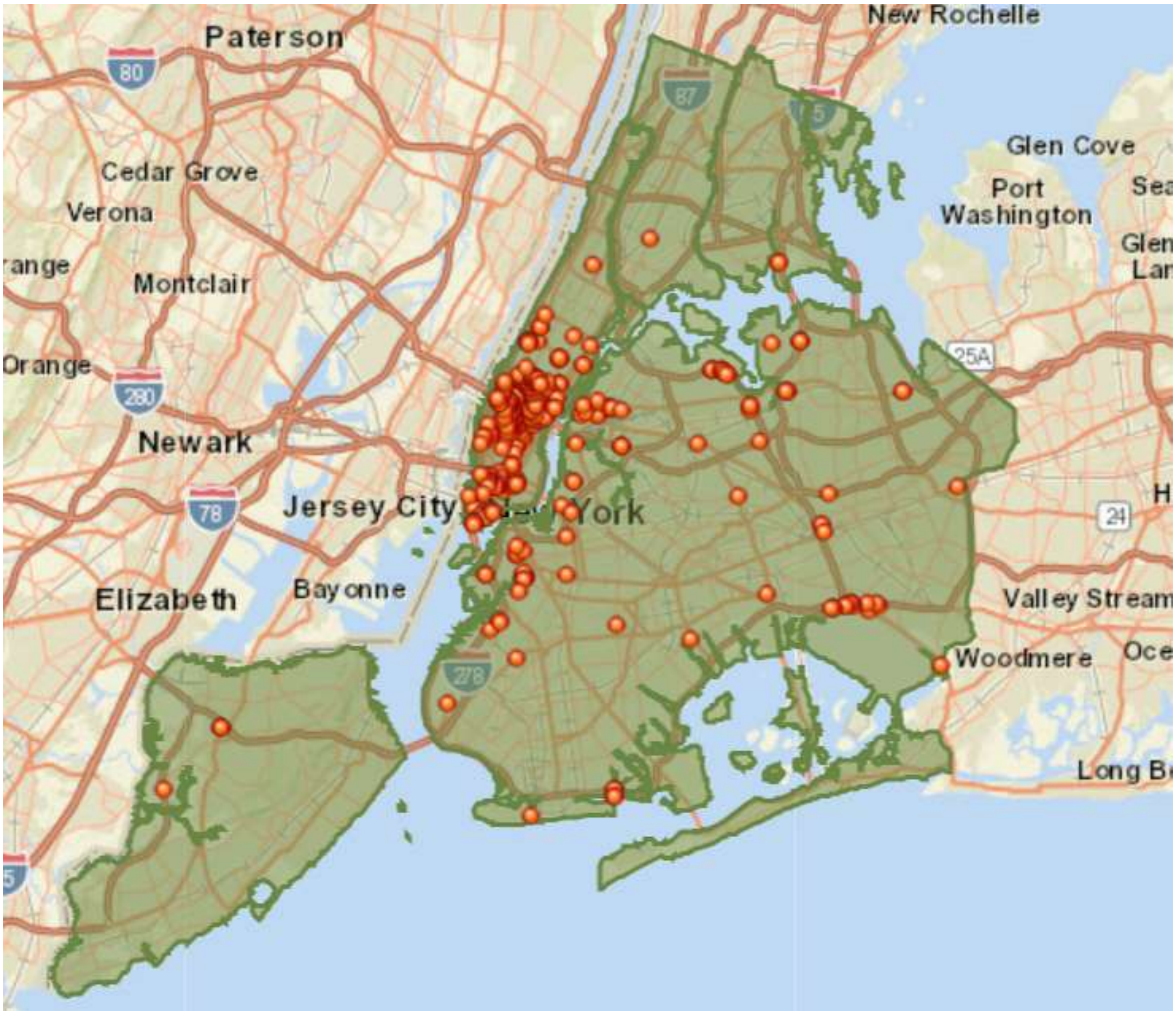
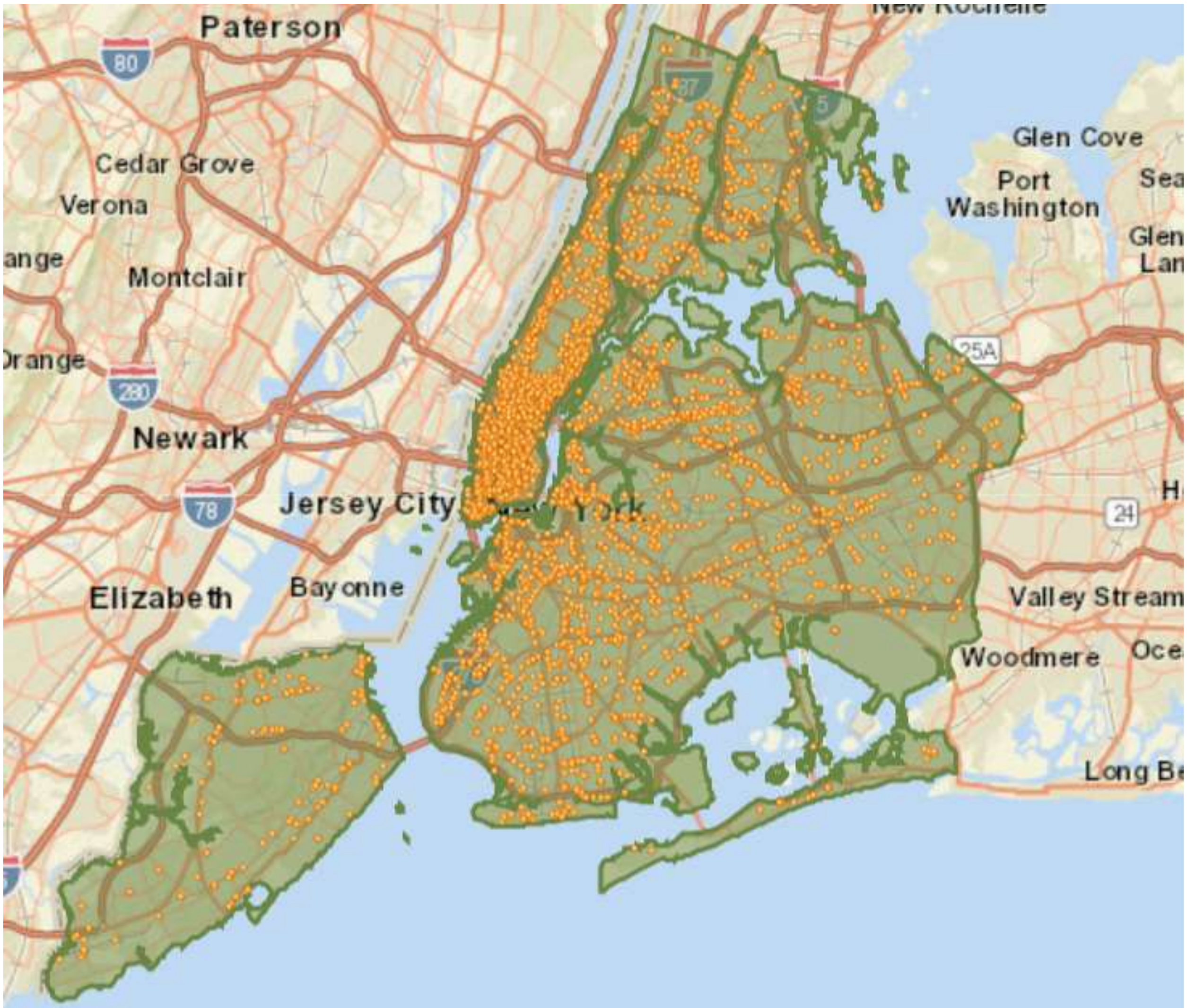
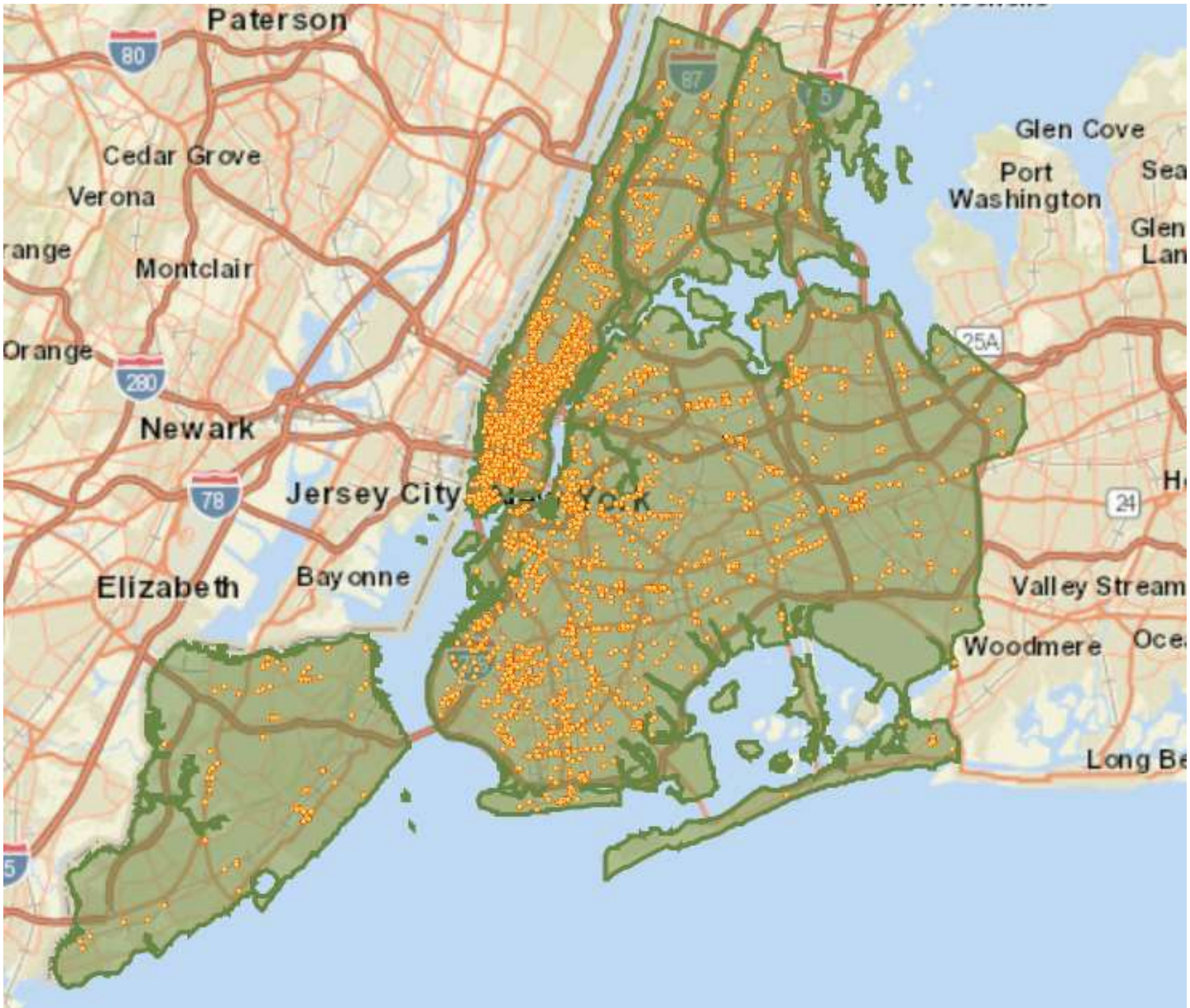
APPENDIX A: Hotel Transaction Map



APPENDIX B: Food and Beverage Destinations Map

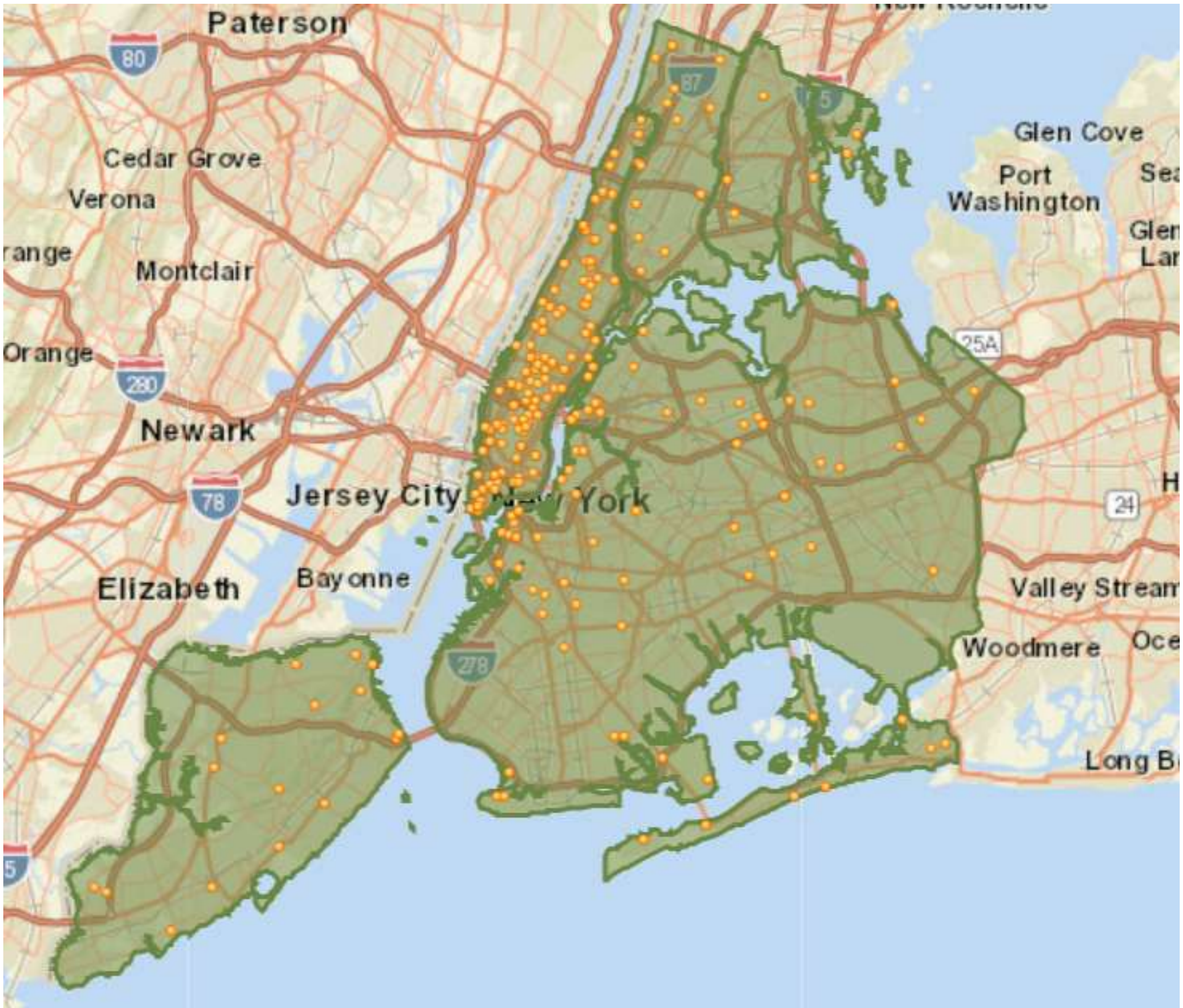


APPENDIX C: Shopping Destinations Map

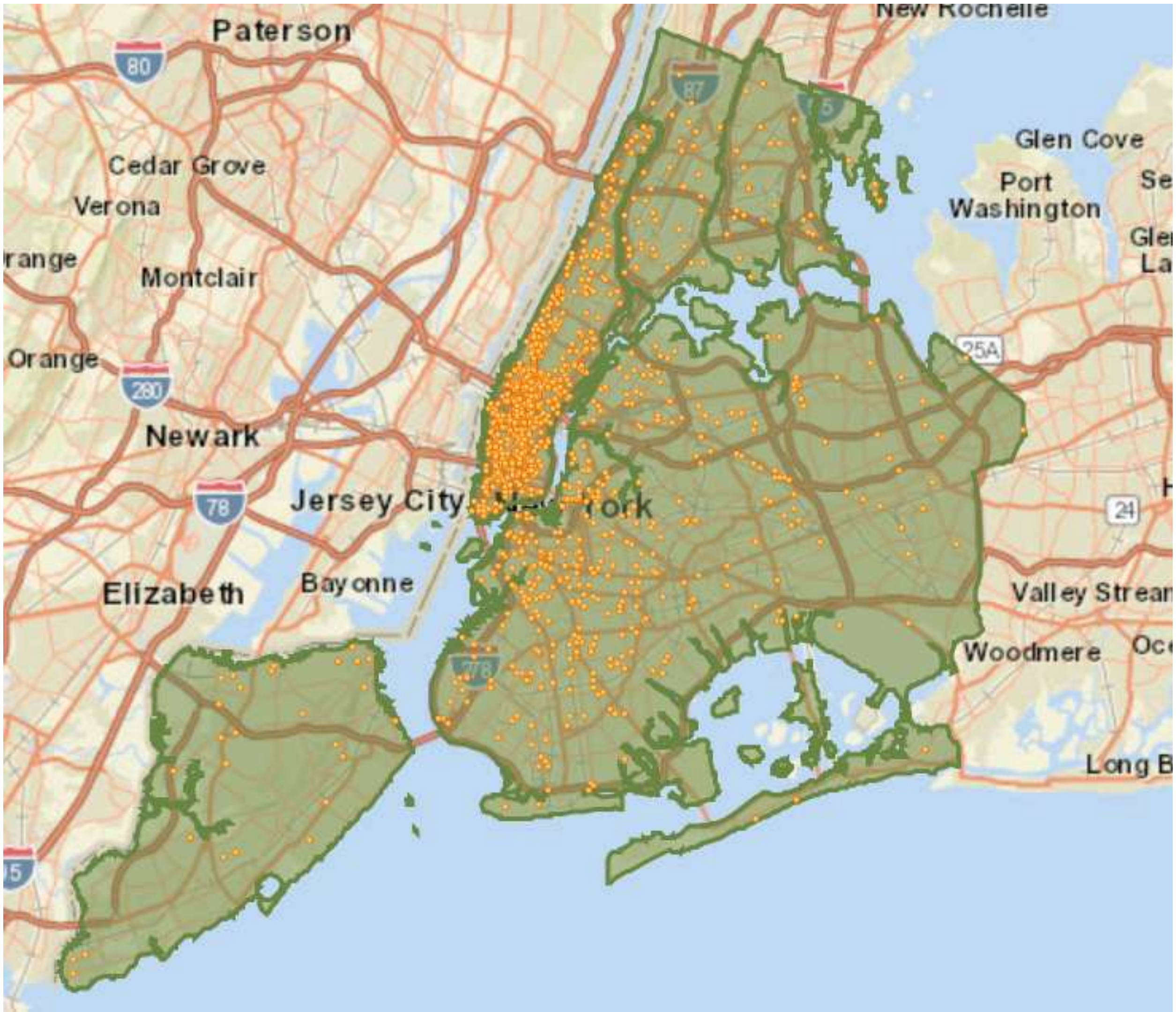


APPENDIX D: Museum Destinations Map

APPENDIX E: Parks Destinations Map



APPENDIX F: Entertainment Destination Map



APPENDIX G: Correlation Matrices

Walkscore and other walkability estimates: Correlations among the regressors

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
1. Walkscore	1.00									
2. Streetscore	0.49	1.00								
3. CitiBike_Trips	0.59	0.43	1.00							
4. Refinance	-0.01	-0.13	0.00	1.00						
5. Units	0.13	0.04	0.27	0.00	1.00					
6. Floors	0.31	0.15	0.38	0.01	0.59	1.00				
7. Full_Service	0.10	0.18	0.25	0.01	0.33	0.29	1.00			
8. Onsite_Retail	0.13	0.07	0.15	-0.03	0.05	-0.01	0.06	1.00		
9. Age	0.17	0.32	0.13	-0.12	0.04	-0.25	0.13	0.14	1.00	
10. Violent_Crime	0.11	-0.05	0.18	0.08	0.15	0.09	0.04	0.03	0.03	1.00

Destinations: Correlations among the regressors

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1. Entertainment_Destinations	1.00											
2. Parks_Destinations	0.36	1.00										
3. Museum_Destinations	0.36	0.58	1.00									
4. Shopping_Destinations	0.32	0.18	0.34	1.00								
5. Food_Bev_Destinations	0.61	0.49	0.51	0.52	1.00							
6. Refinance	0.00	0.00	0.02	0.03	-0.01	1.00						
7. Units	0.35	0.33	0.06	0.04	0.34	0.00	1.00					
8. Floors	0.40	0.39	0.30	0.21	0.44	0.01	0.59	1.00				
9. Full_Service	0.07	0.25	0.19	0.05	0.23	0.01	0.33	0.29	1.00			
10. Onsite_Retail	0.16	0.09	0.17	0.07	0.19	-0.03	0.05	-0.01	0.06	1.00		
11. Age	-0.02	0.12	0.03	0.04	0.17	-0.12	0.04	-0.25	0.13	0.14	1.00	
12. Violent_Crime	0.24	0.08	0.12	0.54	0.24	0.08	0.15	0.09	0.04	0.03	0.03	1.00

APPENDIX H: Averages of Variables by Submarket

	Bronx	Brooklyn	Downtown	Midtown East	Midtown South	Midtown West	Queens	Staten Island	Upper East Side	Upper Manhattan	Upper West Side
Transaction Count	3	32	49	70	43	176	59	4	12	1	13
ln (Ppunit)	11.81	12.14	13.09	13.12	13.11	12.97	12.01	11.16	13.41	11.14	12.66
Walkscore	58	91	99	100	99	99	79	62	97	98	98
Streetscore	6.1	7.2	7.9	8.3	8.4	8.1	7.3	7.2	8.8	8.7	9.0
CitiBike_Trips	0	5,058	22,486	28,771	34,783	30,193	417	0	12,001	0	12,486
Food_Bev_Destinations	1	14	57	84	71	87	4	3	23	8	34
Entertainment_Destinations	0	2	10	14	25	54	0	0	3	5	12
Parks_Destinations	0	0.2	2.9	2.1	1.8	2.3	0.2	0	1.3	0	1.5
Museum_Destinations	0	0.3	4.9	3.3	3.6	4.0	0.1	0	2.1	0	1.5
Shopping_Destinations	0	6	51	104	63	241	2	0	33	3	12
Refinance	0	0.31	0.37	0.26	0.30	0.32	0.39	0	0.25	0	0.15
Full_Service	0	0.22	0.67	0.84	0.77	0.66	0.53	0.75	0.83	0	0.38
Units	82	101	195	365	147	343	149	164	130	29	185
Floors	2	7	17	22	13	25	7	9	15	5	11
Age	34	23	37	71	60	39	22	28	69	100	96
Onsite_Retail	0	0.09	0.27	0.10	0.28	0.19	0.02	0	0.08	0	0
Violent_Crime	793	1,504	650	2,839	582	5,367	979	80	128	1,145	271

APPENDIX I: Walkscore and Hotel Value

Walkscore with Heteroskedasticity-robust Standard Errors

	Dependent Variable: Log of Price per Unit			
	(NYC)	(NYC w Submarket FE)	(Manhattan)	(Manhattan w Submarket FE)
	(1)	(2)	(3)	(4)
Constant	10.173***	11.726***	15.190***	15.850***
	(.282)	(.177)	(2.261)	(2.599)
Walkscore	.022***	.001	-.028	-.034
	(.003)	(.003)	(.023)	(.026)
Refinance	.303***	.283***	.216***	.214***
	(.058)	(.053)	(.061)	(.062)
Units	-.001***	-.001***	-.001***	-.001***
	(.0003)	(.0002)	(.0002)	(.0002)
Floors	.025***	.019***	.017***	.019***
	(.003)	(.003)	(.003)	(.003)
Full_Service	.348***	.274***	.399***	.332***
	(.062)	(.056)	(.067)	(.067)
Onsite_Retail	.176**	.124*	.130*	.128*
	(.079)	(.073)	(.075)	(.076)
Age	.002***	.001	.002**	.002**
	(.001)	(.001)	(.001)	(.001)
Violent_Crime	-.00002**	.00001	-0.00000	.00001
	(.00001)	(.00001)	(.00001)	(.00001)
Observations	450	450	360	360
R^2	.404	.506	.238	.250
Adjusted R^2	.379	.473	.197	.196
Residual Std. Error	.562	.517	.532	.532

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

All Models Include: Year FE

APPENDIX J: Streetscore and Hotel Value

Streetscore with Heteroskedasticity-robust Standard Errors

	Dependent Variable: Log of Price per Unit			
	(NYC)	(NYC w Submarket FE)	(Manhattan)	(Manhattan w Submarket FE)
	(1)	(2)	(3)	(4)
Constant	10.346***	11.321***	11.631***	11.292***
	(.310)	(.289)	(.521)	(.531)
Streetscore	.225***	.079*	.099	.148**
	(.040)	(.043)	(.061)	(.063)
Refinance	.347***	.295***	.232***	.232***
	(.061)	(.053)	(.061)	(.062)
Units	-.001***	-.001***	-.001***	-.001***
	(.0003)	(.0003)	(.0003)	(.0003)
Floors	.028***	.019***	.017***	.019***
	(.003)	(.003)	(.003)	(.003)
Full_Service	.298***	.265***	.372***	.293***
	(.065)	(.056)	(.067)	(.066)
Onsite_Retail	.230***	.125*	.134*	.124
	(.081)	(.074)	(.078)	(.077)
Age	.003***	.001	.001**	.002**
	(.001)	(.001)	(.001)	(.001)
Violent_Crime	-.00002**	.00001	0.00000	.00001
	(.00001)	(.00001)	(.00001)	(.00001)
Observations	450	450	360	360
R^2	.371	.509	.239	.250
Adjusted R^2	.345	.476	.198	.196
Residual Std. Error	.577	.516	.532	.532

Note: *p<0.1; **p<0.05; ***p<0.01

All Models Include: Year FE

APPENDIX K: CitiBike Trips and Hotel Value

CitiBike Trips with Heteroskedasticity-robust Standard Errors

	Dependent Variable: Log of Price per Unit			
	(NYC)	(NYC w Submarket FE)	(Manhattan)	(Manhattan w Submarket FE)
	(1)	(2)	(3)	(4)
Constant	11.912***	11.801***	12.409***	12.426***
	(.095)	(.106)	(.141)	(.144)
CitiBike_Trips	.00002***	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Refinance	.292***	.279***	.216***	.215***
	(.058)	(.053)	(.061)	(.061)
Units	-.001***	-.001***	-.001***	-.001***
	(.0002)	(.0003)	(.0002)	(.0003)
Floors	.025***	.020***	.017***	.020***
	(.003)	(.003)	(.003)	(.003)
Full_Service	.287***	.269***	.386***	.320***
	(.062)	(.056)	(.065)	(.065)
Onsite_Retail	.162**	.124*	.126*	.127*
	(.081)	(.073)	(.076)	(.076)
Age	.003***	.001	.002**	.002**
	(.001)	(.001)	(.001)	(.001)
Violent_Crime	-.00002***	.00001	-0.00000	.00001
	(.00001)	(.00001)	(.00001)	(.00001)
Observations	450	450	360	360
R^2	.395	.505	.235	.250
Adjusted R^2	.370	.472	.194	.196
Residual Std. Error	.565	.518	.533	.533

Note: *p<0.1; **p<0.05; ***p<0.01

All Models Include: Year FE

APPENDIX L: Food and Beverage Destinations and Hotel Value

Food and Beverage Destinations with Heteroskedasticity-robust Standard Errors

	Dependent Variable: Log of Price per Unit			
	(NYC)	(NYC w Submarket FE)	(Manhattan)	(Manhattan w Submarket FE)
	(1)	(2)	(3)	(4)
Constant	11.967***	11.802***	12.532***	12.551***
	(.105)	(.107)	(.107)	(.134)
Food_Bev_Destinations	.006***	-.001	-.002	-.002
	(.001)	(.001)	(.001)	(.001)
Refinance	.318***	.282***	.217***	.216***
	(.064)	(.053)	(.053)	(.062)
Units	-.001***	-.001***	-.001***	-.001***
	(.0003)	(.0002)	(.0002)	(.0002)
Floors	.024***	.019***	.018***	.019***
	(.003)	(.003)	(.003)	(.003)
Full_Service	.307***	.275***	.392***	.325***
	(.065)	(.057)	(.057)	(.066)
Onsite_Retail	.158*	.130*	.140*	.137*
	(.088)	(.073)	(.073)	(.076)
Age	.003***	.001	.002**	.002**
	(.001)	(.001)	(.001)	(.001)
Violent_Crime	-.00003***	.00001	0.00000	.00001
	(.00001)	(.00001)	(.00001)	(.00001)
Observations	450	450	360	360
R^2	.318	.504	.232	.245
Adjusted R^2	.290	.471	.191	.191
Residual Std. Error	.601	.518	.534	.534

Note: *p<0.1; **p<0.05; ***p<0.01

All Models Include: Year FE

APPENDIX M: Entertainment Destinations and Hotel Value

Entertainment Destinations with Heteroskedasticity-robust Standard Errors

	Dependent Variable: Log of Price per Unit			
	(NYC)	(NYC w Submarket FE)	(Manhattan)	(Manhattan w Submarket FE)
	(1)	(2)	(3)	(4)
Constant	12.104***	11.809***	12.519***	12.499***
	(.120)	(.100)	(.100)	(.117)
Entertainment_Destinations	.001	-.005***	-.005***	-.005***
	(.001)	(.001)	(.001)	(.001)
Refinance	.327***	.288***	.225***	.225***
	(.069)	(.052)	(.052)	(.060)
Units	-.001***	-.001***	-.001***	-.001***
	(.0003)	(.0002)	(.0002)	(.0002)
Floors	.032***	.019***	.019***	.019***
	(.003)	(.003)	(.003)	(.003)
Full_Service	.333***	.254***	.344***	.299***
	(.068)	(.056)	(.056)	(.064)
Onsite_Retail	.245***	.149**	.168**	.152**
	(.089)	(.074)	(.074)	(.076)
Age	.004***	.001	.001*	.002**
	(.001)	(.001)	(.001)	(.001)
Violent_Crime	-.00004**	.00001	.00001	.00001
	(.00001)	(.00001)	(.00001)	(.00001)
Observations	450	450	360	360
R^2	.231	.523	.248	.283
Adjusted R^2	.199	.492	.208	.231
Residual Std. Error	.638	.508	.528	.521

Note: *p<0.1; **p<0.05; ***p<0.01
All Models Include: Year FE

APPENDIX N: Parks Destinations and Hotel Value

Parks Destinations with Heteroskedasticity-robust Standard Errors

	Dependent Variable: Log of Price per Unit			
	(NYC)	(NYC w Submarket FE)	(Manhattan)	(Manhattan w Submarket FE)
	(1)	(2)	(3)	(4)
Constant	12.052***	11.806***	12.476***	12.514***
	(.108)	(.107)	(.107)	(.127)
Parks_Destinations	.057***	-.024	-.025	-.029
	(.020)	(.021)	(.021)	(.021)
Refinance	.314***	.284***	.223***	.220***
	(.064)	(.053)	(.053)	(.062)
Units	-.001***	-.001***	-.001***	-.001***
	(.0003)	(.0002)	(.0002)	(.0003)
Floors	.030***	.020***	.018***	.020***
	(.003)	(.003)	(.003)	(.003)
Full_Service	.314***	.277***	.394***	.327***
	(.067)	(.056)	(.056)	(.065)
Onsite_Retail	.235***	.123*	.128*	.122
	(.084)	(.073)	(.073)	(.077)
Age	.004***	.001	.002**	.002**
	(.001)	(.001)	(.001)	(.001)
Violent_Crime	-.00003**	.00001	-0.00000	.00001
	(.00001)	(.00001)	(.00001)	(.00001)
Observations	450	450	360	360
R^2	.309	.508	.238	.247
Adjusted R^2	.280	.475	.198	.194
Residual Std. Error	.605	.516	.532	.533

Note: *p<0.1; **p<0.05; ***p<0.01

All Models Include: Year FE

APPENDIX O: Museum Destinations and Hotel Value

Museum Destinations with Heteroskedasticity-robust Standard Errors

	Dependent Variable: Log of Price per Unit			
	(NYC)	(NYC w Submarket FE)	(Manhattan)	(Manhattan w Submarket FE)
	(1)	(2)	(3)	(4)
Constant	12.051***	11.804***	12.492***	12.543***
	(.111)	(.106)	(.106)	(.133)
Museum_Destinations	.044***	-.023*	-.017	-.022*
	(.012)	(.012)	(.012)	(.012)
Refinance	.313***	.285***	.224***	.221***
	(.066)	(.054)	(.054)	(.063)
Units	-.001**	-.001***	-.001***	-.001***
	(.0003)	(.0003)	(.0003)	(.0003)
Floors	.029***	.020***	.018***	.020***
	(.003)	(.003)	(.003)	(.003)
Full_Service	.300***	.283***	.398***	.331***
	(.069)	(.057)	(.057)	(.067)
Onsite_Retail	.205**	.134*	.139*	.136*
	(.086)	(.072)	(.072)	(.075)
Age	.004***	.001	.002*	.002**
	(.001)	(.001)	(.001)	(.001)
Violent_Crime	-.00003***	.00001	0.00000	.00001
	(.00001)	(.00001)	(.00001)	(.00001)
Observations	450	450	360	360
R^2	.277	.504	.236	.239
Adjusted R^2	.247	.471	.196	.184
Residual Std. Error	.618	.518	.533	.536

Note: *p<0.1; **p<0.05; ***p<0.01
All Models Include: Year FE

APPENDIX P: Shopping Destinations and Hotel Value

Shopping Destinations with Heteroskedasticity-robust Standard Errors

	Dependent Variable: Log of Price per Unit			
	(NYC)	(NYC w Submarket FE)	(Manhattan)	(Manhattan w Submarket FE)
	(1)	(2)	(3)	(4)
Constant	12.220***	11.894***	12.455***	12.470***
	(.255)	(.143)	(.143)	(.136)
Shopping_Destinations	.002	.0002	-.0004	-.0004
	(.002)	(.001)	(.001)	(.001)
Refinance	.327***	.295***	.221***	.222***
	(.087)	(.054)	(.054)	(.062)
Units	-.0005	-.001**	-.001***	-.001***
	(.001)	(.0003)	(.0003)	(.0003)
Floors	.025***	.018***	.018***	.019***
	(.008)	(.004)	(.004)	(.004)
Full_Service	.321***	.274***	.387***	.327***
	(.079)	(.057)	(.057)	(.066)
Onsite_Retail	.235**	.134*	.131*	.127
	(.119)	(.077)	(.077)	(.078)
Age	.003**	.001	.002**	.002**
	(.001)	(.001)	(.001)	(.001)
Violent_Crime	-.0001	-.00001	0.00000	.00001
	(.0001)	(.00002)	(.00002)	(.00002)
Observations	450	450	360	360
R^2	-.033	.508	.231	.254
Adjusted R^2	-.076	.475	.190	.201
Residual Std. Error	.739	.516	.534	.531

Note: *p<0.1; **p<0.05; ***p<0.01

All Models Include: Year FE

APPENDIX Q: Walkability Estimates and Hotel Value Controlling for Neighborhood Wealth

Walkscore and other walkability with neighborhood wealth control and Heteroskedasticity-robust Standard Errors

	Dependent Variable: Log of Price per Unit			
	(NYC)	(NYC w Submarket FE)	(Manhattan)	(Manhattan w Submarket FE)
	(1)	(2)	(3)	(4)
Constant	11.162***	11.532***	14.354***	15.116***
	(.348)	(.308)	(2.292)	(2.623)
Per_Capita_Income	0.00000***	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Walkscore	.005*	.0001	-.028	-.038
	(.003)	(.003)	(.024)	(.028)
Streetscore	.019	.037	.046	.099
	(.044)	(.047)	(.063)	(.070)
CitiBike_Trips	.00001***	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Refinance	.294***	.296***	.232***	.236***
	(.052)	(.051)	(.059)	(.059)
Units	-.001***	-.001***	-.001***	-.001***
	(.0002)	(.0002)	(.0002)	(.0002)
Floors	.018***	.017***	.016***	.017***
	(.003)	(.003)	(.003)	(.003)
Full_Service	.240***	.216***	.310***	.259***
	(.057)	(.056)	(.068)	(.068)
Onsite_Retail	.165**	.152**	.165**	.158**
	(.074)	(.072)	(.075)	(.074)
Age	.001*	.001	.001	.001*
	(.001)	(.001)	(.001)	(.001)
Violent_Crime	-.00001	0.00000	-0.00000	0.00000
	(.00001)	(.00001)	(.00001)	(.00001)
Observations	446	446	360	360
R^2	.489	.514	.289	.312
Adjusted R^2	.464	.479	.245	.256
Residual Std. Error	.511	.503	.516	.512
Note:				*p<0.1; **p<0.05; ***p<0.01
				All Models Include: Year FE