ANALYZING THE ASSOCIATION BETWEEN WALKABILITY AND REGIONAL ECONOMIC VITALITY

by

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A Dissertation
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DEDICATION

I dedicate this dissertation to my beloved husband, Ben. His cheerful support carried me through the challenges of graduate school and life.

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LIST OF ABBREVIATIONS AND SYMBOLS

Alabama	AL
Alpha	α
American Community Survey	ACS
American Public Transportation Association	APTA
Arizona	AZ
Beta	β
Bureau of Transportation Statistics	BTS
California	CA
Colorado	CO
Common factor analysis	CFA
Department of Community Planning and Services	DCPS
District of Columbia	D.C.
Error term	ε
Fatality Analysis Reporting System	FARS
Florida	FL
Gamma	γ
Generalized spatial two-stage least square model	GS2SLS
Geographic Information Systems	GIS
Indiana	IN
Instrumental variable	IV
Irvine-Minnesota Inventory	IMI
Macon-Bibb County Planning and Zoning Commission	MBCPZC
Maryland	MD
Massachusetts	MA
Metropolitan Washington Council of Governments	MWCOG
Michigan	MI
National Highway Traffic Safety Administration	NHTSA
New Jersey	NJ
New Jersey Department of Transportation	NJDOT
New York	NY
Non-standardized index	NSI
Ordinary least square model	OLS
Oregon	OR
Pedestrian and Bicycle Information Center	PBIC
Pennsylvania	PA
Principal component	PC

Principal component analysis .... PCA
Roanoke Valley Area Metropolitan Planning Organization .... RVAMPO
Standardized index .... SI
Texas .... TX
Traffic Analysis Zone .... TAZ
Transportation Planning Board, Metropolitan Washington Council of Governments .. TPB
Two-stage least square model 2SLS
Ulster County Planning Board .... UCPB
United States of America .... U.S.
University of Texas .... UT
U.S. Department of Transportation .... DOT
U.S. Department of Transportation Federal Highway Administration .... DOTFHWA
U.S. Department of Transportation’s Travel Model Improvement Program .... TMIP
Variance Inflation Factor .... VIF
Virginia .... VA
Washington Metropolitan Area Transit Authority .... WMATA
West Virginia .... WV

ABSTRACT

ANALYZING THE ASSOCIATION BETWEEN WALKABILITY AND REGIONAL ECONOMIC VITALITY

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The role of walkability is increasing in the car-oriented United States as the lifestyles and demographics of Americans change. This dissertation contributes to the emerging research on the association between walkability and regional economic vitality. This research develops new location-specific walkability indices and uses a methodological approach that accounts for the endogeneity between walkability and economic vitality and corrects for spatial dependence. The findings of the dissertation indicate that walkability is associated with higher employment in cities in the U.S. and with lower housing vacancy rates in the census tracts in the Washington, D.C. metropolitan area.

CHAPTER I
INTRODUCTION

The United States has depended on the automobile as a predominant means of transportation for most of the past one hundred years. Even urban areas, which traditionally had been designed to accomodate public transit, have become auto-dependent since the emergence of the suburbs in the middle of the 20th century. However, the urban sprawl, suburb-oriented city development, and the reliance on automobile are slowing down as the lifestyles and demographics of Americans change. This dissertation focuses on a complementary mode of transportation that is re-entering the public attention – walkability.

Research Context

Today, the changing sectoral structure of the job market depends less on the presence of employees in the workplace and gives them more freedom of where to perform their duties. It is not unusual for people to work from home or take their personal computer and work from a coffee shop or another public place. Furthermore, dense and diverse places with easy accessibility to multiple destinations are appealing to diverse populations including retirees and young professionals.

These trends reflecting the appreciation of non-automobile solutions to mobility are found in cities nationwide. Redevelopment targeted at curbing the car-reliance and making places more walkable is on the agenda even in cities as spread out as Phoenix, AZ. The city is planning to provide its residents with a complete, connected and walkable street network along with light rail to reduce reliance on the car (Steuteville 2013a). Los Angeles, CA, another predominantly low-density and geographically spread-out city, is working on transforming some of its neighborhoods into pedestrian-friendly. Based on the city council vote, a six-lane road in the Broadway corridor will be limited to three lanes and the remaining right-of-way will be redeveloped to a pedestrian plaza (Jaffe 2013).

Small towns, such as Hamburg, NY, also are investing in walkable environments. In this case, the residents turned down the plan to expand U.S. Route 62 crossing the town. Instead, they pushed and implemented an alternative plan to make the town into more walkable (Gaffney 2013). In the town of Menolo Park in California, neighborhoods are being redeveloped to accommodate the preferences of its future residents who consist of a cluster of Facebook employees. In a survey and through focus groups these potential inhabitants of the so-called "Facebook Town" expressed their inclination towards walkable and bikable living environment and their requests are being met (Xie 2013).

Washington, D.C metropolitan area is one of the most walkable metro areas in the U.S. (Leinberger 2007). The role walkability plays in people's lives is beginning to be recognized and the public interest in walkability is spreading. The trends show that parents in their 30s and early 40s, even as their families grow, reside in Washington's dense and walkable areas longer than the previous generations (Morello 2013). Instead of moving into larger homes in the suburbs, they are moving into larger apartments in pedestrian-oriented neighborhoods. They enjoy the short commute to work and therefore, more time at home with their children. They also emphasize their appreciation of raising their children in a cosmopolitan environment. However, as their children grow, parents tend to find suburban areas more suitable to raise teenagers and move out of the center (APTA 2013, Morello 2013).

It has also been found that walkable areas are supported not only in urban districts but also in suburban parts of the Washington, D.C. metropolitan area (TPB 2013). And, the suburban areas are begining to meet the new demand. Merrifield, VA, and Bethesda Row, MD, have been redesigned to be pedestrian-oriented (Byron and McLean 2013, Benfield 2013). For instance, the Mosaic district in Merrifield offers stretches of visually appealing surroundings with small retail and restaurants. Big-box retailers are skillfully integrated into the environment so that there is no dissonance in the walkable branding of the area. For instance, Target is located on the higher levels of a building instead of on the ground floor. This allows for smaller businesses to face the pedestrian traffic.

These new trends are becoming increasingly apparent so it is time for walkability to become a prominent issue in research and policy and decision-making nationally and locally. In comparison to road and transit research, walkability has been neglected. It is seldom acknowledged as a means of transportation and ignored as a beneficiary of funding.

The research that has been done on walkability primarily has focused on the associations between walkability (action) and public health while the connections between walkability and other areas of research, such as economic vitality, are understudied. This dissertation will contribute to the knowledge base on the association between walkability and economic vitality of cities in the U.S., and neighborhoods in the Washington, D.C. metropolitan area. This research will analyze the impacts of walkability on employment in cities and housing vacancies in neighborhoods using a methodological approach that accounts for the expected endogeneity between walkability and economic vitality. The research also will address the question of the spatial dependency of the key variables on the neighborhood level.

Rationale for the Research

Walkability as a means of transportation has been given little attention in research and policy-making in the auto-oriented United States. In cities, the demographics and peoples' preferences and lifestyles are changing. Also, the types of jobs are changing as is reflected in the expansion of sectors not requiring presence in factories and offices, such as technology-intensive professional and business services. As a result, walkable cities, neighborhoods, and communities are gaining importance. Private and public stakeholders are beginning to acknowledge the growing interest in walkability and walkable infrastructure. However, decisions regarding investment in walkable infrastructure should be based on reliable research. It is important to decrease the gap in the understanding of the role walkability plays in the national and local economies.

This dissertation will contribute to the knowledge of the associations between walkability and regional economic vitality on the city and neighborhood levels. On the macro scale, this research will measure the association between walkability and economic performance of cities; thus it will provide public stakeholders with a basis for considering of changes in regulations to promote walkability (e.g. zoning, minimum parking requirements) and investing public funds to improve walkability conditions. This analysis of neighborhoods in the Washington, D.C. metropolitan area will provide information on locations where it is advantageous for developers and private investors to engage in capital investments to enhance walkability.

The results of this dissertation are intended to provide the foundation for further research on the relationship between walkability and economic conditions, as well as other areas of research, such as health or natural environment. Also, additional research could be conducted regarding association between walkability and entrepreneurship, which is a desired phenomenon in the economy. City economies overall, as well as neighborhoods, are likely to benefit from walkability because the creative class and young professionals are attracted to dense, lively, and pedestrian-oriented areas and tend to locate there. Entrepreneurs tend to follow this young talent (Steuteville 2013b); therefore, it can be expected that cities rich in walkable locations will enjoy more start-ups and entrepreneurial activity than cities reliant solely on auto-oriented mobility.

Advocates of social activism will be interested in broadening the knowledge on walkability. It has been shown, that walkability can encourage social involvement. For example, Knudsen and Clark (2013) found statistical correlation between walkable attributes and social movement organizations based on 30,000 zip codes in America.

Although walkability is an emerging area of research, it is already perceived as the grounds for or a partner of the state-of-the-art concepts in the United States. For instance, walkability is the basis for “sitable” environments characterized by “sidewalk dining and pop-up urbanism;" hence strengthening the community bonds (Wolfe 2013). Moreover, the future of transportation is anticipated to be a multimodal strategy (Blumberg et al. 2012, Payne 2013). Walkability is closely related to transit transportation and innovative means of mobility, such as podcar-oriented infrastructure. Therefore, walkability is one of the core components of the new, creative approach to mobility.

This is a good time to further the research on walkability. Correlation between walkability and regional economic vitality is one of the fundamental issues that needs to be analyzed because no matter if the demand for walkable places is rooted in economical, health, environmental, equity, or other concerns, any investment in walkability is bound to be facilitated because of the economic benefits to be achieved.

Introduction of the Research Questions

This dissertation is designed to answer four research questions. The answers to these questions define and measure the mechanisms underlying the concept of walkability and its contribution to regional economic vitality.

1. What are the components of a walkability index and how can it be constructed?

The objective of Question 1 is to develop a comprehensive index by which walkability can be measured in the U.S. cities, and in neighborhoods in the Washington, D.C. metropolitan area. This index will be later used to analyze the association between walkability and economic vitality in the examined geographies.

2. What is the association between walkability and economic vitality in cities in the United States?

The results of Question 2 will measure the association between walkability and economic performance of cities on the macro scale. These results will address the hypothesis that highly walkable cities are correlated with stronger economic vitality relative to less walkable cities.

3. What is the association between walkability and economic vitality of neighborhoods in the Washington, D.C. metropolitan area?

The objective of Question 3 is to determine the correlation between walkability and economic vitality in neighborhoods in the Washington, D.C. metropolitan area. These results will address the hypothesis that in the Washington, D.C. metropolitan area, neighborhoods with high walkability are associated with greater economic vitality relative to less walkable neighborhoods.

4. What is the spatial dependency pattern in the neighborhoods of the Washington, D.C. metropolitan area?

The objective of Question 4 is to identify the spatial pattern of housing vacancy rates and walkability in the neighborhoods in the Washington, D.C. metropolitan area. The answer to this research question will determine if the spatial pattern affects the housing vacancies in neighboring census tracts.

<u>Research Methodology</u>

This research will focus on the geographic level of cities in the United States and in the neighborhoods in the Washington, D.C. metropolitan area. These analyses include 992 cities and 1,359 neighborhoods, and will be conducted allowing for a time lag. The proxy for regional economic vitality will be employment on the city level, and housing vacancy rates on the neighborhood level.

This analysis is divided into three major components. First, original walkability indices, specific for the cities in the U.S., and neighborhoods in the Washington, D.C. metropolitan area, are developed. Second, the econometric analyses, based on the Ordinary Least Squares and Two-stage Least Square are conducted. Third, the Moran's I statistic and the spatial lag model are used to detect and present the spatial dependency of housing vacancies in adjacent neighborhoods in the Washington, D.C. metropolitan area.

Organization of the Dissertation

Following this Introduction to the Dissertation, Chapter II presents the literature discussing walkability and economic vitality including both theoretical and practical approaches. Based on the literature review, this chapter examines why further analysis of the topic of regional economic condition and walkability is important and explains how the proposed dissertation fits into the existing research.

Chapter III presents the methodology of the analysis to be utilized in the Dissertation, the research questions, units of analysis, timeframe for the analysis, the proxy for regional economic condition, the walkability measure, and explanatory variables. This chapter also presents datasets and data sources and assesses their quality. Further, this chapter details the steps of the econometric and spatial analyses.

Chapter IV will discuss the results of the research.

Chapter V presents research findings and answers to the research questions, discusses the public policy implications of these research findings, and will provide suggestions for further research.

CHAPTER II
LITERATURE REVIEW

This chapter presents a review of the literature on regional economic vitality and walkability. The literature reviewed here concentrates on the theories explaining economic vitality of cities. Additionally, this review focuses on walkability in theory. This literature review also examines the options for geographical delineation of neighborhoods in metropolitan areas.

Economic Vitality of Cities

Theories are just representations of reality and will never perfectly match the conditions of real life events. However, theories help to understand practical events. This section discusses selected theories explaining city economic vitality and its theoretical connection with transportation and walkability.

Theory on City Wealth

It is important to research the economic performance of cities and metropolitan areas because they are the force behind the economic growth of their surrounding regions and entire countries. There are a myriad of theories explaining how cities grow and indicating that cities play a pivotal role in the economic performance of regions and countries. For example, location, entrepreneurship, and agglomeration effects theories agree that metropolitan areas attract economic activity (Porter 1998, Blair and Premus

1993, Glaeser et al.1992). A metropolitan area provides agglomeration effects, including economies of scale, scope and externality effects. Firms tend to locate in areas where they can minimize costs and maximize their access to markets and profits. Entrepreneurs prosper because they are near the concentrations of customers and because they are well exposed to the potential clientele. Moreover, entrepreneurship, as an introduction of innovation can thrive in regions where firms can benefit from knowledge created by other firms located in close proximity. Developments or improvements in some businesses increase the productivity of other firms located nearby, with little or no cost from their end. Additionally, a metropolitan area is likely to provide entrepreneurial capital, including venture capital firms, and legal, institutional and social forces. For these reasons local and foreign entities are capable to create economic activity (Glaeser et al. 1992).

According to the central place theory, firms located within a sufficient market size benefit from the variety of economic functions and activities offered in that area. This ample economic activity enables businesses to achieve administrative, and transport and access optimality. Firms that need high order goods or services, which may not be available outside of central places, benefit from the close proximity to agents able to provide such specialized resources (Getis and Getis 1966, Burns and Hfaly 1978, Eaton and Lipsey 1982).

The growth pole/center theory, referring to a geographic concentration of economic activity, shows that cities and metropolitan areas pull and build on the resources from within and from other locations securing their own economic prosperity.

Such clustering of economic activity contributes more to economic growth and is more effective than dispersion (Morrill 1973, Burns and Hfaly 1978, Richardson 1979). Growth pole is also considered as a region's core basic industry. In such case, a strategy stimulating regional economic growth would focus on investments mainly in this core sector (Perroux 1950).

Another theoretical explanation of city vitality is through import and export perspective. Jane Jacobs (1969) found import replacement and increasing exports as crucial forces behind economically prosperous cities. Jacobs considered import replacement, defined as local production of goods and services that were previously imported, as the most potent force because money earned through import substitution stays and supports the local economy. Exporting goods and services is beneficial for the local economy because it brings money from the outside of the city. This money is then spent locally or put back in the export (e.g. buying ore to produce steel and then export it).

The role of exports in the city economic growth was also a subject of famous debate between Charles Tiebout (1956a, 1956b) and Douglass North (1956). Tiebout claims that residential economic activity is more important than exports; the expansion of local activity is the basis for growth of the export base. Contrarily, North claims that the export base is the major autonomous variable determining long-term regional economic growth. Residentiary activity depends on basic activity which brings money from the outside of a city. The income a region achieves from the exogenous activity serves as a growth driver and stimulator of non-basic activity. The conclusion is that exports and import substitution reinforce each other and cause expanding economic activity in a city. To grow, a city should optimize between export and residentiary activity because they both create local jobs and therefore bring people (workers and their families) into the city.

The theories discussed above represent the traditional trend in the theoretical approach to regional economic growth. This trend places the clustering of firms and industries, efficiency of production and location as the epicenter of economic vitality of cities. This dissertation is not based on these traditional approaches to regional economic prosperity. Rather, this research examines the role of walkability in regional economic vitality as proxied by employment and local human endowment. It investigates if active, walkable places in fact attract people who in turn stimulate city and neighborhood economic vitality. The theoretical foundation for this inquiry is described below.

Jane Jacobs (1969) found people and their diversified and creative work to be the core indicators of city wealth. Jacobs emphasized the importance of diversification of the city economy through innovation measured by adding new work to old work. Although this new work often originates through trial and error – or "inefficiency" – it leads to economic growth of cities. Moreover, when cities stop adding new work, they stagnate. It is beneficial for the city economy if workers separate from their workplaces and pursue new business building upon the ideas of their previous work. Jacobs notes that many of such breakaways and other new inefficient businesses diversify and strengthen city economies more than large specialized companies. Jacobs finds a connection between this innovative and diversified work and high population levels in a city, because many people mean many innovators and workers, and ample economic activity.

According to the human capital theory, regional economic growth is stimulated by human endowment, not location on transportation routes or core industries or natural resources available in the region (Lucas 1988, Glaeser 1998). Richard Florida (2005) elaborates that economic wealth of cities depends on the presence of the so-called Creative Capital – people who "engage in work whose function is to create meaningful new forms" (p.34). This creative class includes, among others, scientists, engineers, artists, entertainers, designers, analysts, high-tech workers, legal and health professionals, and business management. According to Florida, these people stimulate local economic activity, employment and overall economic vitality.

Some theorists include social capital, defined as the quality of residential networks and personal connections (Leyden 2003, Rogers et al. 2011) among the core indicators of economically healthy regions. For instance, Putnam (2000) showed that communities characterized by well-developed social capital perform better economically. Leyden (2003) theorizes that walkable areas boost the development of the social capital in the region; therefore, it can be expected that pedestrian-oriented places will perform better economically than non-walkable areas.

This dissertation corresponds with the theoretical approach that economically vital places are those with ample human endowment. After Jane Jacobs and Richard Florida this research assumes that people do not just happen to live in specific places, but rather consciously choose places to live based on the combination of economic and lifestyle considerations. Regions grow because they are able to draw people from other locations (Florida 2005). These people, rather than following the traditional motives, such as jobs, freeways or urban malls (Florida 2005), are now lured by diverse, active and lively communities. This dissertation considers such locations as walkable. Regions that want to be economically vital should offer this amenity. The findings of this dissertation will show whether the hypothesis that people will cluster in walkable places is warranted on the city and neighborhood levels.

City Vitality and Transportation in Theory

This dissertation investigates walkability as a means of transportation. As such, walkability and walkable infrastructure joins the discussion regarding the simultaneity and causality between transportation infrastructure provision and regional economic growth. This discussion dates back to 1989 when David Aschauer analyzed the impact of public capital on national productivity. He found evidence that higher national productivity results from public sector capital accumulation. Many academics and policy analysts, including transportation specialists, have taken interest in his conclusion. In the context of transportation and regional economic performance, studies undertaking the subject split into two groups: those confirming Aschauer's conclusion that transportation investment has a positive impact on regional growth, and those showing that transport provision does not play a significant positive role in regional prosperity.

The debate spilled over into the issue of causality – whether improved transport is the cause or a result of economic growth. On one hand it has been indicated by Boarnet (1998), Prud'homme (1996 and 2001), and Vickerman (2001) that better transport infrastructure facilitates economic growth through allowing for greater factor mobility, geographical expansion of labor and trade markets, decreasing transportation costs, increasing transport efficiency, and facilitating greater export opportunities. Conversely, it has been observed that the demand for travel and better infrastructure results from increased household incomes, increased commuting, business-related and leisure trips, new technologies, or quantity and quality of goods and services to be transported (Kindleberger and Herrick 1977, Kindleberger 1965, Banister and Berechman 2001). All of these arguments provide the grounds for further investigation of the links between transportation provision and economic performance of regions. The emerging interest in the provision of walkable infrastructure makes it natural to add walkability as a means of transportation into the discussion.

City Vitality and Walkability

Walkability and city vitality have been tied together for decades. Jane Jacobs in her famous book *The Life and Death of Great American Cities* (1961) was joined by Cook (1980), Gehl (1989), and Buchanan (1988) in declaring city street activity and city vitality as the forces behind successful and growing urban areas. Further, they saw urban design of communities not only as arrangement of physical space, but also the activities that happen there.

The current active streets in revitalized cities are diverse. They host cafes, restaurants, galleries, bakeries, bars and clubs, grocery stores, doctors' offices and other businesses, as well as parks, gardens and other public places where people want to play, work and run errands. Active and vital streets experience high pedestrian flows and activities during day and night (Montgomery 2007), therefore events and flexible opening hours are important. Urban renewal is dependent on flexibility and multifunctionality of its communities with sufficient conditions for public transport and even minimization of the need for non-walk travel (Stouten 2010).

Typically, such arrangements are characterized by downtowns or town centers where their economic activity is supported by large populations living nearby and by tourists. However, thanks to high levels of car ownership, small places and suburban walkable communities are capable of attracting enough people to support their economic activity (Montgomery 2007, Byron and McLean 2013).

Colantonio and Dixon (2011), Forkenbrock and Weisbrod (2001), Leeper (2013) and Li Mandri (2013) add that city vitality and revitalization, in addition to activity and business-based approach, requires a community-driven approach and well-prospering social capital networks. Their perception complements Jacobs (1962), Leyden (2003) and Rogers' (2011) arguments that dense, "alive" streets and communities promote bonds between the residents. Still, it has been found, that suburban areas where street connectivity is replaced by cul-de-sacs, also encourage social cohesion. Residents there know and trust each other, and interact at social occasions (Hochschild 2013). Therefore, urban environment is not the only option for community bonding.

Walkability is an enabler of vitality and revitalization of cities. Walkable infrastructure allows people to interact and bond in their communities. Walkability affects residents' habits, attitudes toward their communities and the economic health of their neighborhoods and cities. This dissertation further explores this issue by analyzing the association between walkability and economic vitality of cities in the U.S., and in neighborhoods within the Washington, D.C. metropolitan area.

Walkability

"Walkability" Definition and Measure

"Walkability" is a relatively new term in the academic, professional, or even every-day language. The most comprehensive definitions found in the literature describe walkability as "the quality of walking conditions, including safety, comfort and convenience" (Litman 2003, pg. 3), "the degree to which an area within walking distance of a property encourages walking for recreational or functional purposes" (Pivo and Fisher 2009, pg.1), or "a measure of the effectiveness of community design in promoting walking and bicycling as alternatives to driving cars to reach shopping, schools, and other common destinations" (Rattan et al. 2012, pg. 30). This dissertation builds on these definitions. The focus is put on walking as a mode of transportation. This analysis does not concentrate on walking as an action to improve health and enhance active living (e.g. fight obesity), nor on the associations between walking and protection of the natural environment.

There is no one uniform measure of walkability. Researchers have quantified walkability using objective and subjective variables and measured it on various geographic scales. Selected methods of quantifying walkability are presented below.

Day et al. 2006 and Leinberger and Alfonzo 2012 used the Irvine-Minnesota Inventory (IMI) measure of built environment. The IMI investigates the aspects of accessibility, pleasurability, safety from traffic, and safety from crime. The development of IMI involves literature review, focus groups interviews, a field survey, and a panel of experts.

Pivo and Fisher (2009), Cortright (2009), Duncan et al. (2011), Florida (2011), Weinberger and Sweet (2012) and Leinberger (2013) used the Walk Score index as the measure of walkability in their research. The Walk Score is based on the proximity to amenities (e.g. schools, parks, libraries, retail and commercial places) from residential locations. Places are ranked on the 0-100 scale. Places with amenities within 0.25 mile or less are given the highest score; the larger the distance, the smaller the score.

Context Walkability™ is a walkability ranking developed by Maponics, a company generating geographic boundary data and developing mapping applications. This walkability ranking includes factors such as street type, speed limits, intersection complexity, transportation network, population density, crime, weather, public transit, and freeways and bodies of water (Maponics.com).

Another measure of walkability, Walkonomics, uses various indicators associated with walkability combined in the following categories: road safety, easy to crossing, pavements/sidewalks, hilliness, navigation, fear of crime, smart and beautiful, and fun and relaxing (Walkonomics.com). These categories were based on the findings of Methorst et al. (2010) and Ramirez et al. (2006) who identified potential indicators associated with walkable and bikable locations.

Sehatzadeh et al. (2011) summed up z-scores of four variables (land use entropy, intersection density, population density, and retail employee density) and divided the sum into quartiles to develop walkability score. Frank et al. (2010) quantified walkability as a function of net residential density, retail floor area ratio, land-use mix, and intersection density. Then, Frank et al. normalized the values using z-score and then assigned weights to them (z-score of street connectivity was weighted by a factor of two, while the others were weighted by a factor of one).

Glazier et al. (2012) developed a walkability index for Toronto, Canada, through conducting factor analysis and principal components analysis on candidate walkability indicators, such as density variables and heterogeneity of land use. This method of measuring walkability was based on the indices of built environment used by Ewing et al. (2003), Krizek (2003), and Cervero and Duncan (2003).

In the context of this dissertation, the major limitations of these walkability measures include inconsistency in the geographic coverage and the time periods for which the ratings are available (there are no past ratings available). To answer this dissertation's research questions, a new walkability index must be generated. The walkability index developed in this dissertation mainly follows the ideas of Frank et al. (2010) and Glazier et al. (2012). It also applies walkability components that have been used in the reviewed walkability measures. Walkability is quantified so that it captures the unique characteristics of cities in the United States, and neighborhoods in the Washington, D.C. metropolitan area. The walkability index incorporates multiple indicators associated with walkability, and uses statistical methods to assign weights to them. This prevents the new index from being arbitrary in nature. The detailed method is described in the third chapter of this dissertation.

Walkability in the Literature

Literature on walking and walkability largely focuses on the health aspect. In fact, minimal attention had been paid to walkability before a connection between improved public health and walkability was found (Milczarski 2013). For example, Greenwald and Boarnet (2001), Berrigan and Troiano (2002), Killingsworth and Lamming (2001) found strong positive association between walking and public health and fitness (e.g. weight loss, rehabilitated cardiovascular system). However, there is an increasing interest in the relations between walkability and issues other than health. Litman (2003, 2007, 2011) composed a set of the most common areas of interest:

- equity: walkability allows for greater mobility options especially for the transportation disadvantaged; it helps to decrease the physical, economic and social exclusion providing increased accessibility;
- consumer cost savings: walkability allows for limited usage of private vehicle and savings on gas and maintenance;
- public cost savings: walkable infrastructure is one of the cheapest transportation systems;
- environment: walkability helps to reduce pollution because it encourages non-motorized trips;
- efficient land use: walkable infrastructure takes less land than road and does not require parking facilities, therefore the land may be used for various purposes;
- economic growth: walkability encourages diverse use of land, hence contributes to an increase in local business activity and real estate values.

From the perspective of regional economic growth, the literature on walkability splits into two major paths. First, it is claimed that walkable neighborhoods attract economic activity. For example, associations and companies such as the National Association of Local Government Environmental Professionals and Walkable Communities Inc., or New City America advocate for walkable communities claiming that those communities will have a positive impact on local economies because the modern economy requires accessibility, networking and creativity. Small, decentralized firms and entrepreneurs are drawn to places of pedestrian and transit-oriented character. Ryan (2003) claims that walkable communities are likely to "capture a great share of tourist dollars." Visitors from outside of the communities will come to enjoy the mix of retail, commercial, entertainment and business character of a walkable place and enhance the local economy with their dollars.

Second, it has been shown that walkability has a positive effect on real estate prices and rents in neighborhoods, in metropolitan areas, and nationwide. Based on selected neighborhoods in the Washington D.C. metropolitan area, Leinberger and Alfonzo (2012) found that walkable places are associated with higher office, retail, and residential rents, and residential housing values. Cortright (2009) found strong association between walkability and higher housing values in 13 out of 15 metropolitan areas in the U.S. (the two exceptions were Las Vegas, NV, and Bakersfield, CA). Pivo and Fisher (2009) analyzed 10 years of financial data on the set of 11,000 office, retail, apartment and industrial properties nationwide and found that walkability is associated with higher values of all of these properties.

Factors Attracting and Detracting Walking in Cities

If one accepts the idea that walkability and city vitality are related in one way or another, it is important to consider what makes people want to walk. Investing in walkable cities and neighborhoods will not bring positive effects if the underlying problem is unwillingness and lack of interest in walking. The growing interest in walking for health and environmental protection in cities resulted in conducting surveys and research papers examining the attitudes towards walking of actual or potential pedestrians. The results of the selected literature are summarized below (Table 1). They present the primary reasons why people do and do not walk.

Table 1
Common Reasons for Walking and not Walking

Reason for Walking	**Reasons for not Walking**
Physical (especially fighting obesity) and emotional health	Distance
Accessibility/ close proximity to non-residential destinations/ land use mix	Carrying things
Pleasurability/ Aesthetics/ "streetscape"	Do not want to / Laziness / Prefer other transport
Safety form crime	Time limitations
Safety from traffic	Fear of crime
Freedom from congestion and parking	Weather conditions
Environmental impact	Fear of traffic
Economical (save gas and maintenance)	Disabilities
Recreation/ leisure	Too busy
	Inconvenient / Poor infrastructure

Sources: Compiled from DOTFHWA 2006, Belden Ressonello and Stewart 2003, James et al. 2001, Mackett 2003, Longdill and Associates Ltd 2003, Krizek and Johnson 2007, Royal and Miller-Steiger 2008, NHTSA and BTS 2003a and 2003b, Frank et al. 2004, Day et al. 2006, O'Reilly et al. 2011, Saelens and Handy 2008, Rattan 2012, Sehatzadeh et al. 2011, Handy et al. 2008, Saelens et al. 2003, Frank et al. 2005; Leslie et al. 2005, Rutt and Coleman 2005, Cleland and Walton 2004, Fleury 2013.

The findings show that the most notable factor attracting people to walk is because they want to stay or become healthy and fit. The results show that accessibility and close proximity to non-residential destinations are also major reasons why people walk. Less important reasons include pleasurability, safety and limited congestion of the surroundings, followed by environmental and economic factors.

The major reason for not walking given by participants of surveys is distance, followed by carrying heavy things. Participants of the surveys also do not walk because they are too lazy or not interested in walking, because of time limitations, fear of crime and unfavorable weather conditions. Fewer respondents do not walk due to disabilities, lack of time and the preference of other modes of transport. Inconvenience (walking paths do not lead to desired destinations) and poor walkable infrastructure are a problem for the least surveys' participants. Distance is one of the major reasons for not walking.

The presented results provide only a crude picture of why people are attracted or resistant to walking. Since research on walkability is in its infancy in the United States, there are not enough U.S.-specific surveys and papers that would fully explain domestic attitudes. Furthermore, the strength of the conclusion is limited because the surveys' participants and research papers' samples differ regarding the age, occupations, nationalities, size of the locations where people would walk, and methodologies (opened vs. closed questions in case of surveys, different econometric models in case of the quantitative analyses). The usage of qualitative methods may also bring distorted results due to errors in categorization of the answers and inaccurate answers. Respondents may want to please the researcher, or they may hide their true feelings by, for example, claiming distances are too large while in fact the reason for not walking is laziness. Nonetheless, the conclusions provide an insight into the issue and ignite the curiosity about walkability.

This dissertation includes the majority of the reasons why people walk and do not walk as indicators of walkability (e.g. accessibility, safety from crime and traffic). The analysis does not include primary data, such as survey data on attitudes of pedestrians unique for the U.S. cities and neighborhoods in the Washington, D.C. metropolitan area, so it misses the perceived indicators (i.e. carrying things, personal preferences). This research also excludes the environmental and aesthetics aspects.

The strength and explanatory power of the new walkability index would be improved if survey results conducted on respondents living in geographies included in this dissertation were available. However, such survey has not been conducted, which makes it a logical suggestion for future research.

Walkability and Biking Connection

In public policy and in research, walkability is often combined with bicycling issues. Selected initiatives, projects, and analyses regarding the so-called "ped-bike" issues are described below.

The U.S. Department of Transportation (DOT) released a Policy Statement in 2010 where they recognized that well-connected walking and bicycling networks are "an important component for livable communities, and their design should be a part of Federal-aid project developments" (DOT 2010). The DOT's statement encouraged agencies to "go beyond the minimum requirements, and proactively provide convenient, safe, and context-sensitive facilities that foster increased use by bicyclists and pedestrians of all ages and abilities” (DOT 2010).

The DOT established and sponsors the Pedestrian and Bicycle Information Center (PBIC) which provides information on engineering, encouragement, education, and enforcement topics regarding walking and biking facilities alike (DOTFHWA 2012). The PBIC’ mission is to “improve the quality of life in communities through the increase of safe walking and bicycling as a viable means of transportation and physical activity” (PBIC).

Each state’s DOT has a Bicycle and Pedestrian Coordinator appointed by the Bicycle & Pedestrian Program of the Federal Highway Administration's Office of Human Environment. These coordinators are to promote and facilitate the use of both, pedestrian and bicycling facilities and to develop and implement public educational, promotional, and safety programs for using such facilities (DOTFHA 2013).

Walking and biking issues are often connected in research. A 2012 study by Transportation Alternatives (a walking, biking and public transit advocacy group) on the travel and spending patterns of residents and tourists in Manhattan’s East Village showed that streets with well-functioning bicycling and walking infrastructure positively affect the performance of local businesses. The locations with good walking and biking facilities are visited more often by pedestrians and bicyclists than by drivers. Non-motorized consumers spend more money per capita at local retailers than drivers. Similarly, a study analyzing streets of Toronto, Ontario (Clean Air Partnership 2009) showed that pedestrians and bicyclists spend more money per capita at local businesses than motorized visitors.

Similarly to walkability, biking issues alone have been of interest to researchers. Darren Flusche's (2009) analysis of economic benefits of bicycle infrastructure investments found that bicycle tourism has a positive effect on local employment rates and economic activity. A study of San Francisco's business districts showed that within four and a half years since construction of bike lanes, the local businesses have experienced a "positive overall impact" (Clear Air Partnership 2009).

Lindsey et al. (2004) researched the association between bicycling conditions and home values in neighborhoods surrounding the Monon bike trail in Indianapolis, IN. These researchers analyzed the prices of houses with comparable amenities and found that homes located within one half of a mile from the bike trail would sell for 11 percent more than homes further away (on average). Contradictorily, a study on the impact of bike trails on housing values in Portland, OR, showed that houses located within 200 feet from large regional bike paths were associated with an average of 6.8 percent decrease in the property value than homes located further away (Netusil 2003).

This dissertation does not address issues related to bicycling and bike infrastructure. However, the future research could build on the findings of this dissertation and expand on the findings by including biking conditions in regions.

The sample of literature discussed above shows that there is an interest in both walkable and bicycling conditions in regions. Therefore, it can be assumed that analysis of the associations between non-motorized conditions and regional economic vitality would be of interest to a wide range of public and private stakeholders.

Neighborhood Theory

Neighborhood Delineation in Research

The analysis of walkability on the neighborhood scale is important because walkability is directly related to individuals' quality of life and their freedom to mobility. The demand for walkability or the lack thereof is reflected on local, neighborhood scale. It has been found, that people in the United States care about their immediate surroundings; they want them to be convenient, safe and welcoming (Martin 2003, Messer 2007, Wilson 2009). People living or working in neighboring locations whether in dense or spread-out areas, share the benefits and challenges offered by the local conditions. It is the residents, grassroots organizations, local businesses and local elected officials who understand the local opportunities, and who take action to seize them. Initiating walkability and walkable culture, and integrating them into neighborhoods are bottom-up processes.

The literature shows that there is no single method to delineate neighborhoods. Rather, neighborhoods, as groupings of households, commerce and institutions (Coulton et al. 1999), are created through historical, social, and economic developments; they can also be defined based on stages of urban growth. Neighborhoods are flexible, fluid and dynamic products that change depending on the purpose of delineation and over time. Neighborhood boundaries are continuously redefined; as Buslik (2012, pg. 238) put it: "[n]eighborhoods are organic – they grow, divide, merge, decline, and regenerate."

Vernez Moundon et al. (2006) noted a distinction between the significance of neighborhood delineation in practice and in research. They concluded that in practice, “[neighborhoods] are perceived by both residents and policy makers as meaningful congregations of people with common interests. As a result, they are key spatial units of intervention, planning, and organization for institution and capacity building” (pg. 100). In the same study, Vernez Moundon et al. concluded that in research, “neighborhoods are important spatial units of sampling measurement and analysis” (pg. 100).

In practice, neighborhood boundaries are defined through integration of perspectives of local government personnel and administrators, and community members in order to capture the crucial characteristics of a place and to best serve the residents, for example for deploying police resources, services and maintenance (Wilson 2009, Buslik 2012). In research, the definition of a neighborhood is often based on administrative boundaries, such as zip code or census tract, mostly because of data availability.

In research, it is crucial to delineate neighborhood boundaries in a way so that the results of the research are valid and unbiased. Therefore, it is best if the between group variance is maximized, and the within-group variance is minimized. The problem with heterogeneity (disproportionate variance within the classes) and with homogeneity (not enough variance between classes) is that they may lead to distorted results and measurement error (Foster and Hipp 2011). Therefore, the technical dimension of the neighborhood boundary delineation must be carefully scrutinized.

Although there are many factors and unofficial guidelines to defining neighborhood boundaries, the task of delineation neighborhoods is a challenging one.

The dynamic nature of neighborhoods makes it difficult to generate coherent boundaries bearing long-term significance. As Ian White (2012) pessimistically put it: “[n]eighborhood boundaries cannot be right, but they can absolutely be wrong.” Delineating neighborhoods for analysis in the Washington, D.C. metropolitan area is also challenging because of the mix of different types of communities. To name a few, there are the pre-World War II neighborhoods, the post-World War II neighborhoods, and the neo-traditional neighborhoods. The traditional pre-World War II neighborhoods concentrate residential and commercial areas and provide good walking conditions. The post-World War II suburban areas favor the use of automobiles rather than pedestrian mobility and promote separation between residential and commercial areas. The neo-traditional areas have been turned from favoring car communication to pedestrian oriented havens. The question that needs to be answered before analyzing the correlation between walkability and economic prosperity on the neighborhood scale in the Washington, D.C. metropolitan area is how to define and delineate neighborhoods that will fairly reflect the various characteristics of local areas. The sections below discuss selected examples of neighborhood delineation that have been used to date.

Historical Outlook on Neighborhood Definition

One of the first researchers attempting to define neighborhood boundaries was Clarence A. Perry. In 1929, Perry published a report where he identified basic principles to define a residential neighborhood. Perry proposed the “neighborhood unit,” where children and families were able to walk from their homes to elementary schools and other community places (Perry 1929).

Perry put most emphasis on the major arterials providing boundaries for neighborhoods, construction of cul-de-sacs in the interior street patterns to preserve residential atmosphere, and keeping the population at approximately 5,000 people. The radius of the neighborhood would not exceed a one-quarter mile to allow children to walk to school. Moreover, Perry's neighborhoods would be structured around an elementary school and other institutions serving the neighborhood. Lastly, Perry advocated locating shopping districts at the edge of neighborhoods at major street intersections (Perry 1929).

These principles, with little change, have been applied to defining neighborhoods for decades. However, the critics of the method, the fiercest of which was Reginald Isaacs (1948a and 1948b), pointed out that Perry's principles were applicable only in the suburbs and other by-passed city areas, leaving out the city centers. The second major criticism was that Perry's method of delineating neighborhoods resulted in racial, ethnic, religious and economic segregation, as these enclaves encouraged keeping undesirable people out (Allaire 1961).

However, in the mid-20th century, there was no better alternative to Perry's method and so the trend in the neighborhood delineation continued (Allaire 1961). However, the expanding suburban areas called for further study of the neighborhood delineation standards. Several supplemental methods were applied depending whether the neighborhoods to be defined were new and suburban, or already established.

Allaire (1961) and Vernez Moundon et al. (2006) have collected the most common criteria of delineating residential neighborhoods that have been used since the Perry's initial attempts. The major criteria include:

- physical boundaries: both natural (e.g. rivers or extreme topography) and man-made (e.g. railroads or highways);
- major streets: streets designed with the purpose of keeping the high-speed heavy traffic out of a neighborhood;
- statistical areas (e.g. census tracts): they allow for comparability of demographic, housing and socio-economic data over a period of time;
- focal points: individual neighborhoods delineated based on radial proximity to unique characteristics of an area, such as places of worship;
- residential building type: for example, groupings of single family homes or apartment buildings;
- ethnic groups: based on the dominant racial, religious or national origin characteristics, such as Chinatown, Little Italy, Polish, or Jewish districts;
- neighborhood associations: for instance Parent Teacher associations, home-owner associations or interest groups (this method is especially useful when effective citizen participation is required);
- community facility service areas: based on service areas, such as schools.

Another method of neighborhood definition is based on the stage of local developmental process. These developmental processes are well reflected in the theory developed within the Chicago School of urban sociology (also called Ecological School) in the 1920s and 1930s.

Roderick McKenzie (1924), one of the Chicago School's most prominent researchers, hypothesized that over time, ethnic groups inhabiting geographical units are gradually replaced by other aggregations. After a while, the long-time residents start to move out to be finally replaced by a succeeding group. He called this phenomenon "invasion and succession."

McKenzie's theory was enhanced by Hoover and Vernon in 1959, and by Birch in 1971. As a result of the enhancement, six stages of 50-100 year neighborhood life cycle were developed. The life of neighborhoods starts with an open, undeveloped area with low residential and economic activity density. Then, the residential development begins, usually characterized by single-family structures and occupied by one ethnic group. Next, the area increases in density, with new multi-family structures, more ethnic diversity and higher rents and property values. After reaching its developmental peak, the neighborhood begins to age, new construction cease, residential density decreases, and there is an inflow of lower income and more diverse ethnic and racial groups. Next, there is further deterioration, buildings become abandoned or turn into slums, population and economic activity decreases further. The final stage brings a collapse of the neighborhood or its renewal (Weinstein 2007). This method based on neighborhood life cycle is particularly useful when the purpose of the delineation of neighborhoods is to provide intervention or assistance encouraging improvement in neighborhood quality.

A neighborhood can also be recognized through local political or civic activity. Residents living in a given, officially undefined areas, occasionally act collectively to protect, or change their immediate surrounding so that it fits their desired form (Purcell

2001). Residents can prove their neighborhood activism through protests or organizing local movements and activating the local administrations to achieve the collective goal (Park et al. 1967, Wellman and Leighton 1979, McCann 1999, Martin 2003). Neighborhoods generated based on local activism are relatively short-lived and episodic. It is impossible to divide an entire metropolitan area into neighborhoods based solely on the sporadic civic activity.

Neighborhoods can also be designated based on self-selection (Coulton et al. 2001). People tend to locate in areas where others with the same characteristics already live or migrate to. For instance, parents are likely to reside in neighborhoods where other parents of similar means live, because they want to have convenient access to schools, medical care, and children amenities they can afford. Another example provided by literature (Messer 2007, Banks et al. 2006, Wardle and Steptoe 2003, Resnicow et al. 2001) is clusters of educated people who desire access to similar resources such as libraries or amenities for healthy living (e.g. gym, healthy food store). These neighborhood boundaries, while longer lasting than those based on civic activity, also cannot be used to define neighborhoods within entire metropolitan areas. The number of such clear-cut self-selected neighborhoods is sparse. The majority of the metropolitan areas tend to be more diverse.

Neighborhood boundaries used in research are also delineated based on administrative divisions, such as census tracts, zip codes or block groups (Saelens et al. 2003, Foster and Hipp 2011, Spoon 2013). It has been found that analyses based on administrative boundaries may bring less precise results than when based on other unofficial criteria (Wilson 2009, Foster and Hipp 2011); however, data availability often prompts researchers to choose the administrative boundaries.

Modern Neighborhood Delineation Methods

In practice, the contemporary trends in the neighborhood design in metropolitan areas account for the changing demographics, preferences, and health-oriented attitudes of potential residents. The practices can be divided into two major groups: the first group focuses on design and planning of neighborhoods, and the second group focuses on the technical and virtual neighborhood delineation in dense, urban areas. Selected methods representing both groups and discussed below.

Some of the contemporary neighborhood designs draw on various historical methods. These trends, for example the neo-traditional neighborhoods design and transit villages, encourage the development of local communities, increased opportunities to socialize among residents, and activity in local civic life (WMATA, UCPB 2010). The focal points of the designs are compactness, mixed-use, and access to public transportation.

While these types of modern neighborhoods are attractive to growing numbers of people, such as retirees and young professionals, they are not the perfect match for all. There are people who prefer larger, single family homes, afar from the dense and compact surroundings. For example, some families with young children are likely to choose suburban lifestyle as their priority is the quality of schools, the convenience of mobility by car, and large residential space for children to grow up in. There are communities, such as those in Ventura, California, where residents do not wish to change their neighborhoods into more dense and compact areas. They fear their freedom to mobility by automobile and the accommodation for cars will be limited and that their surroundings will become too busy and crowded (Weir 2013).

Neo-traditional neighborhood design is a nationally recognized technique of planning neighborhoods (UCPB 2010). The neo-traditional neighborhood design is commonplace in infill areas where existing settings are adapted to fit the new demand, as well as in undeveloped greenfield settings. The purpose of the neo-traditional neighborhood design is to construct compact, pedestrian- and bicycle-friendly areas, with multiple and diverse destinations accessible within a short trip. It has been found that a person, on average, will prefer to walk rather than drive if a destination is within a 5-minute walk or a one-quarter mile from their origin (DOTFHWA 2006, Miskowiak and Stoll 2006). Access to public transit is also a focal point of this method of neighborhood design.

The neo-traditional neighborhood design offers its residents a mix of commercial, leisure, and public-use destinations nearby (UCPB 2010). The surroundings are planned to be pleasant, with ample green areas, sidewalks, and housing situated closer to narrow streets than in the suburban developments (UCPB 2010). Walking and biking is promoted, and it is expected that residents will decide to own fewer cars. Even though there is demand for this type of neighborhoods (as indicated by the literature discussed earlier in this literature review), it is anticipated that it will take a while for residents to get used to doing without, or with fewer automobiles (DOTFHWA 2006). Therefore, in the neo-traditional neighborhood design, the car usage is accommodated and parking spaces are available.

Transit villages are another emerging concept in modern neighborhood design. They are compact, mix-use neighborhoods designed around transit hubs. The residential buildings are tall and multi-family, often accommodating retail spaces on the ground floor. The prominent component of the transit villages is the easy access to public transit. It is expected that high density and limited automobile accommodation will result in high demand for public transit. In turn, the transit will be running often and will have ample destinations which will draw passengers even more. Transit villages are expected to be optimally accessible, and to increase equity and provide opportunities for residents of various incomes (WMATA, Martin 2008).

The advancement of computer capabilities and technology has led to development of modern, digital techniques of neighborhood delineation based on geographic information systems (GIS). These emerging methods circumvent the administrative divisions and can account for social, cultural, economic, and historical factors defining neighborhood boundaries. Therefore, the neighborhoods can better reflect individual characteristics of the localities, instead of being delineated in a crude, uniform way. This section will discuss three of these techniques: the Mapfluence, Zillow, and Maponics.

The Urban Mapping Development Center has developed neighborhood boundaries for most of American cities, based on over 10,000 variables from commercially licensed data sources (e.g. Nielsen or Acxiom). The Mapfluence neighborhoods are informally and subjectively delineated areas. They are based on social, cultural, historical, and other elements of the collective experience to define the local environment. The Mapfluence technique of defining neighborhoods works only in dense areas. As the areas become less dense, the neighborhoods tend to blend with municipal designations, such as townships or zip codes (Urbanmapping.com 2013); there are also areas that are completely uncovered by this neighborhood division. However, the coverage of the dense areas is enough for the Mapfluence to be popular among a variety of web portals and search engines. For example, Microsoft Bing, Yahoo!, TraipAdvisor, Care.com, Mapquest, CoStar Group, and Apartments.com use Mapfluence's neighborhood boundary data in their local search tools, navigation, apps, and mobile services for on-the-go users.

Zillow, an online real estate database, published 7,000 neighborhood boundaries for the largest cities in 41 states and the District of Columbia (Zillow.com 2013). Zillow neighborhood boundaries are used mostly in the real estate market; however, they are also widely used in internet search portals, such as Geogram.com, a website helping built email groups in local communities and neighborhoods.

Maponics neighborhood boundaries are another delineation tool based on GIS datasets. They offer boundaries for 146,800 neighborhoods in 2,000 cities in the United States. Their neighborhoods are used in real estate search, search engines, and social media sites (e.g. realtor.com, trulia.com, CitySearch, YellowBook USA, Twitter, Loopt, or Location Labs, TripAdvisor) (Maponics.com 2013). These neighborhood boundaries do not cover the entire Washington, D.C. metropolitan area, and data needed to construct the walkability index would not be available on this scale, or a great deal of data manipulation would be necessary.

The use of GIS in neighborhood delineation makes the boundaries more practical than if they solely depended on administrative divisions. According to Wilson (2009), Schutzberg (2008), and Foster and Hipp (2011), methods based on GIS provide more accurate solutions and better reflect local characteristics. However, as of this moment, these informal neighborhood boundaries cover dense areas that are the most interesting for commercial clients, the residents, and people searching for a place to live in commercially and socially active areas. Therefore, these methods of neighborhood delineation cannot be used to generate neighborhood units across the entire Washington, D.C. metropolitan area. Furthermore, due to the subjectivity, informality, and irregularity of the boundaries, a comprehensive set of data is not available. The boundaries only irregularly follow the basic administratively defined areas, such as blocks or block groups, for which official data are collected. Should these neighborhoods spread to less dense areas and should they cover the entire Washington, D.C. metropolitan area, an analysis on these geographical levels would be beneficial to further the knowledge of the issue of the correlation between walkability and economic vitality of neighborhoods.

T-communities method is another option to integrate GIS into neighborhood delineation. This technique was initiated by Grannis (1998, 2005), who based his definition of "tertiary communities" on social interactions, and delineated his neighborhoods based on the flow of pedestrian traffic channeled by tertiary streets

(Grannis 1998). Foster and Hipp (2011) further explain the delineation of t-communities (pg.27):

> Social closure occurs through the physical barriers imposed through larger arterial streets or other natural boundaries across which it is difficult or impossible to walk. […] Therefore, combining the ease of pedestrian travel within the community with the difficulty of pedestrian travel across certain boundaries surrounding the community, 't-communities' have geospatial boundaries that respect the logic of social interaction.

Construction of t-communities requires a combination of GIS data and survey data integrated into maps, through GIS software, such as ArcGIS. The use of GIS data diminishes the need for extensive field research while still providing information necessary to effective neighborhood delineation (Foster and Hipp 2011).

Methods based on GIS, including the t-communities, are not perfect. The local interactions are complex, and systematic data on micro level (e.g. street-level) are scarce (Wilson 2009, Spoon 2013). T-communities may become very large and lose their ability to emphasize the within-group similarities and between-group differences (Grannis 2005). Furthermore, detailed knowledge of the overall analyzed area is necessary to construct t-communities; for example tertiary street patterns are needed. Lastly, there are no data on the t-communities scale; therefore street-level data must be aggregated on the appropriate level.

In the Washington, D.C. metropolitan area, there is no consensus in regard to the boundaries of single neighborhoods. In the District of Columbia alone, the official micro geographies used by local authorities are neighborhood clusters. There are 39 of them, each consisting of three to five unofficial neighborhoods. The neighborhood clusters are used by the Washington, D.C. government for budgeting, planning, service delivery, and analysis purposes (NeighborhoodInfoDC.com 2013).

In the Washington, D.C. metropolitan area, one of the options for neighborhood boundaries are activity centers. Activity centers were initially developed in 1999 by the Planning Directors Technical Advisory Committee at the Metropolitan Washington Council of Governments (MWCOG) and since then, their boundaries have been updated several times. Activity centers are based on local comprehensive plans and zoning.

The regional activity centers and their clusters were developed to serve as mechanisms to "guide land use and transportation planning decisions" (MWCOG 2006, pg. 1). Activity centers do not cover the entire Washington, D.C. metropolitan area, but only areas with concentrations of activity (housing and employment). Currently, there are 141 activity centers across the metropolitan Washington, D.C., and they are divided into five types, as presented in Table 2.

Table 2
Types of Activity Centers in the Washington, D.C., Metropolitan Area

Activity Center Type	Characteristics	Examples
D.C. Core	Major governmental, cultural, tourism, business and commercial activity	Downtown Washington, Georgetown, New York Avenue
Mixed-use Centers	Dense mix of retail, employment, and residential activity or significant levels of employment and housing	Downtown Alexandria, Crystal City, Rosslyn
Employment Centers	Concentration of employment, urban or becoming urban areas	The Pentagon, Herndon, Tysons Corner
Suburban Employment Centers	More dispersed and lower-density areas	Beltway South, Dulles Corner, Fairfax Center
Emerging Employment Centers	Rapidly developing "campus-style" suburban employment	Largo center, National Harbor, Woodbridge

Source: MWCOG 2006.

Regional activity centers could potentially be used as neighborhoods to analyze the correlation between walkability and economic vitality of neighborhoods in the Washington, D.C. metropolitan area; however, such analysis would circumvent the suburban areas. Therefore, activity centers are not the prime option for neighborhood in this dissertation.

Traffic analysis zones (TAZs) are another feasible option for neighborhood analysis. TAZs are geographical units used in transportation planning, such as in non-motorized activity, transit modeling, or alternatives for land use (RVAMPO 2006, TMIP 2007), and for tabulating traffic data such as journey-to-work statistics (Song and Knapp 2004).

The size of traffic analysis zones can range from census blocks in dense central business districts, to much larger areas, such as census tracts, in the outlying zones. The smaller the traffic analysis zones are (hence, the greater their number in the overall study area), the more comprehensive the analysis results will be. This is especially true when forecasting and modeling non-motorized trips, such as walking or bicycling. The literature shows that it is useful to delineate small traffic analysis zones when the analysis is based on areas that are pedestrian- bicycle-, and transit-oriented, such as neo-traditional neighborhood designs or transit villages (TMIP 2007). However, increasing number of TAZs adds to the computational strain (e.g. file storage space) and can be restricted by data availability and the limitations of time and resources.

The main criterion for the delineation of traffic analysis zones is population density. While there is no set population limit, the U.S. Department of Transportation

(DOT 2013) strongly suggests the minimum of 1,200 residents per zone. However, population is not the only possible criterion and the specific algorithms used to define the zones can change in various geographic areas and over time (Martinez et al. 2009). No matter what the individual algorithm and the size of traffic analysis zones, it is required that the TAZs nest within counties and the entire county units must be covered by TAZs (DOT 2013).

In the Washington, D.C. metropolitan area, traffic analysis zones have been used as units of analysis by an independent non-profit organization, the Metropolitan Washington Council of Governments (WMCOG). The Department of Community Planning and Services within the MWCOG has been using traffic analysis zones since the early 2000s in generating employment, population, and household forecasts in the Washington, D.C. metropolitan area.

Although traffic analysis zones are potentially appropriate geographical units to be used as neighborhood boundaries in the Washington, D.C. metropolitan area, the data on the TAZ level are limited. Therefore, TAZs cannot be used in this analysis, but they remain an option for future research. This dissertation will use an officially delineated subdivision, census tracts, as the unit of analysis on the neighborhood level. Chapter III includes the description of census tracts and the rationale behind their selection.

Summary

This literature review summarized the dominant theories and trends in research on walkability and regional economic vitality from the historical and contemporary perspectives. The emphasis was put on the geographic level of cities, and neighborhoods. It was shown, that it is important to study economic performance of cities because they are the engines of regional and national economic growth. The literature also suggests that walkability is related to vitality of cities and neighborhoods within the cities, which in turn tends to translate into increased economic performance of the regions. However, the discussion of these issues is not abundant. There is scarcity of literature on the connections between walkability and economic performance of cities in the United States. While studies on the connections between walkability and economic performance of small-level regions exist, it is insufficient on the scale of Washington, D.C. metropolitan area – America's leading region in walkability (Leinberger and Alfonzo 2012). Moreover, there is no consensus on the definition and measure of walkability, and there are gaps in the literature in regard to neighborhood delineation that would reflect local characteristics within the Washington, D.C. metropolitan area.

CHAPER III
RESEARCH DESIGN

This chapter presents the research questions and research design of the dissertation. It describes the proxy selected as the measure for regional economic vitality and the explanatory variables. It also presents the data, the time-frame and the units of analysis to be used in the analyses presented in Chapter IV. Finally, it explains the methodological approach employed in addressing each of the research questions.

Research Questions

Question 1: What are the components of a walkability index and how can it be constructed?

The answer to Question 1 will quantify walkability on the levels of cities in the U.S. and neighborhoods in Washington, D.C. metropolitan area. The results will be expressed in location-specific walkability indices that will later be used to analyze the association between walkability and economic vitality in the examined geographies.

Question 2: What is the association between walkability and economic vitality in cities in the United States?

Based on the literature review, it is hypothesized that highly walkable cities are associated with stronger economic condition than less walkable cities. The answer to

Question 2 will determine if this hypothesis is supported. Through econometric analysis the association between walkability and economic condition of cities in the U.S. will be measured.

Question 3: What is the association between walkability and economic vitality of neighborhoods in the Washington, D.C. metropolitan area?

Based on the reviewed literature, it is hypothesized that highly walkable neighborhoods are correlated with stronger economic performance relative to less walkable neighborhoods. This hypothesis will be econometrically tested based on census tracts in the Washington, D.C. metro area.

Question 4: What is the spatial dependency pattern in the neighborhoods of the Washington, D.C. Metropolitan Area?

The objective of Question 4 is to examine the spatial pattern of the analyzed variables in the neighborhoods in the Washington, D.C. metropolitan area. The answer to this question will determine if the spatial pattern affects the housing vacancies in neighboring census tracts.

Research Design

Units of Analysis

This research is based on two geographic levels: cities in the United States and neighborhoods in the Washington, D.C. metropolitan area. The following section explains the choice of these geographies.

Cities

Analysis of walkability on a city level tends to be omitted in the literature because of the risk of losing real diagnostic value due to the large size of the units; also, it can be difficult to minimize the within-unit variance and maximize the between-unit variability. Moreover, walkability is considered local in nature. However, some researchers have undertaken this task anyway because the analysis of walkability in cities provides much needed information for federally supported projects and urban design planning aimed at enhancements in pedestrian accessibility and overall walkable environment (Southworth 2005). These researchers include Cortright (2009), who chose cities to analyze the impact of walkability on housing values and Weinberger and Sweet (2012) who researched walking behavior in cities. Hall (2010) developed a walkability index applicable for Townson, MD, Savannah, GA, Portsmouth, VA, and Sarasota, FL, as a tool to assist the urban design decisions.

Also in theory, cities overall are claimed to be crucial units of analysis even when it is their component geographies that are of the main interest. Jane Jacobs (1961) wrote about analysis of cities:

> We must never forget or minimize this parent community while thinking of a city's smaller parts. This is the source from which most public money flows, even when it comes ultimately from the federal or state coffers. This is where most administrative and policy decisions are made, for good or ill. This is where general welfare often comes into direst conflict, open or hidden, with illegal or other destructive interests. Moreover, up on this plane we find vital special-interest communities and pressure groups.

The section of the dissertation focusing on cities will provide an initial, basic picture of the significance of walkability on the macro scale. The results will indicate if support for walkability in cities – the determinants of national economic strength – is warranted and if changes in policies, regulations and plans targeted at increased walkability should be encouraged.

This dissertation follows the U.S. Census Bureau's definition of cities (incorporated places) as "a type of governmental unit incorporated under state law as a city, town (except the New England states, New York, and Wisconsin), borough (except in Alaska and New York), or village and having legally prescribed limits, powers, and functions" (ACS 2013). The ultimate sample consists of 992 cities with the population of 25,000 or more, as defined by the Census Bureau as of April 1, 2000. The original sample consisted of 1,265 cities (including census designated places of Honolulu, HA, and Arlington, VA), but due to missing values in the data and the presence of outliers (which would lead to distortions in the econometric analysis), 273 cities were dropped from the research.

Neighborhoods

It was shown in the literature review, that it is the local agents who care the most about a city's component areas. The demand for walkability is reflected predominantly on the local level and implementing walkability into the public policy agenda is a bottom-up process. Furthermore, analyzing walkability on the local scale allows minimizing the within-unit variability and maximizing the inter-unit variation.

Washington, D.C. metropolitan area is an interesting case for analyzing walkability. According to Leinberger and Alfonzo (2012), the metropolis is the national pioneer in creating walkable urban places. It could be expected that Washington's inner sections would be walkable, as it is one of the oldest American cities that were meant to be walkable by design. However, it is not only the urbanized parts of the metropolitan area that bear walkable characteristics. Some suburban sections of Virginia (i.e. Merrifield) and Maryland (i.e. Bethesda Row) have been redesigned to be pedestrian-oriented. There are also typical post-World War II car-oriented neighborhoods. This dissertation will analyze the association between walkability and economic vitality in urban and suburban neighborhoods of the region.

In this dissertation, census tracts have been selected to represent neighborhoods. Census tracts are "small, relatively permanent geographic entities within counties (or the statistical equivalents of counties)" (U.S. Census Bureau 2000). Census tracts optimally contain 4,000 inhabitants on average, ranging from 1,200 and 8,000 (between 1,000 and 3,000 housing units). Their boundaries usually follow permanent visible features, such as roads, rivers, canals, or high-tension power lines. The spatial size of census tracts depends on the settlement density. It is intended that the census tract boundaries are maintained over decades to allow for statistical comparisons over time; however, occasionally they are merged or split because of substantial changes in population counts (U.S. Census Bureau 2013a).

Census tracts may be criticized for being too large to analyze walkability in neighborhoods because some specific neighborhood characteristics are lost on this level.

A good alternative are custom-delineated neighborhood boundaries based on street network buffers or neighborhood design (traditional, early modern, late modern) as used by Duncan et al. (2011) and Handy and Clifton (2001) respectively. Such method would allow arbitrarily adjusting the size of neighborhoods to reflect the desired attributes. However, this dissertation was designed to use official geographical subdivisions and secondary data. Neighborhood delineation and gathering primary data are beyond the scope of this dissertation. Analysis of walkability in the metropolitan Washington, D.C. based on custom-delineated neighborhoods and information from surveying local residents and observation-based primary data is an option for future research.

Census tracts are satisfactory for analyzing walkability because their boundaries are relatively stable so the analysis is replicable. Additionally, this is the smallest level for which some of the crucial secondary data for walkability indicators and control variables are collected. Using smaller official subdivisions, such as block groups, would limit the walkability indicators due to the lack of data and would introduce the risk of using less reliable data with higher margin of error. Selection of the census tracts is also supported by literature on walkability; census tracts have been used previously to analyze walkability on the neighborhood level. For example, Frank and Pivo (1994) used census tracts in their research on the impact of mixed land use and density on the transportation mode choice including walking. Cervero and Kockelman (1997) analyzed 50 census tracts in the San Francisco Bay Area in their examination of how the so-called "3Ds" – density, diversity and design – affect trip rates and mode choice in neighborhoods. Booth et al. (2005) considered census tracts as neighborhoods when discussing the relationship between obesity and built environment supporting walking opportunities. Manaugh and El-Geneidy (2011) included census tracts as one of the neighborhood definitions when validating walkability indices. Finally, Clark et al. (2014) studied the impact of the built environment and weather on walking for transportation based on census tracts in Canada.[1]

There are 1,359 census tracts within the Washington, D.C. metropolitan area and all of them are analyzed in this dissertation. They cover the region's 24 component jurisdictions, including the District of Columbia, 5 counties in Maryland (Calvert, Charles, Frederick, Montgomery and Prince George's), 11 counties in Virginia (Arlington, Clarke, Culpeper, Fairfax, Fauquier, Loudoun, Prince William, Rappahannock, Spotsylvania, Stafford and Warren), 6 independent cities in Virginia (Alexandria, Fairfax City, Falls Church, Fredericksburg, Manassas and Manassas Park), and Jefferson County in West Virginia (U.S. Census Bureau 2013b).

Time-frame

It is unlikely that walkability would have an immediate impact on economic vitality. Therefore, this research provides for a time lag. In the analysis of cities, the dependent variable will be captured as of 2007 and the walkability index and the explanatory variables will be captured as of 2000. This will detect the impact of walkability as it was in 2000 on employment in 2007. This time span allows using relatively recent data, but avoids the distortions in the level of employment associated with the economic recession of 2007-2009 (BLS 2012). In the analysis on the local level,

[1] American and Canadian census tracts are comparable in regard to population threshold, purpose of their delineation and the stability of the boundaries over time (Statistics Canada 2009).

the dependent variable will be captured as of 2013 and the independent variables will be expressed as of 2011. The choice of these years is dictated by data availability on the local level. The most comprehensive and reliable dataset for the walkability index components can be generated for 2011.

Dependent Variables

City Analysis

On the city level, the proxy for regional economic vitality is total employment. It is hypothesized that walkable cities will experience higher employment rates than non-walkable cities.

The literature review showed that in theory, one of the reasons why cities prosper is because they are able to attract people from other locations. Rather than following jobs, people increasingly settle in places with desirable amenities (Florida 2005). Footloose employers acknowledge the changing preferences of their potential workforce and locate in areas where they can find suitable labor base.

The new report by the non-profit Endeavor Insight (2013) showed that high-growth entrepreneurial companies open in big cities that are appealing to the young and mobile talent pool. Based on the answers of the founders of 150 fastest growing companies in America, the authors found that quality-of-life, next to availability of an educated workforce, major transportation networks, and proximity to sufficient consumer base, was a crucial factor of high-impact companies in locating in certain cities. It was also found that following their relocation these corporations rarely moved out of the city. Therefore, it is important for cities to attract such businesses at the early stage. The growing popularity of walkability suggests that walkable cities may have higher potential to be chosen than less walkable cities.

The reviewed literature also revealed that walkable places attract people to reside and to visit. This in turn translates into increased local economic activity. More residents mean greater demand for goods and services, expansion of business activity and increased opportunities for employment. Jane Jacobs (1961) argued that active, walkable and livable cities attract people. Higher population levels give people more opportunity to interact, learn and inspire each other. This causes professional development, diversification, and the opening of new business that hire new workers.

Efficient transport solutions contribute to the expansion of the labor markets, as they "ensure that as many people as possible can have access to as many jobs as possible in a given area" (Prud'homme 1997, pg. 10). Walkability as a means of transportation provides people of all income levels with accessibility to jobs and contributes to increased chances of finding employment.

It is acknowledged that walkability alone does not cause higher employment in cities. Rather, it makes cities more competitive and enhances their potential to attract workers and employers. In conjunction with other factors, walkability and all the benefits that come with it may contribute to a city's economic vitality characterized by higher employment level.

The employment data used in this research were collected by the U.S. Census Bureau. These data include paid employment and defines it as "full and part-time employees, including salaried officers and executives of corporations […]. Included are employees on sick leave, holidays, and vacations; not included are proprietors and partners of unincorporated businesses" (U.S. Census Bureau 2013a).

Neighborhood Analysis

The proxy selected for regional economic vitality in neighborhoods is housing vacancies. This is an appropriate proxy for tracking regional economic condition as it incorporates the demand for housing – lower vacancies reflect higher demand for housing in an area.

As was discussed in the literature review, walkable places attract people to reside. This in turn may translate into economic vitality of those places through increased levels of social capital, higher real estate prices and rents and boosted economic activity. This dissertation will contribute to these observations by capturing economic vitality through housing vacancies, a measure that has not been used before when analyzing walkability.

It is hypothesized that economically vital regions are associated with high demand for housing, and hence, lower vacancy rates. From a non-market perspective, this is beneficial because more people living in a neighborhood provides the potential for the development of social capital. Walkable areas have been shown to be associated with higher social capital levels. Social capital, defined as residential networks and personal connections, has been associated with economically healthy regions (Putnam 2000, Leyden 2003, Rogers et al. 2011).

Within the market context, it is hypothesized that there will be an interest in investing in walkable neighborhoods because of the anticipated return on investment. Land owners, developers, and other stakeholders, such as apartment owners who would rent out their property to gain revenue, are likely to invest in real estate in walkable locations as these places will benefit from a higher demand for housing. The advantages of walkable places, which are presumed to attract a consumer base, will be capitalized as lower housing vacancies relative to properties located in non-walkable places. This dissertation will test if walkable neighborhoods are associated with lower housing vacancy rates.

It is further hypothesized that during an economic slowdown or crisis, walkable places contribute to keeping a local economy relatively more viable, or to slowing the rate of economic decline. Residents search and choose places with lower transportation costs, higher accessibility and higher density. Therefore, the demand for housing is likely to be stronger or go down slower than in the non-walkable places during periods of economic weakness. As a result, walkable places sustain economic activity and contribute to their local economies out-performing the economies of non-walkable places.

Because of the likely simultaneity of walkability and economic vitality in neighborhoods (and cities alike), appropriate econometric methods will be used to analyze the relationship. The two-stage least square estimator, which accounts for the endogeneity, is a good choice and it is elaborated on later in this dissertation.

The data for housing vacancies come from the U.S. Census Bureau, American Community Survey. The Census Bureau defines a housing unit as vacant “if no one is living in it at the time of the interview, unless its occupants are only temporarily absent. Units that do not meet the definition of a housing unit, such as those under construction, unfit, or to be demolished, are excluded from the universe" (U.S. Census Bureau 2013b). A housing unit "is a house, an apartment, a mobile home, a group of rooms, or a single room that is occupied (or if vacant, is intended for occupancy) as separate living quarters. Separate living quarters are those in which the occupants live and eat separately from any other persons in the building and which have direct access from the outside of the building or through a common hall" (U.S. Census Bureau 2010).

Independent Variables

Table 3 presents the control variables used in the econometric analysis. The table includes the descriptions of the variables, data sources, geographic levels, the year of measure and variable names as used in the analysis.

Table 3
Profile of Control Variables

Variable	Description	Source	Geographic Level	Year	Variable Name
Walkability	newly developed walkability index	Answer to Q1	City Census tract	2000 2011	wlkbty
Population	no. of population	Census Bureau	City Census tract	2000 2011	pop
Gender	% female population	Census Bureau	City Census tract	2000 2011	fem
Education	% population with a high-school diploma only % population with Bachelor's degree or higher	Census Bureau	City Census tract	2000 2011	bach hsch
Race/Ethnicity	% white pop. % black pop. % Hispanic pop.	Census Bureau	City Census tract	2000 2011	white black hisp
Poverty level	% families under	Census	City	2000	fampov

	poverty level	Bureau			
Foreign-born population	% of foreign-born population	Census Bureau	City	2000	fborn
Retirement	% of population 64-years-old and over	Census Bureau	Census tract	2011	ret
Travel time to work	average time	Census Bureau	Census tract	2011	tttwork
Transit availability	No. of modes available	Census Bureau	Census tract	2011	transmode
Housing value	Median value	Census Bureau	Census tract	2011	housval

Data Sources

This dissertation uses secondary data. The great majority of the data is provided by the U.S. Census Bureau. The data for the control variables were collected through the 2000 Decennial Census on the city level and through the 2011 American Community Survey on the census tract level.

Census Bureau's *County and City Databook: 2007* is the source for the data for the city walkability indicators. This product compiles data from several government and private statistical publications, including the U.S. Department of Justice (violent and property crime) and U.S. National Oceanic and Atmospheric Administration (annual precipitation and temperatures). The *County and City Databook* is not only a convenient reference, but also provides some data unpublished by the contributing agencies (Census Bureau 2007). The limitations of the data include possible errors resulting from "sampling variability (for statistics based on samples), reporting errors in the data for individual units, incomplete coverage, nonresponse, imputations, and processing error" (Census Bureau 2007 pg. V). The data on pedestrian accidents used in this research are reported by the Fatality Analysis Reporting System (FARS) by the National Highway Traffic Administration.

The data for the census tract walkability indicators predominantly are reported by the American Community Survey (5-year estimates). Census Bureau's *On the Map* product is the source for the data on job density. The crime index and retail density were provided by the SimplyMap 3.0 web-based mapping application. The data were integrated into an excel sheet and transferred into Stata software package, Arc GIS and GeoDa for further analysis.

Methodology

The methodology designed to answer the research questions consists of three major components. The steps are summarized in Table 4 and described in detail in the following subsections.

Table 4
Order of the Analysis

Answer to	Method	Geographic level
Question 1	Calculation of z-scores of the indicators Principal Component Analysis Summation of the components Division of the sum of components to acquire walkability indices	City and Census tract
Questions 2 and 3	Ordinary Least Squares (OLS) regression Two-stage Least Squares (2SLS) regression	City and Census tract
Question 4	Moran's I statistic, LISA cluster map Spatial Lag Regression	Census tract

Question 1

The reason for developing the walkability indices for cities and neighborhoods is to combine multiple indicators of a single aspect – walkability – into one measure. The walkability indices will be location-specific combinations of indicators associated with walkability that have been used in the literature thus far. The indicators are characterized in Table 5.

Table 5
Profile of Walkability Indicators on the City Level

Indicator	Assumed Association with Walkability	Source	Measure in this Research	Data Source	Geographic Level
Residential Density	Higher residential density "reduces the number of trips taken by auto, hence indicates higher walkability" (Krizek 2003).	Day et al. 2006, Leslie et al. 2007, Pivo and Fisher 2009, Haelens and Handy 2008, Cortright 2009, Duncan et al. 201, Krizek 2003	Total residential population density divided by land area sq. miles	Census Bureau	City and Census tract
Job Density	Similarly to residential density, higher job density indicates compactness and non-automobile accessibility, hence walkability.	Cervero and Kockelman 1997, Frank and Pivo 1994	Total jobs divided by land area sq. miles	Census Bureau	Census tract
Travel time to work	Shorter travel time to work indicates higher regional accessibility and higher walkability.	Pivo and Fisher 2009	Average travel time	Census Bureau	City and Census tract

Design	Higher percentage of structures built before 1960 indicate higher walkability. Post-1950s developments divided residential from commercial areas, supported auto flow and diminished pedestrian mobility.	Southworth and Ben-Joseph 1995, Smith et al. 2008, Zick et al. 2013	% of structures built before 1960	Census Bureau	City and Census tract
Transit availability	More available public transit modes, indicate higher walkability.	Rodriguez and Joo 2004, Rodriguez et al. 2006	No. of modes of public transit taken to work[1]	Census Bureau	City and Census tract
Transit accessibility	Higher percentage of people using public transit indicates higher walkability.	Rodriguez and Joo 2004, Rodriguez et al. 2006	% of people taking public transit to work	Census Bureau	City and Census tract
Safety from violent crime	Lower rates of violent crime indicate higher walkability.	Day et al. 2006, Aultman-Hall et al. 1997	Violent crime[2] per 100,000 population	Census Bureau[3]	City
Safety from property crime	Lower rates of property crime indicate higher walkability.	Day et al. 2006, Aultman-Hall et al. 1997	Property crime[4] per 100,000 population	Census Bureau[5]	City
Crime Index	Lower crime level indicates higher walkability.	Day et al. 2006, Aultman-Hall et al. 1997	EASI Total Crime Index[6] (includes violent and property crime)	SimplyMap 3.0	Census tract

Safety from traffic	Less pedestrian-involved traffic accidents indicate higher walkability	Day et al. 2006	No. of pedestrians involved in fatal traffic accidents	National Highway Traffic Safety Admin.	City
Weather	"Increase in precipitation is associated with a decrease in the propensity to walk" (Clark et al. 2014)	Clark et al. 2014	Annual inches of precipitation (1971-2000 average)	Census Bureau[7]	City
Connectivity (block face size)	Shorter block face size in a census tract indicates higher connectivity, hence higher walkability.	Cervero and Kockelman 1997, Nasri and Zhang 2014	Average block face size in sq. meters	Census Bureau	Census tract
Retail density	Higher retail density provides more destinations and can produce more walking trips	Cervero and Kockelman 1997	No. of retail establishments divided by land area sq. miles[8]	SimplyMap 3.0	Census tract

[1] Includes bus/trolley bus, streetcar/trolley, subway or elevated, railroad, and ferryboat.
[2] Includes murder and non-negligent manslaughter, forcible rape, robbery, and aggravated assault.
[3] Data retrieved from the Census Bureau's County and City Databook, but the original data come from the U.S. Department of Justice.
[4]Includes burglary, larceny, and motor vehicle theft.
[5] Data retrieved from the Census Bureau's County and City Databook, but the original data come from the U.S. Department of Justice.
[6]EASI Analytic created the crime index where each index value indicates how an area compares to the national average. The national average is 100. The data used by EASI Analytic come from Federal Bureau of Investigation (FBI) & Uniform Crime Reporting (UCR) Program. The data include reported crimes. The weights used for the index are: Murder 20, Forcible Rape 10, Robbery 6, Aggravated Assault 6, Burglary 3, Larceny ,1 and Motor Vehicle Theft 1 (SimplyMap 3.0 2014).
[7] Data retrieved from the Census Bureau's County and City Databook, but the original data come from the U.S. National Oceanic and Atmospheric Administration.
[8]Retail establishments include "convenience stores, supermarkets, restaurants and eateries, general merchandise stores, specialty stops, and entertainment and recreational-oriented establishments." Source: Cervero and Kockelman 1997.

Calculation of Z-scores

The first step in developing the walkability index will be to prepare the indicators for accurate comparison. It is imperative to do so because the indicators have different distributions and measures and are derived from various sources; therefore they must be standardized to be compared and summed-up later in the analysis. Calculation of z-scores gives the indicators comparable scale ranges, because it rescales the variables to have a mean of zero and a standard deviation of one. The analysis then determines how many standard deviations each variable is above or below the mean. Calculating how much each of the indicators deviates from its mean normalizes their distributions and allows for their accurate comparison (Sehatzadeh and Noland 2011, Stanley 2012, Tessler and Altinoglu 2004).

Factor Analysis

The second step will determine the exact number and combination of indicators that will be used to construct the walkability indices. Too many items are likely to increase the risk of making incorrect statistical inferences (Cooksey 2012). Also, the indicators of walkability are most likely correlated. Therefore, they should be grouped in latent variables that are not highly correlated with one another and are unlikely to suffer from multicollinearity (Hutcheson and Sofroniou 1999). Factor analysis (Equation 1) will be used to condense the initial indicators associated with walkability into smaller number of latent variables. Using factor analysis will also circumvent possible double-counting of observations, because it identifies the part of variance of one indicator that overlaps with other variables that might be measuring the same thing (Cooksey 2012).

Equation 1

$$W = \omega_{Di}D_i + \omega_{TTtWi}T_i + \omega_{Ki}K_i + \gamma_i$$

where:
W = walkability
ω = the weight each indicator is given
D = density variable
T = travel time to work variable
K = representation of the other variables
γ – random term

The two most common types of factor analysis are the principal component analysis (PCA) and common factor analysis (CFA). For comparison, this research will conduct both options. The PCA will likely be chosen for the final analysis as this type of factor analysis is preferred when the goal is to compound the data, decrease the number of variables and obtain accurate estimates of the items within the latent variables. Common factor analysis is often used to detect the structure in the dataset (Cureton and D'Agostino 1983, Krishnan 2010). Moreover, principal component analysis assumes that all the variability in an observation can be analyzed while common factor analysis only explains the interrelationships between the variables (Hutcheson and Sofroniou 1999). Finally, PCA is more robust than CFA because it is less disturbed by anomalies in the data, such as missing values or non-normality of distribution (Cooksey 2012).[2]

Individual components in PCA are weighted linear combinations of variables explaining the largest portion of variance in the sample. The first component will use the greatest portion possible, the second component will explain the remaining amount of variance, the third component will use the residual variance, and so on (Equations 2 and

[2] Based on the preliminary analysis, such issues apply to the data used in this research.

3). As a result, a group of correlated variables will be transformed into a smaller number of uncorrelated components (Kim and Mueller 1978, Cooksey 2012, Hutcheson and Sofroniou 1999, Katchova 2014).

Equation 2

$$PC\ 1 = \beta_{1(1)}\ Variable\ 1 + \beta_{2(1)}\ Variable\ 2 + \beta_{K(1)}\ Variable\ K$$

Equation 3

$$PC\ 2 = \beta_{1(2)}\ Variable\ 1 + \beta_{2(2)}\ Variable\ 2 + \beta_{K(2)}\ Variable\ K$$

where:
PC = principal component
β = the weight each indicator
K = representation of the other variables

The process of developing the principal component analysis will begin with data screening and examining correlations. The bivariate correlations will determine which indicators should be dropped from the analysis. Indicators that do not correlate with others will not be used in the analysis (Hutcheson and Sofroniou 1999). Then, the actual principal component analysis will be conducted. The number of components will be determined based on the Kaiser test and the scree plot. Two factor rotations will be used to allow the variables to load on fewer components to achieve the most interpretable results possible. The orthogonal rotation will assume that the items are uncorrelated, while and oblique rotation will allow for correlation between the indicators. This research will focus on the oblique rotation as it can usually be reasonably assumed that components are correlated (Hutcheson and Sofroniou 1999). The final components will be then identified and their reliability will be assessed based on the Cronbach's α rule-of-thumb. Next, the principal components will be given scores and saved as variables. The Kaiser-Meyer-Olkin test will determine if using the principal component analysis was justified.

Index Ranks

The individual components are not equally important in explaining walkability and it has to be accounted for when assigning weights to each component score coefficient. This dissertation will follow the method adopted by Krishnan (2010) when constructing an area-based socioeconomic index. Similar methods were used by Antony and Rao (2007), Hightower (1978), and Sekhar et al. (1991). As in Krishan (2010), a Non-standardized Index (NSI) will be calculated first following Equation 4:

Equation 4

NSI = (B/A)(Factor 1 score) + (C/A)(Factor 2 score) + (D/A)(Factor 3 score)

where:
A = total variance explained by all the factors
B = variance explained by factor 1
C = variance explained by factor 2
D = variance explained by factor 3

Because the value of NSI can be positive or negative making the interpretation difficult, the Standardized Index (SI) will be calculated following Equation 5. The value of the SI will range from 0 to 100.

Equation 5

SI = [(E – MinNSI)/(MaxNSI-MinNSI)]*100

where:
E = NSI of each case
MinNSI = minimum NSI value

MaxNSI = maximum NSI value

Once a score is calculated for each city, five intervals will be generated. The highest interval will be assigned the rank of one and will indicate the highest walkability in an area unit. The middle intervals, indicating medium-high, medium, and medium-low walkability in an area unit, will be assigned the rank of two, three and four respectively. The lowest interval, indicating low walkability in an area unit, will be assigned the rank of five. This walkability rating will be used in the analysis of the correlation between walkability and economic vitality.

Question 2 and Question 3

The objectives of Question 2 and Question 3 are to measure the association between walkability and regional economic vitality. This will be accomplished by conducting two econometric models: ordinary least squares regression and two-stage least squares regression.

The ordinary least squares (OLS) model is one of the most common statistical models in social sciences. It is often a sufficient method to predict and explain the relationship of some variables on another (Hutcheson and Sofroniou 1999). However, it is not a good fit when analyzing the associations between transport and economic growth because of the simultaneity issue. As was discussed in the literature review, it may be reasonably assumed that better transport conditions (in this case walkability) result in higher economic performance of regions. There are also contradictory arguments stating that it is the economic growth that facilitates development and expansion of transport conditions. The statistical implications of not accounting for this endogeneity would result in the violation of the ordinary least squares model's assumptions. Even one endogenous variable can distort the estimates of the OLS model. The biased and inconsistent parameter estimates can cause hypotheses tests to be misleading (Gujarati 1988).

The two-stage least squares (2SLS) model will avoid the biased results that OLS model would generate as it accounts for endogeneity while OLS does not. The 2SLS model will provide relatively unbiased answers regarding the associations between walkability and regional economic vitality, as it will account for the likely simultaneity between the dependent and independent variables.

Ordinary Least Squares Model

The ordinary least squares model (OLS) will not be ultimately used to detect the linkages between walkability and regional economic vitality, but it will provide a preliminary, general picture of the analysis. It will be based on Equation 6.

Equation 6

$$V = \alpha + \beta W + \gamma E_n + \varepsilon$$

where:
V = economic vitality proxy
W = walkability
β = parameter associated with walkability
E_n = explanatory variables
γ = parameters associated with explanatory variables
α = constant term
ε = error term

Running the OLS model will allow for checking for violations of regression assumptions. These assumptions should be met so that the regression results are unbiased and consistent (Washington et al. 2003). The four major assumptions include (Hutcheson and Sofroniou 1999):

(1) normal distribution of the data (normality),
(2) linear relations (straight line) between variables (linearity),
(3) constant variance of one variable at each level of another variable (homoscedasticity),
(4) independence between the variables (freedom from multicollinearity).

If these four assumptions are violated, the problems will be remedied. While it is acknowledged that the perfect condition is unlikely to be achieved, variable transformations and options run in the Stata software package will result in relatively unbiased and consistent conclusions.

Two-stage Least Squares Model

Several strategies can be undertaken to avoid the biased results caused by endogeneity. One of them is the two-stage least square method. This model consists of two stages and uses instrumental variables (IV). A proper IV should be strongly correlated with the endogenous variable, and uncorrelated with the dependent variable. It is better to have more than one IV per endogenous variable because they can be used to increase the precision of the instruments. Also, more instruments allow for construction of tests for overidentifying restrictions and checking for the validity of the instruments. However, moderation is always advisable as too many instruments may result in bias, especially when some or all of them are weakly correlated with the endogenous variables (Gujarati 1988, Maddala 1988, Ramanathan 1989, Kennedy 2004). The main challenge will be to develop appropriate instrumental variables. In this case, the proper IVs have to be strongly correlated employment but uncorrelated with the potentially endogenous variable – walkability. Mathematically, if in the model represented by Equation 4, W was endogenous to V then the instrumental variable Z would have to satisfy two conditions:

1. relevance: $corr(Z_i, W_i) \neq 0$
2. exogeneity: $corr(Z_i, \varepsilon_i) = 0$

In stage one of the 2SLS estimator, the endogenous variable is regressed on all the independent variables, including the instruments; then the predicted values of the endogenous variables are saved and used in the second stage. In stage two, the previously predicted endogenous variable and all the other independent variables are used in the regression. Both stages are run simultaneously in order to generate standard errors that are not too small and not to accidentally exclude exogenous variable from the main model. Again, one has to be cautious with the estimation process because if weak instruments are used in the model, the 2SLS estimator can generate worse results than simple OLS model (Gujarati 1988, Maddala 1988, Ramanathan 1989, Kennedy 2004).

Question 4

Spatial analysis will determine if there is an unmeasured process that affects the outcome of the analysis. This analysis will also identify the distribution of the dependent variable values over space. The spatial regression will enhance the accuracy of the findings regarding the association between walkability and economic vitality in neighborhoods of metropolitan Washington, D.C.

A spatial regression will determine if housing vacancy rate in a census tract is affected by the observations in neighboring census tracts in the Washington, D.C. metro area. The test for spatial dependence – the Moran's I statistic – will indicate the existence of spatial autocorrelation of housing vacancy rates. The value of Moran's I can vary from negative one (perfect dispersion) to positive one (perfect correlation). The value of zero indicates random spatial pattern. The LISA cluster map will visualize the potential clustering of observations. Should the autocorrelation exist, the LM tests will reveal if the potential autocorrelations is in the dependent variable or in the residuals and will determine if Spatial Lag model or Spatial Error model is the appropriate alternative to the classical OLS regression (Ward and Gleditsch 2007, Anselin 2005).

Summary

The methodology underlying the analysis presented in Chapter IV has been presented in this chapter. These methods are designed to answer each of the research questions and include the development of walkability index, ordinary least square model, two-stage least square model and spatial regression.

CHAPTER IV
NATIONAL AND LOCAL WALKABILITY ANALYSIS

This chapter provides the analysis on which answers to the research questions will be developed. First, the walkability indices on city and neighborhood level will be developed. Then, the association between walkability and economic vitality of cities and census tracts will be examined. Finally, the analysis on the census tract level will be supplemented by examination of the spatial patterns.

Development of the Walkability Index

This section will develop the walkability indices on the levels of cities and census tracts. The development process and the distribution of walkability in cities across the United States and census tracts within the Washington, D.C. metropolitan area are discussed below.

The Walkability Index on City Level

The walkability index developed for cities includes ten indicators that have been found in the literature as associated with walkability. The walkability indicators (Table 6) were collected for the initial sample of 1,265 cities. After data screening, the observations with multiple missing values were excluded from the analysis.

In order to be reliably compared, the indicators had to be standardized. Standardization using z-scores is sensitive to non-normality of the distribution, so to correct for skewness the outliers were removed (Hutcheson and Sofroniou 1999). The final sample (after removing observations with multiple missing values and outliers) consists of 992 observations. As the distributions of the 992 cities were still non-normal, the indicators were transformed as presented in Table 6. Transformation of the data means that variables are replaced by a function of those variables; this changes the shape of the distribution (Cox 2007). Based on the theory (Hutcheson and Sofroniou 1999 and Cox 2007) and the statistical testing (*ladder* command in Stata), the most effective transformations for the walkability indicators were logarithm, square and square root. Logarithmic transformation is actually "a class of transformations, rather than a single transformation" (Osborne 2002), where natural logs are used instead of raw values. In effect, "the larger values are squeezed and the smaller values are stretched" (Statisticalconcepts 2010, MedCalc 2014). In the square root transformation, "the square root of every value is taken" (Osborne 2002). If the square transformation is applied, the value for the variables is multiplied by itself (UT 2003).

Table 6
Transformations of Walkability Indicators on the City Level

Indicator	Measure	Transformation	Name
Density	Total residential population divided by land area sq. miles	Log	popden
Travel time to work	Average travel time	Log	tttwork
Design	% of structures built before 1960	Log	bldage
Transit availability	No. of modes of public transit	Square root	transav

	taken to work		
Transit accessibility	% of people taking public transit to work	Square root	transacc
Safety from violent crime	Violent crime per 100,000 population	Log	violcr
Safety from property crime	Property crime per 100,000 population	Log	propcr
Safety from traffic	No. of pedestrians involved in fatal traffic accidents	Square root	pedacc
Average temperature	Average temperature in Fahrenheit	Square root	temp
Precipitation	Annual inches of precipitation (1971-2000 average)	Square	precip

After the transformations the distributions of the data were near-normal and satisfactory for calculation of z-scores. The z-scores of the walkability indicators for 992 cities were used to conduct the principal component analysis (PCA) and common factor analysis. Only the results of the principal component analysis are presented, because based on theory (as discussed in Chapter III) and comprehensibility of the results this technique is more suitable here.

Table 7 presents the correlations between the walkability indicators. If the 0.3 threshold is accepted as indicating correlation, all indicators but temperature and precipitation are mildly or moderately correlated with others. This suggests that including the weather-related indicators in the principal component analysis may not be warranted.

Table 7
Correlation Matrix of Walkability Indicators
City Level

	tttwork	popden	transav	transacc	pedacc	violcr	propcr	bldage	precip	temp
tttwork	1.0000									
popden	0.3380	1.0000								
transav	0.4489	0.4453	1.0000							
transacc	0.4489	0.4453	0.0667	1.0000						
pedacc	0.0975	0.1249	0.0667	0.0667	1.0000					
violcr	-0.0447	0.1435	0.0431	0.0431	0.3557	1.0000				
propcr	-0.3913	-0.1865	-0.2403	-0.2403	0.2519	0.6562	1.0000			
bldage	-0.3286	0.2726	0.0903	0.0903	0.1265	0.3390	0.2613	1.0000		
precip	-0.1003	-0.1776	-0.0874	-0.0874	0.0142	0.1644	0.2814	0.0125	1.0000	
temp	0.1128	0.0138	0.1152	0.1152	-0.0421	0.0079	-0.1044	0.1903	-0.1489	1.0000

In the first attempt, the principal component analysis generated four components comprising the ten walkability indicators. The factors presented in Table 8 could be logically interpreted as representing accessibility (population density, transit availability and transit accessibility), weather (average temperature and precipitation), safety (violent crime, property crime and traffic accidents including pedestrians), and design (travel time to work and building age). However, the Cronbach's alpha rule-of-thumb indicates poor internal consistency in the second component – the weather. The Cronbach's alpha value for the component comprising the weather indicators is 0.1790, which according to guidelines by George and Mallery (2003) and Kline (2000) is unacceptable. Therefore, the second attempt to principal component analysis excluded the weather-related indicators of walkability.

Table 8
Principal Component Analysis with Weather Indicators: Oblique Rotation

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
Population density	0.5256				0.4585
Transit availability	1.0192				0.0754
Transit accessibility	1.0192				0.0754
Av. Temperature		-0.5388			0.5519
Annual precipitation		0.9021			0.3159
Pedestrian accidents			0.8650		0.2970
Violent crime			0.6808		0.3507
Property crime			0.4827		0.2641
Travel time to work				-0.5527	0.2838
Building age				0.8780	0.2088
Eigenvalue	2.86785	1.99985	1.24857	1.00206	
Proportion	0.2868	0.2000	0.1249	0.1002	
Cronbach's α	0.8363	0.1790	0.6275	0.4954	

The principal component analysis without the weather indicators generated three components (Table 9). The scree plot confirmed the number of the components. Both, the orthogonal and oblique rotations generated similar results. The oblique rotation allows for correlation between the indicators and it will be analyzed in this dissertation because, as was discussed in Chapter III, it can be reasonably assumed that the components are correlated (Hutcheson and Sofroniou 1999).

Table 9
Principal Component Analysis without Weather Indicators: Oblique Rotation

Variable	**Factor 1**	**Factor 2**	**Factor 3**	**Uniqueness**
Population density	0.7177			0.4696
Transit availability	0.9357			0.1331
Transit accessibility	0.9357			0.1331
Violent crime		0.7760		0.3264
Property crime		0.6487		0.2945
Pedestrian accidents		0.7847		0.3915
Travel time to work			-0.6425	0.2343
Building age			0.8810	0.1820
Eigenvalue	2.78379	1.97035	1.08147	
Proportion	0.3480	0.2463	0.1352	
Cronbach's α	0.8363	0.6275	0.4954	

It is apparent from Table 9 that population density, transit availability and transit accessibility load highly on Factor 1, violent crime, property crime, and pedestrian accidents load highly on Factor 2, and travel time to work and building age have high loadings on Factor 3. The first factor comprises indicators associated with pedestrian accessibility in cities while the second factor is related to personal and property safety. The third factor contains indicators associated with the design of cities. From this point, the analysis will proceed with three components: Accessibility, Safety, and Design, instead of eight individual walkability indicators.

According to George and Mallery (2003) and Kline (2000), the Cronbach's alpha value would be described as good for Factor 1, acceptable for Factor 2, and borderline acceptable for Factor 3. Overall, the Cronbach's alpha rule-of-thumb indicates that the three components are reliable. Next, the factor scores were assigned. The Kaiser-Meyer-Olkin test showed that the usage of PCA was warranted.

The three components are not equally important in explaining walkability: Accessibility explains 34.80 percent of the variation, Safety explains 24.63 percent, and Design explains 13.52 percent of the variation. Combined, the three components explain 72.95 percent of the variation. This is accounted for when calculating the index scores, as described in Chapter III (Equation 4 and Equation 5). After the index is standardized so that all the values are positive (and range from 0 to 100), the scores are divided into five intervals. The rank of 1 indicates the highest level of walkability and the rank of 5 indicates the lowest walkability (Table 10).

Table 10
Walkability Ranking Profile: City Level

Rank	**Standardized Index Range**	**Definition**
1	80 – 100	High walkability
2	60 – 79.99	Medium-high walkability
3	40 – 59.99	Medium walkability
4	20 – 39.99	Medium-low walkability
5	0 – 19.99	Low walkability

An example of Washington, D.C. is presented below to demonstrate the steps in generation of the walkability ranking on a city level. The standardized index (SI) of Washington, D.C. (80.42) is in the highest interval of the total SI for all the cities, so it is assigned the rank of 1 indicating the highest level of walkability.

Equation 4

NSI_{City} = (B/A)(Factor 1 score) + (C/A)(Factor 2 score) + (D/A)(Factor 3 score)

$NSI_{\text{Washington, D.C.}}$ = (34.80/72.95)*1.63 + (24.63/72.95)*2.27 + (13.52/72.95)*1.07 = 1.74

Equation 5

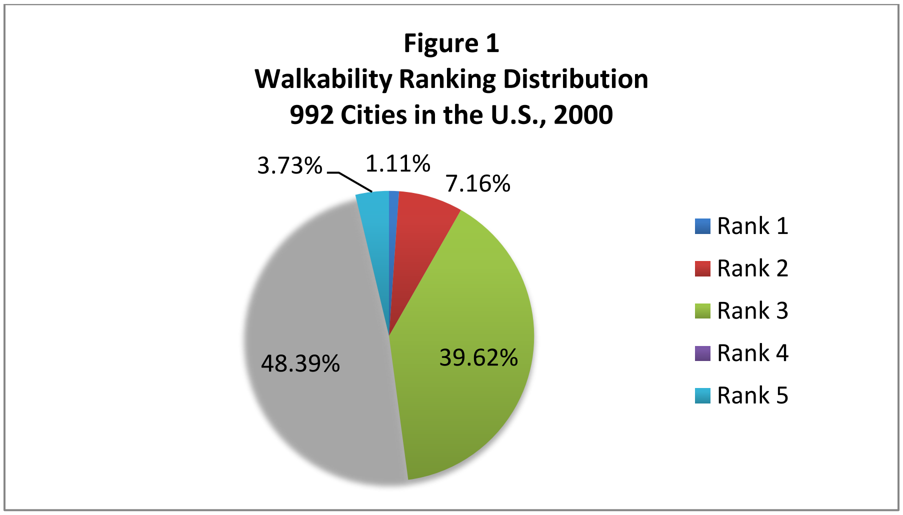
SI_{City} = [(E – MinNSI)/(MaxNSI-MinNSI)]*100

$SI_{\text{Washington, D.C.}}$ = [(1.74- (-1.77))/(2.60 - (-1.77))]*100 = 80.42

where:
A = total variance explained by all the factors
B = variance explained by Factor 1
C = variance explained by Factor 2
D = variance explained by Factor 3
E = NSI of each case
MinNSI = minimum NSI value
MaxNSI = maximum NSI value

Philadelphia, PA is the most walkable city in the sample, with the SI of 100, while Vestavia Hills, AL is the least walkable city with the SI of 0. Out of the sample of 992 cities, 11 (or 1.1%) are in the most walkable category, with the rank of 1. These cities include Philadelphia, PA, Miami, FL, San Francisco, CA, Dallas, TX, Detroit, MI, Jersey City, NJ, Denver, CO, Boston, MA, Oakland, CA, Newark, NJ, and Washington, DC. The rank of 2, indicating medium-high walkability was assigned to 71 cities, accounting for 7.16 percent of the entire sample. The most walkable cities with ranks of 1 and 2 are located in the north-east, along the West coast and in the South of the U.S.

Walkability in most cities was found to be moderate or medium-low, as reflected by rank 3 (with 393 cities) and rank 4 (with 480 cities). These ranks account for 39.62 percent and 48.39 percent of the sample respectively. These cities are dispersed throughout the country. The 37 least walkable cities, ranked 5, make 3.73 percent of the sample and cluster in the Great Lakes area and in the South. The list of all the cities and their walkability ranks is presented in the Appendix.



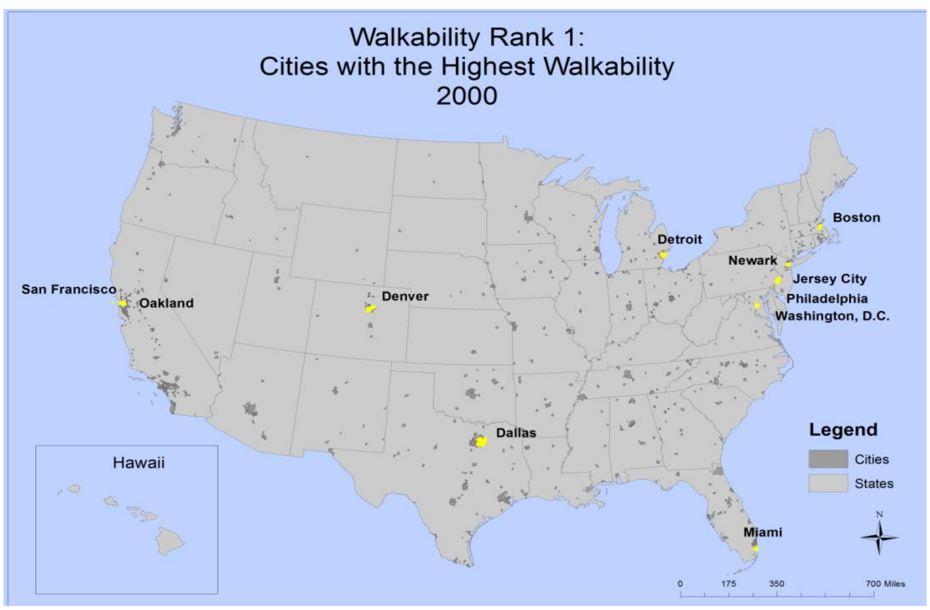


Figure 2

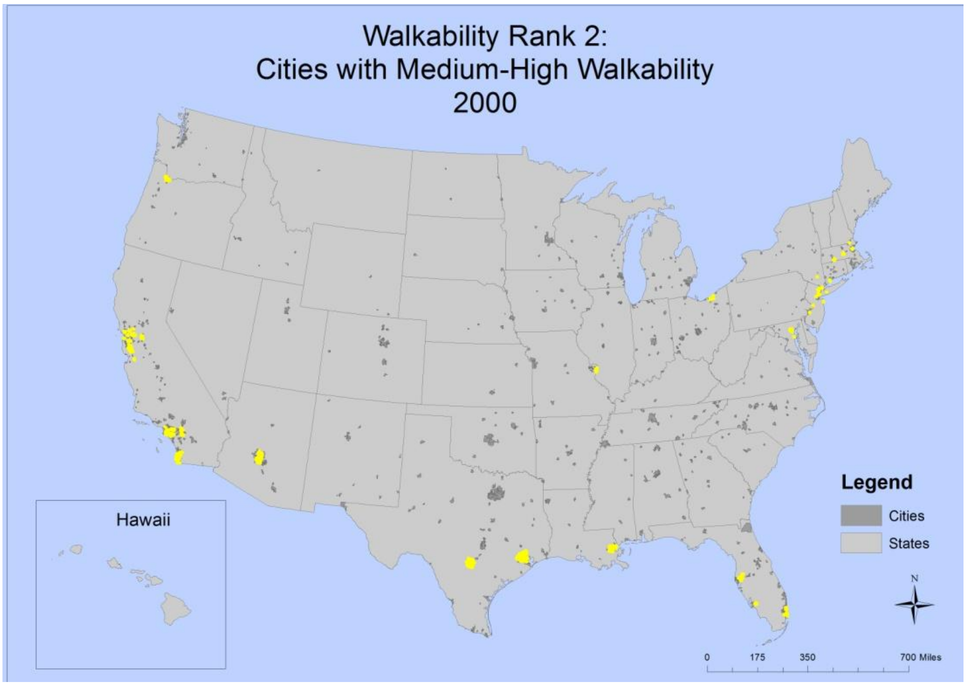


Figure 3

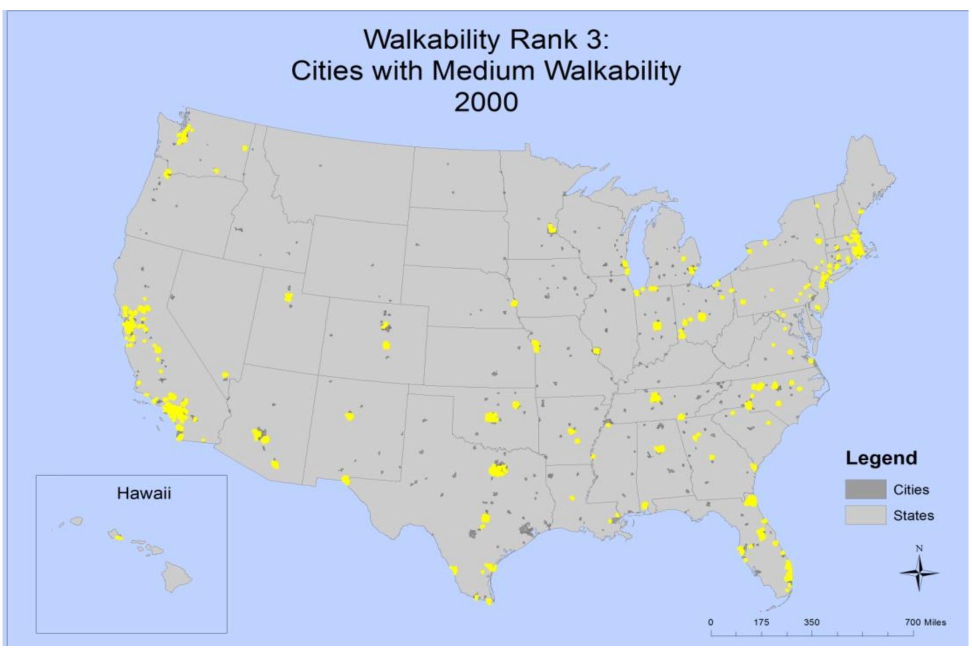


Figure 4

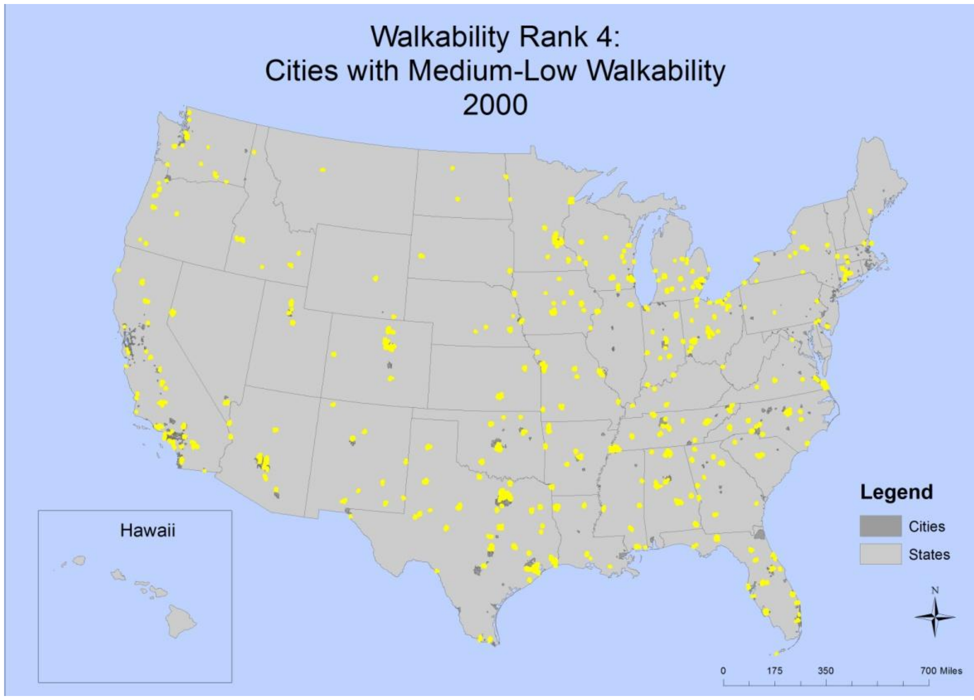


Figure 5

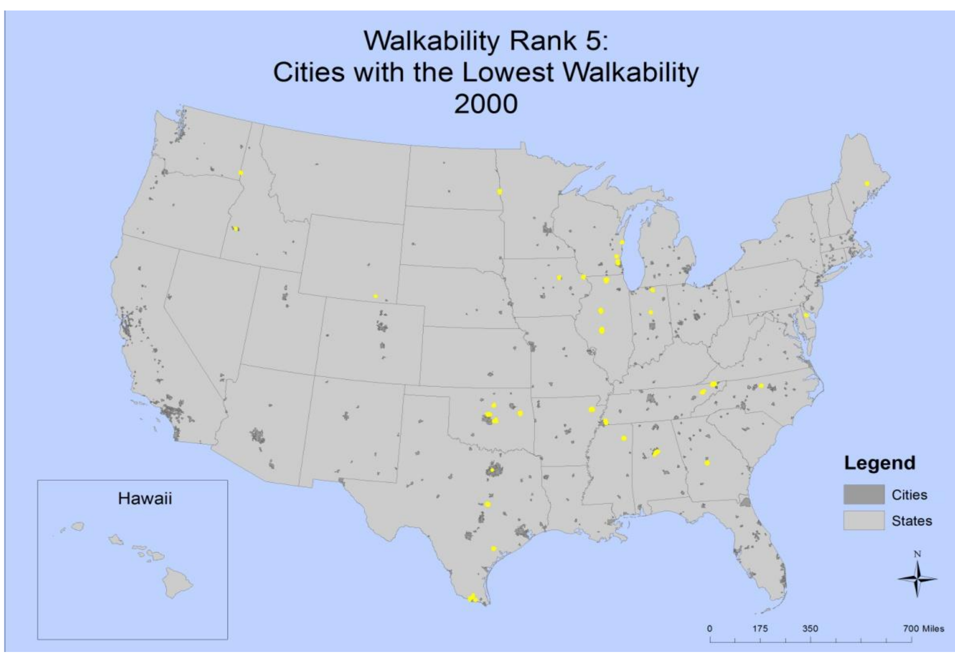


Figure 6

The Walkability Index on the Census Tract Level; Washington Metropolitan Area

The development of the walkability index on the neighborhood level was similar to the process on the city level. The walkability index includes nine indicators that have been found in the literature as associated with walkability. The walkability indicators (Table 11) were collected for the sample of 1,359 census tracts within the Washington, D.C. metropolitan area.

The distributions of the data were non-normal, so the data were transformed as shown in Table 4.6. The transformations that most effectively improved the distributions were logarithm and square root. Once the distributions of the walkability indicators were near-normal, the indicators were standardized using z-scores.

Table 11
Transformations of Walkability Indicators on the Census Tract Level

Indicator	Measure	Transformation	Name
Population density	Total residential population divided by land area sq. miles	Log	popden
Job density	Total employment divided by land area sq. miles	Log	jobden
Retail density	Total retail businesses divided by land area sq. miles[1]	log	retden
Design	% of structures built before 1960	Square root	bldage
Connectivity	Average block face size in sq. meters	Log	blcksize
Travel time to work	Average travel time	Log	tttwork
Transit availability	No. of modes of public transit taken to work	Log	transav
Transit accessibility	% of people taking public transit to work	Log	transacc
Safety from crime	EASI Total Crime Index[2] (includes violent and property crime)	Square root	crime

[1] Calculation of the retail density followed the method of Cervero and Kockelman (1997). Retail represents the number of commercial businesses including "convenience stores, supermarkets, restaurants and eateries, general merchandise, specialty stops, and entertainment and recreational-oriented establishments" (Cervero and Kockelman 1997).
[2] EASI Analytic created the crime index where each index value indicates how an area compares to the national average. The national average is 100. The data used by EASI Analytic come from Federal Bureau of Investigation (FBI) & Uniform Crime Reporting (UCR) Program. The data include reported crimes. The weights used for the index are: Murder 20, Forcible Rape 10, Robbery 6, Aggravated Assault 6, Burglary 3, Larceny 1 and Motor Vehicle Theft 1 (SimplyMap 3.0 2014).

The principal component analysis and factor analysis resulted in similar conclusions. Again, only the results of the principal component analysis are presented because based on theory (as discussed in Chapter III) and comprehensibility of the results this technique is more suitable. The correlation matrix presented in Table 12 shows that the indicators are correlated.

Table 12
Correlation Matrix of Walkability Indicators
Census Tract Level

	popden	jobden	retden	bldage	blcksize	tttwork	transav	transacc	crime
popden	1.000								
jobden	0.6885	1.000							
retden	0.7886	0.6701	1.000						
bldage	0.3029	0.2401	0.2237	1.000					
blcksize	-0.8422	-0.7271	-0.7026	-0.3923	1.000				
tttwork	-0.3249	-0.4782	-0.3621	-0.2975	0.4106	1.000			
transav	0.3479	0.2156	0.2425	0.1374	-0.2730	0.0261	1.000		
transacc	0.6393	0.4670	0.5235	0.3727	-0.5346	-0.0913	0.5578	1.000	
crime	0.2474	0.2287	0.2367	0.5843	-0.2801	-0.1454	0.1450	0.3631	1.000

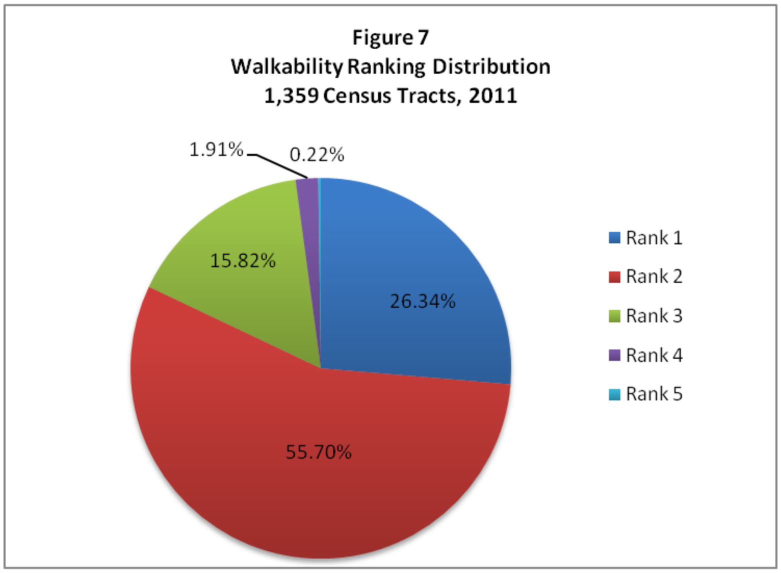
Table 13
Principal Component Analysis: Oblique Rotation
Census Tracts

Variable	Factor 1	Factor 2	Factor 3	Uniqueness
Population density	0.8165			0.1633
Block face size	-0.8728			0.1933
Job density	0.9206			0.2200
Retail density	0.8967			0.2703
Crime		0.8928		0.2133
Building age		0.8925		0.1974
Transit availability			0.6116	0.4347
Transit accessibility			0.5347	0.2341
Travel time to work			0.8649	0.2947
Eigenvalue	4.13061	1.37189	1.27634	
Proportion	0.4590	0.1524	0.1418	

Cronbach's α	0.9037	0.7412	0.5330

The principal component analysis generated three factors (Table 13). Factor 1 comprises four walkability indicators – population density, block face size, job density and retail density – and explains 45.9 percent of the variation. Two indicators – crime and building age – load highly on Factor 2 explaining 15.24 percent of the variation. Transit availability, transit accessibility and travel time to work load highly on Factor 3 and explain 14.18 percent of the variation. The reliability of components is satisfactory; according to George and Mallery (2003) and Kline (2000), the values of Cronbach's alpha for the three factors are excellent, good and satisfactory, respectively. The usage of PCA was warranted as indicated by the Kaiser-Meyer-Olkin test.

Next, the non-standardized index was calculated and then standardized so that all the values are positive and range from 0 to 100. As in the analysis on the city level, the scores were divided into five ranks: the rank of 1 indicates the highest walkability and the rank of 5 indicates the lowest walkability (Table 10).



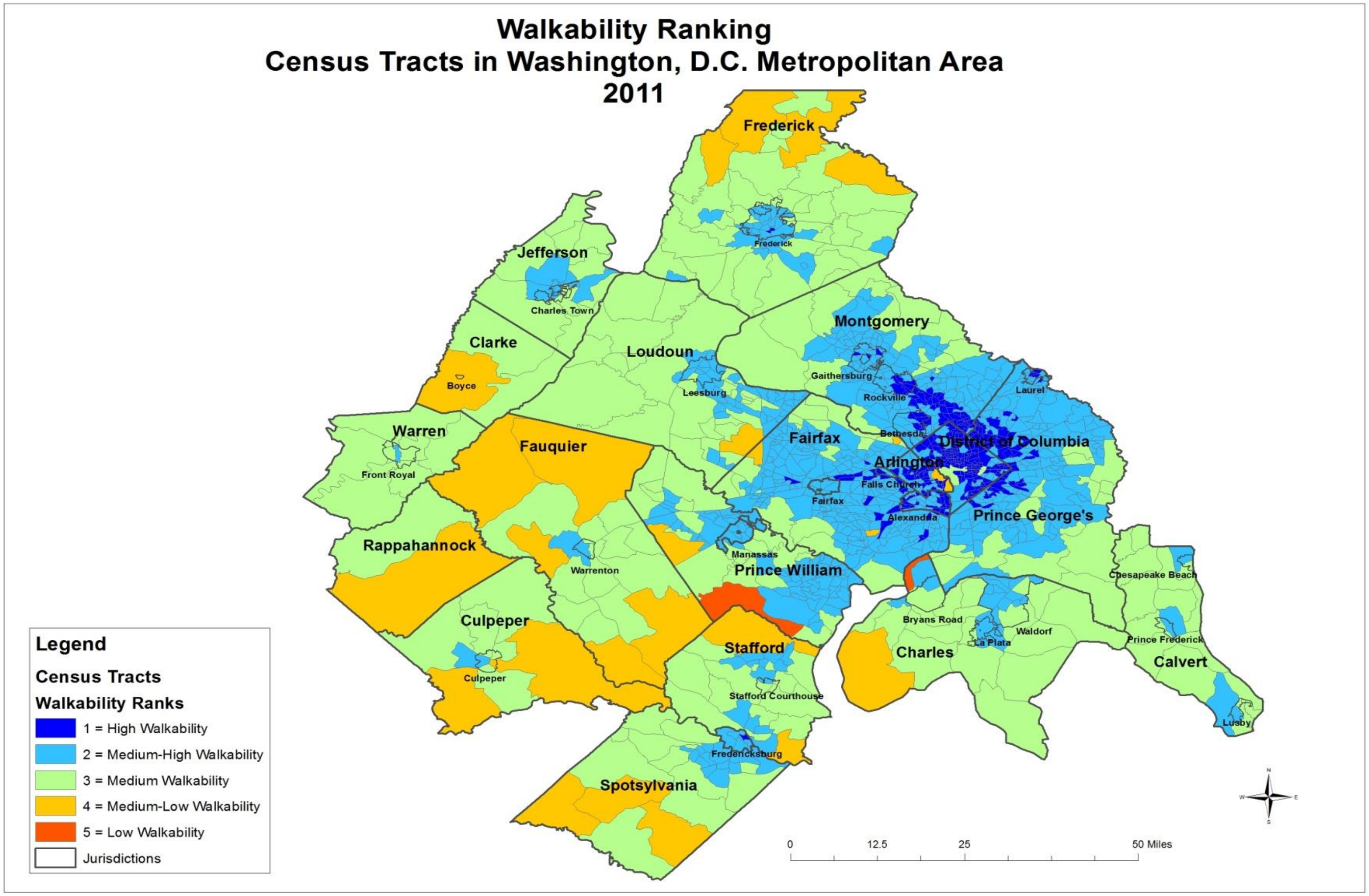
The ranking shows that the Washington, D.C. metropolitan area is walkable. High walkability was indentified in 82.04 percent of the census tracts. These highly walkable tracts are clustered in the core of the metropolitan area.

The 358 most walkable census tracts (ranked 1) account for 26.34 percent of the metropolis and cover the majority of the District of Columbia and the immediate parts of the adjacent jurisdictions: Montgomery and Prince George's Counties in MD, Arlington and Fairfax Counties in VA, and the Cities of Alexandria and Falls Church in VA. Only four census tracts in the outlying areas were found highly walkable and they include three tracts in the city of Frederick (Frederick County), MD, and one tract in the City of Fredericksburg, VA.

Rank 2 indicating medium-high walkability was assigned to the largest number of census tracts in metropolitan Washington. These 757 census tracts, accounting for 55.70 percent of the region, surround the most highly walkable core of the metropolis. These census tracts cover parts of the District of Columbia, the majority of Fairfax and Arlington Counties, VA, parts of Prince William and Loudoun Counties, VA, Cities of Fairfax, Alexandria, Falls Church, VA, and Montgomery and Prince George's Counties, MD. There are also clusters of medium-high walkable census tracts in the outer jurisdictions of the Washington metropolitan area including Frederick and Charles Counties, MD, Stafford and Spotsylvania Counties, VA, City of Fredericksburg, VA, and Jefferson County, WV.

Medium walkability (rank 3) was identified in 15.82 percent of the census tracts. These moderately walkable tracts cover most of the suburban areas of metropolitan Washington. Medium-low walkability (rank 4) was identified in less than 2 percent of the census tracts. These rather unwalkable census tracts are dispersed in the outer parts of the metropolitan area, although there are some tracts ranked 4 in the core of the region (two tracts in Arlington County and three tracts in Fairfax County).

Only 3 census tracts, or 0.22 percent of the sample, were assigned the rank of 5 indicating the lowest walkability. Two of these tracts (located in Charles and Calvert Counties in MD) are entirely covered by water; they have no land area. Therefore, the least walkable census tract that contains land area is located in Prince William County in VA.



Walkability Ranking
Census Tracts in Washington, D.C. Metropolitan Area
2011
Frederick
Jefferson
Charles Town
Clarke
Boyce
Loudoun
Leesburg
Montgomery
Gaithersburg
Rockville
Laurel
Bethesda
District of Columbia
Arlington
Falls Church
Fairfax
Alexandria
Prince George's
Warren
Front Royal
Fauquier
Rappahannock
Warrenton
Manassas
Prince William
Culpeper
Stafford
Stafford Courthouse
Fredericksburg
Spotsylvania
Charles
Bryans Road
La Plata
Waldorf
Chesapeake Beach
Prince Frederick
Calvert
Lusby
Legend
Census Tracts
Walkability Ranks
1 = High Walkability
2 = Medium-High Walkability
3 = Medium Walkability
4 = Medium-Low Walkability
5 = Low Walkability
Jurisdictions
0
12.5
25
50 Miles

Figure 8

Summary

The newly developed index shows that walkability is limited in the majority of American cities analyzed. Only eight percent of the sample of 992 cities is characterized as highly walkable (this statistic combines the two highest ranks of walkability). The walkability index developed for neighborhoods in the Washington, D.C. metropolitan areas shows that highly walkable census tracts are predominantly clustered in the District of Columbia and other urban centers across the metropolitan area.

Walkability and Economic Vitality in Cities

This section will analyze the association between walkability and economic vitality of cities as measured by employment. The descriptive statistics and the econometric analysis are presented below.

Descriptive Statistics

The sample consists of 992 observations. Table 14 presents the descriptive statistics including the means, standard deviations, and minimum and maximum values of the variables included in the analysis.

Table 14
Descriptive Statistics

Variable	Obs.	Mean	St. Dev.	Min	Max
employment (dep.var.)	992	60.42	6.265	39.4	77.5
walkability	992	2.53	0.730	1	5
population	992	94,818.12	149,809	25,099	1,957,018
% of female population	992	51.36	1.512	42.8	56.9
median age	992	34	4.38	21	52
% of population with a bachelor's degree or higher	992	17.07	7.80	1.5	41.9
% of population with a high school degree as the highest level of education	992	25.46	7.12	5.6	49.9
% of white population	992	72.68	18.54	3.8	97.9
% of black population	992	11.68	15.36	0.2	89.5
% of hispanic population	992	15.93	18.77	0.6	96.4
% of families under poverty level	992	9.99	6.67	0.8	46.7
% of foreign-born population	992	13.41	11.83	0.7	72.1

Ordinary Least Square Estimator

The ordinary least square (OLS) estimator was run to provide an overview of the model quality and a baseline to test for regression assumptions violations. The fit of the OLS model is satisfactory with 61.83 percent of the variation in employment being explained by the independent variables. The Variance Inflation Factor (VIF) values for all the variables are below 10, so there is no multicollinearity problem (Gujarati and Porter 2009). The robust option of the OLS estimator controls for the heteroskedasticity problem. However, the distributions of the variables are skewed. The *ladder* command in Stata showed that the best transformation for most of the variables was into logarithmic form. For two exceptions (population, and % of white population), the log transformation was the second best option. Logarithm form was chosen because it allows for the most comprehensive interpretation. The logarithm transformation corrected the skewness and the distributions are near-normal and near-linear.

Next, the OLS regression was run with all the variables transformed into logarithmic terms. The fit of the model is weaker than before transformations; 53.38 percent of the variation is explained by the independent variables. However, the transformations of the variables were retained because they corrected the skewness and improve the comprehensibility of the results. The test for omitted variable bias (ovtest) showed that there is a sufficient number of explanatory variables (p-value = 0.5420). Also the test checking the model specification (*linktest*) shows that additional variables are not necessary in this model (p-value = 0.588).

The OLS estimator shows that walkability is positively associated with employment in cities. On average, one percent increase in walkability is associated with two percent increase in employment, or else being equal. This is not a final conclusion, because based on theory (as discussed in Chapters II and III), it is expected that there is endogeneity between walkability and employment. If the endogeneity was present, this condition must be addressed. The two-stage least square regression is one of the options to account for endogeneity.

<u>Two-stage Least Square Estimator</u>

The two-stage least square regression requires using instrumental variables. Five variables were tested as potential instruments[3]:

(1) percentage of residential structures with 20 units and more (units20),

(2) percentage of residential structures with 10 units and more (units10),

(3) percentage of people biking to work (bike),

(4) percentage of people walking to work (walk),

(5) percentage of households with no vehicles (noveh).

In theory, the share of residential structures with 20 units and more, and 10 units and more are related to walkability because they indicate high residential density and pedestrian-oriented design of regions (multi-family structures are rare in spread-out, car-oriented areas). Biking- and walking-oriented environments are associated in theory and practice (as was discussed in Chapter II). Moreover, the proportion of people biking to work was considered as one of the dimensions of a walkable area in the analysis by Zick

[3] The potential instrumental variables were transformed into logarithmic terms due to non-normal distributions. The transformations corrected the non-normality problem.

et al. (2013). The share of people walking to work and the percentage of households with no vehicle has logical connection to walkability. If a region is unwalkable, the percentage of people walking to work is expected to be lower than in a walkable area. Similarly, the percentage of households with no vehicle is likely to be lower in an unwalkable area than in a walkable region.

Table 15 shows the correlations between the potential instrumental variables, the dependent variable (employment), and the expected endogenous variable (walkability). Since the instruments must be correlated with the endogenous variable and uncorrelated with the dependent variable, only the variable for the percentage of residential structures with 20 units or more can be used in this model. None of the remaining four options meets the criteria. The correlation between walkability and the percentage of residential structures with at least 20 units is weak and it would be preferable for the correlation to be stronger. However, values that exceed 0.3 are considered as correlated (Hutcheson and Sofroniou 1999), so this variable is an acceptable instrument.

Although it is more efficient if there are two instruments per endogenous variable (Woolridge 2009), it is correct to use only one instrument. As Cameron and Trivedi (2005, p. 41) state, "[t]he order condition requires that the number of instruments must at least equal the number of endogenous components, so that $r \geq K$" (where r = instrument and K = endogenous variable). This model is called just-identified.

Table 15
Correlations between Potential Instrumental Variables

Instrumental Variables	Employment	Walkability
% of structures with at least 20 units	0.0381	0.3317
% of structures with at least 10 units	-0.4291	0.1674
% of people biking to work	-0.0727	0.1332
% of people walking to work	-0.2875	0.0967
% of households with no vehicle	-0.4376	0.2017
average no. of vehicles per household	0.3304	-0.1111

The two-stage least square model was run with the percentage of residential structures with 20 units or more as the instrument. About 40.34 percent of the variance in employment can be explained by the independent variables. In the first stage, the instrumental variable is statistically significant at one percent significance level which suggests that the instrument is strong. However, this indication is contradicted in the second stage, as the coefficient for walkability is statistically insignificant (p-value = 0.176). Moreover, the post-estimation tests for the validity of the instrumental variable indicate that the instrument is weak. The partial R^2 is low ($R^2 = 0.01$) and the F-statistic of 13.72 slightly exceeds the requirement of 10. It is concluded that the instrumental variable is weak and does not suffice to bring reliable results. In conclusion, the results using the instrument are likely to be less reliable than the results of the OLS model.

The weakness of the instrument may not be a problem because the post-estimation test for endogeneity does not indicate endogeneity. The null hypothesis of the Durbin-Wu-Hausman test is that the variables are exogenous. The p-value is 0.1938, so it exceeds the 5 percent and even 10 percent significance level thresholds. The hypothesis that the variables are exogenous cannot be rejected. The conclusion is that the two-stage least square model is not appropriate because endogeneity is not identified. Therefore, the weakness of the instrument is irrelevant. The OLS model is more appropriate in this analysis than the two-stage least square model.

Based on the OLS regression output, one percent increase in walkability is associated with an increase in employment by two percent, on average, ceteris paribus. Walkability is statistically significant at five percent significance level.

<u>Other Explanatory Variables</u>

Education has the highest association with employment out of the analyzed explanatory variables. One percent increase in the population with a high-school diploma as the highest level of education is associated with an increase in employment by 11 percent, on average, ceteris paribus, while one percent increase in population with a bachelor's degree or higher is associated with ten percent increase in employment, on average, ceteris paribus. Both education variables are statistically significant at one percent significance level.

Other statistically significant explanatory variables positively associated with employment include population, percent of white population, and percent of Hispanic population. Median age and the percentage of families under poverty level are negatively associated with employment and both are statistically significant at one percent significance level. Three variables (% of female population, % of black population and % of foreign-born population) are not statistically significant.

Summary

The results of the analysis indicate that walkability is positively associated with economic vitality of cities as measured by employment. This conclusion supports the hypothesis that on average walkable cities experience higher employment rates than non-walkable cities. The findings support the previous research indicating that active and livable cities contribute to economic prosperity of the regions.

The analysis results do not support the theory that there is simultaneity between walkability as a means of transportation and economic vitality. This conclusion is to be considered with caution as the structure of the walkability index may affect the results. However, it is beyond the scope of this dissertation to further examine the issue of endogeneity.

Table 16

Results of the Ordinary Least Squares and Two-Stage Least Squares Estimators

Variables	**OLS Coefficients**	**Two-stage Least Squares**	
		1st Stage Coef.	**2nd Stage Coef.**
Walkability Index	0.021775**		0.1446745
IV: % of residential structures with 20 units or more		0.464594*	
population	0.0076291**	0.0754103*	-0.0030888
% of female population	0.1132449	-0.443515	0.1056322
median age	-0.2662855*	0.1634987**	-0.286408*
% of population with a bachelor's degree or higher	0.1013981*	-0.1248446*	0.1179052*
% of population with a high school degree as the highest level of education	0.1183487*	-0.0133038	0.1216469*
% of white population	0.0431845*	-0.l687608*	0.0607359*
% of black population	-0.0032755	0.233933*	-0.0071086**
% of Hispanic population	0.0077164***	0.0028724	0.0084916**
% of families under poverty level	-0.0718913*	-0.052439*	-0.0662555*
% of foreign-born population	0.0211368	0.1184113*	0.0035273
N	992	988	988
F-Test	95.16	67.87	
Wald chi2			861.30
Prob>F	0.0000	0.0000	0.0000
R^2	0.5338	0.4100	0.4631
Adj. R^2		0.4034	

* $p < 0.01$
** $p < 0.05$
*** $p < 0.1$

Walkability and Economic Vitality in the Metropolitan Washington, D.C.

This section will analyze the association between walkability and economic prosperity of census tracts in the Washington, D.C. metropolitan area as measured by housing vacancy rates. The descriptive statistics and the econometric analysis are discussed below.

Descriptive Statistics

The sample consists of 1,359 census tracts within the Washington metropolitan area. Table 17 presents the descriptive statistics of the variables included in the analysis.

Table 17
Descriptive Statistics

Variable	Obs.	Mean	St. Dev.	Min	Max
housing vacancies (dep.var.)	1359	6.0475	5.154	0	100
walkability	1359	1.9396	0.717	1	5
travel time to work	1359	33.446	6.453	0	56.4
no. of transportation modes	1359	2.1972	0.845	0	4
population	1359	4172.1	1640.3	0	15,899
median housing value	1359	436,730	175,158	0	1,000,000
age (median)	1359	37.008	6.334	0	84.8
% of female population	1359	51.078	5.452	0	70.47
% of population 65-years-old and over	1359	10.156	6.691	0	89.2
% of black population	1359	27.122	28.941	0	98.38
% of population with a high-school diploma as highest level of education	1359	20.493	11.705	0	100

Ordinary Least Square Estimator

The fit of the ordinary least square estimator with the robust option (to control for heteroskedasticity) shows that 24.15 percent of the variation in housing vacancies is explained by the independent variables. The Variance Inflation Factor (VIF) test concludes that there is no multicollinearity problem as all the values are below 10 (Gujarati and Porter 2009). The distributions of the variables are skewed, so the variables were transformed into logarithmic terms (as suggested by the *ladder* command in Stata). As a result, the transformation corrected for skewness and non-linearity and allows for comprehensive interpretation of the coefficients.

The fit of the OLS model run with transformed variables is stronger than before transformations; 38.59 percent of the variation is explained by the independent variables. There is no omitted variable bias as confirmed by the *ovtest* (p-value = 0.3634) and *linktest* (p-value = 0.351).

The OLS estimator shows that walkability is statistically significant at one percent significance level and positively associated with housing vacancies in the census tracts. On average, one percent increase in walkability is associated with 32 percent decrease in housing vacancies, all else being equal. Final conclusion cannot be drawn at this stage as, based on theory (as discussed in Chapters II and III), it is expected that there is endogeneity between walkability and employment. The following section analyzes this condition.

Two-Stage Least Square Estimator

On the census tract level, four variables were tested as potential instruments. The rationale behind the choice of these variables is the same as described in the section analyzing walkability in cities. The variables considered as instruments included[4]:

(1) percentage of residential structures with 20 units and more (units20),

(2) percentage of residential structures with 10 units and more (units10),

(3) percentage of households with no vehicles (noveh),

(4) and average number of vehicles per household (avveh).

The correlations matrix presented in Table 18 shows that only the variable for the percentage of structures with 20 units and more is correlated with the potential endogenous variable – walkability – and uncorrelated with the dependent variable – housing vacancies. As in the analysis of cities, it would be preferable if there were more than one instrument. However, as indicated by Woolridge (2009), it is acceptable to use only one instrument per endogenous variable.

Table 18
Correlations between Potential Instrumental Variables

Instrumental Variables	**Housing vacancies**	**Walkability**
% of structures with at least 20 units	0.2868	-0.4039
% of structures with at least 10 units	0.3398	-0.4071
% of households with no vehicle	0.5340	-0.6233
average no. of vehicles per household	-0.5088	0.6572

[4] The potential instrumental variables were transformed into logarithmic terms due to non-normal distributions. The transformations corrected the non-normality and non-linearity problem.

The first stage of the two-stage least square (2SLS) model run with the percentage of residential structures with 20 units and more as the instrument shows that 39.29 percent of the variance in housing vacancies can be explained by the independent variables. The instrumental variable is statistically significant at the one percent significance level suggesting that the instrument is strong. The strength of the instrument is confirmed in the second stage, as the coefficient for walkability is statistically significant at the one percent significance level. The post-estimation tests for the validity of the instrumental variable also indicate that the instrument is strong: the F-statistic of 59.6969 exceeds the requirement of 10 and the partial R^2 is 0.0648. In conclusion, the instrumental variable is strong and brings reliable results. The Durbin-Wu-Hausman post-estimation test indicated endogeneity between walkability and housing vacancies (p-value = 0.0000). Therefore, the two-stage least square model is the appropriate estimator in this case.

Housing in walkable census tracts is highly demanded. Walkability has the highest impact on housing vacancies out of the examined independent variables. On average, one percent increase in walkability is associated with 147 percent decrease in housing vacancies, all else being equal.

There is a concern regarding spatial dependence of walkability, as Figure 8 indicated spatial clustering of walkability over the Washington metropolitan area. This concern will be addressed in the next section.

Other Explanatory Variables

Other explanatory variables indicating high demand for housing in census tracts include the number of available transit modes and median housing value (statistically significant at 1% significance level). One percent increase in transit availability is associated with a 56 decrease in housing vacancies, on average, ceteris paribus. All else being equal, one percent increase in median housing value is associated with a 38 percent decrease in housing vacancies, on average.

The percentage of black population and the percentage of population with a high school diploma or less are both statistically significant (at 5% and 10% significance levels, respectively) and positively associated with housing vacancies. On average, one percent increase in black population is associated with seven percent increase in housing vacancies, ceteris paribus, while one percent increase in population with a high school diploma or less is associated with a ten percent increase in housing vacancies, ceteris paribus.

Travel time to work, the percentage of female population, median age of population, and the percentage of population 65-years-old and older are statistically insignificant.

Summary

The results of the analysis on the census tract level confirm the prior theoretical and empirical research suggesting a positive relationship between walkability and economic prosperity. The econometric analysis shows that walkability has a strong, positive association with economic vitality as measured by housing vacancies. In other words, walkable regions are attractive residential destinations.

These findings also support the theory claiming that there is endogeneity between transportation, in this case walkability, and economic vitality. However, the results are not distorted by the simultaneity between the two phenomena, because the two-stage least square model accounts for endogeneity and allows to draw unbiased conclusions.

It is expected that there is spatial dependence of walkability (as indicated by Figure 8). Failure to account for spatial autocorrelation results in inefficiency of the regression findings. Spatial dependency is addressed in the next section.

Table 19
Results of the Ordinary Least Squares and Two-Stage Least Squares Estimators

Variables	**OLS**	**Two-stage Least Squares**	
	Coefficients	**1st Stage Coef.**	**2nd Stage Coef.**
Walkability Index	-0.3225305*		-1.470972*
IV: % of structures with 20 units and more		-0.0550195*	
travel time to work (average)	-0.3337045**	0.287713**	-0.0648465
no. of transportation modes	-0.2826588*	-0.3527789*	-0.5654105*
Population	-0.1473416*	0.0798891**	-0.053217
median housing value	-0.488568*	0.0.0235525	-0.3838076*
age (median)	-0.5441132*	0.442635*	0.0701503
% of female population	-0.6169871**	0.0683565	-0.3531971
% of population 65-years-old and over	0.2838396*	-0.1133136*	0.0876447
% of black population	0.1753328*	-0.0893602*	0.0789133**
% of population with a high-school diploma as highest level of education	-0.0053233	0.1060231*	0.1083442***
N	1,299	930	930
F-Test	79.97	94.43	
Wald chi2			348.81
Prob>F	0.0000	0.0000	0.0000
R^2	0.3859	0.3995	0.1062
Adj. R^2		0.3929	

* $p < 0.01$
** $p < 0.05$
*** $p < 0.1$

Spatial Analysis on the Census Tract Level; Metropolitan Washington, D.C.

Spatial analysis allows learning more about the distribution of the variable values over space and better understanding of the relationships among the variables. The spatial analysis will enrich the accuracy of the findings regarding the association between walkability and economic vitality in neighborhoods of metropolitan Washington, D.C.

Spatial Distribution of Housing Vacancy Rates

Figure 9 presents the distribution of housing vacancy rates over the Washington, D.C. metropolitan area. The map applies the Jenks natural breaks classification method.[5] This classification scheme allows preserving the actual clustering of data values, minimizing the within-class difference and maximizing the between-class difference (Price 2010).

Census tracts with the lowest rates of housing vacancies surround the District of Columbia, especially to the North and West. The areas with the highest vacancies are located not only in the outlying regions of the metropolitan area (Stafford and Spotsylvania Counties in VA and Charles and Calvert Counties in MD), but also are scattered across the District of Columbia and Prince George’s County, MD. Figure 10 zooms in to the District of Columbia comparing the spatial distribution of walkability ranks and housing vacancies in the census tracts. It is evident that, geographically, high walkability does not align with low housing vacancy rates. This observation is particularly evident in the south-eastern part of the District of Columbia, where walkability is high (ranks 1 and 2), but the demand for housing is low. This is an

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[5] Jenks natural breaks classification method divides the data based on “naturally occurring gaps between groups of data” (Price 2010, p. 68).

interesting finding because the analysis of the association between walkability and economic vitality of census tracts revealed high and positive association between walkability and high demand for housing in the area units.

The univariate Moran's I statistic determines if there is spatial correlation in housing vacancy rates in the census tracts. The Moran's I statistic of 0. 5013 indicates that there is high positive spatial association in housing vacancies and the p-value of 0.01 means that the spatial association is statistically significant at five percent significance level. In other words, strong clustering of similar values was identified.

Figure 11 shows statistically significant (at 5% significance level) clusters of observations by type of association. The areas in dark blue reflect census tracts with low housing vacancies surrounded by census tracts with low average vacancy rates. Clustering of census tracts with low vacancy rates is evident in the suburban parts of Virginia (Prince William and Fairfax counties) and Maryland (Montgomery county) surrounding the core of the metropolis to West and North. Localities in red represent census tracts with high housing vacancies surrounded by census tracts with high average housing vacancy rates. Clustering of census tracts with high vacancy rates are located in the South-East of the District of Columbia and adjacent part of Prince George's county, MD, as well as outlying areas of the region. The pink color marks census tracts with high vacancy rates surrounded by tracts with low average vacancies, while the light blue marks census tracts with low housing vacancy rates surrounded by tracts with high average vacancies.

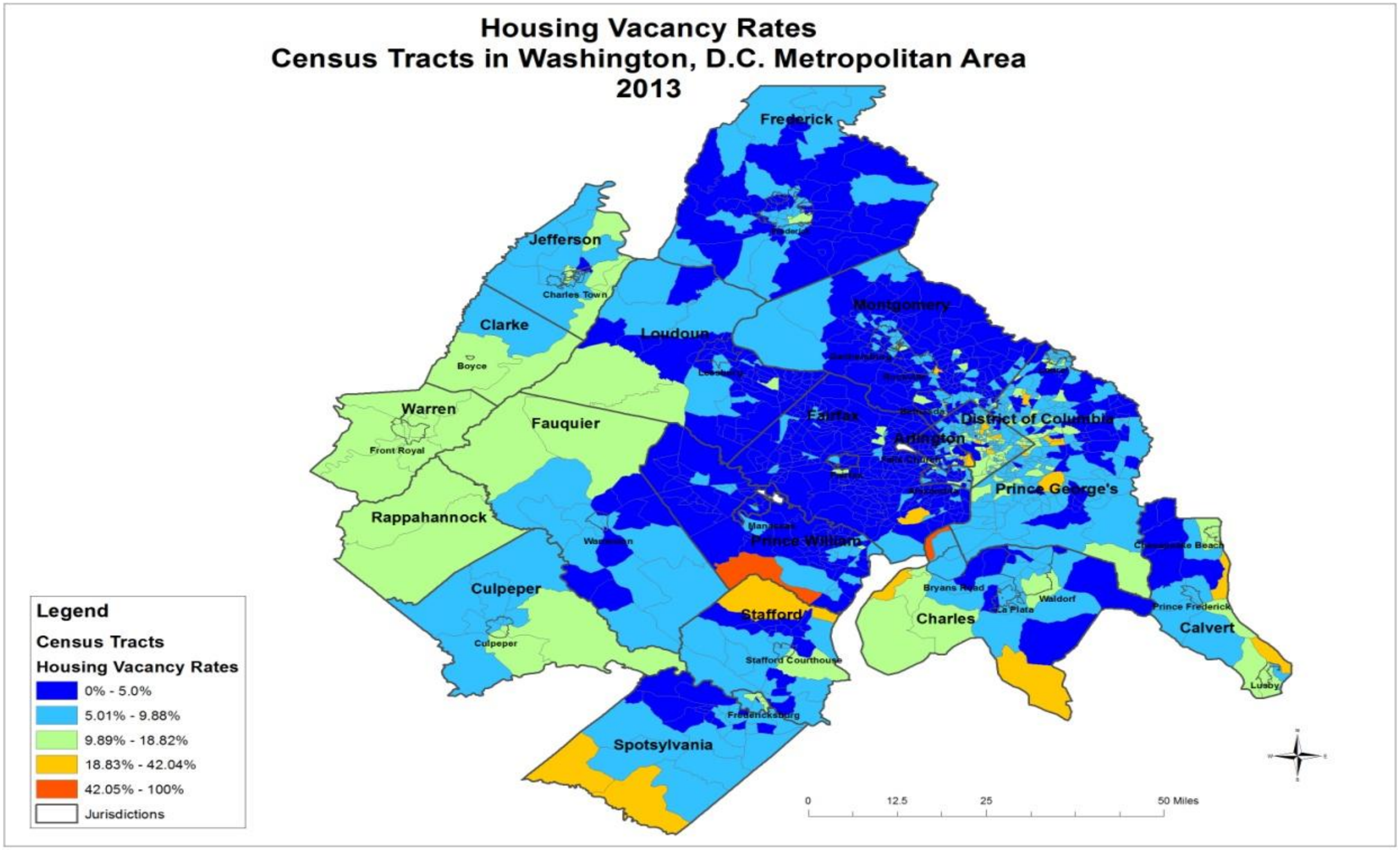
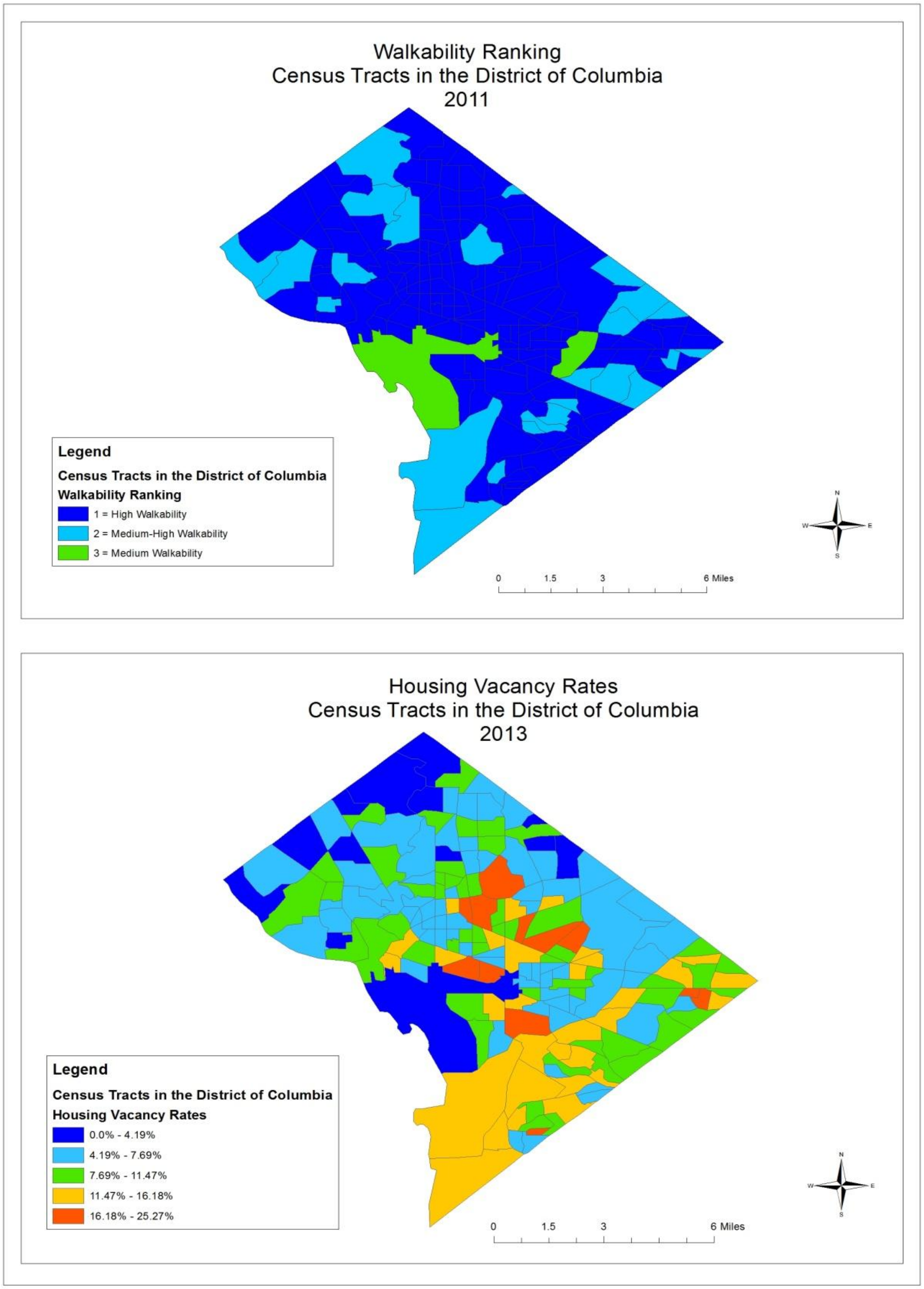

Housing Vacancy Rates
Census Tracts in Washington, D.C. Metropolitan Area
2013
Frederick
Jefferson
Charles Town
Clarke
Boyce
Loudoun
Leesburg
Montgomery
Warren
Front Royal
Fauquier
Fairfax
Arlington
District of Columbia
Prince George's
Rappahannock
Prince William
Manassas
Warrenton
Culpeper
Stafford
Stafford Courthouse
Fredericksburg
Spotsylvania
Charles
Bryans Road
Waldorf
La Plata
Calvert
Prince Frederick
Lusby
Legend
Census Tracts
Housing Vacancy Rates
0% - 5.0%
5.01% - 9.88%
9.89% - 18.82%
18.83% - 42.04%
42.05% - 100%
Jurisdictions
0
12.5
25
50 Miles

Figure 9



Walkability Ranking
Census Tracts in the District of Columbia
2011
Legend
Census Tracts in the District of Columbia
Walkability Ranking
1 = High Walkability
2 = Medium-High Walkability
3 = Medium Walkability
0 1.5 3 6 Miles
Housing Vacancy Rates
Census Tracts in the District of Columbia
2013
Legend
Census Tracts in the District of Columbia
Housing Vacancy Rates
0.0% - 4.19%
4.19% - 7.69%
7.69% - 11.47%
11.47% - 16.18%
16.18% - 25.27%
0 1.5 3 6 Miles

Figure 10

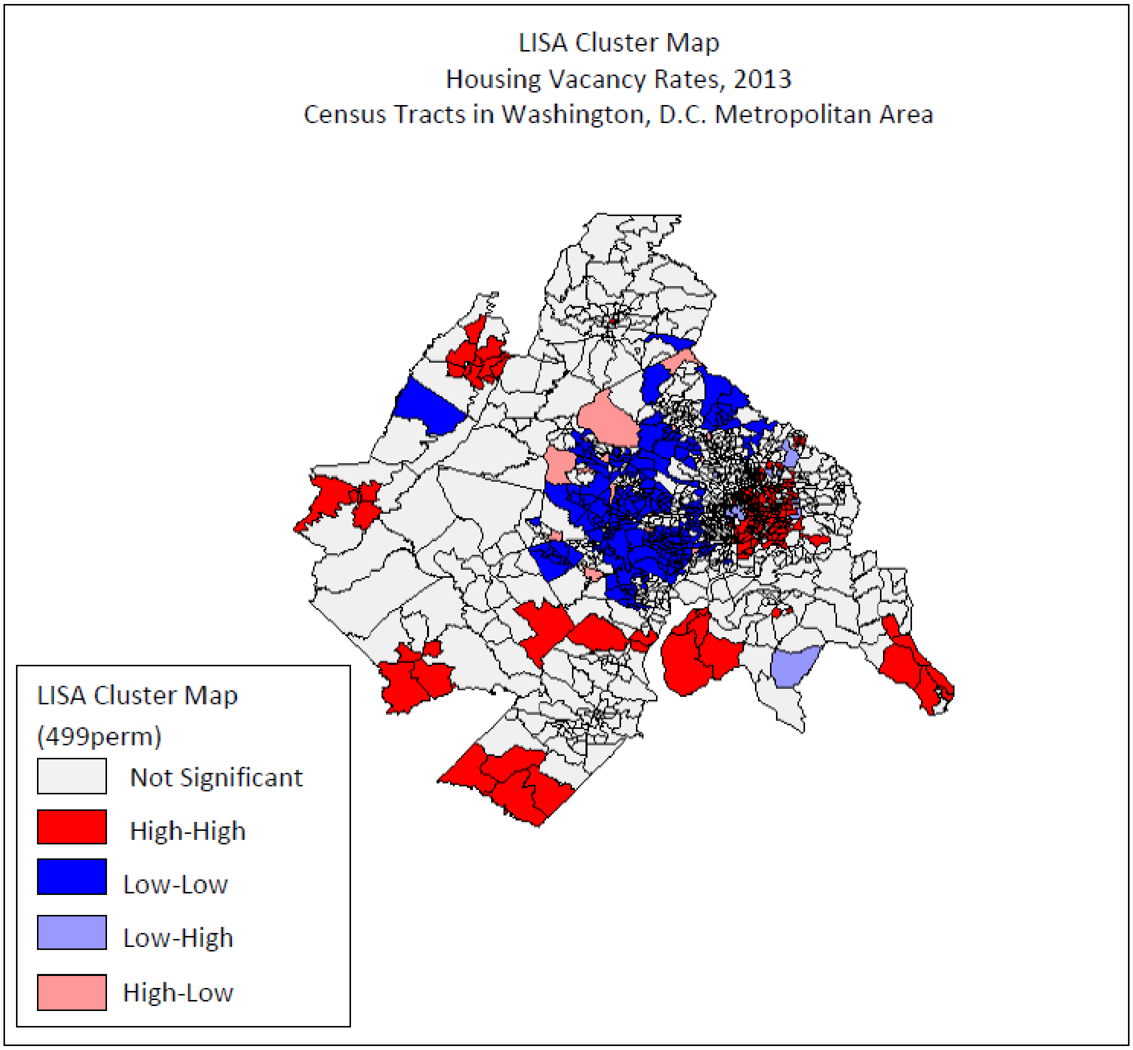


Figure 11

It was determined in the analysis of the association between walkability and economic vitality in census tracts that the ordinary least square (OLS) model is inappropriate to explain the association between walkability and economic vitality due to endogeneity. However, the diagnostics of the OLS model (LM testes) indicate the type of spatial effects (Brasier 2005). The weight created to analyze the spatial dependence is first order Queen contiguity.

The results presented in Table 20 show that there is spatial dependence on both sides of the equation. The LM-lag and robust LM-lag statistics are statistically significant at the one percent significance level (p-values for both statistics are 0.0000) indicating spatial autocorrelation in the dependent variable. The LM-error is statistically significant at the one percent significance level (p-value is 0.0000) while robust LM-error is statistically insignificant (p-value = 0.4773). It means that spatial autocorrelation is a concern in the independent variables. Moran's I statistic for walkability is 0.64 and it is statistically significant at the 5 percent level (p-value = 0.01), indicating positive autocorrelation. Also, Figure 12 shows that the independent variable of walkability is spatially clustered. The area in dark blue represents a cluster of census tracts with high walkability (ranks 1 and 2), located in the core of the metropolis (the District of Columbia and surrounding regions). The areas in red represent clustering of census tracts with low walkability (ranks 4 and 5), located in the outer parts of the metropolis.

Table 20
Diagnostics for Spatial Dependence

Diagnostics for Spatial Dependence	**Prob.**
Moran's I (MI/DF = 0.3176)	0.0000
Lagrange Multiplier (lag)	0.0000
Robust LM (lag)	0.0000
Lagrange Multiplier (error)	0.0000
Robust LM (error)	0.4773

Fit of the Model	
Adj. R2	0.3066
Likelihood (L)	-1158.99
Akaike Info Criterion	2339.99

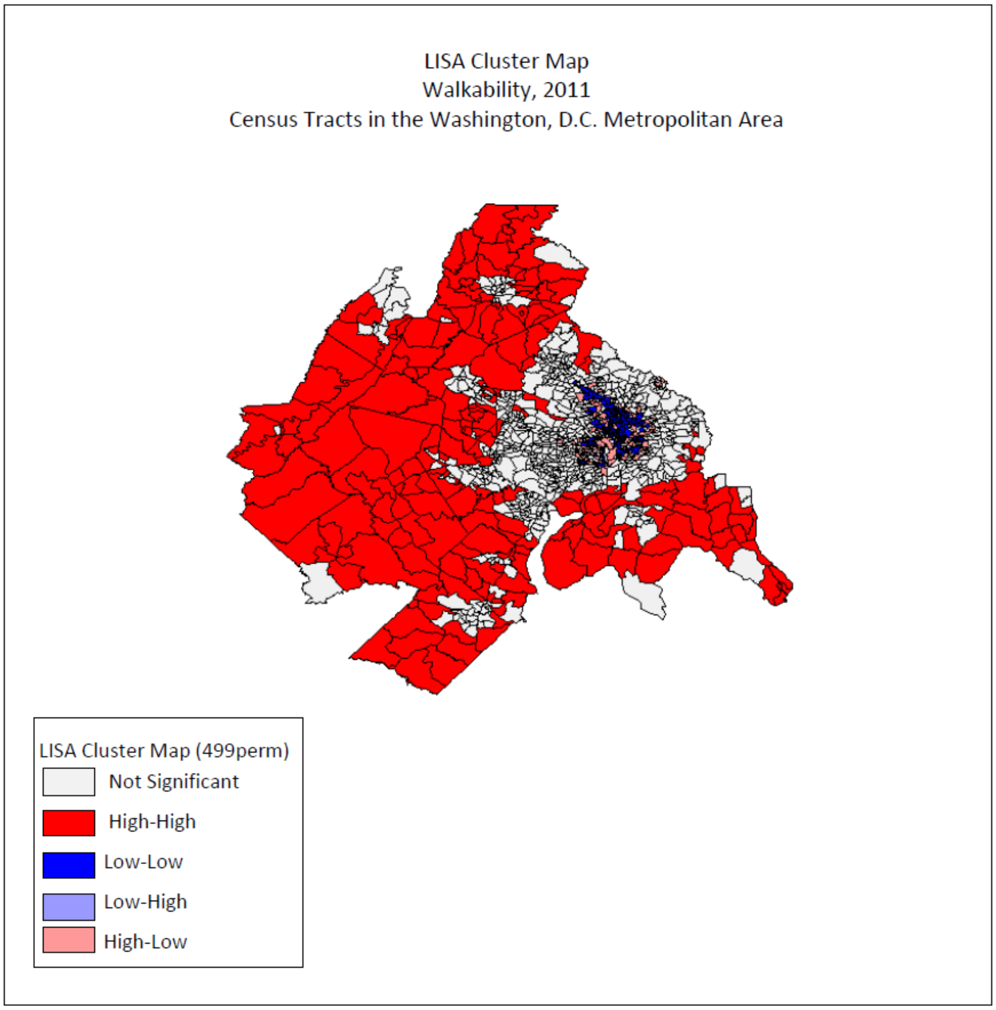


Figure 12

Two-Stage Least Square Estimator Controlling for Sub-regions

Spatial dependence of the variables leads to inefficiency of the regression results (the assumption of independent observations is violated). The first approach to remedy this problem is to supplement the same two-stage least square model that was analyzed in the previous section by additional independent variables representing the sub-regions in which each of the census tracts is located. This approach, if successful, would account for endogeneity and spatial autocorrelation.

After Sturtevant (2009), the sub-regions are categorized as: Center City (District of Columbia), Inner Core (City of Alexandria and Arlington County), Inner Suburbs (Montgomery and Prince George's Counties, MD, Fairfax County, Cities of Fairfax and Falls Church, VA), Outer Suburbs (Frederick County, MD, Loudoun and Prince William Counties, VA, Cities of Manassas and Manassas Park, VA), and Far Flung Suburbs (Charles and Calvert Counties, MD, Clarke, Warren, Fauquier, Culpeper, Rappahannock, Stafford, Spotsylvania Counties, VA, and City of Fredericksburg, VA).

Dummy variables are created for each census tract indicating if the tract is located in a specific region (dummy = 1) or not (dummy = 0). For example, a dummy variable for the Center City sub-region has the value of 1 for all the census tracts located in the District of Columbia (the only jurisdiction in the Center City sub-region), and the value of 0 for all the other census tracts.

The two-stage least square model controlling for sub-regions is run with the same instrumental variable as before (% of residential structures with 20 units and more). The fit of the model improved as now 51 percent of the variance in housing vacancies can be explained by the independent variables. The output of the regression shows that the instrumental variable (IV) is strong. In the first stage the instrument is statistically significant (p- value = 0.000) and in the second stage, the coefficient for walkability is also statistically significant at the one percent significance level. The post-estimation test for the validity of the instrument confirms the strength of the IV (F-statistic = 38). The Durbin-Wu-Hausman test indicated endogeneity between walkability and housing vacancy rates (p-value = 0.0000).

The demand for housing in walkable census tracts was found higher after controlling for sub-regions. On average, a one percent increase in walkability is associated with a 195 percent decrease in housing vacancy rates, all else being equal. Walkability still has the highest impact on housing vacancies out of the analyzed independent variables (Table 21).

Table 21
Results of the Two-Stage Least Squares Estimator Controlling for Sub-regions

Variables	**1st Stage Coef.**	**2nd Stage Coef.**
Walkability Index		-1.958274*
IV: % of structures with 20 units and more	-0.402774*	
travel time to work (average)	0.0014489	-0.3969105**
no. of transportation modes	-0.2462942*	-0.4721008*
population	-0.0279638	-0.1921968*
median housing value	0.1367305*	-0.1908583
age (median)	0.2307049**	0.1113586
% of female population	0.164445	-0.1012456
% of population 65-years-old and over	-0.0496127**	0.0931015
% of black population	-0.0059419	0.163602*
% of population with a high-school diploma as	0.0320081	0.0169278

highest level of education		
Center city	-0.4126657*	-0.4330375**
Inner core	-0.2905463*	-0.3601849**
Inner suburbs	-0.0438448**	-0.0079093
Outer suburbs	-.1253097*	0.3059876*
Far flung suburbs	0.192498*	0.8712511*
N	930	930
F-Test	130.67	
Wald chi2		726.40
Prob>F	0.0000	
Adj. R^2	0.5139	
Adj. R^2		

* p < 0.01
** p < 0.05

Next, the LM tests were run again to check if the spatial autocorrelation was corrected by adding the sub-region dummy variables. P-values for LM-lag and robust LM-lag are statistically significant at one percent level. The LM-error test is still statistically significant while the robust LM-error is statistically insignificant. The spatial autocorrelation is still a concern. The conclusion is that the results of the regression are limited by inefficiency due to the presence of spatial autocorrelation.

Spatial Regression

As was mentioned earlier, spatial autocorrelation is more significant in the dependent variable (both LM-lag and the robust LM-lag statistics are significant at the one percent significance level). It means that the value of housing vacancy rate in one census tract is influenced by values of housing vacancies in neighboring census tracts. The Spatial Lag model (Equation 7) is run to check if adding a spatially lagged dependent variable (average of the neighboring values) on the right-hand side of the equation removes the spatial effects. It must be noted that the Spatial Lag model ignores endogeneity between walkability and economic vitality.

Equation 7

$$y = \beta Wy + \gamma E_n + \varepsilon$$

where:
y = dependent variable
W = weight
β = parameter associated with the spatially weighted dependent variable
E_n = explanatory variables
γ = parameters associated with explanatory variables
ε = error term

The results of the Spatial Lag Model (Table 22) show an improvement of the model fit (the log likelihood increased from -1158.99 to -984.75 and the AIC decreased from 2339.99 to 1993.5). The newly created spatial lag term of housing vacancy rates has a positive effect and is highly significant at the five percent significance level. It means that even if there was no change in the independent variables, the housing vacancy rate in one census tract would still be explained by housing vacancy rates in surrounding tracts. The diagnostics for spatial dependence demonstrate strong significance in the spatial autoregressive coefficient as the p-value of the likelihood ratio test is still below five percent. It is concluded that adding a spatially lagged dependent variable on the right-hand side of the equation did not remove the spatial effects.

Table 22
Spatial Lag Model

	Coefficient	**Probability**
W_lvac (housing vacancy rate)	0.5722	0.0000
Likelihood Ratio Test		0.0000

Spatial Two-Stage Least Square Estimator

Controlling for sub-regions and conducting spatial regression (Spatial Lag) did not eliminate the spatial effects. The next approach to correct for spatial dependence is to use the generalized spatial two-stage least square regression (GS2SLS). The GS2SLS, developed by Kelejian and Prucha (1998), corrects the spatial autocorrelation in the dependent variable (spatial lag) and in the independent variables (spatial error). Another benefit of using the GS2SLS estimator is that it generates consistent estimates even when heteroskedasticity is present. However, the GS2SLS estimator ignores endogeneity.

The spatial weight used in this analysis is the first order Queen contiguity, which means that area units that share a border are treated as neighbors. The instrumental variables are spatially lagged variables used by the Stata software by default. The GS2SLS consists of three steps. First, the two-stage least square method (2SLS) with instrumental variables is used to estimate the regression. Second, the generalized method of moments, using the 2SLS residuals, estimates the autoregressive parameter and the variance. Third, 2SLS estimates a Cochrane-Orcutt type transformed regression (Lee 2003).

Table 23 presents the results of the generalized two-stage least square regression. It is evident that the magnitude of the association between walkability and economic vitality is lower when the model corrects for the spatial effects, as on average, a one percent increase in walkability is associated with a 36.8 percent decrease in housing vacancy rates, all else being equal.

Table 23
Results of the Spatial Two-Stage Least Squares Estimator

Variable	Coefficient
walkability	-0.3682496*
travel time to work (average)	0.0260402
no. of transportation modes	-0.2551998*
population	-0.0019084
median housing value	-0.0813168**
age (median)	-0.1477038
% of female population	0.2164974
% of population 65-years-old and over	0.1431523*
% of black population	0.1389586*
% of population with a high-school diploma as highest level of education	0.1678791*
N	1,359
Lambda	0.2189398
Rho	1.827439*

* $p < 0.01$
** $p < 0.05$

Spatial IV Regression

The final regression in this dissertation accounts for endogeneity between walkability and economic vitality and corrects the spatial autocorrelation in the dependent and independent variables. Such approach contributes to the current research as endogeneity and spatial dependence have been ignored thus far in the analysis of walkability.

This analysis follows the approach developed by Drukker et al. (2013) implementing the generalized method of moments and instrumental variable estimation strategy. The instrumental variable for walkability is, again, the percentage of residential structures with 20 units and more. Table 24 shows that when the model accounts for endogeneity and corrects the spatial autocorrelation in the dependent and independent variables, the association between walkability and economic vitality is positive, strong and statistically significant.

Table 24
Results of the Spatial IV Estimator

Variable	Coefficient
walkability	-1.063673*
travel time to work (average)	0.0898435
no. of transportation modes	-0.4572301*
population	-0.044778
median housing value	-0.0799603**
age (median)	0.053229
% of female population	-0.0518418
% of population 65-years-old and over	0.1063939**
% of black population	0.0724768**

% of population with a high-school diploma as highest level of education	0.2503372*
N	1,359
Lambda	.2306412***
Rho	1.716491 *

* $p < 0.01$
** $p < 0.05$
***$p < 0.1$

Summary

The spatial analysis strengthens the accuracy of the findings regarding the association between walkability and economic vitality in census tracts of metropolitan Washington, D.C. The pattern of spatial dependency shows clustering of observations with similar values of walkability and housing vacancy rates.

The findings improve the understanding of the association between walkability and economic vitality by showing that there is a previously unmeasured, spatial dimension to explaining the housing vacancy rates in census tracts. In addition to walkability and other explanatory variables, the magnitude of housing vacancies in a census tract is also explained by the values of housing vacancies in this tract's immediate neighbors. Moreover, the magnitude of housing vacancies is also affected by the spatial pattern on walkability.

The spatial IV regression is the most appropriate model for this analysis as it accounts for endogeneity between walkability and economic vitality, and corrects the spatial dependence in the dependent and independent variables. The spatial IV model shows that there is a strong positive, and statistically significant association between walkability and housing vacancy rates in the neighborhoods of metropolitan Washington, D.C.

Summary

This chapter developed walkability indices on the geographical levels of cities and census tracts. Indicators that have been found as associated with walkability in prior research were used to conduct principal component analysis and a set of equations generated walkability rankings.

The analysis clearly indicates positive relationship between walkability and economic vitality. Modest positive association was identified in cities in the U.S. and a strong association occurs in neighborhoods within the Washington, D.C. metropolitan area. However, there is no consistency regarding simultaneity between walkability and economic prosperity of regions – endogeneity was revealed on the census tract level, but not on a city level. Therefore, two different estimators were used to draw the conclusions: the ordinary-least-square model was appropriate for the analysis of cities and the two-stage least square was more appropriate for the analysis on the census tract level.

The conclusions on the neighborhood level are supplemented by spatial analysis. It was found that the spatial autocorrelation of housing vacancies and of walkability affects the values of housing vacancy rates across metropolitan Washington, D.C. The spatial IV model was conducted to simultaneously correct for spatial autocorrelation and endogeneity.

CHAPTER V

RESEARCH FINDINGS AND RESEARCH IMPLICATIONS

The findings of this dissertation not only contribute to academic research but also have relevant implications for public policy on the national and local levels. Researchers, urban planners and policy decision makers will benefit from this research. This chapter summarizes the research findings, policy implications, research limitations and directions for future research.

Research Findings

Question 1: What are the components of a walkability index and how can it be constructed?

Walkability indices on the city and census tract levels consist of indicators representing accessibility, density, design and safety of the area units. Four main actions are performed to construct the walkability indices: the generation of z-scores for the indicators, the principal component analysis, the development of the standardized index scores and categorization into ranks indicating the level of walkability.

The statistical testes showed that components generated through the principal component analysis are reliable on both geographical levels of analysis. The components of the city level explain 72.95 percent of the variation, while the components on the census tract level explain 75.32 percent of the variation.

Walkability in the majority of the analyzed cities is poor. Cities with low walkability (rank 5) and medium-low walkability (rank 4) make 52.12 percent of the sample. Only 1.1 percent of the cities are ranked as highly walkable (rank 1)[6] and 7.16 percent are characterized by medium-high walkability (rank 2). Forty percent of the cities are moderately walkable (rank 3).

Census tracts in the Washington, D.C. metropolitan area are highly walkable. Over one quarter of the sample was ranked as highly walkable (rank 1) while walkability in 55.70 percent of the sample was ranked as medium-high (rank 2). Rank 3 was assigned to 15.82 percent of the sample. Census tracts with low walkability (ranks 4 and 5) made up less than two percent of the sample.

Question 2: What is the association between walkability and economic vitality in cities in the United States?

There is a positive and statistically significant association between walkability and economic vitality in the 992 analyzed cities in the U.S. It was found that on average, a one percent increase in walkability is associated with a two percent increase in employment, all else being equal. Compared to other explanatory variables, the magnitude of walkability's association with employment is modest on the city level. For example, employment has a much stronger relationship with educational attainment of

[6] Eleven cities (or 1.1% of the sample) were ranked as highly walkable (rank 1). These cities include: Philadelphia, PA, Miami, FL, San Francisco, CA, Dallas, TX, Detroit, MI, Jersey City, NJ, Denver, CO, Boston, MA, Oakland, CA, Newark, NJ, and Washington, DC.

the population (positive association) and median age of the population (negative association).

While the finding that walkability is positively associated with economic vitality aligns with the findings of the previous research, another result of the analysis differs from what was theorized before. It was hypothesized that there would be endogeneity between transportation provision, in this case walkability, and economic prosperity of regions. However, endogeneity between walkability and economic vitality was not identified on the city level (the p-value for the Durbin-Wu-Hausman test was more than 0.05).

As endogeneity was not found, the appropriate model for the analysis was the ordinary least square estimator. The fit of the model shows that 53 percent in variation is explained by the independent variables. There is no omitted variables bias as indicated by the ovtest ($p > 0.05$) and linktest ($p > 0.05$).

Question 3: What is the association between walkability and economic vitality of neighborhoods in the Washington, D.C. metropolitan area?

Strong, positive and statistically significant association was found between walkability and economic vitality in the census tracts in the Washington D.C. metropolitan area. On average, a one percent increase in walkability is associated with a 147 percent decrease in housing vacancy rates, all else being equal. In comparison to other explanatory variables, walkability has the strongest relationship with housing vacancies.

Endogeneity between walkability and economic vitality was identified on the census tract level (the p-value for the Durbin-Wu-Hausman test was less than 0.01). The two-stage least square estimator was used with one instrumental variable – the percent of residential structures with 20 units and more. The instrument was strong and reliable as indicated in the first stage (p-value for the instrument was statistically significant at the 1% level) and in the post-estimation test (F-statistic = 60).

Question 4: What is the spatial dependency pattern in the neighborhoods of the Washington, D.C. metropolitan area?

Spatial dependency and clustering of walkability and housing vacancy rates with similar values is present across the metropolitan Washington, D.C. There are concentrations of census tracts with high rates of housing vacancies and with low vacancy rates (Moran's I = 0.50, p-value = 0.01). There are also clusters of census tracts with high walkability and with low walkability (Moran's I = 0.64, p-value = 0.01). These findings improve the understanding of the association between walkability and economic vitality of neighborhoods by identifying the spatial dimension that was ignored in the previous analysis. The magnitude of housing vacancy rates in census tracts is explained not only by walkability and other explanatory variables, but also by housing vacancies in the neighboring area units and by the spatial pattern of walkability. A spatial IV regression (that simultaneously corrects the spatial autocorrelation of the variables and accounts for endogeneity between walkability and economic vitality) concluded that there is strong, positive and statistically significant association between walkability and economic vitality of neighborhoods in the metropolitan Washington, D.C.

Policy Implications

City Level

The main findings on the macro level are that walkability in the majority of the 992 analyzed cities is poor and that walkable cities experience higher employment rates than non-walkable cities. The main policy implication is that the benefits of walkability are not fully recognized yet nationwide. Although it cannot be concluded that walkability directly causes economic prosperity, it can be concluded that on average walkable cities experience higher employment rates than unwalkable cities. To improve economic vitality, a city could make incremental changes in individual walkability components to attract people and businesses and to increase its own competitiveness among other urban places.

The walkability ranking shows that over 50 percent of the analyzed cities are unwalkable and therefore not taking advantage of the economic potential of walkability. More nationwide education and awareness campaigns are needed to spread the information of the positive effects walkability has on the economic condition of cities. This dissertation contributes to generating and spreading the knowledge as it is the first research to demonstrate walkability's positive association with employment based on statistically reliable econometric analysis. This research is also the first to be based on such a large sample.

While it is not evident how exactly walkability contributes to employment, the findings of this dissertation suggest that walkability is a desirable amenity on the city level. The findings of this research support the theoretical hypothesis indicating that "alive", walkable cities attract people which in turn increases the demand for goods and services, contributes to the expansion of economic activity, creative networking and more opportunities for employment. Walkability improves the quality-of-life of workers and companies, especially the mobile ones. Walkability is also likely to contribute to the expansion of the labor markets allowing people of all income levels to reach jobs without depending on transportation by car.

Urban planners, city leaders and transportation policy makers should be more proactive in including walkability in their plans and actions to enable local economic vitality. Potential practices can range from setting general standards and guidelines aimed at improving the overall pedestrian environment to implementing specific policies and strategies targeted at improvement of walkability components. Specific actions include conducting focus groups and workshops to identify the most relevant pedestrian concerns and to determine which specific locations need the pedestrian upgrades, re-engineering streets (i.e. changing a four-lane road into two-lane with a designated turn lane in the middle, therefore providing extra space for sidewalk and making it safer for pedestrians), re-opening closed crosswalks, giving extra crossing time at intersections, improving public transit (i.e. increasing transit frequency, extending transit routes), concentrating new development in existing urban centers, decreasing parking minimums or repurposing the street curbs. Similar practices were implemented by cities that are the walkability leaders, such as San Francisco, CA or Denver, CO (MacNeil 2012).

These examples of policies and best practices should be customized to address the individual needs of cities. It is recommended that both policy makers and the public are better educated about the contribution of walkability to cities' economies. It is also recommended that urban planners and public officials acknowledge the benefits of walkability and take action to improve walkability conditions to increase the competitiveness and the economic condition of their cities. The findings of this dissertation show that the improvement of walkability in cities is worth the effort.

Census Tract Level; Washington, D.C. Metropolitan Area

It was found that walkability is associated with great economic benefits to neighborhoods. While over 80 percent of the census tracts are walkable, these neighborhoods cover less than half of the land area of the metropolis and are concentrated in the most urbanized and dense locations of the metropolitan region. Therefore, there is still room for improvement and it is recommended that local decision-makers take note of the economic potential walkability can bring to the region.

This dissertation results in some useful, if only preliminary, implications to economic developers, urban planners and policy makers. The findings of this dissertation contribute to the knowledge of economic developers when assessing where to locate their investments in the Washington, D.C. metropolitan region. As walkable neighborhoods experience much lower housing vacancy rates than unwalkable neighborhoods, economic developers can safely expect high demand for residences constructed or redeveloped in walkable census tracts. While walkability is not attractive to everybody, there is an ample consumer base that will support the supply of residential properties in walkable neighborhoods.

While it was found that on average walkable areas experience low vacancy rates, it is not certain where exactly improvements in walkability would bring the best effects. The spatial patterns of walkability and housing vacancies in the District of Columbia are noteworthy. While walkability is high across the District, the housing vacancy rates are not uniformly low, as could be expected based on the finding that walkability is associated with low housing vacancies. One explanation could be that there are blighted neighborhoods so the housing would be less demanded there despite good walkability conditions. However, the data source – Census Bureau – excludes housing units that are under construction, unfit, or to be demolished from the sample,[7] so dilapidated construction is unlikely to affect the results. Still, the census tracts with high vacancy rates (located in the south eastern part of the District of Columbia and the adjacent areas in the Prince George's County, MD) have been widely considered as economically depressed and experiencing high crime rates for decades. The slow process of gentrification in these areas could potentially explain the high vacancy rates despite high walkability. The implication for urban planners and policy makers is that such areas with high walkability potential but poor economic condition should be the prime locations for intervention. It is possible that through improvement in even one walkability component, such as safety from crime, the immediate area as well as the whole metropolitan region would benefit economically.

[7] The Census Bureau defines a housing unit as vacant "if no one is living in it at the time of the interview, unless its occupants are only temporarily absent. Units that do not meet the definition of a housing unit, such as those under construction, unfit, or to be demolished, are excluded from the universe" (U.S. Census Bureau 2013b).

While it is now confirmed, based on statistically reliable, unbiased and efficient econometric analysis, that the demand for residences in walkable neighborhoods of Washington, D.C. is high, it is important to consider who are the people attracted by walkability. More research is needed, but the literature review in this dissertation showed that predominantly young professionals seek to live in the walkable environment. Now, parents with children are moving into the suburbs in search for sufficient space. In order to retain young professionals in walkable jurisdictions as their families grow, more residences that can accommodate families are needed (i.e. row houses, multiple-bedroom apartments). For outer suburban jurisdictions it is recommended that walkability pockets are developed to attract young, long-haul residents. Some actions that are suggested include incentives for developers to build and renovate appropriately sized residential structures (i.e. easing zoning restrictions), improving safety, or easing the pop-up infrastructure restrictions as pop-up entertainment and pop-up retail are related to walkability and have become demanded in the recent years.

Another group that was found attracted to walkable residential environment is retirees. In this case, city planners in neighborhoods aspiring to be walkable should focus on streetscape (i.e. sidewalk benches, trees providing shade), and solutions to ease mobility, such as curb cuts or extending the crossing time at intersections.

Currently, the demand for residences in walkable neighborhoods is very high and underserved. The suburban and outer suburban jurisdictions of the metropolitan Washington have a great opportunity to over-take the quality residents from overcrowded urbanized areas of the region. The findings of this dissertation show that improving walkability will result in increased economic vitality of the regions who undertake this task.

Contribution to Research

An important contribution of this dissertation is the walkability index developed for the entire Washington metropolitan region. Such a comprehensive measure of walkability was not available previously. This measure can be used by researchers to further explore the issue of walkability in the region whether to measure the impact of walkability on public health, environment, economy or equity and quality-of-life conditions. Moreover, the structure and the method of calculation make the index replicable, so it can be constructed for other regions.

The index on the city level could also be replicated using more recent data to show if the walkability conditions in cities changed since 2000 or to measure the impact of walkability in other research areas. Rankings for additional cities could also be developed if the complete data become available.

The findings of this dissertation contribute to the literature by supporting the findings of researches, such as Jacobs, Florida, Putnam or Leyden, who found that active, walkable cities and neighborhoods stimulate regional economic prosperity. Walkable areas attract people providing the potential for social bonding, creative networking, economic activity and employment opportunities.

The statistical findings were not consistent in regard to simultaneity between transportation provision – walkability – and economic vitality. Endogeneity, that can result from the two phenomena affecting each other (walkability stimulates economic prosperity and vice versa), was found on neighborhood level (as suggested by theory), but not on the city level. More research is needed to better understand this discrepancy. The potential cause of not finding endogeneity on the city level may be a measurement error, for example the structure of the walkability index. If different walkability indicators were included, endogeneity could be identified.

Importantly, this dissertation provides the first analysis that not only accounts for endogeneity, but also corrects for spatial autocorrelation when researching the association between walkability and economic vitality of neighborhoods in the Washington metropolitan area. Therefore, the conclusions are drawn based on statistically reliable, unbiased and efficient analysis.

Research Limitations and Directions for Future Research

The main limitations of the walkability indices generated in this dissertation include that the indices were not validated and that the indices do not distinguish which walkability indicators are the most significant. Validation of the indices is beyond the scope of this dissertation, but it is a logical direction for future research. Disaggregating the index and measuring the impact of each of the components of walkability on regional economic vitality is another direction for future research. These findings would inform which dimensions of walkability should be primarily focused on and improvement in which components would bring the best results in the short- and long-term.

To further strengthen the explanatory power of the walkability indices, the aesthetics and streetscape dimension should be included. These indicators are suggested by the literature, but relevant data are not available at this time.

The limitation of this research on the association between walkability and economic vitality of the census tracts in metropolitan Washington, D.C. is that the analysis either controls for endogeneity but ignores spatial dependency, or corrects for spatial autocorrelation but ignores endogeneity. Therefore, the reliability of the results is limited. It is suggested that analysis that simultaneously accounts for endogeneity and corrects for spatial autocorrelation is conducted in the future.

The visual examination indicated that walkability is a part of the urban domain and is seldom found in the outlying or rural regions of the metropolis. However, the findings do not distinguish if walkability is equally demanded in urban, suburban, or rural regions. Rather, the conclusions are drawn on an average of all census tracts whether residential, commercial, recreational or specialty use, such as federal (i.e. National Mall area) or military property (i.e. Marine Corps Base Quantico area). Not accounting for the specific characteristics of census tracts is another limitation of this dissertation and it is suggested that further research is conducted to address this concern.

Lastly, this dissertation does not examine natural (i.e. rivers, lakes) and man-made (i.e. train tracks, highways) barriers to walkability in the analysis. Future research that accounts for such detractions to walkability would enrich the understanding of walkability on the local level.

Summary

This dissertation shows that walkability is an important factor contributing to economic prosperity of cities nationwide and in neighborhoods within metropolitan Washington, D.C. Walkability was quantified by the newly developed five-rank indices. Walkability was found to be positively associated with employment in cities and negatively associated with housing vacancy rates in neighborhoods. Therefore, walkability is an economically desirable amenity in places where people work and in places of residence. Also, this dissertation provides the first analysis of walkability and regional economic vitality that simultaneously accounts for endogeneity and corrects the spatial autocorrelation.

The potential of walkability as a contributor to economic vitality is underutilized by cities. Less than 10 percent of the analyzed cities are walkable and over 50 percent of the sample is ranked as unwalkable. By focusing on improving walkability conditions, cities can gain economically by becoming more competitive in attracting workers. There is also room for improvement in the neighborhoods in the Washington metropolitan area. Although 82 percent of the census tracts are walkable, these areas are concentrated in urban setting and cover less than half of the land area of the metropolis. Suburban and outer suburban neighborhoods have an opportunity to advance economically by developing walkability pockets that attract the quality social capital, such as young professionals, to reside for the long-term.

It is concluded, that improvement in walkability is associated with increased regional vitality. While this research has its limitations, the findings are based on statistically reliable econometric analysis and can be used by advocacy groups to educate the public and policy officials of the economic benefits of walkability. The conclusions also contribute to academic knowledge and have policy implications relevant to developers, urban planners and policy makers.

APPENDIX

Table 1
Walkability Index Ranks
City Level, 2000

State	City	SI	Rank	State	City	SI	Rank
PA	Philadelphia	100.00	1	NJ	Camden	68.91	2
FL	Miami	99.52	1	CA	Compton	68.41	2
CA	San Francisco	98.28	1	MA	Chelsea	68.33	2
TX	Dallas	88.02	1	TX	San Antonio	68.10	2
MI	Detroit	87.57	1	FL	North Miami Beach	67.25	2
NJ	Jersey City	87.36	1	NJ	Trenton	67.22	2
CO	Denver	86.36	1	LA	New Orleans	66.97	2
MA	Boston	84.38	1	CA	Huntington Park	66.87	2
CA	Oakland	83.84	1	NJ	Elizabeth	66.42	2
NJ	Newark	82.31	1	CA	Berkeley	66.05	2
DC	Washington	80.42	1	FL	North Miami	65.86	2
MO	St. Louis	79.24	2	MA	Everett	65.54	2
NY	Hempstead village	78.23	2	MD	Annapolis	65.20	2
FL	Hialeah	77.08	2	NY	Newburgh	64.92	2
CA	Pomona	76.88	2	OH	Cleveland	64.63	2
CA	Long Beach	75.44	2	MA	Worcester	64.57	2
NJ	East Orange	74.78	2	CA	San Rafael	64.45	2
CA	San Diego	73.98	2	CA	West Covina	64.06	2
FL	Miami Beach	73.85	2	CA	Vallejo	63.97	2
TX	Houston	72.85	2	CA	Bell Gardens	63.78	2
MD	Baltimore	72.65	2	CA	Norwalk	63.60	2
FL	Tampa	72.44	2	CA	Santa Ana	63.54	2
CA	Hayward	71.93	2	NJ	Bayonne	63.54	2

State	City	SI	Rank	State	City	SI	Rank
OR	Portland	71.89	2	CA	Pittsburg	60.40	2
CA	San Jose	70.19	2	NY	Yonkers , NY	60.14	2
AZ	Phoenix	70.09	2	CA	West Hollywood	60.12	2
CA	Stockton	69.88	2	NJ	Paramus borough	60.09	2
CA	Lynwood	69.87	2	OR	Gresham	60.04	2
CA	Bellflower	69.00	2	CA	San Leandro	59.63	3
MA	Cambridge	63.44	2	CA	Fairfield	59.58	3
CA	Moreno Valley	63.42	2	CA	Rialto	59.48	3
NJ	Plainfield	63.27	2	NJ	Englewood	59.44	3
MA	Lawrence	62.61	2	UT	Salt Lake City	59.35	3
CA	San Bernardino	62.47	2	FL	North Lauderdale	59.07	3
CA	South Gate	62.46	2	FL	Lauderhill	59.06	3
CA	Daly City	62.45	2	CA	Fontana	59.00	3
FL	Fort Lauderdale	62.44	2	NJ	Fort Lee borough	58.98	3
MA	Springfield	62.43	2	NJ	Kearny town	58.66	3
NJ	Long Branch	62.34	2	FL	Fort Pierce	58.51	3
CA	Suisun City	62.29	2	MA	Somerville	58.39	3
CA	La Puente	62.27	2	CA	Palmdale	58.26	3
NJ	Paterson	61.76	2	CA	Alameda	58.15	3
CA	Carson	61.40	2	MA	Medford	58.12	3
CA	Paramount	61.38	2	CA	Watsonville	58.07	3
NJ	Passaic	61.31	2	PA	Reading	58.05	3
FL	Fort Myers	61.21	2	RI	Providence	57.75	3
CA	Concord	61.15	2	CA	Fullerton	57.71	3
CA	Downey	61.04	2	MA	Quincy	59.99	3
CA	Cerritos	61.02	2	MA	Brockton	59.92	3
CA	Pico Rivera	61.00	2	NJ	New Brunswick	59.87	3
CT	Bridgeport	60.97	2	CA	Sacramento	59.85	3
CA	Anaheim	60.73	2	NY	Mount Vernon	59.84	3
CA	Antioch	60.66	2	CA	Lawndale	56.97	3
CA	Hollister	60.45	2	FL	Greenacres	56.95	3

State	City	SI	Rank	State	City	SI	Rank
CA	Montebello	56.93	3	PA	Easton	54.50	3
UT	Murray	56.84	3	CA	Salinas	54.49	3
CA	Tracy	56.79	3	CA	Gardena	54.46	3
CA	National City	56.69	3	FL	Pembroke Pines	54.32	3
OH	Lakewood	56.66	3	WI	Milwaukee	54.28	3
PA	Pittsburgh	56.43	3	CA	Hawthorne	54.28	3
NY	New Rochelle	56.39	3	CA	Cypress	54.21	3
CA	San Bruno	56.32	3	IN	Gary	54.11	3
WA	Tacoma	56.19	3	NJ	Rahway	54.03	3
MA	Lowell	56.19	3	CA	Benicia	54.02	3
CA	Manteca	56.12	3	CA	Lake Elsinore	53.92	3
CA	Covina	56.07	3	CA	Inglewood	53.80	3
CA	Union City	56.03	3	CA	Lancaster	53.55	3
PA	Norristown borough	55.77	3	CA	Burlingame	53.54	3
IN	Merrillville town	55.69	3	FL	Deerfield Beach	53.47	3
FL	Orlando	55.52	3	MD	Frederick	53.42	3
FL	Lake Worth	55.32	3	CA	Lakewood	53.34	3
RI	Pawtucket	55.31	3	MA	Taunton	53.34	3
CA	Pasadena	55.29	3	NJ	Hackensack	53.30	3
CA	East Palo Alto	57.71	3	NJ	Garfield	55.21	3
CA	South San Francisco	57.68	3	GA	Marietta	55.18	3
TX	Lancaster	57.65	3	CA	Temple City	55.07	3
FL	Pompano Beach	57.59	3	CA	Oceanside	55.02	3
CA	Pleasant Hill	57.52	3	CA	Corona	55.02	3
CA	Walnut Creek	57.51	3	CA	San Mateo	55.00	3
NJ	Linden	57.50	3	FL	St. Petersburg	54.90	3
CA	Montclair	57.49	3	CA	Whittier	54.81	3
NY	Long Beach	57.38	3	TX	Arlington	52.73	3
NY	Buffalo	57.10	3	CA	Milpitas	52.70	3
OR	Beaverton	54.72	3	CA	Colton	52.70	3
CA	Chino	54.70	3	CA	Santa Monica	52.66	3

State	City	SI	Rank	State	City	SI	Rank
CA	Vacaville	52.60	3	FL	Oakland Park	51.46	3
CA	Highland	52.60	3	CA	Ontario	51.41	3
UT	Midvale	52.58	3	FL	Clearwater	51.36	3
CT	New Haven	52.45	3	CA	Garden Grove	51.03	3
CA	Petaluma	52.40	3	CA	San Gabriel	50.98	3
NJ	Fair Lawn borough	52.40	3	TX	Irving	50.90	3
NY	Spring Valley village	52.36	3	CA	Maywood	50.84	3
NJ	Sayreville borough	52.34	3	NJ	Westfield town	50.70	3
VA	Manassas	52.31	3	MO	Florissant	50.70	3
CA	San Ramon	52.27	3	CA	El Monte	50.69	3
MA	Salem	52.19	3	PA	Lancaster	50.63	3
NJ	Perth Amboy	52.18	3	CA	Orange	50.63	3
FL	Hollywood	52.17	3	CA	Bell	50.62	3
FL	Coral Gables	52.13	3	CA	San Dimas	50.60	3
CA	Baldwin Park	52.12	3	CA	El Cajon	50.56	3
CA	Upland	52.04	3	MO	KS City	50.44	3
OH	Cincinnati	52.02	3	CT	Hartford	50.40	3
WA	Vancouver	51.99	3	TN	Nashville-Davidson (balance)	50.35	3
CA	Menlo Park	51.92	3	CA	West Sacramento	50.31	3
MA	Watertown	53.02	3	CA	Fresno	51.91	3
TX	Duncanville	52.99	3	CA	Burbank	51.89	3
CA	Placentia	52.98	3	CA	Pacifica	51.85	3
CA	Stanton	52.92	3	CA	Santa Clarita	51.81	3
FL	Tamarac	52.89	3	NJ	Clifton	51.75	3
NC	Charlotte	52.83	3	MS	Greenville	51.63	3
CA	Imperial Beach	52.79	3	NM	Albuquerque	49.96	3
WA	Seattle	52.76	3	WA	Lynnwood	49.93	3
OH	Columbus	51.56	3	CA	Cupertino	49.87	3
CO	Thornton	51.54	3	RI	Newport	49.78	3
CA	Belmont	51.52	3	LA	Slidell	49.69	3
MI	Flint	51.47	3	TX	Fort Worth	49.63	3

State	City	SI	Rank	State	City	SI	Rank
CA	Buena Park	49.56	3	CA	Novato	48.51	3
OR	Tigard	49.55	3	FL	Margate	48.48	3
CA	Modesto	49.54	3	CA	Morgan Hill	48.46	3
RI	East Providence	49.53	3	CA	Rancho Cucamonga	48.43	3
CA	Laguna Hills	49.53	3	IN	Indianapolis (balance)	48.42	3
WA	Bremerton	49.50	3	GA	Alpharetta	48.40	3
CA	Newark	49.50	3	CA	Claremont	48.40	3
OH	Shaker Heights	49.44	3	UT	West Jordan	48.32	3
CA	Redwood City	49.36	3	FL	West Palm Beach	48.29	3
TX	Richardson	49.33	3	CA	Glendale	48.12	3
WA	Kent	49.31	3	CA	Palo Alto	48.10	3
MN	St. Paul	49.28	3	PA	Allentown	48.07	3
FL	Homestead	49.27	3	CA	Tustin	48.05	3
MA	Newton	49.22	3	CA	Newport Beach	48.04	3
CA	Santa Clara	49.21	3	MA	Attleboro	47.98	3
WA	Renton	49.19	3	CA	Mountain View	47.96	3
GA	Smyrna	49.19	3	CA	Oxnard	47.86	3
CA	Foster City	49.07	3	NY	Schenectady	47.83	3
CA	Perris	48.97	3	TX	El Paso	47.82	3
CA	Gilroy	50.26	3	CA	Azusa	48.96	3
CA	Arcadia	50.20	3	FL	Coral Springs	48.83	3
CA	Riverside	50.18	3	FL	Davie town	48.78	3
CA	Brea	50.15	3	FL	Jacksonville	48.70	3
AZ	Tucson	50.02	3	FL	Sanford	47.76	3
CA	La Mirada	49.98	3	TX	Austin	47.67	3
CA	Walnut	48.66	3	CA	Chula Vista	47.61	3
TN	Chattanooga	48.66	3	FL	Daytona Beach	47.58	3
MO	University City	48.64	3	CT	Stamford	47.55	3
CA	Diamond Bar	48.64	3	CA	Hemet	47.53	3
NC	Durham	48.57	3	TX	Mesquite	47.50	3
NC	Winston-Salem	48.56	3	CA	Martinez	47.48	3

State	City	SI	Rank	State	City	SI	Rank
CA	Vista	47.44	3	CA	Los Banos	46.11	3
AL	Birmingham	47.37	3	FL	Weston	46.10	3
HI	Honolulu CDP	47.37	3	CA	Santa Cruz	46.06	3
FL	Lauderdale Lakes	47.36	3	OR	OR City	46.05	3
MN	Brooklyn Park	47.33	3	WA	Everett	46.03	3
FL	Wellington village	47.30	3	WA	Pasco	45.96	3
UT	Sandy	47.28	3	CA	Pleasanton	45.95	3
CA	Hesperia	47.21	3	CA	Yucaipa	45.95	3
TX	Farmers Branch	47.19	3	AZ	Chandler	45.93	3
NE	Omaha	47.19	3	NY	Troy	45.93	3
FL	Boynton Beach	47.11	3	CA	Yuba City	45.84	3
AK	Little Rock	47.06	3	GA	Savannah	45.82	3
CA	Alhambra	46.95	3	CT	Danbury	45.82	3
OK	Tulsa	46.92	3	FL	Plantation	45.81	3
WA	Lakewood	46.86	3	CT	New Britain	45.73	3
CA	Dublin	46.84	3	NJ	Bergenfield borough	45.72	3
CA	Redondo Beach	46.73	3	NY	Poughkeepsie	45.69	3
AL	Mobile	46.66	3	CA	Campbell	45.63	3
MA	Waltham	46.55	3	AK	Pine Bluff	45.61	3
CA	Glendora	47.80	3	CT	Norwich	46.47	3
NC	Fayetteville	47.79	3	CA	Livermore	46.46	3
NY	Rochester	47.78	3	TX	Corpus Christi	45.55	3
NC	Greensboro	47.78	3	WA	Shoreline	45.51	3
CA	Roseville	46.46	3	MA	Leominster	45.46	3
CA	Fremont	46.41	3	WA	Spokane	45.41	3
CA	La Verne	46.34	3	CA	Palm Desert	45.30	3
CA	San Marcos	46.30	3	AZ	Avondale	45.26	3
MA	Haverhill	46.26	3	TX	Cedar Hill	45.18	3
FL	Delray Beach	46.26	3	CA	La Habra	45.17	3
FL	Altamonte Springs	46.21	3	IN	South Bend	45.15	3
CA	Folsom	46.15	3	LA	Alexandria	45.04	3

State	City	SI	Rank	State	City	SI	Rank
FL	Palm Bay	44.94	3	FL	Plant City	43.86	3
AL	Prichard	44.89	3	MO	St. Charles	43.78	3
MS	Southaven	44.81	3	CA	Seaside	43.76	3
CA	Costa Mesa	44.81	3	MD	Hagerstown	43.72	3
TX	Grand Prairie	44.81	3	MA	New Bedford	43.65	3
GA	Macon	44.78	3	CT	New London	43.58	3
OK	OK City	44.78	3	FL	Kissimmee	43.54	3
SC	Spartanburg	44.74	3	OH	Springfield	43.54	3
TX	Kingsville	44.67	3	UT	South Jordan	43.41	3
OH	Hamilton	44.62	3	CA	Santa Paula	43.41	3
CA	Rosemead	44.57	3	NY	Middletown	43.38	3
SC	Florence	44.54	3	WI	Racine	43.34	3
CO	Northglenn	44.49	3	AZ	Glendale	43.32	3
CO	CO Springs	44.45	3	CO	Wheat Ridge	43.32	3
CA	Madera	44.43	3	MA	Holyoke	43.27	3
CA	Hanford	44.42	3	CT	West Haven	43.26	3
PA	State College borough	44.35	3	TX	Laredo	43.25	3
CA	San Carlos	44.30	3	WA	Federal Way	43.25	3
CA	Santa Rosa	44.30	3	CA	Napa	43.21	3
CA	Chino Hills	45.59	3	TX	DeSoto	43.19	3
MA	Melrose	45.56	3	TX	Hurst	43.16	3
MA	Fall River	44.29	3	CA	La Mesa	43.15	3
MN	Minneapolis	44.29	3	CA	Yorba Linda	43.13	3
MA	Peabody	44.25	3	MO	MD Heights	43.10	3
FL	Pinellas Park	44.23	3	OH	Youngstown	43.00	3
WA	University Place	44.20	3	RI	Cranston	43.00	3
CA	Mission Viejo	44.12	3	CA	Westminster	42.85	3
NY	Albany	44.08	3	FL	Jupiter town	42.83	3
MI	Inkster	44.07	3	CA	Sunnyvale	42.70	3
WA	Des Moines	44.06	3	TX	Brownsville	42.64	3
NC	Rocky Mount	43.87	3	TX	Pharr	42.57	3

State	City	SI	Rank	State	City	SI	Rank
FL	Apopka	42.52	3	MA	Marlborough	40.68	3
CA	Carlsbad	42.49	3	NC	Chapel Hill town	40.66	3
CA	Santa Maria	42.48	3	FL	Boca Raton	40.66	3
LA	Kenner	42.44	3	CA	Santa Barbara	40.64	3
CA	Apple Valley town	42.31	3	NC	High Point	40.60	3
MN	Coon Rapids	42.28	3	CA	Ceres	40.56	3
FL	Sunrise	42.17	3	CA	Woodland	40.56	3
WI	Kenosha	42.05	3	NV	North Las Vegas	40.54	3
MI	Southfield	42.03	3	CA	San Juan Capistrano	40.48	3
CA	Danville town	41.99	3	NC	Greenville	40.46	3
VA	Richmond	41.86	3	VA	Charlottesville	40.43	3
MI	Eastpointe	41.81	3	OH	Canton	40.40	3
OH	Euclid	41.81	3	CA	Davis	40.40	3
NC	Salisbury	41.70	3	IN	MI City	40.36	3
VT	Burlington	41.69	3	CA	Lodi	40.32	3
CA	Dana Point	41.59	3	CA	Lake Forest	40.23	3
TX	Euless	41.55	3				
IN	Mishawaka	41.51	3	MI	Lincoln Park	40.22	3
MA	Woburn	41.48	3	VA	Norfolk	40.22	3
CA	Temecula	41.44	3	WA	Burien	40.20	3
RI	Woonsocket	41.38	3	IN	Elkhart	40.20	3
MA	Fitchburg	41.24	3	CT	Milford (balance)	40.20	3
CA	El Centro	41.18	3	CA	Delano	40.16	3
MI	Dearborn	41.13	3	CA	Saratoga	40.14	3
RI	Warwick	41.09	3	TX	San Marcos	40.10	3
AZ	Surprise	41.06	3	FL	Sarasota	40.03	3
OH	Dayton	40.94	3	ME	Portland	40.01	3
AZ	Mesa	40.91	3	ID	Nampa	39.36	4
NJ	Vineland	40.85	3	CA	Santee	39.97	4
WA	Marysville	40.74	3	MI	Grand Rapids	39.92	4
CA	Escondido	40.69	3	FL	Port St. Lucie	39.89	4

State	City	SI	Rank	State	City	SI	Rank
OR	Keizer	39.87	4	AL	Tuscaloosa	38.81	4
MI	Livonia	39.79	4	CO	Broomfield	38.80	4
CA	Simi Valley	39.73	4	VA	Petersburg	38.69	4
GA	Gainesville	39.72	4	CA	Huntington Beach	38.66	4
NV	Sparks	39.72	4	FL	Miramar	38.62	4
MI	Battle Creek	39.71	4	GA	Dalton	38.56	4
FL	Coconut Creek	39.69	4	CA	Merced	38.54	4
CA	Monterey Park	39.67	4	AK	Jacksonville	38.54	4
CA	Palm Springs	39.65	4	CA	Redlands	38.52	4
MI	Madison Heights	39.64	4	GA	Rome	38.49	4
WV	Huntington	39.62	4	VA	Newport News	38.44	4
WA	Wenatchee	39.53	4	NY	Syracuse	38.43	4
NC	Hickory	39.44	4	FL	Largo	38.42	4
TX	Bryan	39.43	4	CO	Fort Collins	38.38	4
NM	Santa Fe	39.42	4	NC	Raleigh	38.30	4
CA	Napa	39.36	4	LA	Monroe	38.29	4
OH	Cleveland Heights	38.26	4	CA	Irvine	38.18	4
CA	Culver City	38.24	4	CA	Thousand Oaks	38.12	4
AZ	Tempe	38.22	4	TX	Del Rio	38.09	4
TX	Beaumont	39.33	4	OH	Fairfield	38.01	4
WA	Kirkland	39.33	4	FL	Bradenton	38.00	4
CA	Laguna Niguel	39.32	4	TX	Pasadena	37.99	4
VA	Leesburg town	39.32	4	TN	Columbia	37.88	4
CA	Torrance	39.27	4	CA	San Clemente	37.85	4
CO	Aurora	39.25	4	MI	Lansing	37.83	4
AZ	Bullhead City	39.14	4	MO	St. Peters	37.81	4
CA	Victorville	39.02	4	LA	Lafayette	37.81	4
OH	Toledo	39.01	4	TN	Murfreesboro	37.74	4
GA	LaGrange	38.98	4	CA	Los Gatos town	37.71	4
AL	Bessemer	38.90	4	UT	West Valley City	37.70	4
TN	Memphis	38.87	4	UT	Layton	37.68	4

State	City	SI	Rank	State	City	SI	Rank
TX	Killeen	37.68	4	MI	Saginaw	36.15	4
MO	O'Fallon	37.64	4	MO	Independence	36.14	4
CA	Los Altos	37.58	4	IL	Aurora	36.01	4
WA	Longview	37.55	4	TX	Pearland	35.99	4
CA	Manhattan Beach	37.54	4	FL	Winter Haven	35.96	4
FL	Titusville	37.53	4	MA	Methuen	35.95	4
MI	Taylor	37.51	4	CA	Monterey	35.93	4
AK	Hot Springs	37.50	4	IN	New Albany	35.88	4
NC	Wilmington	37.48	4	WA	Puyallup	35.87	4
MO	Jefferson City	37.42	4	CT	Naugatuck borough	35.81	4
TX	Mo City	37.36	4	NC	Monroe	35.81	4
FL	Key West	37.21	4	WI	Beloit	35.78	4
WI	Greenfield	37.11	4	CA	Cathedral City	35.75	4
IN	Lawrence	37.00	4	TX	Denton	35.71	4
MI	Kalamazoo	36.99	4	TX	Flower Mound town	35.69	4
FL	Ocala	36.94	4	FL	Gainesville	35.68	4
UT	Ogden	36.94	4	MN	Brooklyn Center	35.68	4
LA	Shreveport	36.82	4	WA	Yakima	35.65	4
MI	Wyoming	36.72	4	NY	Niagara Falls	35.65	4
TX	Plano	36.65	4	NY	Saratoga Springs	35.61	4
MI	Southgate	36.64	4	NC	Wilson	35.55	4
CA	Visalia	36.55	4	AZ	Scottsdale	35.54	4
CA	Redding	36.54	4	TX	Texarkana	35.54	4
MI	Westland	36.53	4	TX	Conroe	35.48	4
MI	Garden City	36.52	4	CA	Turlock	35.48	4
NC	Gastonia	36.48	4	TX	Copperas Cove	35.46	4
TN	Knoxville	36.47	4	OR	Salem	35.39	4
SC	Greenville	36.44	4	OH	Lorain	35.39	4
OK	Lawton	36.40	4	MI	Jackson	35.37	4
FL	Tallahassee	36.26	4	MA	Gloucester	35.28	4
LA	Houma	36.20	4	MI	Muskegon	35.22	4

State	City	SI	Rank	State	City	SI	Rank
AK	Conway	35.21	4	IN	Greenwood	34.14	4
CA	Porterville	35.19	4	TX	Sugar Land	34.13	4
TX	Carrollton	35.18	4	WA	Olympia	34.11	4
WA	Kennewick	35.18	4	TX	North Richland Hills	34.08	4
MA	Agawam	35.18	4	WA	Lacey	34.02	4
CA	Rohnert Park	35.17	4	WI	Wausau	33.94	4
MI	Roseville	35.06	4	TX	Amarillo	33.93	4
AZ	Flagstaff	34.99	4	AZ	Gilbert town	33.84	4
CA	Indio	34.98	4	CA	Murrieta	33.81	4
MI	Burton	34.95	4	PA	Altoona	33.81	4
CA	Fountain Valley	34.88	4	CA	Lompoc	33.76	4
CA	Calexico	34.84	4	CA	Monrovia	33.74	4
TX	Garland	34.83	4	ID	Coeur d'Alene	33.63	4
IN	Noblesville	34.74	4	IN	Portage	33.63	4
PA	New Castle	34.68	4	OR	Eugene	33.61	4
OH	Mansfield	34.61	4	CA	Camarillo	33.56	4
IN	Fort Wayne	34.61	4	NE	Lincoln	33.54	4
TN	Jackson	34.60	4	FL	Panama City	33.54	4
IN	West Lafayette	34.46	4	CA	Bakersfield	33.47	4
TX	Baytown	34.44	4	LA	Bossier City	33.47	4
IA	Council Bluffs	34.43	4	CA	Tulare	33.43	4
CO	Lakewood	34.37	4	GA	Hinesville	33.33	4
AL	Montgomery	34.36	4	ID	Caldwell	33.30	4
CO	Pueblo	34.34	4	NC	Goldsboro	33.27	4
CA	Rocklin	34.34	4	MI	Farmington Hills	33.27	4
TN	Clarksville	34.30	4	GA	Peachtree City	33.17	4
CA	Moorpark	34.29	4	CA	Poway	33.16	4
KS	Wichita	34.29	4	MO	Springfield	33.12	4
TX	La Porte	34.27	4	CT	Shelton	33.08	4
AK	West Memphis	34.21	4	TX	Waco	33.03	4
WA	Bellingham	34.20	4	AL	Auburn	32.94	4

State	City	SI	Rank	State	City	SI	Rank
MI	Allen Park	32.93	4	IA	Mason City	32.00	4
MI	St. Clair Shores	32.92	4	TX	Odessa	31.99	4
CT	Meriden	32.92	4	FL	Winter Park	31.99	4
TN	Bristol	32.88	4	TN	Smyrna town	31.93	4
OH	Lima	32.81	4	FL	Palm Beach Gardens	31.92	4
NV	Reno	32.80	4	NJ	Millville	31.91	4
CO	Arvada	32.78	4	CA	Eureka	31.85	4
IN	Richmond	32.72	4	KS	Topeka	31.84	4
NV	Henderson	32.54	4	TX	The Colony	31.67	4
FL	Oviedo	32.53	4	TX	Longview	31.66	4
OH	Trotwood	32.48	4	OH	Newark	31.65	4
NY	Binghamton	32.47	4	CA	Rancho Palos Verdes	31.64	4
LA	New Iberia	32.44	4	MN	Richfield	31.64	4
MS	Gulfport	32.44	4	AK	Texarkana	31.61	4
FL	Lakeland	32.42	4	CO	Loveland	31.58	4
TX	Haltom City	32.40	4	IA	Ankeny	31.54	4
MI	Bay City	32.39	4	IN	Lafayette	31.38	4
MI	Ann Arbor	32.39	4	IN	Valparaiso	31.36	4
NM	Las Cruces	32.37	4	TX	Rowlett	31.34	4
NM	Clovis	32.36	4	NY	North Tonawanda	31.34	4
OH	Strongsville	32.34	4	AK	North Little Rock	31.33	4
MN	Bloomington	32.27	4	MI	Port Huron	31.33	4
IA	Des Moines	32.18	4	MI	Novi	31.31	4
GA	Albany	32.18	4	TX	Texas City	31.31	4
NM	Farmington	32.16	4	TX	College Station	31.30	4
MI	Dearborn Heights	32.15	4	TX	Lewisville	31.27	4
ID	Boise City	32.11	4	OH	Barberton	31.27	4
TX	Round Rock	32.11	4	WI	Madison	31.24	4
FL	Cooper City	32.10	4	MI	Troy	31.24	4
TX	Harlingen	32.08	4	TX	Big Spring	31.22	4
NE	Grand Island	32.01	4	UT	Bountiful	31.17	4

State	City	SI	Rank	State	City	SI	Rank
MI	Sterling Heights	31.14	4	AL	Prattville	30.14	4
WI	West Allis	31.11	4	OH	Sandusky	30.14	4
MN	St. Louis Park	31.07	4	FL	Cape Coral	30.14	4
OH	Stow	31.05	4	CA	San Luis Obispo	30.13	4
MA	Northampton	31.04	4	WA	Mount Vernon	30.08	4
AZ	Oro Valley town	31.03	4	IN	Evansville	30.02	4
IN	Bloomington	31.03	4	KY	Paducah	30.02	4
NC	Huntersville town	31.00	4	TN	Hendersonville	29.99	4
TX	Keller	30.90	4	MN	Andover	29.98	4
UT	Roy	30.89	4	OK	Bartlesville	29.96	4
FL	Dunedin	30.86	4	TX	Cleburne	29.95	4
OH	Westlake	30.81	4	MN	Woodbury	29.95	4
MN	Eden Prairie	30.80	4	TX	Wichita Falls	29.94	4
AL	Phoenix City	30.80	4	IN	Columbus	29.93	4
AL	Huntsville	30.74	4	OH	Fairborn	29.92	4
TX	New Braunfels	30.71	4	PA	Bethlehem	29.88	4
OH	Huber Heights	30.70	4	NC	Asheville	29.79	4
TX	Tyler	30.65	4	CO	Greeley	29.79	4
OR	Corvallis	30.51	4	WI	Wauwatosa	29.78	4
MO	Raytown	30.51	4	OR	Springfield	29.75	4
OR	Albany	30.37	4	FL	Ormond Beach	29.74	4
MT	Great Falls	30.34	4	NY	Utica	29.67	4
MI	Wyandotte	30.32	4	MS	Pascagoula	29.64	4
OH	Reynoldsburg	30.32	4	TX	Mansfield	29.63	4
FL	Port Orange	30.31	4	WA	Bothell	29.62	4
MN	Mankato	30.29	4	CT	Bristol	29.60	4
FL	Winter Springs	30.29	4	WI	Superior	29.56	4
SC	Columbia	30.25	4	WI	Eau Claire	29.56	4
MS	Biloxi	30.24	4	AZ	Peoria	29.56	4
TX	Lubbock	30.20	4	ME	Lewiston	29.34	4
TX	Port Arthur	30.18	4	WA	Edmonds	29.32	4

State	City	SI	Rank	State	City	SI	Rank
AL	Homewood	29.26	4	ID	ID Falls	27.82	4
AZ	Lake Havasu City	29.26	4	CO	Boulder	27.79	4
TX	Allen	29.24	4	MN	Oakdale	27.72	4
AK	Fort Smith	29.24	4	WA	Redmond	27.69	4
OR	Grants Pass	29.21	4	MS	Meridian	27.68	4
OH	Kent	29.12	4	OH	Middletown	27.62	4
MO	St. Joseph	29.06	4	IA	Waterloo	27.62	4
TX	McAllen	29.04	4	TX	Sherman	27.58	4
WY	Cheyenne	29.00	4	CA	Atascadero	27.50	4
AZ	Casa Grande	28.96	4	IL	Naperville	27.47	4
CA	Paradise town	28.91	4	MO	Gladstone	27.46	4
NM	Roswell	28.90	4	TN	Johnson City	27.43	4
PA	Erie	28.82	4	SD	Sioux Falls	27.42	4
MI	East Lansing	28.80	4	OK	Moore	27.41	4
OH	Kettering	28.77	4	TX	Midland	27.37	4
OH	DE	28.68	4	MO	Columbia	27.33	4
WI	Green Bay	28.65	4	AL	Dothan	27.31	4
TX	Grapevine	28.60	4	OH	Grove City	27.23	4
IA	Marshalltown	28.57	4	NC	Kannapolis	27.19	4
NM	Hobbs	28.45	4	CO	Grand Junction	27.10	4
IA	Cedar Rapids	28.44	4	WI	Janesville	27.07	4
CA	Clovis	28.36	4	ID	Twin Falls	27.05	4
MI	Portage	28.34	4	TN	Cleveland	27.00	4
VA	VA Beach	28.32	4	NM	Alamogordo	26.85	4
MS	Vicksburg	28.17	4	MI	Midland	26.83	4
TX	Friendswood	28.09	4	OH	Gahanna	26.82	4
WA	Bellevue	28.06	4	TN	Cookeville	26.80	4
NM	Rio Rancho	28.03	4	AL	Fayetteville	26.80	4
WY	Casper	28.01	4	OR	Medford	26.70	4
VA	Lynchburg	27.94	4	MI	Kentwood	26.67	4
OK	Midwest City	27.88	4	SD	Rapid City	26.57	4

State	City	SI	Rank	State	City	SI	Rank
UT	Clearfield	26.56	4	CT	Middletown	25.44	4
MN	Apple Valley	26.46	4	KY	Owensboro	25.37	4
CA	Chico	26.38	4	OH	Dublin	25.32	4
KY	Bowling Green	26.37	4	IA	Burlington	25.28	4
TN	Collierville town	26.35	4	NY	Watertown	25.07	4
NY	Auburn	26.20	4	ND	Minot	25.03	4
IA	Urbandale	26.20	4	OR	McMinnville	25.02	4
MO	Ballwin	26.14	4	MN	Eagan	25.01	4
VA	Blacksburg town	26.13	4	TX	San Angelo	25.01	4
WA	Walla Walla	26.12	4	OK	Norman	25.00	4
TX	Cedar Park	26.09	4	MS	Columbus	24.89	4
IN	Terre Haute	25.92	4	TX	Abilene	24.87	4
ND	Bismarck	25.92	4	IA	Fort Dodge	24.75	4
OH	Cuyahoga Falls	25.91	4	AL	Florence	24.70	4
NM	Carlsbad	25.86	4	OR	Bend	24.61	4
NY	Jamestown	25.86	4	TX	League City	24.52	4
WI	Appleton	25.85	4	WA	Sammamish	24.52	4
IA	IA City	25.85	4	WI	Oak Creek	24.49	4
TX	Socorro	25.85	4	OR	Lake Oswego	24.43	4
GA	Athens-Clarke County	25.84	4	MO	Kirkwood	24.41	4
OK	Broken Arrow	25.75	4	MN	Inver Grove Heights	24.31	4
WI	La Crosse	25.72	4	MN	Duluth	24.21	4
MN	Maple Grove	25.71	4	TX	Nacogdoches	24.12	4
TX	Lufkin	25.67	4	TX	Frisco	24.11	4
MO	Joplin	25.65	4	UT	Provo	23.88	4
OH	Mentor	25.62	4	OH	Westerville	23.81	4
TN	Brentwood	25.61	4	NE	Bellevue	23.77	4
MO	Chesterfield	25.53	4	ND	Grand Forks	23.74	4
MN	Plymouth	25.51	4	NC	Cary town	23.74	4
DE	Wilmington	25.48	4	WI	Waukesha	23.65	4
CT	Torrington	25.45	4	WI	Oshkosh	23.44	4

State	City	SI	Rank	State	City	SI	Rank
IA	Ames	23.42	4	AK	Rogers	20.91	4
MO	Cape Girardeau	23.41	4	WA	Richland	20.77	4
MS	Hattiesburg	23.36	4	IA	Bettendorf	20.72	4
NE	Fremont	23.33	4	TX	Georgetown	20.29	4
WI	Sheboygan	23.13	4	OH	Beavercreek	20.25	4
OH	Upper Arlington	23.07	4	MN	Lakeville	20.22	4
MN	Cottage Grove	23.02	4	MI	Mount Pleasant	20.15	4
MI	Holland	22.95	4	IN	Jeffersonville	20.09	4
MO	Lee's Summit	22.93	4	MN	Moorhead	20.03	4
MN	Edina	22.93	4	DE	Newark	20.02	4
AK	Springdale	22.66	4	IA	Dubuque	20.00	5
IA	Sioux City	22.62	4	MS	Tupelo	19.93	5
NY	Rome	22.31	4	WI	West Bend	19.91	5
IA	West Des Moines	22.28	4	WI	Brookfield	19.71	5
NE	Kearney	22.28	4	ID	Lewiston	19.64	5
MN	Winona	22.19	4	WY	Laramie	19.48	5
MN	Rochester	22.14	4	ND	Fargo	19.05	5
OK	Enid	22.00	4	OK	Stillwater	19.05	5
MO	Liberty	21.99	4	IA	Cedar Falls	19.02	5
WI	Fond du Lac	21.94	4	OK	Edmond	18.58	5
UT	Orem	21.89	4	WI	Manitowoc	18.37	5
AL	Madison	21.85	4	ME	Bangor	18.30	5
MA	Pittsfield	21.58	4	NC	Burlington	15.56	5
OK	Ponca City	21.55	4	TX	Victoria	15.46	5
ID	Pocatello	21.53	4	WI	Menomonee Falls village	15.07	5
MN	St. Cloud	21.49	4	TX	Weslaco	15.00	5
WI	Franklin	21.49	4	TX	Edinburg	14.62	5
MN	Minnetonka	21.48	4	TX	Bedford	13.99	5
OH	Bowling Green	21.35	4	IN	Goshen	12.76	5
WI	New Berlin	21.28	4	GA	Warner Robins	12.43	5
TX	Lake Jackson	21.07	4	DE	Dover	12.00	5

State	City	SI	Rank	State	City	SI	Rank
IL	Rockford	11.85	5	ID	Meridian	7.71	5
TN	Morristown	11.01	5	TX	Mission	7.59	5
IN	Kokomo	10.19	5	AL	Hoover	7.30	5
IL	Peoria	8.80	5	TN	Germantown	7.21	5
TN	Bartlett	8.79	5	OK	Shawnee	5.57	5
TN	Kingsport	8.67	5	TX	Temple	4.41	5
OK	Muskogee	8.55	5	AK	Jonesboro	2.87	5
IL	Springfield	7.72	5	AL	Vestavia Hills	0.00	5

Notes: SI = Standardized walkability index score before a rank was assigned to it.

Table 2
Walkability Index Ranks
Census Tracts in the Washington, D.C. Metropolitan Area, 2011

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Washington, DC	11001004400	100.00	1	Washington, DC	11001006600	93.98	1
Washington, DC	11001003000	99.93	1	Washington, DC	11001008701	93.98	1
Washington, DC	11001002802	99.65	1	Washington, DC	11001003400	93.97	1
Washington, DC	11001004201	99.29	1	Washington, DC	11001006500	93.91	1
Washington, DC	11001005002	98.31	1	Washington, DC	11001000202	93.66	1
Washington, DC	11001002702	98.09	1	Washington, DC	11001002900	93.51	1
Washington, DC	11001005201	97.63	1	Washington, DC	11001008001	93.39	1
Washington, DC	11001004001	97.14	1	Washington, DC	11001004802	93.19	1
Washington, DC	11001008301	97.12	1	Washington, DC	11001010100	93.18	1
Washington, DC	11001004902	97.03	1	Washington, DC	11001002101	93.17	1
Washington, DC	11001004300	96.96	1	Washington, DC	11001004801	93.15	1
Washington, DC	11001003100	96.91	1	Washington, DC	11001007403	93.11	1
Washington, DC	11001005600	96.87	1	Washington, DC	11001010800	93.08	1
Washington, DC	11001002801	96.87	1	Washington, DC	11001008402	93.04	1
Washington, DC	11001005500	96.85	1	Washington, DC	11001004002	92.89	1
Washington, DC	11001004202	96.82	1	Washington, DC	11001007000	92.88	1
Washington, DC	11001008302	96.33	1	Washington, DC	11001003600	92.78	1
Washington, DC	11001005900	96.33	1	Washington, DC	11001001302	92.70	1
Washington, DC	11001000702	95.94	1	Alexandria City, VA	51510201600	92.61	1
Washington, DC	11001003800	95.88	1	Washington, DC	11001002701	92.56	1
Arlington, VA	51013101702	95.47	1	Washington, DC	11001008410	92.38	1
Washington, DC	11001008100	95.38	1	Washington, DC	11001010600	92.35	1
Montgomery, MD	24031702601	94.95	1	Washington, DC	11001004901	92.31	1
Washington, DC	11001003900	94.90	1	Washington, DC	11001002201	92.26	1
Washington, DC	11001003302	94.85	1	Washington, DC	11001006700	92.24	1
Washington, DC	11001010500	94.32	1	Washington, DC	11001006801	92.20	1

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Washington, DC	11001001200	91.72	1	Washington, DC	11001002102	90.21	1
Arlington, VA	51013103402	91.70	1	Montgomery, MD	24031705602	90.19	1
Washington, DC	11001002502	91.65	1	Prince George's, MD	24033805601	90.16	1
Washington, DC	11001006900	91.61	1	Washington, DC	11001005001	90.13	1
Washington, DC	11001003200	91.59	1	Washington, DC	11001006802	89.98	1
Washington, DC	11001010200	91.58	1	Washington, DC	11001003700	89.96	1
Prince George's, MD	24033805602	91.45	1	Prince George's, MD	24033804801	89.81	1
Washington, DC	11001000501	91.44	1	Washington, DC	11001001401	89.51	1
Arlington, VA	51013101701	91.26	1	Washington, DC	11001001804	89.44	1
Washington, DC	11001001702	91.20	1	Washington, DC	11001002400	89.40	1
Washington, DC	11001000300	91.19	1	Washington, DC	11001004701	89.35	1
Washington, DC	11001001100	91.14	1	Washington, DC	11001005301	89.24	1
Washington, DC	11001008802	91.12	1	Washington, DC	11001001001	89.24	1
Washington, DC	11001007100	91.09	1	Washington, DC	11001004702	89.10	1
Arlington, VA	51013101404	91.08	1	Montgomery, MD	24031702602	88.99	1
Washington, DC	11001003500	91.06	1	Washington, DC	11001002002	88.96	1
Arlington, VA	51013101602	90.99	1	Montgomery, MD	24031701102	88.73	1
Montgomery, MD	24031701702	90.98	1	Arlington, VA	51013101500	88.66	1
Washington, DC	11001004600	90.93	1	Washington, DC	11001000502	88.61	1
Washington, DC	11001009501	90.89	1	Arlington, VA	51013102001	88.57	1
Arlington, VA	51013101802	90.89	1	Alexandria City, VA	51510201900	88.57	1
Montgomery, MD	24031704806	90.80	1	Washington, DC	11001002301	88.48	1
Washington, DC	11001000100	90.72	1	Washington, DC	11001009811	88.47	1
Washington, DC	11001008904	90.67	1	Washington, DC	11001009301	88.46	1
Arlington, VA	51013101603	90.63	1	Montgomery, MD	24031704804	88.45	1
Washington, DC	11001001901	90.56	1	Washington, DC	11001007903	88.41	1
Washington, DC	11001007901	90.48	1	Washington, DC	11001008903	88.40	1
Montgomery, MD	24031702500	90.47	1	Prince George's, MD	24033805907	88.32	1
Arlington, VA	51013103601	90.29	1	Washington, DC	11001009204	88.30	1
Washington, DC	11001010700	90.26	1	Prince George's, MD	24033806501	88.26	1
Arlington, VA	51013103503	90.24	1	Prince George's, MD	24033805201	87.96	1

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Washington, DC	11001009400	87.95	1	Montgomery, MD	24031702402	86.25	1
Prince George's, MD	24033801805	87.93	1	Washington, DC	11001008804	86.23	1
Washington, DC	11001009102	87.92	1	Washington, DC	11001009603	86.19	1
Washington, DC	11001007502	87.77	1	Washington, DC	11001008803	86.13	1
Prince George's, MD	24033804802	87.74	1	Washington, DC	11001006400	86.11	1
Alexandria City, VA	51510200107	87.72	1	Washington, DC	11001007703	86.10	1
Washington, DC	11001009201	87.58	1	Montgomery, MD	24031700901	86.09	1
Prince George's, MD	24033806000	87.46	1	Prince George's, MD	24033801600	86.09	1
Prince George's, MD	24033802404	87.45	1	Montgomery, MD	24031703902	86.05	1
Prince George's, MD	24033804600	87.41	1	Fairfax, VA	51059451601	86.04	1
Montgomery, MD	24031701701	87.35	1	Prince George's, MD	24033802407	85.99	1
Arlington, VA	51013103800	87.23	1	Arlington, VA	51013102002	85.96	1
Montgomery, MD	24031700905	87.22	1	Washington, DC	11001009504	85.95	1
Washington, DC	11001008200	87.20	1	Montgomery, MD	24031702000	85.93	1
Arlington, VA	51013103200	87.18	1	Washington, DC	11001009807	85.84	1
Fairfax, VA	51059420400	87.10	1	Arlington, VA	51013101703	85.78	1
Alexandria City, VA	51510201204	87.09	1	Prince George's, MD	24033805700	85.71	1
Washington, DC	11001007707	87.09	1	Washington, DC	11001007200	85.70	1
Washington, DC	11001000701	87.06	1	Prince George's, MD	24033805802	85.70	1
Washington, DC	11001007503	86.94	1	Montgomery, MD	24031704000	85.57	1
Washington, DC	11001002501	86.77	1	Arlington, VA	51013102003	85.51	1
Washington, DC	11001002202	86.76	1	Alexandria City, VA	51510200702	85.44	1
Montgomery, MD	24031701900	86.71	1	Arlington, VA	51013102500	85.44	1
Montgomery, MD	24031702301	86.68	1	Prince George's, MD	24033805202	85.40	1
Prince George's, MD	24033804700	86.66	1	Washington, DC	11001010400	85.32	1
Fairfax, VA	51059420600	86.54	1	Alexandria City, VA	51510200406	85.30	1
Washington, DC	11001008702	86.53	1	Montgomery, MD	24031701800	85.29	1
Washington, DC	11001011000	86.52	1	Washington, DC	11001007408	85.23	1
Prince George's, MD	24033805000	86.50	1	Washington, DC	11001009203	85.22	1
Washington, DC	11001004100	86.41	1	Arlington, VA	51013101803	85.20	1
Washington, DC	11001007601	86.30	1	Washington, DC	11001009810	85.18	1

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Frederick, MD	24021750200	85.15	1	Alexandria City, VA	51510200703	83.99	1
Washington, DC	11001000600	85.10	1	Montgomery, MD	24031700904	83.98	1
Prince George's, MD	24033806601	85.09	1	Washington, DC	11001007409	83.95	1
Arlington, VA	51013101402	85.01	1	Washington, DC	11001007809	83.85	1
Fairfax, VA	51059451501	85.00	1	Washington, DC	11001007304	83.85	1
Alexandria City, VA	51510201203	84.99	1	Washington, DC	11001007603	83.84	1
Montgomery, MD	24031704803	84.89	1	Fairfax, VA	51059452802	83.83	1
Arlington, VA	51013102902	84.88	1	Washington, DC	11001010300	83.82	1
Arlington, VA	51013102701	84.86	1	Arlington, VA	51013101801	83.76	1
Washington, DC	11001001002	84.85	1	Washington, DC	11001007808	83.68	1
Prince George's, MD	24033803700	84.84	1	Prince George's, MD	24033806713	83.67	1
Frederick, MD	24021750300	84.82	1	Prince George's, MD	24033806200	83.56	1
Montgomery, MD	24031702800	84.65	1	Prince George's, MD	24033802700	83.55	1
Fairfax, VA	51059451400	84.62	1	Prince George's, MD	24033803612	83.51	1
Prince George's, MD	24033802901	84.61	1	Arlington, VA	51013103501	83.41	1
Montgomery, MD	24031702900	84.59	1	Prince George's, MD	24033802301	83.40	1
Montgomery, MD	24031703800	84.50	1	Prince George's, MD	24033806900	83.38	1
Washington, DC	11001002001	84.49	1	Fairfax, VA	51059461602	83.36	1
Prince George's, MD	24033804002	84.41	1	Montgomery, MD	24031703601	83.29	1
Prince George's, MD	24033805908	84.37	1	Washington, DC	11001001803	83.24	1
Montgomery, MD	24031704503	84.33	1	Washington, DC	11001009509	83.23	1
Montgomery, MD	24031701201	84.26	1	Prince George's, MD	24033800102	83.20	1
Montgomery, MD	24031703901	84.25	1	Prince George's, MD	24033805500	83.19	1
Arlington, VA	51013101100	84.21	1	Washington, DC	11001009700	83.18	1
Prince George's, MD	24033801802	84.21	1	Washington, DC	11001009302	83.11	1
Fairfax, VA	51059452700	84.18	1	Fredericksburg, VA	51630000100	83.08	1
Alexandria City, VA	51510201000	84.17	1	Washington, DC	11001001402	83.08	1
Montgomery, MD	24031701219	84.08	1	Prince George's, MD	24033805101	83.07	1
Alexandria City, VA	51510200103	84.06	1	Washington, DC	11001001902	83.07	1
Alexandria City, VA	51510201802	84.06	1	Montgomery, MD	24031700902	83.06	1
Montgomery, MD	24031704805	84.02	1	Washington, DC	11001009505	83.05	1

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Prince George's, MD	24033807200	83.03	1	Prince George's, MD	24033806100	82.21	1
Prince George's, MD	24033805801	83.01	1	Washington, DC	11001009508	82.20	1
Montgomery, MD	24031703100	82.99	1	Prince George's, MD	24033800109	82.17	1
Prince George's, MD	24033800108	82.98	1	Montgomery, MD	24031700719	82.14	1
Montgomery, MD	24031703702	82.92	1	Alexandria City, VA	51510200404	82.12	1
Fairfax, VA	51059491702	82.90	1	Fairfax, VA	51059421500	82.07	1
Arlington, VA	51013101300	82.89	1	Montgomery, MD	24031703501	82.07	1
Washington, DC	11001007803	82.88	1	Montgomery, MD	24031703502	82.02	1
Montgomery, MD	24031705000	82.87	1	Prince George's, MD	24033803200	81.99	1
Arlington, VA	51013103602	82.81	1	Montgomery, MD	24031704700	81.98	1
Montgomery, MD	24031702700	82.80	1	Arlington, VA	51013101601	81.95	1
Alexandria City, VA	51510201801	82.75	1	Montgomery, MD	24031701213	81.94	1
Prince George's, MD	24033804900	82.75	1	Montgomery, MD	24031701101	81.90	1
Montgomery, MD	24031705501	82.75	1	Prince George's, MD	24033801808	81.89	1
Falls Church City	51610500200	82.72	1	Prince George's, MD	24033802502	81.82	1
Fairfax, VA	51059430600	82.67	1	Washington, DC	11001009906	81.82	1
Washington, DC	11001009907	82.66	1	Montgomery, MD	24031703213	81.79	1
Alexandria City, VA	51510200500	82.65	1	Prince George's, MD	24033803001	81.77	1
Arlington, VA	51013103502	82.59	1	Washington, DC	11001007604	81.76	1
Montgomery, MD	24031703602	82.52	1	Montgomery, MD	24031701202	81.72	1
Prince George's, MD	24033801707	82.44	1	Montgomery, MD	24031701703	81.71	1
Arlington, VA	51013102600	82.38	1	Fairfax, VA	51059450300	81.70	1
Arlington, VA	51013101403	82.37	1	Montgomery, MD	24031704200	81.69	1
Washington, DC	11001009905	82.35	1	Prince George's, MD	24033801908	81.54	1
Alexandria City, VA	51510202002	82.34	1	Fairfax, VA	51059471301	81.53	1
Washington, DC	11001007804	82.30	1	Prince George's, MD	24033804001	81.51	1
Washington, DC	11001009802	82.28	1	Fairfax, VA	51059450100	81.47	1
Fairfax, VA	51059421002	82.28	1	Montgomery, MD	24031702302	81.47	1
Prince George's, MD	24033802405	82.28	1	Prince George's, MD	24033806602	81.43	1
Fairfax, VA	51059452600	82.27	1	Alexandria City, VA	51510200802	81.40	1
Fairfax, VA	51059421600	82.24	1	Prince George's, MD	24033803402	81.40	1

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Arlington, VA	51013102400	81.33	1	Montgomery, MD	24031704404	80.57	1
Prince George's, MD	24033804200	81.32	1	Prince George's, MD	24033801702	80.56	1
Alexandria City, VA	51510200405	81.31	1	Prince George's, MD	24033806300	80.53	1
Fairfax, VA	51059461601	81.30	1	Washington, DC	11001009801	80.52	1
Arlington, VA	51013101900	81.25	1	Fairfax, VA	51059461700	80.46	1
Montgomery, MD	24031701216	81.17	1	Washington, DC	11001009503	80.41	1
Montgomery, MD	24031703404	81.12	1	Washington, DC	11001007708	80.41	1
Washington, DC	11001000901	81.09	1	Prince George's, MD	24033802501	80.40	1
Arlington, VA	51013100900	81.03	1	Prince George's, MD	24033802001	80.40	1
Alexandria City, VA	51510200105	81.00	1	Arlington, VA	51013102200	80.38	1
Montgomery, MD	24031703401	80.99	1	Prince George's, MD	24033802103	80.35	1
Washington, DC	11001007404	80.92	1	Montgomery, MD	24031701001	80.27	1
Alexandria City, VA	51510200303	80.90	1	Prince George's, MD	24033803508	80.25	1
Fairfax, VA	51059420501	80.87	1	Washington, DC	11001000802	80.23	1
Montgomery, MD	24031702200	80.86	1	Alexandria City, VA	51510201400	80.18	1
Fairfax, VA	51059452200	80.86	1	Washington, DC	11001011100	80.17	1
Prince George's, MD	24033804101	80.84	1	Montgomery, MD	24031700820	80.17	1
Prince George's, MD	24033802600	80.83	1	Alexandria City, VA	51510200104	80.14	1
Montgomery, MD	24031703701	80.82	1	Washington, DC	11001009804	80.13	1
Fairfax, VA	51059471401	80.81	1	Montgomery, MD	24031702401	80.13	1
Prince George's, MD	24033803900	80.78	1	Prince George's, MD	24033807102	80.12	1
Washington, DC	11001007401	80.77	1	Washington, DC	11001007807	80.08	1
Prince George's, MD	24033803613	80.77	1	Prince George's, MD	24033804102	80.07	1
Washington, DC	11001009604	80.77	1	Montgomery, MD	24031700724	80.03	1
Prince George's, MD	24033804300	80.74	1	Washington, DC	11001009507	79.97	2
Alexandria City, VA	51510201300	80.68	1	Prince George's, MD	24033801704	79.95	2
Washington, DC	11001001600	80.66	1	Falls Church City	51610500300	79.94	2
Prince George's, MD	24033800209	80.65	1	Prince George's, MD	24033802203	79.94	2
Montgomery, MD	24031701215	80.61	1	Prince George's, MD	24033803605	79.92	2
Arlington, VA	51013100700	80.60	1	Prince George's, MD	24033805906	79.91	2
Arlington, VA	51013103000	80.59	1	Montgomery, MD	24031703209	79.85	2

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Prince George's, MD	24033802107	79.85	2	Washington, DC	11001000801	79.32	2
Fairfax, VA	51059471201	79.78	2	Arlington, VA	51013103700	79.31	2
Fairfax, VA	51059452801	79.78	2	Fairfax, VA	51059440502	79.31	2
Prince George's, MD	24033807000	79.75	2	Prince George's, MD	24033802408	79.28	2
Fairfax, VA	51059450200	79.72	2	Prince William, VA	51153900300	79.28	2
Montgomery, MD	24031701218	79.69	2	Washington, DC	11001009803	79.25	2
Fairfax, VA	51059421400	79.66	2	Montgomery, MD	24031701005	79.21	2
Prince George's, MD	24033806710	79.62	2	Prince George's, MD	24033807410	79.16	2
Montgomery, MD	24031704300	79.60	2	Montgomery, MD	24031701214	79.11	2
Arlington, VA	51013102302	79.60	2	Washington, DC	11001007709	79.08	2
Prince George's, MD	24033803801	79.60	2	Montgomery, MD	24031701004	79.04	2
Prince George's, MD	24033803300	79.60	2	Prince George's, MD	24033800213	79.02	2
Fairfax, VA	51059452301	79.58	2	Montgomery, MD	24031700818	79.01	2
Prince George's, MD	24033803509	79.57	2	Prince George's, MD	24033802805	78.94	2
Prince George's, MD	24033801405	79.54	2	Prince George's, MD	24033803100	78.93	2
Washington, DC	11001009602	79.54	2	Montgomery, MD	24031700723	78.92	2
Arlington, VA	51013100600	79.49	2	Alexandria City, VA	51510201500	78.86	2
Washington, DC	11001009902	79.49	2	Montgomery, MD	24031700721	78.81	2
Prince George's, MD	24033801801	79.48	2	Fairfax, VA	51059452502	78.73	2
Washington, DC	11001009000	79.47	2	Prince George's, MD	24033800103	78.72	2
Washington, DC	11001007605	79.47	2	Montgomery, MD	24031705502	78.69	2
Montgomery, MD	24031701704	79.44	2	Montgomery, MD	24031704403	78.69	2
Prince George's, MD	24033800516	79.44	2	Montgomery, MD	24031700310	78.59	2
Montgomery, MD	24031701602	79.41	2	Arlington, VA	51013102801	78.59	2
Washington, DC	11001001301	79.41	2	Prince George's, MD	24033802106	78.58	2
Arlington, VA	51013102901	79.41	2	Fairfax, VA	51059491303	78.54	2
Montgomery, MD	24031703403	79.40	2	Montgomery, MD	24031703402	78.54	2
Arlington, VA	51013100100	79.40	2	Frederick, MD	24021750702	78.52	2
Prince George's, MD	24033806400	79.36	2	Prince George's, MD	24033803401	78.50	2
Fairfax, VA	51059461802	79.35	2	Washington, DC	11001002600	78.49	2
Montgomery, MD	24031700717	79.35	2	Arlington, VA	51013101000	78.45	2

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Montgomery, MD	24031700711	78.40	2	Prince George's, MD	24033805909	77.69	2
Prince George's, MD	24033803803	78.40	2	Montgomery, MD	24031700824	77.62	2
Montgomery, MD	24031700309	78.38	2	Montgomery, MD	24031703214	77.60	2
Arlington, VA	51013101401	78.34	2	Prince George's, MD	24033801701	77.59	2
Montgomery, MD	24031700713	78.30	2	Fairfax, VA	51059422101	77.58	2
Prince George's, MD	24033804400	78.30	2	Fairfax, VA	51059450601	77.54	2
Fairfax, VA	51059451900	78.29	2	Fairfax, VA	51059461902	77.42	2
Fairfax, VA	51059422302	78.29	2	Alexandria City, VA	51510200407	77.41	2
Prince George's, MD	24033803513	78.27	2	Prince George's, MD	24033806711	77.39	2
Montgomery, MD	24031705300	78.27	2	Montgomery, MD	24031705200	77.33	2
Washington, DC	11001009601	78.26	2	Fairfax, VA	51059452400	77.32	2
Washington, DC	11001007806	78.23	2	Montgomery, MD	24031700817	77.25	2
Fairfax, VA	51059415500	78.22	2	Fairfax, VA	51059416000	77.23	2
Montgomery, MD	24031700816	78.21	2	Fairfax, VA	51059471202	77.18	2
Prince George's, MD	24033802406	78.20	2	Fairfax, VA	51059450702	77.12	2
Fairfax, VA	51059461901	78.18	2	Washington, DC	11001010900	77.10	2
Fairfax, VA	51059421800	78.16	2	Fairfax, VA	51059451502	77.09	2
Fairfax, VA	51059421701	78.13	2	Prince George's, MD	24033803606	77.06	2
Fairfax, VA	51059450602	78.10	2	Prince George's, MD	24033802002	77.06	2
Montgomery, MD	24031700718	78.07	2	Fairfax, VA	51059491803	77.06	2
Washington, DC	11001000400	78.06	2	Prince George's, MD	24033801804	77.05	2
Prince George's, MD	24033800413	77.99	2	Falls Church City	51610500100	77.04	2
Washington, DC	11001007407	77.93	2	Montgomery, MD	24031701420	77.03	2
Prince George's, MD	24033801708	77.85	2	Prince George's, MD	24033806800	77.02	2
Fairfax, VA	51059471304	77.84	2	Fairfax, VA	51059491704	77.00	2
Montgomery, MD	24031701211	77.83	2	Arlington, VA	51013100500	76.99	2
Alexandria City, VA	51510201202	77.81	2	Montgomery, MD	24031702102	76.99	2
Montgomery, MD	24031703301	77.78	2	Montgomery, MD	24031700716	76.93	2
Prince George's, MD	24033806708	77.78	2	Washington, DC	11001001500	76.92	2
Fairfax, VA	51059482100	77.70	2	Arlington, VA	51013100200	76.92	2
Montgomery, MD	24031704401	77.70	2	Prince George's, MD	24033800606	76.90	2

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Prince William, VA	51153900901	76.90	2	Prince George's, MD	24033803524	76.22	2
Fairfax, VA	51059420503	76.89	2	Fairfax City, VA	51600300300	76.18	2
Prince George's, MD	24033803002	76.88	2	Arlington, VA	51013103100	76.15	2
Fairfax, VA	51059460502	76.86	2	Alexandria City, VA	51510202001	76.11	2
Montgomery, MD	24031701505	76.76	2	Washington, DC	11001009903	76.02	2
Prince George's, MD	24033802803	76.75	2	Fairfax, VA	51059430700	75.99	2
Montgomery, MD	24031700815	76.74	2	Fairfax, VA	51059451300	75.96	2
Montgomery, MD	24031703302	76.70	2	Prince George's, MD	24033807409	75.95	2
Prince George's, MD	24033801807	76.69	2	Fairfax, VA	51059480801	75.92	2
Prince George's, MD	24033807405	76.69	2	Montgomery, MD	24031705800	75.89	2
Montgomery, MD	24031703210	76.66	2	Alexandria City, VA	51510200600	75.85	2
Fairfax, VA	51059420502	76.65	2	Prince George's, MD	24033800105	75.84	2
Prince George's, MD	24033803514	76.64	2	Montgomery, MD	24031701509	75.80	2
Fairfax, VA	51059450500	76.63	2	Prince George's, MD	24033807404	75.79	2
Washington, DC	11001007504	76.62	2	Montgomery, MD	24031703000	75.74	2
Montgomery, MD	24031705100	76.61	2	Manassas Park City, VA	51685920200	75.73	2
Fairfax, VA	51059460701	76.59	2	Manassas Park City, VA	51685920100	75.69	2
Arlington, VA	51013101200	76.58	2	Montgomery, MD	24031705601	75.67	2
Frederick, MD	24021750503	76.58	2	Prince George's, MD	24033802804	75.63	2
Washington, DC	11001000902	76.54	2	Alexandria City, VA	51510200106	75.62	2
Montgomery, MD	24031705400	76.51	2	Montgomery, MD	24031701506	75.61	2
Fairfax, VA	51059481102	76.51	2	Montgomery, MD	24031700826	75.56	2
Arlington, VA	51013103300	76.50	2	Washington, DC	11001002302	76.26	2
Montgomery, MD	24031700704	76.48	2	Prince George's, MD	24033805904	76.25	2
Fairfax, VA	51059461500	76.40	2	Fairfax, VA	51059420300	75.55	2
Montgomery, MD	24031704100	76.38	2	Montgomery, MD	24031701417	75.53	2
Fairfax, VA	51059422000	76.38	2	Charles, MD	24017850709	75.51	2
Prince George's, MD	24033801905	76.32	2	Fairfax, VA	51059470800	75.48	2
Arlington, VA	51013102301	76.28	2	Fairfax, VA	51059460702	75.46	2

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Prince George's, MD	24033806714	75.46	2	Montgomery, MD	24031705701	74.63	2
Montgomery, MD	24031702101	75.45	2	Prince George's, MD	24033800511	74.61	2
Alexandria City, VA	51510200302	75.45	2	Fairfax, VA	51059491401	74.60	2
Prince George's, MD	24033803527	75.43	2	Montgomery, MD	24031703212	74.60	2
Montgomery, MD	24031700306	75.41	2	Fairfax, VA	51059440202	74.60	2
Fairfax, VA	51059420202	75.41	2	Montgomery, MD	24031700823	74.59	2
Montgomery, MD	24031703207	75.41	2	Montgomery, MD	24031700811	74.56	2
Prince George's, MD	24033800106	75.34	2	Fairfax, VA	51059482302	74.51	2
Montgomery, MD	24031701423	75.33	2	Fairfax, VA	51059432201	74.44	2
Fairfax, VA	51059450400	75.32	2	Washington, DC	11001009901	74.44	2
Arlington, VA	51013100800	75.32	2	Prince William, VA	51153901223	74.43	2
Fairfax, VA	51059491703	75.24	2	Montgomery, MD	24031701503	74.41	2
Montgomery, MD	24031700819	75.20	2	Prince George's, MD	24033801907	74.41	2
Alexandria City, VA	51510200301	75.18	2	Alexandria City, VA	51510200403	74.39	2
Washington, DC	11001007406	75.17	2	Montgomery, MD	24031701508	74.38	2
Fairfax, VA	51059440100	75.16	2	Manassas, VA	51683910201	74.37	2
Montgomery, MD	24031700722	75.14	2	Frederick, MD	24021750600	74.37	2
Prince George's, MD	24033801901	75.13	2	Montgomery, MD	24031701601	74.34	2
Fairfax, VA	51059481202	75.12	2	Fairfax, VA	51059422401	74.34	2
Prince William, VA	51153900600	75.11	2	Fairfax, VA	51059471100	74.33	2
Fairfax, VA	51059420100	75.09	2	Prince George's, MD	24033800412	74.29	2
Prince George's, MD	24033802204	75.08	2	Fairfax, VA	51059451602	74.29	2
Arlington, VA	51013102100	74.90	2	Prince George's, MD	24033800520	74.28	2
Montgomery, MD	24031701422	74.90	2	Prince William, VA	51153901008	74.25	2
Loudoun, MD	51107610505	74.86	2	Prince George's, MD	24033802104	74.22	2
Montgomery, MD	24031705903	74.86	2	Prince William, VA	51153901602	74.21	2
Fairfax, VA	51059452101	74.77	2	Fairfax, VA	51059461202	74.21	2
Washington, DC	11001009904	74.77	2	Fairfax, VA	51059480901	74.16	2
Prince William, VA	51153901900	74.76	2	Montgomery, MD	24031700903	74.15	2
Fairfax, VA	51059491701	74.76	2	Alexandria City, VA	51510200201	74.13	2
Fairfax, VA	51059421101	74.66	2	Fairfax, VA	51059430400	74.13	2

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Fairfax, VA	51059470700	74.11	2	Montgomery, MD	24031703208	73.25	2
Prince William, VA	51153901221	74.03	2	Prince George's, MD	24033801212	73.24	2
Prince William, VA	51153901701	74.03	2	Fairfax, VA	51059415300	73.20	2
Alexandria City, VA	51510200900	74.01	2	Charles, MD	24017850901	73.20	2
Prince George's, MD	24033803608	73.96	2	Alexandria City, VA	51510201100	73.20	2
Fairfax, VA	51059422402	73.93	2	Prince George's, MD	24033806712	73.19	2
Alexandria City, VA	51510200102	73.87	2	Montgomery, MD	24031704501	73.17	2
Fairfax, VA	51059415200	73.84	2	Montgomery, MD	24031700812	73.15	2
Montgomery, MD	24031704600	73.81	2	Fairfax, VA	51059431600	73.15	2
Fairfax, VA	51059480902	73.79	2	Fairfax, VA	51059470900	73.14	2
Montgomery, MD	24031700710	73.73	2	Montgomery, MD	24031701414	73.12	2
Frederick, MD	24021750504	73.63	2	Fairfax, VA	51059451800	73.09	2
Prince George's, MD	24033803607	73.60	2	Fairfax, VA	51059461000	73.08	2
Montgomery, MD	24031701314	73.57	2	Prince George's, MD	24033800210	73.04	2
Fairfax, VA	51059421001	73.55	2	Prince George's, MD	24033803516	73.04	2
Fairfax, VA	51059432000	73.54	2	Frederick, MD	24021750100	72.99	2
Prince George's, MD	24033803610	73.53	2	Montgomery, MD	24031700830	72.99	2
Loudoun, MD	51107611300	73.51	2	Prince George's, MD	24033803519	72.96	2
Montgomery, MD	24031701006	73.51	2	Prince George's, MD	24033807305	72.96	2
Prince George's, MD	24033801214	73.49	2	Fairfax, VA	51059452501	72.90	2
Frederick, MD	24021750505	73.46	2	Fairfax, VA	51059480903	72.87	2
Montgomery, MD	24031706012	73.45	2	Montgomery, MD	24031700614	72.82	2
Prince George's, MD	24033800214	73.45	2	Manassas, VA	51683910401	72.81	2
Montgomery, MD	24031701205	73.39	2	Fairfax, VA	51059422301	72.74	2
Prince William, VA	51153900203	73.38	2	Prince George's, MD	24033803602	72.73	2
Prince William, VA	51153900905	73.33	2	Fairfax, VA	51059440201	72.71	2
Prince George's, MD	24033801408	73.30	2	Prince George's, MD	24033801500	72.70	2
Fairfax, VA	51059432702	73.30	2	Manassas, VA	51683910202	72.66	2
Fairfax, VA	51059460800	73.28	2	Montgomery, MD	24031700813	72.62	2
Fairfax, VA	51059452302	73.27	2	Prince George's, MD	24033801904	72.56	2
Fairfax, VA	51059415401	73.26	2	Arlington, VA	51013102702	72.54	2

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Prince William, VA	51153901209	72.51	2	Fairfax, VA	51059491404	71.87	2
Charles, MD	24017850202	72.51	2	Montgomery, MD	24031700706	71.84	2
Fairfax, VA	51059480203	72.47	2	Prince George's, MD	24033800208	71.84	2
Fairfax, VA	51059450800	72.44	2	Prince George's, MD	24033801407	71.74	2
Montgomery, MD	24031703215	72.41	2	Montgomery, MD	24031700720	71.68	2
Fairfax, VA	51059481000	72.40	2	Prince George's, MD	24033807301	71.66	2
Montgomery, MD	24031700105	72.37	2	Prince William, VA	51153901212	71.63	2
Fredericksburg, VA	51630000500	72.35	2	Prince George's, MD	24033800409	71.62	2
Fairfax, VA	51059491405	72.33	2	Prince George's, MD	24033803526	71.58	2
Fairfax, VA	51059415100	72.32	2	Montgomery, MD	24031700607	71.58	2
Montgomery, MD	24031705702	72.26	2	Fairfax, VA	51059432701	71.54	2
Prince William, VA	51153901407	72.23	2	Frederick, MD	24021775400	71.49	2
Fairfax, VA	51059432100	72.20	2	Charles, MD	24017850906	71.48	2
Montgomery, MD	24031700304	72.20	2	Montgomery, MD	24031701312	71.47	2
Montgomery, MD	24031701007	72.15	2	Fairfax, VA	51059490502	71.43	2
Montgomery, MD	24031700833	72.10	2	Fredericksburg, VA	51630000400	71.39	2
Prince George's, MD	24033807304	72.10	2	Fairfax, VA	51059421702	71.39	2
Montgomery, MD	24031700834	72.10	2	Montgomery, MD	24031704502	71.38	2
Prince William, VA	51153900701	72.09	2	Fairfax, VA	51059430901	71.37	2
Prince William, VA	51153900501	72.09	2	Prince William, VA	51153900404	71.36	2
Frederick, MD	24021751202	72.06	2	Fairfax, VA	51059481702	71.36	2
Stafford, VA	51179010405	72.04	2	Prince William, VA	51153901222	71.36	2
Prince William, VA	51153901408	72.04	2	Montgomery, MD	24031703220	71.34	2
Frederick, MD	24021750803	72.01	2	Fairfax, VA	51059482602	71.32	2
Fairfax, VA	51059452000	71.99	2	Fairfax, VA	51059431001	71.31	2
Fairfax, VA	51059421102	71.97	2	Prince George's, MD	24033807407	71.30	2
Montgomery, MD	24031701415	71.95	2	Loudoun, MD	51107610504	71.22	2
Prince George's, MD	24033801404	71.93	2	Fairfax, VA	51059490501	71.19	2
Manassas, VA	51683910301	71.90	2	Fairfax, VA	51059471000	71.17	2
Manassas, VA	51683910302	71.88	2	Fairfax, VA	51059440800	71.16	2
Montgomery, MD	24031700715	71.88	2	Fairfax, VA	51059430202	71.09	2

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Prince William, VA	51153900407	71.09	2	Fairfax, VA	51059430801	70.51	2
Prince William, VA	51153901403	71.09	2	Prince George's, MD	24033803512	70.50	2
Fairfax, VA	51059430902	71.09	2	Fairfax, VA	51059482501	70.48	2
Prince George's, MD	24033800402	71.07	2	Fairfax, VA	51059432800	70.44	2
Fairfax City, VA	51600300100	71.07	2	Fairfax City, VA	51600300200	70.41	2
Fairfax, VA	51059460600	71.05	2	Prince William, VA	51153901702	70.41	2
Fairfax, VA	51059421103	71.05	2	Fairfax, VA	51059422102	70.37	2
Fairfax, VA	51059482203	71.03	2	Loudoun, MD	51107611601	70.36	2
Fairfax, VA	51059482601	71.02	2	Fairfax, VA	51059461801	70.34	2
Arlington, VA	51013102802	70.97	2	Montgomery, MD	24031701315	70.33	2
Prince George's, MD	24033800513	70.94	2	Fairfax, VA	51059450701	70.30	2
Montgomery, MD	24031701410	70.93	2	Fairfax, VA	51059491302	70.29	2
Fairfax, VA	51059470500	70.92	2	Charles, MD	24017851500	70.26	2
Montgomery, MD	24031700104	70.92	2	Fairfax, VA	51059420800	70.24	2
Montgomery, MD	24031700308	70.91	2	Fairfax, VA	51059451100	70.23	2
Fairfax, VA	51059431500	70.90	2	Fredericksburg, VA	51630000200	70.22	2
Fairfax, VA	51059430102	70.89	2	Loudoun, MD	51107611803	70.19	2
Prince William, VA	51153900502	70.86	2	Montgomery, MD	24031705902	70.18	2
Fairfax, VA	51059460400	70.85	2	Prince William, VA	51153901224	70.18	2
Prince William, VA	51153901237	70.83	2	Prince George's, MD	24033803521	70.15	2
Alexandria City, VA	51510200801	70.83	2	Fairfax, VA	51059482001	70.14	2
Frederick, MD	24021765100	70.79	2	Prince George's, MD	24033803601	70.13	2
Fairfax, VA	51059432500	70.76	2	Arlington, VA	51013100300	70.07	2
Fairfax, VA	51059470600	70.75	2	Fairfax, VA	51059491602	70.07	2
Fairfax, VA	51059481103	70.74	2	Prince George's, MD	24033801211	70.04	2
Frederick, MD	24021752202	70.70	2	Prince George's, MD	24033800519	70.00	2
Montgomery, MD	24031703201	70.70	2	Prince George's, MD	24033807408	69.95	2
Montgomery, MD	24031701418	70.64	2	Prince George's, MD	24033800403	69.95	2
Alexandria City, VA	51510200701	70.63	2	Fairfax, VA	51059432300	69.94	2
Fairfax, VA	51059491201	70.62	2	Fairfax City, VA	51600300500	69.85	2
Frederick, MD	24021750801	70.54	2	Fairfax, VA	51059431400	69.81	2

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Loudoun, MD	51107610603	69.80	2	Fairfax, VA	51059440702	69.13	2
Fairfax, VA	51059420700	69.78	2	Montgomery, MD	24031700810	69.07	2
Fairfax, VA	51059482002	69.77	2	Prince William, VA	51153900403	69.07	2
Prince George's, MD	24033800211	69.77	2	Fairfax, VA	51059460501	69.04	2
Fairfax, VA	51059482201	69.75	2	Prince George's, MD	24033800212	69.03	2
Prince George's, MD	24033800515	69.72	2	Prince William, VA	51153900410	69.01	2
Jefferson, WV	54037972401	69.71	2	Fairfax, VA	51059430101	68.99	2
Fairfax, VA	51059470300	69.67	2	Fairfax, VA	51059440600	68.98	2
Montgomery, MD	24031701206	69.67	2	Prince George's, MD	24033801906	68.93	2
Manassas, VA	51683910100	69.65	2	Prince George's, MD	24033806706	68.86	2
Stafford, VA	51179010108	69.62	2	Prince William, VA	51153901225	68.85	2
Prince George's, MD	24033801207	69.61	2	Prince William, VA	51153900201	68.85	2
Spotsylvania, VA	51177020202	69.59	2	Montgomery, MD	24031703216	68.80	2
Charles, MD	24017850902	69.58	2	Prince William, VA	51153900702	68.72	2
Montgomery, MD	24031701507	69.51	2	Fairfax, VA	51059415600	68.69	2
Charles, MD	24017850905	69.50	2				
Frederick, MD	24021750701	69.47	2				
Fairfax, VA	51059482202	69.46	2				
Montgomery, MD	24031703206	69.43	2				
Fairfax, VA	51059415700	69.39	2				
Fairfax, VA	51059470400	69.39	2				
Fairfax, VA	51059432202	69.38	2				
Montgomery, MD	24031700822	69.37	2				
Prince George's, MD	24033800504	69.35	2				
Fairfax, VA	51059491501	69.30	2				
Fairfax, VA	51059431900	69.29	2				
Montgomery, MD	24031703221	69.27	2				
Fairfax, VA	51059491601	69.21	2				
Montgomery, MD	24031700835	69.21	2				
Fairfax, VA	51059471402	69.20	2				
Prince William, VA	51153900409	69.19	2				

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Prince William, VA	51153901228	68.69	2	Fairfax, VA	51059431300	67.85	2
Prince George's, MD	24033801411	68.62	2	Loudoun, MD	51107611002	67.82	2
Fairfax, VA	51059482301	68.62	2	Fairfax, VA	51059491403	67.76	2
Prince George's, MD	24033801217	68.59	2	Prince George's, MD	24033803522	67.74	2
Prince George's, MD	24033801706	68.58	2	Fairfax, VA	51059460300	67.72	2
Fairfax, VA	51059431802	68.57	2	Fairfax, VA	51059471303	67.70	2
Fairfax, VA	51059461100	68.49	2	Fairfax, VA	51059432600	67.70	2
Fairfax, VA	51059420203	68.48	2	Montgomery, MD	24031706013	67.68	2
Prince William, VA	51153900408	68.45	2	Fairfax, VA	51059491801	67.67	2
Fairfax, VA	51059430203	68.34	2	Fairfax, VA	51059430201	67.66	2
Prince George's, MD	24033800203	68.31	2	Prince William, VA	51153901010	67.65	2
Fairfax, VA	51059422202	68.31	2	Loudoun, MD	51107611102	67.61	2
Prince George's, MD	24033803525	68.26	2	Fairfax, VA	51059440501	67.54	2
Montgomery, MD	24031701313	68.24	2	Fairfax, VA	51059491802	67.54	2
Fairfax, VA	51059491502	68.20	2	Fairfax, VA	51059452102	67.41	2
Prince William, VA	51153901416	68.16	2	Fairfax, VA	51059432402	67.40	2
Montgomery, MD	24031703202	68.15	2	Prince George's, MD	24033800607	67.39	2
Fairfax, VA	51059415900	68.15	2	Frederick, MD	24021750802	67.34	2
Fairfax, VA	51059431801	68.14	2	Prince William, VA	51153900202	67.31	2
Montgomery, MD	24031701002	68.11	2	Prince William, VA	51153901303	67.29	2
Fairfax City, VA	51600300400	68.06	2	Fairfax, VA	51059422403	67.11	2
Loudoun, MD	51107611006	68.06	2	Fairfax, VA	51059481900	67.10	2
Fredericksburg, VA	51630000302	68.06	2	Fairfax, VA	51059482503	67.09	2
Montgomery, MD	24031700207	68.01	2	Manassas, VA	51683910402	67.05	2
Prince William, VA	51153901208	67.99	2	Washington, DC	11001007301	67.05	2
Prince George's, MD	24033800505	67.97	2	Fairfax, VA	51059491103	67.00	2
Charles, MD	24017850710	67.96	2	Fairfax, VA	51059440701	66.87	2
Prince William, VA	51153901413	67.94	2	Prince George's, MD	24033801305	66.86	2
Stafford, VA	51179010103	67.93	2	Loudoun, MD	51107610604	66.82	2
Fairfax, VA	51059432401	67.92	2	Fairfax, VA	51059440300	66.80	2
Fairfax, VA	51059482502	67.89	2	Fairfax, VA	51059415402	66.75	2

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Frederick, MD	24021750506	66.72	2	Prince George's, MD	24033801006	65.90	2
Fairfax, VA	51059481101	66.72	2	Fairfax, VA	51059480802	65.89	2
Fairfax, VA	51059415800	66.69	2	Charles, MD	24017850706	65.89	2
Spotsylvania, VA	51177020114	66.69	2	Fairfax, VA	51059460900	65.76	2
Fairfax, VA	51059430802	66.61	2	Fairfax, VA	51059492400	65.72	2
Prince George's, MD	24033800410	66.53	2	Prince George's, MD	24033800408	65.71	2
Fairfax, VA	51059491402	66.50	2	Loudoun, MD	51107611209	65.69	2
Fairfax, VA	51059480202	66.50	2	Fairfax, VA	51059492202	65.69	2
Prince William, VA	51153901236	66.50	2	Fairfax, VA	51059430500	65.69	2
Frederick, MD	24021751902	66.49	2	Prince William, VA	51153901507	65.66	2
Prince William, VA	51153901012	66.43	2	Fairfax, VA	51059482504	65.65	2
Prince William, VA	51153901211	67.28	2	Loudoun, MD	51107610503	66.36	2
Montgomery, MD	24031700616	67.27	2	Charles, MD	24017850711	66.36	2
Loudoun, MD	51107611805	67.26	2	Fairfax, VA	51059460100	66.33	2
Warren, VA	51187020500	67.23	2	Stafford, VA	51179010404	66.29	2
Fairfax, VA	51059420201	67.21	2	Fairfax, VA	51059451200	66.27	2
Fairfax, VA	51059491705	67.20	2	Prince George's, MD	24033800401	66.23	2
Stafford, VA	51179010207	67.17	2	Charles, MD	24017851002	66.22	2
Frederick, MD	24021751003	66.20	2	Fairfax, VA	51059480502	65.48	2
Montgomery, MD	24031700829	66.20	2	Loudoun, MD	51107611700	65.46	2
Spotsylvania, VA	51177020201	66.18	2	Prince William, VA	51153900802	65.46	2
Spotsylvania, VA	51177020204	66.18	2	Prince George's, MD	24033803523	65.38	2
Fairfax, VA	51059480503	66.18	2	Washington, DC	11001000201	65.37	2
Fairfax, VA	51059492300	66.14	2	Fairfax, VA	51059461201	65.32	2
Montgomery, MD	24031701221	66.12	2	Montgomery, MD	24031703218	65.31	2
Arlington, VA	51013100400	66.03	2	Montgomery, MD	24031701210	65.29	2
Prince William, VA	51153901601	66.01	2	Montgomery, MD	24031701220	65.28	2
Loudoun, MD	51107611014	65.99	2	Prince George's, MD	24033801209	65.25	2
Montgomery, MD	24031705901	65.94	2	Montgomery, MD	24031706009	65.23	2
Fairfax, VA	51059481701	65.93	2	Fairfax, VA	51059481201	65.21	2
Charles, MD	24017850801	65.91	2	Fairfax, VA	51059431002	65.20	2

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Montgomery, MD	24031706007	65.17	2	Prince George's, MD	24033800605	64.21	2
Fairfax, VA	51059480505	65.13	2	Prince William, VA	51153900801	64.16	2
Prince George's, MD	24033800701	65.01	2	Montgomery, MD	24031706011	64.13	2
Prince George's, MD	24033801308	64.95	2	Loudoun, MD	51107611019	64.11	2
Loudoun, MD	51107611400	64.93	2	Frederick, MD	24021751201	64.07	2
Fairfax, VA	51059451000	64.90	2	Fairfax, VA	51059481106	64.07	2
Montgomery, MD	24031706010	64.81	2	Montgomery, MD	24031700606	64.06	2
Prince William, VA	51153901230	64.79	2	Montgomery, MD	24031701304	64.01	2
Fairfax, VA	51059480300	64.76	2	Prince William, VA	51153901411	63.92	2
Prince William, VA	51153901227	64.75	2	Prince William, VA	51153901506	63.91	2
Spotsylvania, VA	51177020110	64.74	2	Fairfax, VA	51059492000	63.90	2
Prince George's, MD	24033800206	65.65	2	Prince George's, MD	24033801410	63.89	2
Fairfax, VA	51059416100	65.64	2	Arlington, VA	51013103401	63.83	2
Frederick, MD	24021751002	65.52	2	Fairfax, VA	51059481600	63.80	2
Fairfax, VA	51059481105	65.52	2	Prince William, VA	51153900100	63.79	2
Stafford, VA	51179010212	65.51	2	Culpeper, VA	51047930201	63.78	2
Spotsylvania, VA	51177020108	64.73	2	Loudoun, MD	51107611206	63.65	2
Montgomery, MD	24031700832	64.70	2	Frederick, MD	24021751004	63.63	2
Loudoun, MD	51107611802	64.69	2	Montgomery, MD	24031700206	63.61	2
Prince George's, MD	24033800215	64.68	2	Prince George's, MD	24033800707	63.59	2
Loudoun, MD	51107611009	64.66	2	Loudoun, MD	51107611005	63.54	2
Frederick, MD	24021752301	64.58	2	Fairfax, VA	51059421300	63.54	2
Spotsylvania, VA	51177020307	64.58	2	Fairfax, VA	51059481104	63.53	2
Loudoun, MD	51107611602	64.51	2	Prince William, VA	51153901226	63.50	2
Prince William, VA	51153901415	64.43	2	Montgomery, MD	24031701421	63.49	2
Stafford, VA	51179010206	64.42	2	Spotsylvania, VA	51177020304	63.48	2
Prince George's, MD	24033801216	64.39	2	Montgomery, MD	24031701409	63.43	2
Prince George's, MD	24033801307	64.34	2	Jefferson, WV	54037972501	63.41	2
Fairfax, VA	51059482400	64.30	2	Fairfax, VA	51059421200	63.41	2
Fairfax, VA	51059481400	64.29	2	Fairfax, VA	51059416200	63.39	2
Prince George's, MD	24033800514	64.28	2	Prince William, VA	51153901011	63.36	2

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Prince George's, MD	24033800706	63.31	2	Spotsylvania, VA	51177020305	62.27	2
Spotsylvania, VA	51177020308	63.21	2	Montgomery, MD	24031701408	62.17	2
Stafford, VA	51179010502	63.11	2	Fairfax, VA	51059490101	62.13	2
Prince William, VA	51153901233	63.11	2	Jefferson, WV	54037972503	62.13	2
Calvert, MD	24009860900	63.07	2	Fairfax, VA	51059450900	62.10	2
Prince George's, MD	24033801312	63.02	2	Prince George's, MD	24033800704	62.09	2
Prince George's, MD	24033801406	63.01	2	Stafford, VA	51179010205	62.08	2
Loudoun, MD	51107611502	63.01	2	Prince William, VA	51153901229	62.07	2
Prince William, VA	51153901508	63.00	2	Loudoun, MD	51107611022	62.07	2
Fairfax, VA	51059482303	62.99	2	Stafford, VA	51179010210	62.04	2
Loudoun, MD	51107610601	62.97	2	Montgomery, MD	24031700828	62.02	2
Montgomery, MD	24031701407	63.77	2	Fairfax, VA	51059422201	61.97	2
Montgomery, MD	24031700615	63.75	2	Montgomery, MD	24031700205	61.81	2
Charles, MD	24017850708	63.74	2	Loudoun, MD	51107611205	61.79	2
Calvert, MD	24009860401	62.93	2	Calvert, MD	24009860702	61.75	2
Charles, MD	24017850101	62.92	2	Loudoun, MD	51107610400	61.73	2
Prince William, VA	51153901005	62.90	2	Fauquier, VA	51061930302	61.71	2
Prince William, VA	51153901009	62.89	2	Montgomery, MD	24031706005	61.66	2
Spotsylvania, VA	51177020112	62.87	2	Montgomery, MD	24031700608	61.64	2
Prince George's, MD	24033801005	62.72	2	Prince William, VA	51153901505	61.63	2
Prince William, VA	51153901409	62.72	2	Loudoun, MD	51107611023	61.62	2
Prince George's, MD	24033801208	62.67	2	Montgomery, MD	24031700613	61.58	2
Loudoun, MD	51107611202	62.67	2	Prince George's, MD	24033800411	61.53	2
Prince George's, MD	24033801213	62.67	2	Fredericksburg, VA	51630000301	61.47	2
Prince William, VA	51153901203	62.53	2	Loudoun, MD	51107611101	61.42	2
Montgomery, MD	24031700611	62.52	2	Montgomery, MD	24031701212	61.13	2
Loudoun, MD	51107610506	62.50	2	Prince William, VA	51153901001	61.11	2
Prince George's, MD	24033800509	62.50	2	Stafford, VA	51179010304	61.11	2
Loudoun, MD	51107611004	62.44	2	Montgomery, MD	24031700311	60.98	2
Loudoun, MD	51107611208	62.39	2	Prince William, VA	51153901412	60.90	2
Loudoun, MD	51107611204	62.29	2	Jefferson, WV	54037972402	60.86	2

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Montgomery, MD	24031700610	60.81	2	Fauquier, VA	51061930401	59.73	3
Prince George's, MD	24033801409	60.78	2	Calvert, MD	24009860402	59.69	3
Stafford, VA	51179010214	60.75	2	Fairfax, VA	51059480401	59.55	3
Spotsylvania, VA	51177020107	60.63	2	Fairfax, VA	51059490103	59.51	3
Fairfax, VA	51059481500	60.62	2	Loudoun, MD	51107611801	59.46	3
Spotsylvania, VA	51177020306	60.60	2	Prince William, VA	51153901231	59.45	3
Fairfax, VA	51059492203	60.58	2	Prince William, VA	51153901232	59.45	3
Prince George's, MD	24033801313	60.57	2	Stafford, VA	51179010204	59.40	3
Fairfax, VA	51059491102	60.56	2	Stafford, VA	51179010406	59.40	3
Loudoun, MD	51107611207	60.55	2	Prince George's, MD	24033800608	59.38	3
Jefferson, WV	54037972601	60.55	2	Prince William, VA	51153901304	59.35	3
Alexandria City, VA	51510200202	61.76	2	Prince George's, MD	24033801309	59.33	3
Prince George's, MD	24033801310	60.52	2	Montgomery, MD	24031706008	59.31	3
Montgomery, MD	24031701307	60.37	2	Prince William, VA	51153901414	59.26	3
Spotsylvania, VA	51177020309	60.36	2	Prince William, VA	51153901219	59.25	3
Frederick, MD	24021752601	60.35	2	Stafford, VA	51179010303	59.15	3
Fairfax, VA	51059421900	60.34	2	Prince George's, MD	24033800518	59.14	3
Fairfax, VA	51059491301	60.33	2	Montgomery, MD	24031701306	58.97	3
Prince George's, MD	24033801210	60.28	2	Stafford, VA	51179010105	58.87	3
Prince George's, MD	24033803520	60.26	2	Prince William, VA	51153901410	58.81	3
Frederick, MD	24021752204	60.24	2	Calvert, MD	24009860102	58.67	3
Frederick, MD	24021772200	60.22	2	Prince George's, MD	24033800601	58.65	3
Prince George's, MD	24033801004	60.12	2	Charles, MD	24017850904	58.65	3
Frederick, MD	24021752001	60.09	2	Jefferson, WV	54037972506	58.53	3
Spotsylvania, VA	51177020109	60.07	2	Calvert, MD	24009860502	58.42	3
Jefferson, WV	54037972505	60.06	2	Loudoun, MD	51107611501	58.38	3
Prince George's, MD	24033802201	59.97	3	Fairfax, VA	51059460200	58.19	3
Charles, MD	24017850802	59.82	3	Montgomery, MD	24031701316	58.09	3
Prince George's, MD	24033801311	59.81	3	Fairfax, VA	51059492100	57.98	3
Prince William, VA	51153900904	59.74	3	Prince William, VA	51153901306	57.97	3
Fairfax, VA	51059480201	59.74	3	Stafford, VA	51179010403	57.90	3

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Loudoun, MD	51107611900	57.89	3	Prince William, VA	51153901100	55.78	3
Loudoun, MD	51107611012	57.88	3	Montgomery, MD	24031700208	55.52	3
Charles, MD	24017850713	57.86	3	Frederick, MD	24021775600	55.43	3
Montgomery, MD	24031701308	57.84	3	Culpeper, VA	51047930300	55.27	3
Charles, MD	24017851400	57.81	3	Loudoun, MD	51107611025	55.20	3
Montgomery, MD	24031700312	57.31	3	Loudoun, MD	51107611804	55.17	3
Montgomery, MD	24031701303	57.17	3	Prince George's, MD	24033800507	55.12	3
Montgomery, MD	24031700103	57.17	3	Loudoun, MD	51107611013	55.10	3
Montgomery, MD	24031701317	57.11	3	Spotsylvania, VA	51177020106	54.90	3
Stafford, VA	51179010211	57.07	3	Prince William, VA	51153901305	54.90	3
Spotsylvania, VA	51177020310	57.03	3	Charles, MD	24017850201	54.87	3
Fairfax, VA	51059480402	57.02	3	Fairfax, VA	51059480501	54.79	3
Loudoun, MD	51107610507	56.96	3	Charles, MD	24017851001	54.78	3
Spotsylvania, VA	51177020203	56.95	3	Frederick, MD	24021752802	54.77	3
Fairfax, VA	51059480504	56.79	3	Montgomery, MD	24031700101	54.75	3
Loudoun, MD	51107611011	56.59	3	Fairfax, VA	51059470100	54.71	3
Fairfax, VA	51059492500	56.57	3	Calvert, MD	24009860701	54.64	3
Prince George's, MD	24033801003	56.54	3	Spotsylvania, VA	51177020111	54.51	3
Prince George's, MD	24033800705	56.43	3	Loudoun, MD	51107611017	54.46	3
Prince William, VA	51153901235	56.37	3	Prince George's, MD	24033800517	54.42	3
Calvert, MD	24009861004	56.36	3	Loudoun, MD	51107610102	54.41	3
Loudoun, MD	51107611020	56.36	3	Stafford, VA	51179010305	54.32	3
Warren, VA	51187020400	56.35	3	Stafford, VA	51179010107	54.27	3
Frederick, MD	24021752101	56.21	3	Frederick, MD	24021752501	54.17	3
Spotsylvania, VA	51177020408	56.15	3	Prince George's, MD	24033801302	54.05	3
Fairfax, VA	51059491202	56.10	3	Loudoun, MD	51107610201	54.01	3
Frederick, MD	24021751903	56.05	3	Frederick, MD	24021752303	53.99	3
Montgomery, MD	24031703219	56.01	3	Frederick, MD	24021751901	53.96	3
Montgomery, MD	24031700604	55.87	3	Frederick, MD	24021752603	53.89	3
Calvert, MD	24009861003	55.84	3	Jefferson, WV	54037972701	53.69	3
Frederick, MD	24021752102	55.79	3	Calvert, MD	24009860300	53.62	3

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Prince William, VA	51153901509	53.48	3	Prince George's, MD	24033801104	50.78	3
Charles, MD	24017850712	53.06	3	Loudoun, MD	51107610300	50.68	3
Montgomery, MD	24031700500	53.05	3	Frederick, MD	24021767600	50.62	3
Prince George's, MD	24033801215	53.05	3	Loudoun, MD	51107611016	50.59	3
Jefferson, WV	54037972204	53.04	3	Loudoun, MD	51107611015	50.53	3
Spotsylvania, VA	51177020113	53.00	3	Calvert, MD	24009860101	50.05	3
Charles, MD	24017850600	52.95	3	Fairfax, VA	51059416300	49.83	3
Jefferson, WV	54037972201	52.95	3	Stafford, VA	51179010202	49.83	3
Warren, VA	51187020601	52.81	3	Frederick, MD	24021753001	49.76	3
Prince George's, MD	24033800604	52.64	3	Spotsylvania, VA	51177020205	49.75	3
Stafford, VA	51179010213	52.55	3	Loudoun, MD	51107611021	49.69	3
Frederick, MD	24021775302	52.52	3	Frederick, MD	24021773500	49.47	3
Fauquier, VA	51061930402	52.37	3	Fairfax, VA	51059492201	49.37	3
Charles, MD	24017851200	52.20	3	Fauquier, VA	51061930303	49.21	3
Frederick, MD	24021766800	52.19	3	Warren, VA	51187020700	49.18	3
Fauquier, VA	51061930403	52.19	3	Frederick, MD	24021752502	49.16	3
Charles, MD	24017851302	52.18	3	Loudoun, MD	51107610900	48.98	3
Loudoun, MD	51107610701	52.14	3	Stafford, VA	51179010503	48.97	3
Prince William, VA	51153901234	52.13	3	Frederick, MD	24021753002	48.92	3
Loudoun, MD	51107610702	52.03	3	Fauquier, VA	51061930304	48.89	3
Montgomery, MD	24031700400	51.98	3	Prince William, VA	51153901510	48.85	3
Calvert, MD	24009860200	51.77	3	Loudoun, MD	51107611018	48.77	3
Loudoun, MD	51107610202	51.50	3	Frederick, MD	24021752302	48.77	3
Calvert, MD	24009860501	51.49	3	Fairfax, VA	51059491000	48.75	3
Jefferson, WV	54037972602	51.47	3	Fairfax, VA	51059480100	48.71	3
Calvert, MD	24009860802	51.44	3	Prince William, VA	51153901504	48.58	3
Stafford, VA	51179010301	51.44	3	Washington, DC	11001006804	48.56	3
Charles, MD	24017850102	51.36	3	Stafford, VA	51179010106	48.46	3
Calvert, MD	24009860703	51.27	3	Montgomery, MD	24031700204	48.44	3
Calvert, MD	24009860600	50.93	3	Calvert, MD	24009860801	48.36	3
Frederick, MD	24021740200	50.79	3	Warren, VA	51187020100	48.35	3

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Spotsylvania, VA	51177020311	48.28	3	Prince George's, MD	24033800900	44.56	3
Prince George's, MD	24033800800	48.26	3	Warren, VA	51187020602	44.45	3
Loudoun, MD	51107611010	48.23	3	Loudoun, MD	51107610703	44.19	3
Spotsylvania, VA	51177020104	48.13	3	Fauquier, VA	51061930206	44.05	3
Fauquier, VA	51061930706	48.10	3	Charles, MD	24017851301	43.97	3
Spotsylvania, VA	51177020105	47.99	3	Charles, MD	24017851100	43.85	3
Fauquier, VA	51061930705	47.94	3	Fauquier, VA	51061930707	43.67	3
Frederick, MD	24021751801	47.66	3	Frederick, MD	24021751301	43.66	3
Fairfax, VA	51059491101	47.63	3	Clarke, VA	51043010100	43.63	3
Jefferson, WV	54037972800	47.62	3	Culpeper, VA	51047930202	43.38	3
Loudoun, MD	51107611024	47.57	3	Clarke, VA	51043010300	43.12	3
Frederick, MD	24021752201	47.50	3	Frederick, MD	24021751701	42.98	3
Frederick, MD	24021752602	47.40	3	Calvert, MD	24009861001	42.78	3
Loudoun, MD	51107611806	46.97	3	Warren, VA	51187020200	42.40	3
Prince William, VA	51153901503	46.93	3	Charles, MD	24017850500	42.24	3
Prince William, VA	51153901511	46.72	3	Warren, VA	51187020300	42.15	3
Loudoun, MD	51107610101	46.41	3	Frederick, MD	24021751802	42.00	3
Fauquier, VA	51061930204	46.40	3	Rappahannock, VA	51157950100	41.90	3
Culpeper, VA	51047930502	46.35	3	Washington, DC	11001006202	41.62	3
Jefferson, WV	54037972300	46.11	3	Culpeper, VA	51047930102	41.36	3
Spotsylvania, VA	51177020407	45.97	3	Culpeper, VA	51047930101	41.05	3
Frederick, MD	24021751904	45.94	3	Frederick, MD	24021751702	40.52	3
Frederick, MD	24021751001	45.90	3	Spotsylvania, VA	51177020404	40.41	3
Jefferson, WV	54037972203	45.82	3	Frederick, MD	24021751302	40.19	3
Frederick, MD	24021751203	45.73	3	Spotsylvania, VA	51177020405	39.85	4
Loudoun, MD	51107610800	45.62	3	Fauquier, VA	51061930100	39.48	4
Loudoun, MD	51107610602	45.39	3	Frederick, MD	24021752900	39.43	4
Fauquier, VA	51061930207	45.14	3	Prince William, VA	51153901417	39.34	4
Frederick, MD	24021770700	45.12	3	Rappahannock, VA	51157950200	38.97	4
Jefferson, WV	54037972702	45.12	3	Charles, MD	24017850400	38.94	4
Charles, MD	24017850300	44.89	3	Clarke, VA	51043010200	38.92	4

County	Tract ID	SI	Rank	County	Tract ID	SI	Rank
Culpeper, VA	51047930501	38.91	4	Spotsylvania, VA	51177020406	33.48	4
Fauquier, VA	51061930203	38.23	4	Fauquier, VA	51061930703	32.22	4
Stafford, VA	51179010504	37.72	4	Arlington, VA	51013980100	31.43	4
Spotsylvania, VA	51177020403	37.34	4	Fairfax, VA	51059980200	25.68	4
Culpeper, VA	51047930400	37.09	4	Arlington, VA	51013980200	24.48	4
Frederick, MD	24021751600	37.01	4	Fairfax, VA	51059980100	24.23	4
Frederick, MD	24021767500	35.29	4	Loudoun, MD	51107980100	20.52	4
Fauquier, VA	51061930704	35.10	4	Fairfax, VA	51059980300	20.01	4
Frederick, MD	24021752801	34.69	4	Prince William, VA	51153980100	11.18	5
Stafford, VA	51179010201	34.54	4	Calvert, MD	24009990100	0.46	5
Fauquier, VA	51061930205	33.92	4	Charles, MD	24017990000	0.00	5

Notes: SI = Standardized walkability index score before a rank was assigned to it.

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