WALKING TO THE STATION: THE EFFECTS OF STREET

CONNECTIVITY ON WALKABILITY AND ACCESS TO TRANSIT

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WALKING TO THE STATION: THE EFFECTS OF STREET CONNECTIVITY ON WALKABILITY AND ACCESS TO TRANSIT

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SUMMARY

This thesis analyzes an on-board transit survey conducted by the Atlanta Regional Commission in order to determine how far urban density, mixed land-uses, and street network connectivity are related to different walking behaviors, namely transit walk-mode shares and walking distances to/from stations. The data are drawn from all the stations of Atlanta's rapid transit network (MARTA). Allowing for quite a bit of noise in the data, some of the findings confirm for the case of Atlanta what a review of existing literature would lead one to expect: mixed land-use and denser street networks are associated with higher proportion of riders traveling to/from the station "walking" (noise in the data does not allow to fully distinguish with certainty walking as the sole mode of access to/from the station from walking combined with the use of bus services). The thesis also explores questions that have not been previously covered systematically in the literature. First, does urban form (including street configuration and connectivity as well as land-use patterns) affect the distance transit patrons are willing to walk? Findings suggest that street networks with denser intersections and more linear alignments of road segments support greater walking distance thresholds. Second, does the location of the station relative to the street hierarchy of the surrounding area affect the proportion of patrons walking or the distance walked? The thesis answers this question negatively. If the surrounding area, at a one mile radius, is a transit friendly urban form, the location of the station within the street hierarchy does not have a major impact on walk mode share and the distance walked. In light with the various conclusions presented in this thesis, the

finding regarding the association between street connectivity and distances walked appears to be the most critical.

The research findings have several implications. They confirm that urban form (including density, land-use and street network configuration) affects the proportions of patrons walking to/from the station. Thus, they also confirm that transit oriented policies are better supported by urban development policies and zoning and subdivision regulations that encourage transit-friendly urban forms. More specifically, they suggest that the scale at which urban form has an impact on pedestrian travel is of the order of a mile radius, rather than a few blocks around the station. Findings also suggest that transit oriented policies are compatible with policies aimed at the enhancement of health and the reduction of obesity through daily physical activity (walking to/from the station can contribute a significant part of the daily activity recommended by Healthy Living Guidelines). Finally findings augment the knowledge-base that supports transit oriented development by emphasizing the contribution of the spatial structure of the street network, over and above the impact of side-walk provision and design and pedestrian safety.

CHAPTER 1

INTRODUCTION

This research addresses the impacts of urban form, in general, and street network, in particular, on public transport-related walking. Urban form is defined in terms of three core dimensions: population densities, land-use patterns, and street networks. Existing literature suggests that population, employment and development densities (Cervero, 1996, Holtzclaw, 1994, Parsons Brinkerhoff Quade and Douglas Inc., 1996a); number of non-residential destinations and the mix of land-uses (Cervero, 2002, Kockelman, 1997); and intersection densities of street networks (Handy, 1996b, Moudon et al., 2006) support walking and contribute to transit ridership.

The aim of this thesis is to better understand how street network connectivity affects the decision to walk to/from rail stations and the willingness to walk longer distances after controlling for population density, land-use mix, household income, and car ownership. The underlying hypothesis being tested is that environments that are connected so as to support different kinds of walking also support public transportation. To date, research on the built environment and walking has generally turned to analysis at the macro-scale, such as census tracts and traffic analysis zones (TAZs), that overlooks fine-grained design features (Ewing, 1995, Frank and Pivo, 1994, Frank et al., 2005, Hoehner et al., 2005, Holtzclaw, 1994). This study gauges the significance of urban form measured at a smaller unit of analysis: neighborhood-scale. As such, the focus is specifically on the associations between local urban conditions around stations and walking for transit. In this study the terms "station-area" and "station-environment" are

used interchangeably to refer to the areas within 0.25, 0.5, and 1 mile-wide walkable rings around rail stations. The areas surrounding the stations are characterized by the number of people per gross acres, diversity of land-uses, and the densities of available streets and street connections.

This research builds on the existing literature by investigating to what extent local conditions of station environments contribute to an explanation of variations in transit-access/egress modes of walking. One aim is to assess how far established findings are valid in Atlanta, a city and a metropolitan area which is generally developed in ways which do not particularly support either walking or public transportation. In addition, the thesis extends past studies on two fronts.

First, this study expresses walking as a proportion of total ridership. The goal is to reveal the urban form correlates of this relationship and the degree to which local pedestrian culture is responsive to differences in urban form.

Second, by gauging the link between urban form and distances walked to/from the station, this study aims to determine the primary factors that can aid in extending acceptable walking distances. The findings of this analysis can guide researchers and planners to induce riders to walk more often and for greater distances. Clearly, this has implications for concomitant positive health effects on travelers as well as transportation benefits.

In addition, this thesis explores the association of distances walked for transit with the proportion of walking in order to identify whether differences in travel patterns among urban areas may have implications for shaping policy on public health and environmental welfare as well as transportation.

The aim of many recent planning investments is to reduce automobile dependence and induce non-auto commuting by implementing various urban design principles along with the ideals of New Urbanism and smart growth in re-shaping the urban form. How can urban form support pedestrian and transit-friendly development? Can the policies and design strategies which encourage the use of public transportation also promote better public health? What are the determinants of the link between urban form and non-motorized travel, namely walking and transit usage? Specifically, which urban form characteristics have more explanatory power in revealing this relationship? These motivating questions have given rise to numerous studies on how design of the built environment can change travel behavior. To date, studies of the local environment's impact on individual travel have focused on land-use mixes and densities, yet there has been relatively little explicit research on the role of street layout.

Transportation and urban planners have focused on the design of street networks, usually characterized according to the density of street intersections per area (Frank et al., 2005, Kerr et al., 2007, Lee and Moudon, 2006), block size per area (Hess et al., 1999, Krizek, 2000), cul-de-sacs per road mile (Handy, 1996a), and the links-nodes ratio (American Planning Association, 2006). These measures describe the average properties of street systems, but they fall short in capturing variations in the internal spatial structure of urban areas at relevant scales. Of course, underlying differences of street types can be expressed by measures of average properties. Studies have usually proposed comparative typological schemes discriminating between rectilinear and curvilinear layouts (Crane and Crepeau, 1998, Ewing and Cervero, 2001, Southworth and Owens, 1993) or traditional and suburban planned units (Ewing et al., 1994, Handy et al., 2005, Rodriguez

et al., 2006) to characterize structurally different urban networks. Such studies use simple measures of street networks such as the number of street intersections per unit area, proportion of 4-way intersections, and the ratio of number of intersections to number of cul-de-sacs. In addition, more discriminating measures, such as pedestrian route directness, which is the ratio of network distance to straight line distance (Hess, 1997, Lee and Moudon, 2006, Randall and Baetz, 2001, Handy et al., 2003), and pedestrian catchment areas capturing all destinations reachable within a walking distance from a specific point (Hess, 1997, Hess et al., 1999) are used to describe structural differences in street networks.

There is, however, a more refined analysis which can differentiate between well and less well connected road segments and streets within a given area, whether it is a grid, a curvilinear pattern or a cul-de-sac. To what degree might the location of a station within an area, on a well or less well connected road segment, play a role in influencing walking behavior? This question has not been discussed extensively in the literature in its own right.

This question can naturally be addressed within the framework of configurational analysis such as exemplified by space syntax. As used here, the terms "configurational analysis" refer to any kind of spatial analysis which characterizes the relation of each elementary spatial unit, here the road segment, to all others. In the case of space syntax, particular attention is given to the number of direction changes that are needed in order to move from one location to another. The claim that the ordering of connectivity, measured by direction changes, plays an important role in determining the distribution of movement is consistent with research findings in spatial cognition which suggest that

direction changes, as an aspect of configuration, are related with the cognitive effort required to navigate through an area (Bailenson et al., 2000, Crowe et al., 2000, Hillier and Iida, 2005, Jansen-Osmann and Wiedenbauer, 2004, Montello, 1991, Sadalla and Magel, 1980). Since most transit trips involve some degree of pedestrian movement, understanding the ways in which people move through and conceive street networks is useful to planners and architects. The connectivity measures applied in this research (Peponis et al., 2008) offer a systematic framework through which to evaluate street connectivity from two points of view: metric accessibility and density on the one hand, and directional accessibility on the other. More specifically, three measures are used.

First, the density of streets and street connections accessible from each individual road segment. This is measured by the total street length accessible from each road segment moving in all possible directions up to a parametrically specified metric distance threshold. This measured is called Metric Reach.

Second, the extent to which the entire street network is accessible with few direction changes. This is measured by the street length which is accessible from each road segment without changing more than a parametrically specified number of directions. This measure is called Directional Reach.

Third, the average number of turns needed to access all portions of streets within Metric Reach.

The decision to include these measures bears on the relationship between urban planning and urban design. Urban planning is oriented towards principles of general applicability and tends to be concerned with the average or aggregate properties of areas. Urban design must, by definition, address the fine grain of specific contexts. It is

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concerned with the internal structure of areas and with the way in which street layout impacts the nature, orientation and performance of building developments for which it provides the context. Walking is, after all, a pre-eminently context-dependent activity and one which occurs according to the fine grain of environment as well as according to its larger scale structure. That is why appropriately discriminating measures of street connectivity are essential to better design for walkability.

Street connectivity, as discussed above, is the interface between design and planning variables. It is related to land-use and population density (Peponis et al., 2007) and movement patterns (Ozbil and Peponis, 2007) as well as to architecturally significant factors such as block size and intersection distances. Architectural research has shown that urban liveliness is a function of street connectivity (Hillier et al., 1987, Hillier et al., 1993, Peponis et al., 1989, Peponis et al., 1997). By better understanding the effect of street connectivity upon walking for transit, we can better integrate the knowledge base that informs not only planning but also architectural design. This link becomes even more important if we are to develop more sustainable cities. Also, it can contribute to an understanding of the ways in which transit systems can become integrated within urban culture. Implementation of these new measures may help define more clearly how connectivity encourages walking and thus supports transit shares.

This study focuses on the City of Atlanta (Fulton and DeKalb counties) as the case context. Using travel data from the 2001-2002 Regional On-Board Transit Survey, the link between connectivity and walking is addressed within the scaffold of two main questions. The first question concerns itself with the number of riders walking from within a range as a proportion of total ridership. Bivariate and multivariate regression

equations are estimated within 0.25, 0.5, and 1 mile radii around MARTA rail stations predicting walking shares. The hypothesis is that environments are not isotropic. Some are more conducive to walking due to connectivity patterns and local spatial structure of street networks, as well as diverse land-use patterns. The aim is to enhance the comprehensive models which can specify the correlation between individual urban form attributes and walking behavior. Empirical research on transit mode shares have estimated variation in walk-mode shares by station as a function of population density and proximity (Cervero, 1993, Parsons Brinkerhoff Quade and Douglas Inc., 1996a, Parsons Brinkerhoff Quade and Douglas Inc., 1996b). This analysis seeks to extend past studies by asking whether walkability as a proportion of ridership is affected by fine-grain street connectivity measures. Findings of this analysis are relevant in assessing the sensitivity of transit access/egress walk-mode choices to changes in urban form.

The second, and more original, question that this thesis addresses is related to the link between urban form and distance walked to/from the transit station. The volume of literature on how built environments influence ridership has concluded that pedestrian access gradient –how quickly walking mode shares fall off with walking distances to stations– is set at ⅓ of a mile to a ¼ of a mile, with 1 mile being the upper limit (Bernick and Cervero, 1997, JHK and Associates, 1987, Stringham, 1982). While several studies have examined the relationship between ridership elasticities and catchment areas around stations (Cervero, 1993, Frank and Pivo, 1994), research on whether and how the distance people are willing to walk can be increased has been very limited (Fruin, 1992, Untermann and Lewicki, 1984). More often than not, empirical literature has failed to account for the differentiation between metric distance and perceived distance (Handy,

1996b), and the role of street configuration on the distance walked. The underlying premise is that station-area characteristics affect convenient distance thresholds and that walkable environments encourage higher average walking distances by creating vibrant and safe urban conditions. This prospect of extending walking distances through design has significance beyond pedestrian concerns of mobility. Defining walkable urban conditions provides social benefits of interaction as well as benefits of personal health through active living. Consequently, extending acceptable walking distances to generate more walking trips represents a real economic benefit, measured in increased transit mode shares and reduced vehicle miles traveled.

Thus, the thesis tests the premise that local urban conditions affect not only transit riding and transit access walk-mode shares but also the distance people are willing to walk to/from a station. Appropriately planned street networks can expand the catchment areas around stations by offering a variety of choices for meeting people's daily travel needs and creating more opportunities for appealing, purpose-driven walks. In addition to facilitating "walking to the station", local urban conditions can encourage a larger sense of pedestrian oriented community and indirectly support ridership. The research is also pointed towards practical implications. It is likely to strengthen the existing and increasingly extensive knowledge base that supports public transport oriented policy whether such policy is aimed towards a reduction of traffic congestion, emissions or energy consumption, or to an increase in active healthy living. In addition it may support the evaluation of development proposals around transit stations from the point of view of local network properties, so as to maximize the advantages of relative proximity to stations.

The remainder of this study is divided into six main chapters. The next chapter presents an overview of related literature to set the context for the research. This is followed by a description of the methodological framework of the study. Chapter 4 characterizes the urban form around MARTA rail stations. Chapters 5 and 6 present the model results for walk-mode shares and walking distances respectively. The final chapter summarizes the key findings and their implications.

CHAPTER 2

RESEARCH BACKGROUND

Much empirical literature dealing with how the built environment can influence travel behavior has been framed around three dimensions, or the 3Ds, of urban form: *density*, diversity of *land-use* and *street design*. Of course each of these ideas, which are intuitively understandable, needs clarification before they can become analytically precise. Density, for example, usually refers to development density (square feet of building per acre of land) but it also refers to population density (residential units per acre or population per acre) or indeed to street density (intersections per acre for example). Similarly, land-use is described in terms of zoning categories, or in terms of indices of land-use mix, either at the scale of the parcel or at larger scales ranging from the urban block to the census tract. Finally, street design often refers to street section dimensions and design standards; it can also refer to perceptual qualities of the local environment (ranging from material textures to tree canopies); sometimes it refers to the design of the street network.

In this thesis the word "density" will be used to describe population per acre; the word "land-use" will be used to describe land-use mix using a particular index (see Equation 1 in Chapter 3). Regarding design, the emphasis is upon the street network. No variables describing street sections or the perceptual qualities of streets are evoked, simply because no relevant data was available (a limitation which will be taken up in the concluding chapter). However, the presence or absence of side-walks is one of the variables included in the analysis. Throughout the thesis, the term "street design" will be

used to refer to street sections, street standards and the local qualities of street, including visual qualities, signage, or the design of pedestrian crossings. "Street network design" on the other hand, will refer to the configuration of the street network as a whole, and the alignment of road segments into streets. The main emphasis of the thesis is to examine the contribution of street network design to walking to transit and to the distances that can be walked.

In the following discussion of the literature in this chapter, the definitions of terms provided by different authors will be clarified, to introduce the reader to a field of studies which is quite diversified from the point of view of the quantification or the precise definition of variables.

By and large, related literature reviewed seeks to explain 3 sub-categories of travel demand: transit share (the proportion of travel that occurs by transit rather than private vehicles or other means); transit ridership (the number of trips per person or household); the number of boardings per station; the number of people that walk to transit stations (as opposed to the number that drive or are dropped off from a vehicle); and trip lengths and times. Accordingly, the conceptual underpinnings and relevant findings from past research on the relationship between urban form and non-motorized travel are briefly reviewed below from the point of view of four key questions: how do the 3Ds affect any of the aspects of transit ridership mentioned above; how do they affect walking, in general; how do they affect walking to/from transit, in particular; and what are the walking distances to/from transit?

Generally, dense, diverse, and pedestrian-friendly neighborhoods are thought to reduce auto trips, expressed in VMT (vehicular miles traveled) and auto trips per

person/household. Also, it is claimed that the 3Ds affect mode choice including the preference for transit use and walking. Finally, higher population and residential densities, mixed land-uses, and well-connected urban networks are thought to reduce trip lengths by diminishing travel distances.

It is relatively easy to conceptualize how population and development density induces transit use and encourages non-motorized travel. Density is thought to shape travel demand directly by establishing a larger pool of potential riders and indirectly by bringing numerous activities closer together, thus increasing their accessibility from transit nodes. It is suggested that people are willing to use slower modes of travel, such as transit and walking, for shorter distances, especially if many trips can be chained.

Similarly, land-use mix increases accessibility by increasing the number of available destinations within walking range. It is argued that commingling of offices, shops, restaurants, residences and other activities influences the decisions to use transit and also to walk to/from transit by allowing riders to link their trips along their routes to/from transit. This is reflected in higher number of station boardings and non-motorized mode shares in mixed-use urban areas.

The connectivity of street networks increases accessibility in two ways. First it makes it more likely that a short or more direct routes is available for any given pair of origin and destination. Second, the more the length of streets in a given area, the greater the number of frontages, and thus of destinations, that are likely to be available at walking range. Fine-grained urban networks of densely interconnected streets improve transit and pedestrian travel by providing relatively direct routes, thus reducing the distance between origins and destinations.

Similarly, the provision of appropriate side-walks, the visible linkages between premises and the street, the presence of pedestrian friendly land-uses such as cafes, the presence of tree canopies or sheltering arcades, and the design of safe and convenient pedestrian crossings helps pedestrians feel comfortable and safe when they walk, thus increasing the proportion of people that walk to transit stations.

Existing studies have quantified transit and non-motorized travel in 2 dimensions: as absolute numbers –focusing on number of transit trips per person, auto trips per household, VMT per capita, station boardings, walking trips per person/household– and as proportions –namely the proportion of trips by transit and walking. Hence, the following literature reviewed is categorized according to these two dimensions.

How do the 3Ds affect transit ridership?

Impacts of Density

Recent studies support the conclusion that compact developments with higher densities reduce vehicle trips and encourage non-motorized travel by reducing the distance between origins and destinations; by offering a wider variety of choices for commuting; and by providing additional factors, such as better quality of transit services, limited parking supply, and lower auto ownership levels, that reduce car usage (Cervero and Kockelman, 1997, Ewing et al., 1994, Holtzclaw, 1994, Krizek, 2003). The first two implications of density directly affect non-motorized travel whereas the latter exerts an indirect influence. Thus, existing research is discussed under two categories: *direct effects of density* on ridership and *indirect effects of density* on various design-related attributes affecting transit patronage.

Direct effects of density on ridership

The effects of density on non-motorized travel and ridership are well documented. The studies reviewed explore ridership from two distinct aspects: absolute numbers, namely transit trips per person, auto trips per person/household, VMT (vehicle mile traveled) per capita/household, and station boardings on one hand, and the proportion of trips by transit on the other.

After comparing individual trips and residential densities for 6 US urban areas, Smith (1984) reported that higher residential densities (an increase from 7 to 16 units per acre) were strongly correlated with a substantial reduction in auto trips and increase in transit trips per person per day. Results of regional studies point to similar conclusions to those suggested by national surveys. A 1990 study by Harvey (1990) suggested that a doubling of residential densities (persons per residential acre) yielded in a 30% decrease in VMT per capita. This density-VMT relationship was confirmed by Holtzclaw (1994), whose analysis of 29 communities in San Francisco Bay Area suggested that doubling of residential densities resulted in a 20-to-30% reduction in VMT per household. None of these study explicitly discusses whether the reduction of VMT implies an inclease in the use of other modes of transportation, or merely a reduction of distances travelled to satisfy similar needs. However, Dunphy and Fisher (1996) were able to demonstrate higher transit trips per capita and lower VMT per capita both at urban regions and urban zones with higher densities. In this case, at least, lowering VMT and increasing transit use seem to work synergistically.

Following the "pro-density" argument, data from a national sample showed that doubling of station-area residential densities yields in an increase in light-rail boardings

by almost 60% (Parsons Brinkerhoff Quade and Douglas Inc., 1996a). Similarly, after evaluating transit-oriented land-use proposals for Charlotte, the San Francisco Bay Area, and south St. Louis County, Cervero (2006) found that the ridership-to-density elasticities (% increases in rail boardings as residential densities increase by 1%) were substantial in the estimate of ridership as a function of station environments. Cervero demonstrated that raising density within half-mile of a station by one dwelling unit per gross acre increased weekly boardings by nearly 1,100. It stands to reason that in order for a transit station to be economically viable, increasing the number of station boardings or the number of transit trips per capita/household helps reduce the cost of providing transit service in a community. However; the role of density in affecting ridership is not limited to increasing the absolute number of riders only; increased station-area densities were also shown to be related to higher transit mode shares.

Pushkarev and Zupan (1977) documented that residential densities in transit corridors, together with the size of downtown and distance of stations from downtown, explained demand for a variety of transit modes. The authors concluded that with a density increase of between 7 and 30 unites per acre, transit demand, measured as proportion of all trips, tripled. Carrying out matched pair analyses of transit- and auto-oriented neighborhoods in San Francisco Bay Area, Cervero and Gorham (1995) showed that increases in residential density are clearly associated with higher transit shares in both types of neighborhoods. In a subsequent study, the analysis of the 1985 American Housing Survey data led Cervero (1996) to conclude that residential density exerted a strong influence on transit commuting, controlling for auto ownership per household. Similarly, based on an analysis of the 1995 National Personal Transportation Survey,

Ross and Dunning (1997) came to the conclusion that transit mode share drastically increased for population densities over 10,000 people per square mile.

However, as pointed out by Ewing and Cervero (2001) in their comprehensive review of the literature, the preoccupation of existing research with residential density may be misguided. In fact, employment densities at trip ends have been argued to exert as important an influence as population densities on transit and walking trips. In a report prepared for the Transit Cooperative Research Program (Parsons Brinkerhoff Quade and Douglas Inc., 1996a), where a sample of 11 metropolitan US cities was analyzed, higher population densities were found to affect commuter mode choices, transit trips per person, and the proportion of transit trips per capita, while station-area employment densities were found to affect the number of station boardings at rail stations. Gomez-Ibanez (1996) also found that ridership levels in Boston between 1970 and 1990 were affected largely by employment levels: each percentage decrease in CBD jobs was associated with a 1.24 to 1.75 percent decline in ridership patronage. Similarly, Frank and Pivo (1994) demonstrated reduction in SOV (single occupancy vehicle) travel to be more significantly associated with employment densities at destinations than with population densities at origins.

While these studies have demonstrated a clear pattern of higher levels of non-motorized trips per capita, including pedestrian and transit trips, and lower VMT in higher density neighborhoods, others have argued that benefits of density are in fact dependent on accessibility to regional activities and job-housing balance, which significantly reduces vehicular travel (Cervero, 1989, Ewing, 1995, Giuliano, 1991). A number of empirical studies have calculated various residential and employment density

thresholds to ensure the feasibility of transit service. Newman and Kenworthy (1989) recommended densities above 12 to 16 persons per acre for public transit-oriented urban lifestyles. Frank and Pivo (1994) studied travel behavior in the Seattle metropolitan area and concluded that there existed a threshold of 50-75 employees per acre at which transit work trips showed a significant increase. However; these numbers are not meaningful alone due to the intervening relationship between density and a multitude of design related variables as well as socio-demographic characteristics of households.

Indirect effects of density on ridership

A number of other researchers have suggested that residential density thresholds are interrelated with various factors such as income levels, auto ownership rates, cost and efficiency of transit service, and the supply and price of parking (Meyer, 1989, Parsons Brinkerhoff Quade and Douglas Inc., 1996a, Pushkarev and Zupan, 1982). Including a per capita income variable in his ridership model for Boston, Gomez-Ibanez (1996) found that the positive impact of employment densities on ridership was offset by the increase in income levels.

A study on the comparison of different US centers based on 1991 FHWA Highway Statistics (1991) and 1990 National Personal Transportation Survey indicated a clear pattern of lower levels of auto ownership in higher urban densities (Dunphy and Fisher, 1996). As the authors have noted, the inverse relationship between density and auto ownership levels reflected the limitations of parking supplies and increasing costs in denser areas. Similarly, studies investigating the role of density in influencing rail ridership found supply of park-and-ride to have a significant effect on ridership. Analysis

of the of 11 light rail and six commuter rail cities showed that a light rail station with parking has on average about 50 percent more boardings than a station without parking (Parsons Brinkerhoff Quade and Douglas Inc., 1996a). In addition, research shows that denser areas typically have higher service frequencies and better quality service, which, in return, promote lower auto ownership rates (Holtzclaw, 1994). Thus, it seems imperative that conclusions regarding density should be considered in conjunction with transit service and socio-demographic attributes.

Impacts of Land-Use

Studies regarding the measurable impacts of land-use characteristics on transit use and mode of access to transit have verified that high levels of land-use mix at the trip origins and destinations yield an increase in transit shares and non-auto commuting (Cervero, 1996, Cervero, 2006, Holtzclaw, 1994, Krizek, 2003).

The report prepared by Parsons Brinkerhoff, Quade and Douglas Inc. (1996a) with the particular aim of identifying the link between transit and urban form selected San Francisco (BARTA) and Chicago (METRA and CTA) transit systems for the study. It was reported that 10% increase in station-environment commercial activities resulted in, on average, 30% more riders for CTA stations. Similarly, in his study, in which he analyzed travel data based on a 1991 diary-based travel survey in Palm Beach County, Ewing (1995) found that development patterns had a significant impact on household travel behavior beyond their relationship with other socio-demographic characteristics of households. Since origins and destinations are a function of land-use, boardings would

naturally increase in areas where more people live or more activities become available within reach of commuters.

A second group of studies concerns themselves with the impacts of land-use on transit mode shares. In his analysis of 57 suburban activity centers across US, Cervero (1989) noted that every 10% increase in floor space of retail and commercial uses was associated with 3% increase in transit shares. Although centers had comparable employment levels, no socio-economic control variables were introduced in the models produced. Complementing this finding, Cambridge Systematics' (1994) study, which characterized the employment centers in Los Angeles using a composite land-use mix variable, concluded that transit share increased substantially with higher land-use mixing within a quarter mile of the sites. Kockelman (1997) utilized the 1990 San Francisco Bay Area Travel Survey to conclude that land-use balance and mix had more impact on mode choice and VMT per household than socio-demographic characteristics. In a more recent study, using trip records for Montgomery County residents from the 1994 Household Travel Survey, Cervero (2002) developed binomial and multinomial models to analyze the link between the built environment and mode choice. Transit mode shares were found to be most sensitive to land-use diversity.

The availability of non-residential component nearby a transit node is thought to induce transit riding for primarily two reasons. First, daily activities, such as visits to stores, can be easily integrated to the routine pedestrian trip between the station and the home/workplace. Retail uses located along transit corridors, for example, might encourage a subgroup of people to commute by transit by providing them the option to shop en route from transit nodes to their homes at the end of the day (Cervero, 1996).

Second, land-use mix around stations provides workers, whose jobs are in walking distance of station, mid-day mobility. Suburban workers, in particular, are less inclined to use SOV if there are personal services within walking range of their offices during mid-day (Cervero, 1988).

Impacts of Street Design and Street Network Design

While the impacts of density and land-use on travel behavior have long been acknowledged, street network design has received less attention. Thus, literature on network effects on travel is relatively limited. Design of street networks are shown to be significantly related to the decision to patronize transit and other non-motorized modes. Connectivity patterns and local spatial structure of street networks bring origins and destinations closer by providing relatively direct routes. They also generate different densities of interface between streets and premises, thus different opportunities to combine a walk to/from the station with other activities. Finer-meshed urban grids are found to offer a variety of choices for meeting people's daily travel needs and creating more opportunities for shorter, purpose-driven walks. Thus, people are less likely to drive and more likely to use transit and walk for transit in well structured and differentiated street networks. This is reflected in lower VMTs and higher non-motorized trip rates and ridership levels.

Various quantitative measures have been suggested by the urban-design literature to measure street connectivity. Block sizes, the density and pattern of intersections, and block face lengths among other factors have been employed to describe connectivity (Siksna, 1997, Southworth and Owens, 1993). Using such measures, several studies have

reported significant relationships between transit and street network design. In a study by Cervero and Kockelman (1997) VMT for non-work trips was found lower in neighborhoods with higher proportion of 4-way intersections or quadrilateral-shaped blocks ratios. Frank et al. (2000) reported lower vehicular travel in areas with small blocks similar to traditional grid pattern. A few studies employed simulation models to forecast travel impacts of neo-traditional communities. Kulash, Anglin, and Marks (1990) used travel models to conclude that neighborhoods with rectilinear street layouts averaged 43% lower VMT.

A California Air Resources Board study (Kitamura et al., 1994) examined household travel behavior in the San Francisco Bay Area using 3-day travel diaries. The models developed using 13 street characteristics (i.e. sidewalk width, intersection characteristics) showed specific individual street design characteristics to be significant in predicting transit choice model. The term "street design" refers to street cross sections, including types, widths, and standards of streets. A research project completed for the Transit Cooperative Research Program (Parsons Brinkerhoff Quade and Douglas Inc., 1996b) suggested that the probability of generating non-auto trips was about twice as great in the "traditional" Bay Area neighborhoods as in their "suburban" counterparts. Using a comparative method, Hsiao et al. (1997) studied two pairs of areas in Orange County, CA, one with grid street patterns, the latter with irregular street patterns. Results of bivariate and multiple regression analyses showed a strong relationship between bus ridership rates and pedestrian access, characterized by population density quantified for each catchment area based on the ratio of street length within the area to the total street length in the census tract.

Using recently developed segment-based measures of connectivity, which are explained in detail in Chapter 3, Ozbil et al. (2009) examined the impact of street connectivity on average daily station rail boardings in Chicago (CTA), Dallas (DART), and Atlanta (MARTA), controlling for population density, transit service features, and the effect of walking distance from transit station. Results of multiple regression analyses suggested that metric reach, which measures the street length that is accessible within a walking range, was a stronger predictor of transit use than station area population densities. (The full study is presented in Appendix A.)

Contrarily, a second line of research on network design and travel patterns points in the opposite direction. In a study where they analyzed San Diego household travel diary, Crane and Crepeau (1998) could find no evidence regarding the effects of street network patterns on either short or long distance non-work travel decisions. Similarly, after testing household travel behavior after re-location in the Central Puget Sound metropolitan area using a composite "Less Auto Dependent Urban Form" (LADUF) factor based on residential density, land-use mix and average block area, Krizek (2000) argued that differing levels of accessibility levels in each urban form type was an artifact of individual preference. Thus, he concluded that the role of urban form was limited to changing household attitudes towards travel.

While the literature presents mixed results with respect to this issue, the weight of studies reviewed in this section points to the relationship between non-motorized travel and street network design. In fact, in general the discussion between these studies is on the relative significance of street network design in comparison to other factors, not whether it is important.

Figure 1 represents a simplified summary of the findings of previous research regarding the causal links between urban form and transit ridership.
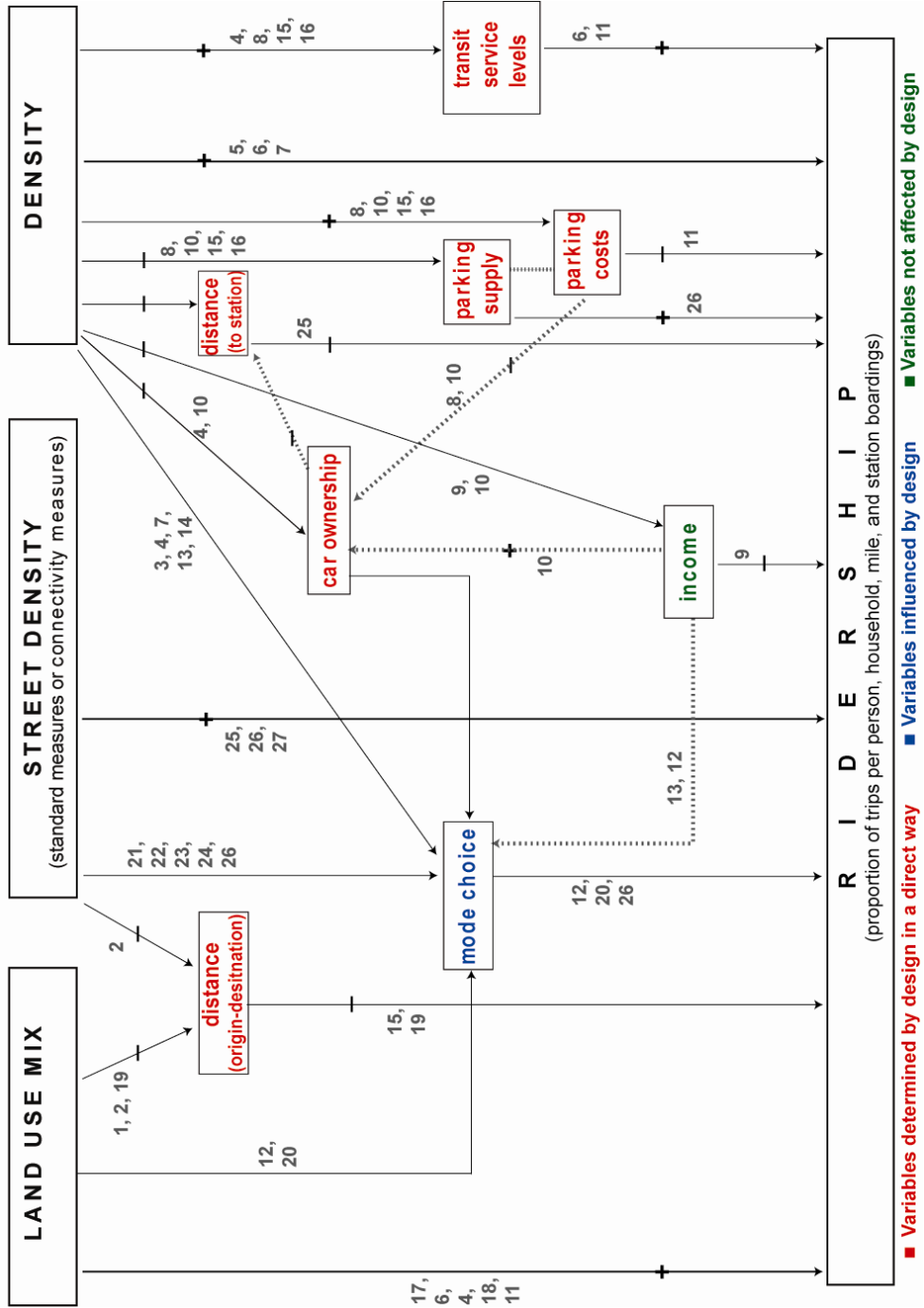
Figure 1. Impacts of three primary attributes of urban form –density, land-use mix, and

1. Impacts of three primary attributes of urban form –density, land-use mix, and

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Table 1. References for Figure 1 showing the link between urban form factors and transit ridership.

1. (Crane and Crepeau, 1998);
2. (Handy, 1996a);
3. (Pushkarev and Zupan, 1977);
4. (Holtzclaw, 1994);
5. (Badoe and Miller, 2000);
6. (Cervero, 2006);
7. (Frank and Pivo, 1994);
8. (Parsons Brinkerhoff Quade and Douglas Inc., 1996a);
9. (Gomez-Ibanez, 1996);
10. (Dunphy and Fisher, 1996);
11. (Cervero, 1989);
12. (Kockelman, 1997);
13. (Smith, 1984)

14. (Harvey, 1990)
15. (Meyer, 1989)
16. (Pushkarev and Zupan, 1982)
17. (Cervero, 1996)
18. (Krizek, 2003)
19. (Cambridge Systematics, 1994)
20. (Ewing, 1995)
21. (Cervero and Kockelman, 1997)
22. (Frank and Stone, 2000)
23. (Hsiao et al., 1997)
24. (Kulash et al., 1990)
25. (Kitamura et al., 1994)
26. (Parsons Brinkerhoff Quade and Douglas Inc., 1996b)
27. (Ozbil et al., 2009)

How do the 3Ds affect walking?

In spite of the well-documented research on travel behavior regarding vehicular travel (VMT, trip frequencies) and transit travel (transit share, rail/bus ridership rates), studies on walk trips and walk-modes shares are relatively limited. The growing body of sizeable transportation-, planning- and physical activity-related literature on walking as mode of transit have used various approaches, such as correlational designs and multiple regression analyses, to understand the underlying urban form variables affecting walking besides the variation explained by demographics. The evidence from existing research demonstrates consistent associations of the 3Ds of urban form with pedestrian travel. Studies vary in their strengths of association but are generally shown to be substantial.

Impacts of Density

Studies relating urban densities to pedestrian travel share similar findings with transit-related research. Employment and population densities at origins and destinations are significant in increasing the probability of walking. However, considerable debate exists over whether the observed changes in pedestrian travel patterns are due to density itself or density acting as a proxy for other attributes, i.e. household characteristics, vehicle ownership, parking supply, etc.

Analyzing the 1990 Nationwide Survey, Dunphy and Fisher (1996) were able to demonstrate that walk trips became more frequent at higher densities, growing from about 0.3 daily walking trips to 1.5 trips by average resident within an increase from 4,500 to 40,000 residents per square mile. An analysis on the complementary influences of density and land-use mix on the choice of SOV, transit, and walking (Frank and Pivo,

1994) suggested that walk share of work trips increased at higher population densities (gross population density at trip origins and destinations) and at higher employment densities (gross employment density at origins only). Findings suggested a minimum of 13 residents per acre for changes in mode choice from SOV to walking to occur. In a comparative study, Kitamura et al. (1997) analyzed travel behavior in San Francisco Bay Area in five neighborhoods matched by median income, controlling for household size, auto ownership, and income. The results of regression analysis showed greater walk shares of trips at higher densities. At a nationwide scale, studying the 1995 Nationwide Survey, Ross and Dunning (1997) concluded that walk-mode share increased at higher population densities.

Impacts of Land-Use

Explanations regarding the measurable impact of land-use characteristics on pedestrian travel and how land-use mix play a significant role in encouraging walking follow similar logics. Increased levels of land-use mix at trip origins and destinations yield in increase in walking. Walking occurs within the constraints of distance and time. Naturally, the number of destinations available within walking range is likely to influence walking behaviors. In fact, studies regarding how pedestrian movement is affected by land-use mix have verified that dense land-use patterns play a significant role in encouraging walks.

Handy (1996b) explored the relationship between urban form and choices about pedestrian trips based on data collected in Austin area, where she analyzed three pairs of neighborhoods, each pair described as "traditional", "early modern", or "late modern".

She concluded that even though individual motivations were central to the decision to walk, urban form, and in particular the distance from home to destination as determined by number of commercial activities available within walking distance of homes and connectivity, played a greater role in the choice to walk to a destination. In a more recent study, Cao et al. (2007) used data collected on four traditional and four suburban neighborhoods in Northern California to explore the link between changes in the built environment and changes in travel behavior. The models developed pointed to an increase in accessibility –measured as the distance along the street network from home to a variety of destinations– and the availability of shopping area within walking distances as the most significant factor in reducing driving and encouraging walking. Based on a cross-sectional study on the link between environmental measures and physical activity, Hoehner et al. (2005) found that transportation activity (walking and bicycling) was positively associated with the number of destinations available within walking range. With regard to the accessibility of activity nodes within walking distances, Hanson and Schwab (1995) has also demonstrated that walking was more likely for certain types of trips (i.e. work versus shopping).

In a study conducted in the Seattle area, Frank and Pivo (1994) showed that only average land-use mix at origins and destinations remained significant in explaining percent walking for work trips once non-urban form factors, namely household-type variables, were accounted for. In a similar vein, modeling household travel data extracted from the 1985 American Housing Survey, Cervero (1996) developed logit and regression models, statistically controlling for household size, income, and auto ownership. The findings of his study demonstrated that mixed-use development around residences

(approximately 300 feet) exerted a stronger influence on the frequency of walk trips than residential densities.

Impacts of Street Design and Street Network Design

There is a sizeable literature relating street network design and walking behavior. However; researchers have put emphasis on walking trips and walking rates, which may not be linked to other modes of travel necessarily, than on walk-mode share, which is by necessity associated with the changes in other modes of travel simultaneously. For street network design, prevalent measures of connectivity have been limited to average measures of street networks, such as the number of intersections, percent of gridded streets, and average block sizes per area.

One study, which is germane to this research –since it focused on the Atlanta region, examined the relationship between objectively measured urban form variables and walking, and controlled for participant demographics –is that by Kerr et al. (2007). Using data collected by the Strategies for Metro Atlanta's Regional Transportation and Air Quality Study (SMARTRAQ) household travel survey in the Atlanta region in 2001-2002, the authors explored urban form correlates of walking among youth. Urban form variables included residential density and land-use mix within 1 kilometer buffer, and street connectivity measured by the number of intersections per square kilometer. Of particular interest to this dissertation was the finding that intersection density was positively related to walking rates for transport. Logistic regression analyses also found weaker impact of urban form measures in explaining walking as access-mode choice in low-income households with no access to a car. Thus, the authors concluded that lack of

vehicle ownership created a necessity to walk, suppressing the benefits of walkable communities.

Hess et al. (1999) investigated pedestrian volumes into 12 neighborhood commercial centers in the central Puget Sound region controlling for density, land-use mix, and income within 0.5 mile catchment areas. Urban sites with small blocks (200 to 300 feet or 61-91 meters) and complete sidewalk systems were found to have, on average, triple amount of pedestrian volumes in neighborhoods with large blocks (around 600 feet or 183 meters) and discontinuous sidewalks. Moudon et al. (2006) tried a similar approach to analyze the environmental attributes associated with pedestrian travel. Bivariate and multivariate models were developed to analyze the environmental attributes associated with self-reported neighborhood walking in King County, Washington. Apart from residential density threshold values and the availability of attractor destinations within walking distances, block sizes were found to be significantly correlated with walking rates. Authors reported that reducing block size (less than 500 hundred feet or 152 meters) could enhance neighborhood walkability.

These findings are supported by Handy (1992), who, after studying non-work trips in the Bay Area, showed that high-local accessibility areas, defined as comprising smaller blocks (higher number of blocks per square mile), more intersections, and higher total road length per square mile, produced nearly two-to-four more walking trips to downtown than low-accessibility areas. In a recent work by Lee and Moudon (2006), micro-level land-use and urban form variables related to walking were modeled in the City of Seattle. The findings emphasized the significance of route characteristics, in

particular route directness between respondent's home and daily destinations, in explaining neighborhood walking rates.

Apart from average measures of street density, some studies have studied the underlying differences of street types, such as the distinctions between traditional vs. suburban/modern, and grid vs. cul-de-sac, to reveal the link between street network and pedestrian behavior. Shriver (1997) compared pedestrian travel behavior in Austin based on the comparison of two pairs of traditional and modern developments, characterized by types of blocks and intersections. The study showed that the share of utilitarian walks were three times more in the traditional neighborhoods, which have grid layouts with shorter blocks and more intersections. In an another comparative study, Greenwald and Boarnet (2001) used a derivative of the Pedestrian Environmental Factor (PEF) that included street connectivity (grid vs. cul-de-sac) as well as sidewalk continuity, ease of street crossing, and topography. The results revealed that PEF score was significant in determining the probability of non-work walking travel at the neighborhood level.

However; there is an extensive body of research which suggests that pedestrian densities are distributed according to a measure of accessibility, namely syntactic integration, which is not associated with metric distance (Hillier et al., 1987, Hillier et al., 1993, Peponis et al., 1997). Syntactic integration measures the number of direction changes needed to move from each street line to all others. The fact that direction changes influence the distribution of pedestrians is not surprising. Direction changes are associated with cognitive effort (Bailenson et al., 2000, Crowe et al., 2000, Montello, 1991, Sadalla and Magel, 1980). Thus, it seems intuitively plausible that pedestrian movement is drawn to those streets that act as a primary reference system, providing

pedestrians with cues that let them locate themselves within the global environment, hence, allowing for exploration without the fear of getting lost. Walking, therefore, also occurs within the constraints of directional accessibility offered by street networks. This is confirmed by research findings (Conroy-Dalton, 2003, Moeser, 1988, O'Neill, 1991) indicating that people orient themselves with respect to frames of reference that are as linear as possible.

Recent studies have integrated syntactical properties of space with GIS technology to model pedestrian volumes. Raford and Ragland (2004) used GIS centerline maps of the city of Oakland to compute syntactic values of street networks in an attempt to study pedestrian safety. Based on the model developed, available pedestrian counts as well as population and employment densities were used to create estimates of pedestrian volumes. The findings of this study showed that high-collision intersections tended to have in fact low relative risk indices due their high pedestrian volumes.

Ozbil and Peponis (2007) studied three 1 mile x 1mile areas in Atlanta in order to establish correlations between street configuration and densities of pedestrian movement. They compared syntactic measures of integration and more recent measures of segment-based connectivity measures implemented on a GIS platform in explaining the distribution of movement. Results of bivariate correlations demonstrated that segment-based connectivity measures post-dict movement densities as well as the standard syntactic measures, and that both non-parametric (standard syntax) and parametric (segment-based measures) definition of changes are important in determining how likely it is that a given space will attract greater flows of movement as compared to its surroundings. (The full paper is presented in Appendix B.)

How do the 3Ds affect walking to/from transit?

There has been far more research on leisure walking, walking for shopping or strolling, than on walking as transit access/egress mode. Thus, the literature reviewed below is limited in comparison to the previous literature dealing with ridership and walking in general. In addition, the investigation into the roles of density, land-use, and street network is not equally balanced. Hence, additional research in this area can help arrive at firmer conclusions.

Impacts of Density

The significance of density in explaining walk access modes to transit is consistent with the findings of studies related to the choice to walk for other utilitarian or recreational purposes.

In an analysis of three California Metropolitan areas, in which transit commute shares and transit mode of access were regressed on variables such as employment density and land-use mix variables, Cervero (1994b) found that at higher density work settings rail users had higher shares of midday walk trips. In a study that investigated walk trips for riders using BART system Loutzenheiser (1997) found that the variation in walk-mode share by station was best explained by population density around stations. In addition, in the same study parking capacity was found to be negatively correlated with walk-mode shares.

Impacts of Land-use

The empirical evidence suggests that public transport-related walking depends as much on mixture of land-uses as on population and employment densities around transit nodes.

The analysis of 11 metropolitan areas found rail access walk-mode shares to be affected by mixture of land-uses within a short distance of home and work (Parsons Brinkerhoff Quade and Douglas Inc., 1996a). Complementing this finding, in the case of the Bay Area analysis reported previously, in addition to the impact of densities on walk-mode shares, Loutzenheiser (1997) showed that likelihood of walking to station was higher in station-environments (0.5 mile of station) where retail uses predominated.

The general inferences that can be drawn from these studies are that the characteristics of areas around stations strongly influence the ways in which people travel. In employment centers mixed land-use contributes to increasing levels of transit, while in residential neighborhoods land-use patterns that support mixture of developments influence the mode of access to transit. Local land-use patterns with high degree of land-use mixing are claimed to be more congenial to transit use as well as to walking.

Impacts of Street Design and Street Network Design

Interest in the impacts of street network design on public transport-related walking are far less numerous, and street connectivity variables are limited to measures of average properties of street networks.

A study on the Bay Area travel behavior (Cervero and Gorham, 1995) found that "transit neighborhoods", built around a rail station with higher percent of gridded street patterns, averaged higher pedestrian modal shares than did their auto-oriented counterparts. The finding of this study lends evidence that the density of available streets and street connections within walking distance of a station encourages walking as transit access/egress mode choice. However; there is prior research, as discussed above, associated with space syntax which has shown that the distribution of pedestrian movement is also related to the internal spatial structure of an area. In space syntax, spatial structure is an aspect of directional accessibility provided by the urban network. Based on the theory that direction changes appear to have significant impact on movement within an urban environment the location of the station relative to the internal structure of an area might be expected to influence walk-mode share for transit. Therefore, it can be hypothesized that the relative attractiveness of walking as an alternative mode depends partly on the character of the road segment, with regard to its spatial structure –i.e. whether it is well or less well connected within the network– that a particular station is located on.

How do the 3Ds affect walking distances to/from transit?

Despite the long recognized benefits of public transport-related walking by public health community, policy makers, and urban planners, very little is known about how far people actually walk to/from transit. While many walking distance guidelines, such as the

Sacramento Regional Transit District guidelines[1], Mid-America Regional Council (MARC)[2] and New Jersey Transit Handbook[3], have been developed based on the findings of surveys with regard to walking distance distributions traveled by riders, there has been only a small amount of research on walking distance thresholds. Because the existing body of research by transportation planning community was usually designed with the particular aim of discovering the factors underlying changes in travel behavior (from driving towards transit or walking), the majority of studies have focused on annualized person miles traveled, person miles per trip or individual trips that have not been classified according to modal splits. Hence, the evidence relating urban form correlates of walking distance thresholds must be deemed inconclusive.

Impacts of Density

In their pivotal study, Newman and Kenworthy (1989) observed the association between high fuel consumption and low urban density in Northern American and Australian cities as compared to higher density, more energy efficient European cities. Based on their findings the authors concluded that due to the multiplicative effect of low density on travel distances, walking as a transit access/egress mode became impossible since a higher percent of population lived outside of walking distance thresholds. Besser and Dannenberg (2005) used the 2001 National Household Travel Survey (NHTS) to

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[1] Transit/Lnad-use Co-ordination. Transportation Master Plan, Sacramento Regional Transit District, California, 1992.

[2] http://www.marc.org/transportation/pdf/TSD_Guidebook.pdf/ (Accessed: May 2010)

[3] http://www.som.com/content.cfm/new_jersey_transit_planning_for_transit-friendly_land_use/ (Accessed: May 2010).

assess Americans' daily activity levels based on walk-mode choice to transit. All walking trip times to/from transit for 1 day were summed to calculate the total transit-related walking time for each individual. The findings of this study indicated that people in high-density urban areas (with a population >4000 per square mile) had significantly higher mean total walking times compared with people living in less dense areas. However; there was no indication whether or not the reported walking times were directly representative of actual walking distances; thus, it was not possible to conclude that people walking for a longer duration, on average, necessarily achieved higher mean distances walking to/from station.

After examining work and shopping trips in the Seattle Area, Frank and Pivo (1994) found shorter shopping trip distances within origin tracts with higher population densities as well as shorter work trip distances within higher employment density origin tracts. Similarly, Ross and Duning (1997) analyzed the 1995 NPTS data to investigate the interaction between land-use and transportation. The findings demonstrated lower person miles traveled (PMT) associated with higher population and residential density, and increased PMT levels with higher household income. However; in both studies trip distances were not distinguished between various modes, which made any conclusions on walk trip distances unclear.

Impacts of Land-Use

In a study where they examined and discussed approaches for improving access to public transportation in the South East Queensland region of Australia, Murray et al. (1998) suggested that certain land-use categories (high density dwellings and public

housing) should be placed on access routes to public transport to maximize their effects on improving access.

Handy (1992) compared non-work walking trips in two pairs of Bay Area communities, one with high, the latter with low local and regional accessibility resulting from the distribution of non-work activities. Simple correlations without any socio-demographic controls suggested that though trip frequencies appeared to be independent of land-use variables, shopping trips were shorter at more accessible locations due to the availability of increased amount of destinations within walking distances. Similarly, examining the relationship between mixed land-uses and commuting modal choices in US metropolitan areas, Cervero (1996) found shorter work trips in mixed-use neighborhoods. Yet, due to the nature of the survey used, land-use mix was identified coarsely using a binary variable indicating either non-residential uses existed or not within a defined unit of analysis.

Impacts of Street Design and Street Network Design

There is not a well-established literature regarding how street design and street network design affects the distances people are willing to walk for public transport. Between the 70s and 90s studies investigating the link between the local built environment and walking have generally focused on aspects of street design, such as traffic volumes (Shriver, 1997, Lovemark, 1972), ease of street crossings (Agrawal et al., 2008), and traffic signaling (Knoblauch et al., 1996, Virkler, 1998). Relatively recently research developed interest for taking on the design aspect of street networks more rigorously. Researchers have tackled the connection between street network design and

walking distance thresholds through two distinct but related aspects. First; by developing functional definitions of transit catchment areas based on the ridership gradient and assessing the pedestrian accessibility within these areas. Second; by determining the distribution of walking distances traveled to/from transit.

The literature on how the built environment influences walk-mode choice for transit has concluded that pedestrian access gradient –how quickly walking mode shares fall off with walking distances to stations– is set at between 0.25 mile and 0.5 mile, with 1 mile being the upper limit (JHK and Associates, 1987, Stringham, 1982). Research in Chicago (Parsons Brinkerhoff Quade and Douglas Inc., 1996c) suggested that the proportion of all trips to/from CTA on foot decreased around 1.1% for each 100 feet (30.5 meters) of airline distance (crow-fly distance between two points) between the home and station up to 1.5 mile. The same study reported elasticities ranging from 1.3-to-1.4% decrease in walk-mode shares per each 100 feet increase between distances 1 and 1.25 mile for the BART system.

Various quantitative measures have been suggested by the urban design literature to evaluate pedestrian accessibility within an area. Pedestrian catchment areas capturing all destinations reachable within a walking distance from a specific point, as proposed by Hess (1997), Hess et al. (1999), and Aultman-Hall et al. (1997), are used to describe structural differences in street networks. *Pedestrian Route Directness (PRD),* which measures the ratio of network distance to straight line distance, has been studied (Randall and Baetz, 2001) as an indicator of how accessible a neighborhood is to the pedestrians. Olszewski and Wibowo (2005) proposed a similar measure, the *detour factor* defined as

the ratio of averaged walking distance to airline distance, to evaluate the quality of street network around rapid transit stations in Singapore.

While studies have probed the link between pedestrian accessibility and surrounding areas, research on whether and how the distance people are willing to walk can be increased has been very limited (Fruin, 1992). Stringham (1982) and Untermann and Lewicki (1984) have shown that acceptable walking distances can be stretched by creating pleasant urban spaces and corridors. In addition, a comprehensive report on "Mode of Access and Catchment Areas for Rail Transit" (Parsons Brinkerhoff Quade and Douglas Inc., 1996c) underscored the importance of multiple factors, such as station parking supplies and transit service characteristics, in affecting walking distances. In a recent study, Agrawal et al. (2008) investigated survey results of pedestrians walking to five rail stations in California and Oregon to conclude that pedestrians prioritized choosing the most direct route to the station. Based on these findings the authors recommended improving street networks by offering direct connections between origins and destinations. Yet, this study defaults to two drawbacks in understanding walk trip distances with precision. First, no statistical models were developed to test the strength of these factors in explaining the distribution of distances walked; second, the reasons affecting trip distances (shorter routes, safety, sidewalk quality, waiting time at traffic lights) were not objectively measured urban form factors, but rather depended on the perception of individual traveler. Addressing this gap in the literature, one of the hypotheses to be tested in this research is whether the decision to walk a slightly longer but still very manageable distance is affected by the density of accessible streets and street connections within the surrounding area of a station.

Figure 2 presents an overview of research findings regarding the relationship between urban form and three walking indices: walking, in general; walking to/from transit, in particular; and walking distances to/from transit.

Figure 2. Impacts of three primary attributes of urban form – density, and walking distances to/from transit.
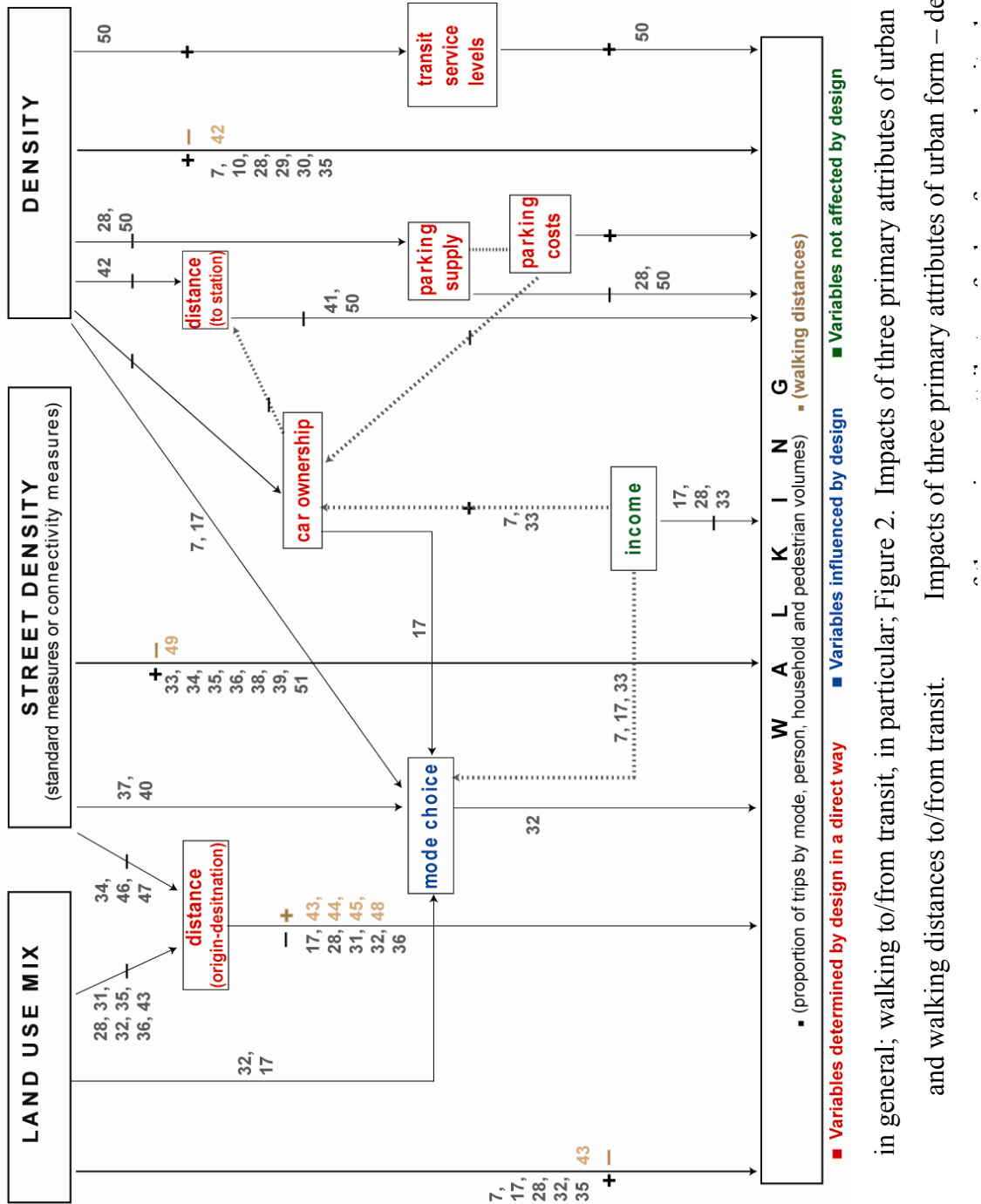
Table 2. Reference for Figure 2 showing the link between urban form factors and walking in general; walking to/from station in particular; and walking distances to/from transit.

28. (Loutzenheiser, 1997)

29. (Cervero, 1994)

30. (Ross and Dunning, 1997)

31. (Handy, 1996b)

32. (Cao et al., 2007)

33. (Kerr et al., 2007)

34. (Hess et al., 1999)

35. (Moudon et al., 2006)

36. (Handy, 1992)

37. (Cervero and Gorham, 1995)

38. (Shriver, 1997)

39. (Handy et al., 2005)

40. (Greenwald and Boarnet, 2001)

41. (Newman and Kenworthy, 1999)

42. (Besser and Dannenberg, 2005)

43. (Murray et al., 1998)

44. (JHK and Associates, 1987)

45. (Stringham, 1982)

46. (Hess, 1997)

47. (Randall and Baetz, 2001)

48. (Allan, 2001)

49. (Agrawal et al., 2008)

50. (Parsons Brinkerhoff Quade and Douglas Inc., 1996c)

51. (Ozbil and Peponis, 2007)

Concluding comments regarding the literature

Weighing the evidence presented here, a number of generalizations can be drawn with a degree of confidence about the relationship between urban form and non-motorized travel behavior. Among the four sub-categories of non-motorized travel measures, transit travel has received the most emphasis within the literature. Even within this category, however; the distinction between ridership defined as absolute numbers, i.e. station boardings, transit trips per person/household, and ridership defined as proportion of all trips by other modes, namely transit mode share, needs to be drawn. While it stands to reason that increasing the volume of riders patronizing a station by increasing station-area densities allows for the economical efficiency of transit service, it does not necessarily lead to any conclusions regarding the variation in modal splits. On the other hand, increasing the proportion of trips by transit by changing the built environment is a subtler aspect of the travel behavior-urban form link, because it reflects the changes in the shares of other modes of travel concurrently. Walking in general, i.e. between origins and destinations, for work and shopping purposes, etc., has attracted considerable academic interest, whereas walking to/from the transit station has not. Walking distances to/from stations have received attention in relatively recent studies.

As the literature reviewed in this Chapter demonstrates, transit use appears to be primarily affected by station-area development densities (both residential and employment) and secondarily by land-use mix while pedestrian travel seems to be dependent equally on densities and land-use compositions. Yet studies differ on their conclusions regarding the significance of density in explaining transit patronage. The "pro-density" argument considers density as the most important factor affecting travel

choices. Contrarily, other studies suggest that density impacts travel patterns through its effects on various factors such as income levels, auto ownership rates, cost and efficiency of transit service, and the supply and price of parking.

Impacts of land-use mix on transit travel and walking have not been investigated by the literature to the same extent as those of density, but the findings are quite consistent. Studies regarding the measurable impacts of land-use characteristics on travel have verified that high levels of land-use mix at the trip origins and destinations are the primary driver of mode choice.

Particularly in the last decade, researchers have focused on the importance attributed to street network design. A common theme of this body of research is that inordinate size of street blocks or the lack of a fine-grained urban network of densely interconnected streets fails to promote greater transit mode shares, higher proportion of walking, more walk trips, and shorter trips, thereby yielding in reductions in VMT.

Yet, in spite of the burgeoning literature concerned with street connectivity, the effect of street network configuration on overall travel remains unclear. One reason is the absence of commonly accepted measures that capture the internal structure of urban areas. The significance of spatial structure in affecting pedestrian movement has been addressed through the framework of configurational analysis of space syntax. Empirical studies have shown that road segments that are accessible from their surroundings with fewer direction changes tend to attract higher flows. From a point of view of this thesis, the key implication of previous syntactic studies is that our understanding of how street networks impact behaviors and performances of different kinds is significantly improved when we apply stronger descriptive methods and better measures of spatial properties.

A second reason for the weak explanatory power of street network design in urban models is the absence of rich land-use and urban design data. Travel data is commonly obtained from national censuses for large scale models at the tract level. This poses a significant limitation in carrying out neighborhood-scale studies investigating how urban form shapes travel patterns. The models employed by the broader literature on urban form and pedestrian behavior have turned to relatively larger units of analyses, such as Traffic Analysis Zones (TAZs), census tracts, or block groups. These gross geographic units estimate average regional urban form characteristics, failing to capture fine-grained land-use and design aspects essential for understanding travel impacts of small-scale place-oriented projects.

Another methodological dilemma of studying the travel impacts of street network design is the multicollinearity between urban features. Clearly, the foregoing findings point to the fact that the 3Ds of urban form are interrelated since denser areas typically have higher land-use mixtures, on average higher street intersections per area with more gridiron street network patterns (Parsons Brinkerhoff Quade and Douglas Inc., 1996a). A number of studies have attempted to improve the explanatory power of street network design by developing composite variables that account for multiple dimensions of urban form, such as the " Pedestrian Environmental Factor" (Parsons Brinkerhoff Quade and Douglas Inc. et al., 1993) or "walkability index" (Goldberg et al., 2006). While they capture the multi-faceted dimensions of urban form, relative contribution of each variable remains inconclusive. The question of multicollinearity is addressed in the course of the analysis in Chapter 4.

The emphasis of the review of literature presented above is upon what Hillier has called "the regularity of phenomena" (Hillier, 1996), in this case the associations between variables that describe aspects of urban form and variables that describe aspects of travel behavior. To establish regularities, however, is not the same as to propose theories that can *explain* them. There could be a number of alternative explanations of behavior. To list but a few: people may decide what travel share based on economic cost (Cervero and Seskin, 1995, Crane, 1996b); they might decide whether to walk to the station or not based on the amount of effort required –a minimization of effort function (Crane, 1996a); or they might decide to walk based on various benefits that can range from the pleasure of walking to compliance with healthy living prerogatives (Frank et al., 2003, Rodriguez et al., 2006, Sallis et al., 1998) to opportunities to combine their trip to the station with the satisfaction of other needs, such as shopping (Cervero and Kockelman, 1997, Ewing et al., 1994); walking might be deterred by lack of safety or perceived lack of safety (Gehl, 1986, Appleyard, 1981); distances walked can be increased due to lack of alternative means (such as car ownership or bus availability) (Loutzenheiser, 1997, Olszewski and Wibowo, 2005), or they might be increased due to environmental qualities (good sidewalks, or tree canopies) (Cambridge Systematics, 1994, Ewing et al., 2003, Kitamura et al., 1997), or they might even be increased due to perceptual factors (straight paths feel less lengthy than paths with many direction changes) (Sadalla and Magel, 1980).

Given the complexity of the factors reviewed in this chapter any attempt to summarize alternative behavioral theories and to arrive at coherent and powerful explanatory models would exceed the scope of the thesis. Rather, the strategy in the

following chapters will be to focus on some particular regularities of interest –how far do street networks encourage more people to walk to the station, as a proportion of total ridership; how far do they affect the distances people are willing to walk– delaying any interpretative discussion until the concluding chapter.

CHAPTER 3

ANALYTICAL FRAMEWORK

Case Context and Data Inputs

MARTA stations are characterized not only by their own characteristics, including the frequency of service and ridership levels, but also by the properties of the surrounding areas. Surrounding areas are identified as circles of 0.25, 0.5 and 1 mile radius. This study relies on currently available data sources on socio-demographics, land-use compositions, gross densities, and street networks for such areas.

To address the link between urban form and public transport-related walking it was necessary to compile data from different sources and merge them into a single database using GIS technology. Overall seven kinds of data were used in this analysis: the 2001-2002 Regional On-board Transit Survey, street network data based on ESRI Streetmap 2003, parcel-based land-use data, census data (2000), socio-demographics of households, transit service features, and various measures of street connectivity.

2001-2002 Regional On-Board Transit Survey

The most recent regional On-Board Transit survey was used for this study: the Regional On-board Transit Survey 2001-2002. The survey provides unique information on travel patterns and socio-demographics of transit riders. The survey, developed jointly with Atlanta Regional Commission and NuStats, was conducted among fixed route riders (of both bus and rail) of MARTA (Metropolitan Atlanta Rapid Transit Authority), CCT (Cobb Community Transit), Clayton County Transit (C-TRAN), and Gwinnett County

Transit (GCT) systems. The respondents completed surveys during the 2001 fall season (10.13-12.09), and February 2002. The dataset contains 31,244 records providing origin-destination data, demographics (including household size and vehicle availability), access and egress modes, and public transit use. The spatial connection between the participant's information and the Traffic Analysis Zones was created by address geocoding the trip origin, boarding location, trip destination, alighting location, and final destination using GIS software. In addition to these geocoded (x/y coordinates) variables, access and egress modes, number of vehicles within the household, household size, and annual household income are the primary variables used for modeling mode choice in this study.

Street Network Data

Census 2003 TIGER/Line data were used to analyze the street network of Atlanta. The street network contains precise geometric information on street layout, but sidewalks, pedestrian walkways, and topographical features are not included in the existing dataset. The data is appropriate for the application of the connectivity measures used in this study. It was assumed that streets served as walk paths for pedestrians, with the exception of freeways. To prevent distortions in the characterizations of the street network, highways were removed from the data set before calculating the various connectivity measures and network distance traveled by respondents. The Census TIGER file, which uses the standard Geodetic reference system, the North American Datum of 1983 (NAD 83) in decimal degrees, was re-projected using the Universal Transverse Mercator Model (UTM 16) in order to minimize any metric distortions.

Land-Use Data

Parcel-based land-use data was acquired from the data-base developed at the Center for GIS at Georgia Tech for the SMARTRAQ program (Strategies for Metro Atlanta's Regional Transportation and Air Quality) under the leadership of Steve French. Land-use data include the total square footage of different categories of buildings. A mixed-use entropy index was computed based on a formula derived from Cervero and Kockelman (1997), Cervero (2006), and Greenwald (2006):

$$Mixed-use\ entropy = -1 \times \left(\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right) \tag{1}$$

where: p_i = proportion land in use i of total of all land; and k = 6 categories of land-use (single family housing units, multifamily housing units, commercial use, institution use, office use, industrial use). The entropy value ranges between 0 (perfectly homogenous land-use composition, wherein one single use dominates) and 1 (perfectly heterogeneous land-use composition, with uses evenly spread among six categories). Separate entropy indices were computed for 0.25, 0.5, and 1 mile radii around each MARTA rail station.

2000 Census Data

Population and housing unit densities for the same surrounding areas were established using US 2000 census data. Gross population and housing unit densities of each transit surrounding area were measured by the total number of persons and housing

units in the 2000 census block divided by the size of the area. Population and housing unit figures were obtained by aggregating the census blocks whose centroids fell within the selected buffer. Due to the lack of data on employment at the block or block-group level census data, employment density was not included in the study.

Demographics

The socio-demographic characteristics included controlling for the differences in transit access/egress mode shares (walking, bus, transfer from bus/rail, bicycle, auto) and walking distances to/from stations (from origin to station, or from station to destination) were the median household income, household size and vehicle availability. These data were obtained from the On-Board Transit survey at the level of the individual commuter.

Transit Service Features

Transit service features, namely supply of park-and-ride facilities[4], service frequency[5], feeder bus services[6], and station structures[7] were included in order to control for the impacts of transit operational and design factors on walking levels. Omitting these variables might result in overestimating the effect of population density on ridership and walk-mode shares since density levels are known to be interrelated with transit service levels (Holtzclaw, 1994, Messenger and Ewing, 1996).

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[4] number of station parking spaces
[5] number of inbound trains in am peak hour (7am-9am)
[6] availability and number of feeder buses arriving at station
[7] types of station structure: at-grade, elevated, underground

Measures of Street Connectivity

Both standard planning measures of connectivity and segment-based connectivity measures were used to quantify street connectivity. The aim is to test and compare the potency of each set of variables in explaining the impact of street connectivity on walking to/from station.

Standard Measures of Connectivity describing the average properties of areas

The most prevalent measures of connectivity in the planning literature were computed based on street segments that lie within each buffer. *Total Street Length* was calculated as the total linear footage of road segments captured within each buffer. Since buffers have all the same area, depending on radius, this is equivalent to a measure of street density, namely street length divided by unit area. *Total numbers of road segments* (every street segment and portion of street segment)*, dead ends* (cul-de-sacs), and *'real' intersections* (both 3- and 4-way) that lie within the buffers were computed for station-areas for each range of analysis. These measures are also equivalent to densities, given buffers of comparable areas. Approximate *average distance between intersections* for a particular area was defined as the ratio of the total street length divided by the total number of road segments within that area. This particular variable indirectly measures the mean block face length within the surrounding area of the station.

In addition, a derivative of the "*Pedestrian Environmental Factor*" (PEF), implemented in the planning of transportation systems in Oregon, Kansas, and others, was developed based on sidewalk availability, distance between intersections, and surface roughness. Since data on actual sidewalk structure was unavailable, a surrogate measure

was estimated by using existing data on bus stop attributes obtained from ARC (Atlanta Regional Commission). A detailed method for calculating sidewalk availability is explained further in Chapter 4. Surface roughness was measured using a web-based software "Terrain" (Zonum Solutions) which is based on USGS Seamless Elevation data sets. Elevation values were obtained for a randomly selected 100 points within a 1mile x 1mile square buffer zone around each station. A surface roughness value (mt) was calculated for each station based on these elevation values using the following equation:

$$z_r = \sqrt{\frac{\sum_{i=1}^{n}(z_i - z_{mean})^2}{n}} \qquad (2)$$

where z_r is the surface roughness, z_i is the elevation for point i, z_{mean} is the average elevation for all points within the buffer, n is the number of points (n=100 in this study). Following the method used in the LUTRAQ study, each station-area was scored on a 3 point scale for each of the three measures described. Values for each set of measure for all stations were ranked from low to high, and were divided into three groups. Each group was then given a value between 1 and 3, 1 for lowest and 3 for highest. In the end, a composite score (3 to 9) was developed for each station.

Above mentioned standard (and interrelated) measures of street connectivity describe the average properties of street systems. They have been used very successfully to describe the difference between areas, for example, between downtown areas which tend to have small blocks and almost no dead ends and suburban areas that tend to have large blocks and many dead ends. The measures, however, cannot be used to differentiate

one road segment from another, inside an area. Thus, they fall short in capturing variations in the internal spatial structure of urban areas at relevant scales. Structural properties cannot be expressed by measures of average properties, not even by common measures of dispersion. Spatial structures pertain to how proximate road segments with different characteristics are put together to create a network with systematic rather than statistically random properties of internal differentiation. For example, wider streets are expected to lead to more destinations, at greater ranges of distance, than narrower streets. Streets offering more extensive linear vistas are expected to continue beyond their apparent termination; this does not apply to short meandering streets that, at least in Atlanta, have a high probability of coming to a dead-end.

Efforts to capture the typological differences between areas in a way that implicitly addresses internal structure have tended to rely on intuitive typological distinctions to discriminate between rectilinear and curvilinear layouts (Crane and Crepeau, 1998, Ewing and Cervero, 2001, Southworth and Owens, 1993); traditional, early modern and late modern neighborhoods (Handy, 1996b); or traditional and suburban planned units (Ewing et al., 1994, Rodriguez et al., 2006). Sometimes such studies use simple measures of street networks such as the number of street intersections per unit area, proportion of 4-way intersections, and the ratio of number of intersections to number of cul-de-sacs in order to quantify typological distinctions and make them more rigorous.

Measures of walking catchment areas and route directness in the planning literature

In addition to these measures, prior research has recognized the importance of walking catchment areas and direction changes for travel behavior. Pedestrian route directness (Hess, 1997, Randall and Baetz, 2001) is commonly used to describe the sinuosity of streets. Walking catchment areas describe the street length that lies within walking distance from destinations of interest such as shopping malls or schools (Hess, 1997, Hess et al., 1999). Route directness and walking catchment areas have the power to describe a specific location within an area, rather than the average properties of the area. However, as applied so far, even measures of walking catchment areas and route directness have not been generalized so as to describe street networks as purely relational patterns. They have tended to be applied to particular locations of interest and not to every road segment in a system.

Syntactic descriptions of street systems

Space syntax still represents a rare attempt to develop an empirically tested model of the distribution of pedestrian movement according to the spatial structure of street layouts (Hillier, 1996, Hillier and Hanson, 1984, Peponis and Wineman, 2002) and thus is of particular relevance to this research. Traditionally, space syntax analysis begins by constructing a particular representation of street networks called the "axial map" or the "lines map". This comprises the fewest and longest straight lines that are necessary in order to cover the network. Drawing these lines is dependent on the prior availability of accurate maps (in the UK Ordnance Survey Maps) that show street width (axial lines are not street center lines; rather they are placed diagonally so as to be tangent upon street

boundary vertices and extend as far as possible). Once the lines map is drawn, the pattern of intersection of lines is analyzed in graph-theoretic terms to compute measures equivalent to degree, closeness centrality and betweenness centrality. When the axial map is treated as a graph, axial lines are represented as nodes and intersections as arcs.

Degree simply measures the number of intersections of each line. Closeness centrality measures the shortest paths from each line to all others, where path length is calculated according to the number intervening lines (or graph nodes) rather than metric distance. Betweenness centrality measures the number of shortest paths between possible pairs of other origin and destination lines that go through each line. In space syntax the terms "degree", "closeness centrality", and "betweenness centrality", which are common in network theory (Brandes and Erlebach, 2005, Scott, 1991), are replaced by the terms "connectivity", "integration", and "choice". Integration is not exactly equivalent to closeness centrality. It is a relativized measure that takes into account the empirical fact that as the number of lines increases, closeness centrality values increase at a slower rate. The intent is to have an empirically relativized (not merely a statistically normalized) measure that allows comparisons across systems of different size. This becomes critical when radius analysis is performed as described below. Since axial lines are added to the map in proportion to the sinuosity of the system, the syntactic measure of integration is essentially a measure of directional distance: to change from one line to another is to change direction. Integration, therefore, can be thought of as a measure of directional accessibility.

In space syntax, integration and choice are computed to different ranges. Sometimes the whole system represented is taken into account in the calculation. At other

times, analysis is constrained by specifying how many lines away from each line are taken into account in the calculation. Thus, for example, integration radius 3 means that closeness centrality is computed by considering each line as a root and allowing up to two additional lines to be taken into account in all possible directions. When small radii such as 3 or 5 are used in order to constrain the analysis, the results are taken to describe the "local structure" of areas. When the radius is not constrained, or when it is very large, the results are taken to describe the "global structure" of an area. Areas are then also described according to the relationship between "local" and "global" values. The relationship is taken to describe the "interface" between local and global properties. For example, some streets contribute critically to the connectivity of both the surrounding neighborhood and the larger urban context; other streets contribute more to the long distance connections and less to the connectivity of the surrounding neighborhood; finally, some streets contribute to the connectivity of the neighborhood but have much less power when treated as part of the larger system. In this sense, the properties that are described as "local-global interfaces" are conceptually related to street classifications (arterials, distributors and local for example). There is a caveat: in space syntax the criterion used is purely the structure of the network of connections while street classifications typically take into account the dimensions associated with street sections as well as other provisions that affect traffic, ranging from the nature of crossings and frequency of intersections to the availability of sidewalks.

The key finding presented in the space syntax literature regarding pedestrian movement is that the distribution of pedestrians over an area is a function of integration, usually of integration radius 3. This has been confirmed in a number of studies in London

(Hillier et al., 1987, Hillier et al., 1993), Greece (Peponis et al., 1989), Atlanta (Peponis et al., 1997) and other places (Baran et al., 2008, Eisenberg, 2005, Raford and Ragland, 2004). A number of inferences have been drawn from this finding. First, it is suggested that the finding reflects a cognitive relationship between pedestrian behavior and the structure of the street network (Hillier and Iida, 2005). Second, it is suggested that it impacts the spatial economy of cities. Streets that draw more pedestrians by virtue of their syntactic position in the network also attract lnad-uses, such as retail, which take advantage of pedestrians, giving rise to a "multiplier effect", whereby the number of pedestrians increases beyond what one would expect based on pure configuration, as a result of the added attraction exercised by land-use. This condition seems to prevail in many traditional urban environments, but is of course not universal. It is not typical in American cities such as Atlanta (Peponis et al., 1997), and it is not typical in urban areas in London where modernist and post-modernist principles of housing estate design have replaced traditional street environments by large urban blocks with intricate internal structures of passages, or by large urban blocks with free standing slab-buildings surrounded by open spaces.

The fundamental results published in the literature regarding the association between syntactic spatial variables and pedestrian movement (or in some cases vehicular movement also) have depended on labor-intensive field counts of pedestrian rates. Gate counts are taken when the observer remains stationary and counts the number of people crossing a notional line transverse to the street center line; walking counts are taken when the observer walks along a pre-specified path counting the number of people he/she crosses along each axial line segment that is part of the path. There are few published

studies that rely on larger bodies of data, direct or indirect, such as the body of data on walking to transit stations that is analyzed in this thesis.

In more recent years syntactic analysis has been refined in several ways. One major path of refinement has been to break axial lines into shorter segments, usually equivalent to road segments spanning between successive street intersections. The impetus for this change has been the desire to account for pronounced differences in pedestrian counts along different spots on the same axial line. The other major path of refinement has been the desire to not count all "direction changes" as equivalent. In fractional depth analysis, for example (Dalton, 2001), a 90 degree intersection is taken as a "full direction change" and more obtuse angles are taken to represent factions of a full direction change. The impetus for this change has been the desire to capture the quasi-continuity of lines meeting at very wide angles to form the spine of traditional urban environments, or the quasi-continuity of sinuous streets in cities around the world (Figueiredo and Amorim, 2005).

At the Georgia Institute of Technology, new syntactic measures were invented not only to respond to recent trends in syntactic analysis, as described in the preceding paragraph, but also to enable the direct application of syntactic analysis to GIS-based street center line maps, without constructing new representations such as the axial map. These measures, originally proposed by Peponis, Bafna and Zhang (2008), are introduced in the following section and are used in this thesis. Early work (Ozbil and Peponis, 2007) has shown that the new measures, even though they are conceptually simpler, produce as powerful correlations (and sometimes more powerful) with densities of pedestrian movement as the old measures, at least in a sample of areas in Atlanta.

Syntactic measures and standard measures of street networks

The thrust of space syntax methods of analysis is upon the description of the internal spatial structure of areas. The aim is to understand what are the elementary generative principles that can account for the observed patterns of cultural differentiation between urban patterns: for example cities in Britain have a core of most integrated lines that traverse their whole surface creating a "deformed wheel" while Islamic cities tend to have linear cores with branches, such that large parts of the surface (the residential parts) are not traversed by integrated lines (Karimi, 1997). By contrast, as shown above, the traditional measures used to describe street networks are aimed at capturing intuitive typological differences (for example between traditional grids and suburban enclaves), or at quantifying specific functional relationships (for example walking distance or route directness to schools). Thus, at first glance, one is dealing with a difference between pragmatically derived measures (planning literature) versus theoretically motivated measures (space syntax).

Leaving aside the conceptual background, however, the main technical difference can be stated as follows: space syntax is a configurational theory of space in that it seeks to describe each spatial pattern, including a street network, from the point of view of each of its constituent elements –in the case of a street network, each axial line or road segment–; planning measures describe either the average properties of areas, or the way in which specific locations of functional interest feature with the network. As a consequence, and as was explained above, planning measures cannot be typically used to describe the internal spatial structure of an area.

These differences, however, become increasingly shadowy and irrelevant. With the new GIS segment-based measures that are introduced below, it becomes possible to capture the properties that are typically of interest in space syntax, while at the same time being able to express the properties that have typically been measured in the planning literature. Rather than ask "whether one should use space syntax" or "use standard measures", it is easier to ask "which measures of connectivity yield the best insights and empirical findings?" This is the spirit in which measures are used in this thesis.

Segment-based Measures of Connectivity

Segment-based connectivity measures applied in this research (Peponis et al., 2008) offer a systematic framework through which to evaluate the urban fabric in terms of its potentiality (density of streets) and structure (directional bias based on configuration). The analysis is based on standard segment-based representations of street networks according to street center-lines. The unit of analysis is the *road segment*. Road segments extend between choice nodes, or street intersections at which movement can proceed in two or more alternative directions. Road segments may contain one or more line segments. A line segment is the basic unit of the map drawn and is always defined as a single straight line. Thus, the analysis treats the unit of analysis (the road segment, for which the individual values are computed) and the unit of computation (the line segment which provides the base metric for values) as different entities. Figure 3 illustrates the new unit of analysis by clarifying the difference between road segments and line segments.
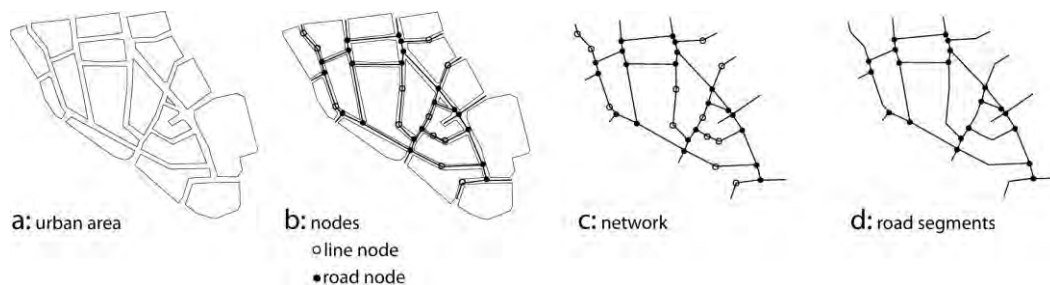
Figure 3. Definition of line segments and road segments. Source: (Peponis et al., 2008)

Potentiality, defined as the availability of accessible streets and destinations offered by the urban fabric, is germane to pedestrian travel. Destinations are certainly an aspect of land-use, but their number is generally proportional to the street length (and therefore the potential street frontage) accessible within a walking distance. *Metric reach* is a measure of the total street length accessible within a specific walking distance from the centre of each street segment in an urban network. In essence, metric reach is another way of expressing the density of streets per unit area and the density of intersections per unit area (Peponis et al., 2007) with the advantage that the value associated with proximate road segments can differ according to their exact location within the street network.

In this study, *directional reach* is a measure of the total street length accessible within a specific number of direction changes from the centre of each street segment in an urban network. While metric reach extends uniformly along the streets surrounding a given road segment, directional reach may extend much less uniformly, because it is sensitive to the shape and alignment of streets, not merely to their density. The connectivity measures used in this paper are inherently parametric, in that one can vary what rotation angle counts as a direction change or what walking threshold is used to

measure the catchment area associated with each individual road segment. Figure 4 illustrates the two measures. The inclusion of directional reach in the analysis is a direct response to the research findings suggesting that the distribution of pedestrian movement may have cognitive dimensions associated with it. Metric reach and directional reach function as measures of street connectivity that can discriminate between proximate street segments, capturing the spatial structure of an area.
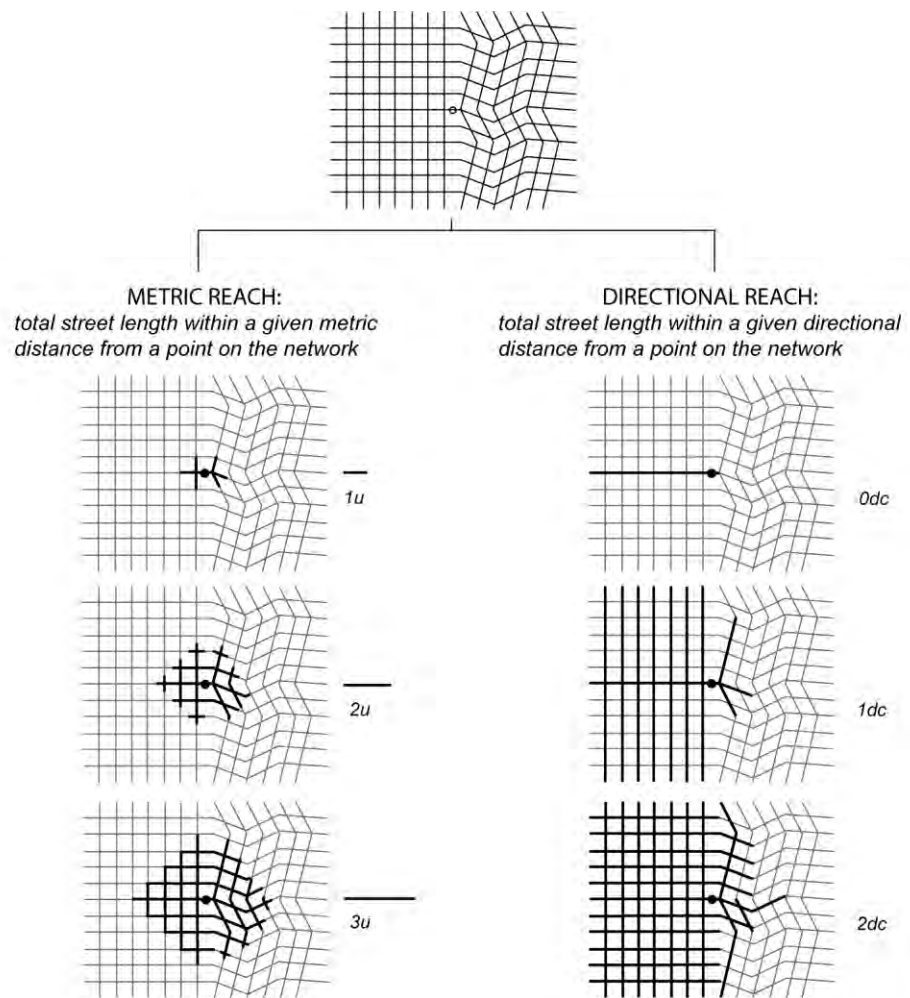
Figure 4. Diagrammatic definition of segment-based connectivity measures.

Source: Peponis et al. 2008.

While the average metric reach of an area is correlated with the number of intersections and total street length by unit area, it is not equivalent to any of the standard measures of connectivity applied in the planning literature. Differences between the average metric reach values of theoretical urban grids having equal street length, number of intersections, and number of blocks are shown in Figure 5.

same street length
higher mean   lower mean
metric Reach   metric Reach

same street length and same number of intersections
higher mean   lower mean
metric Reach   metric Reach

same number of blocks and same
number of intersections
higher mean   lower mean
metric Reach   metric Reach

metric threshold for calculation of Reach ⎯⎯⎯⎯

source: Peponis et. al 2008
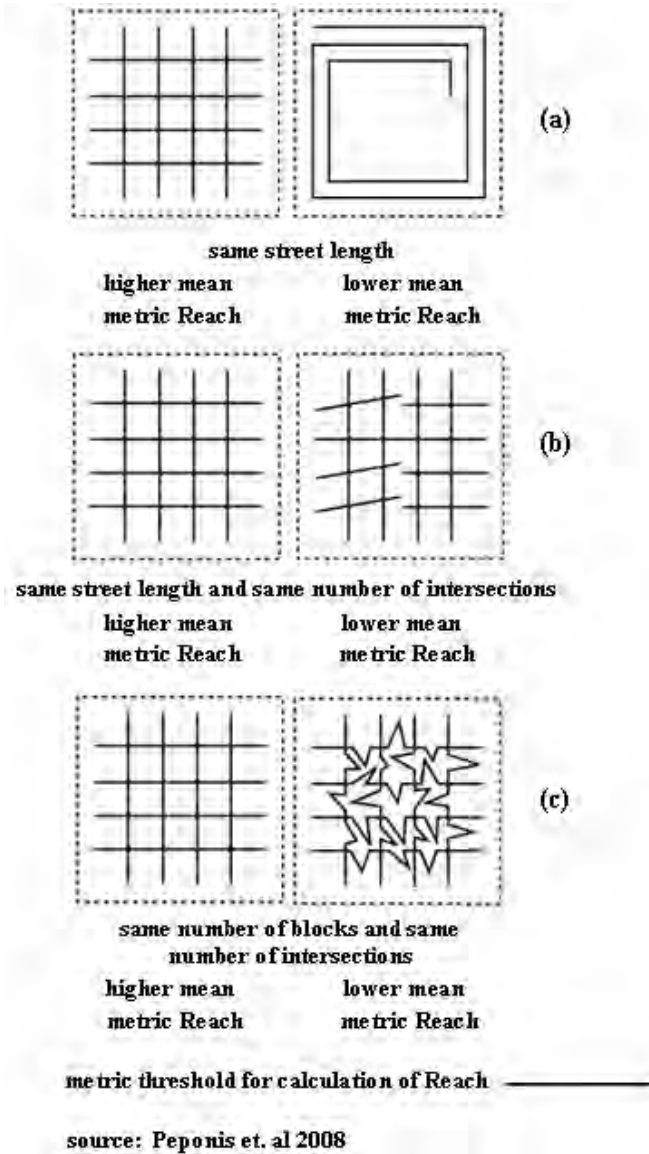
Figure 5. Comparisons of average Reach values between the pairs of theoretical urban grids with the same standard network measures

In this thesis metric and directional reach were computed for the 10-county Atlanta area using a GIS-based software, "Spatialist_Lines", developed by Zhang at Georgia Tech. The software was developed in order to allow parametric estimates of all variables. Parameters include: 1) the distance threshold used to calculate metric reach; 2) the number of turns used to calculate directional reach; 3) the threshold angle used to determine what counts as a direction change; 4) and the size of the line segment which is taken as a threshold below which the turns associate with successive line segments are added rather than independently assessed (Peponis et al., 2008). In this thesis, 10° was used as a threshold angle. The aim was to make the analysis more sensitive to the distinction between linear and curvilinear systems. The choice, however, is also consistent with literature suggesting that turns that vary minimally (between 10° and 15°) from an axis orthogonal to the direction of travel are the least disorienting (Montello, 1991, Sadalla and Montello, 1989).

Other work at Georgia Tech has suggested that 30° is a better threshold, in the sense that it reveals continuities that correspond to named streets and also in the sense that it helps identify stronger associations between street connectivity and non-residential land-uses, as well as stronger associations between street connectivity and vehicular traffic (Scoppa et al., 2009). Based on such work, developed in parallel by other researchers at Georgia Tech, a future fresh analysis of the data presented in this thesis using a 30° angle threshold is more likely to reinforce findings than to challenge them.

In this research metric reach was computed for 1, 0.5 and 0.25 mile walking distance thresholds. Directional reach was computed for two direction changes subject to a 10° angle threshold. Computing directional reach for two direction changes provides an

estimate of how well a street segment is embedded in its surroundings from the point of view of directional distance. The average directional distance of the street segments within metric reach was also computed. Thus, each street segment is associated with five primary connectivity measures: metric reach for 1 mile, 0.5 mile and 0.25 mile walking ranges; directional reach for 2 direction changes; and directional distances associated with metric reach. A *composite connectivity measure* (metric reach divided by the corresponding directional distance, subject to a 10° angle threshold) was also added to calculate the ratio of metric reach to the average directional distance associated with it. This composite variable takes higher values as street density increases and as access to streets becomes more direct. In other words, road segments from which more street length is accessible within the walking radius, taking fewer turns to get everywhere, draw greater volumes of pedestrians. In the course of the analysis, when analyzing station-areas at 1, 0.5, and 0.25 mile radii, the corresponding values of metric reach computed for 1 mile, 0.5 mile, and 0.25 mile ranges were averaged and assigned respectively for each related buffer. Similarly, 2-directional reach (10°) was also averaged by buffers. These values constitute the average segment-based connectivity measures associated with the surrounding areas of stations. .Figures 6 and 7 illustrate a visual representation of the study design based on the characterizations of surrounding areas in terms of street connectivity and land-use in the case of Ashby and Indian Creek Stations.

In addition, a relative connectivity measure was developed to determine the effect accruing from the specific location of the station within the buffer (i.e. whether the station is situated on a relatively intensified urban grid with regard to its surroundings). The relative measure of connectivity is defined as:

$$\frac{value - average\ value}{std.\ dev.\ of\ value} \quad\quad (3)$$

In computing the values of road segments on which individual stations are located, multiple exits associated with each transit node were assigned to their nearest segments, and the values of these segments were then averaged to arrive at a single value associated with each station. For example, for Midtown Station, individual road segment values for 10th Street and Peachtree Pl. were averaged.

Since the analysis is based on GIS-based representation of street networks, it allows for the analysis of large commonly accessible data bases, including the street networks of US metropolitan areas. Accordingly the new measures express the density of street connectivity directly. Here the term density refers to the amount of street which is available within a given metric range. The values can be assigned to individual road segments so that spatial urban structures can be differentiated by streets, block faces or parts of block faces. Thus, they offer a systematic discrimination of urban conditions throughout the network, describing both the internal spatial structure of urban areas and their average properties.

The underlying hypotheses to be tested are that the average properties of street networks within the surrounding areas of stations and the location of the station relative to the internal spatial structure of these areas would affect both the proportion of riders walking to/from the station and the distance walked. The exact re-formulation of these hypotheses in terms of the measures used is offered in Chapter 4.
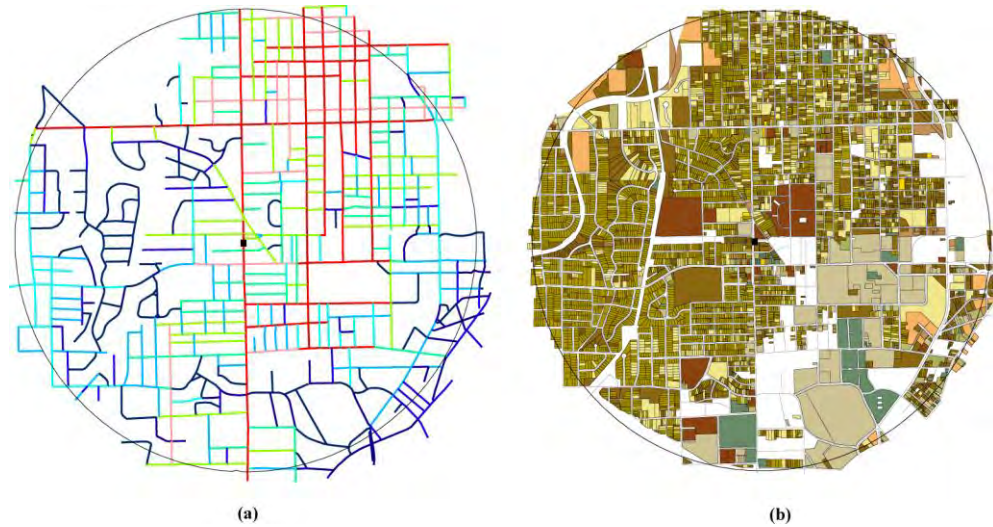
Figure 6. (a) Street network layout, and (b) parcel-based land-use compositions captured within 1 mile radius of Ashby station. Streets are color-coded according to 2-directional Reach (10°) with regard to the entire network. Parcels are color-coded with regard to land-use type.

Figure 7. (a) Street network layout, and (b) parcel-based land-use compositions captured within 1 mile radius of Indian Creek station. Streets are color-coded according to 2-directional Reach (10°) with regard to the entire network. Parcels are color-coded with regard to land-use type.

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Transcription of Travel Data

Since this study focuses on MARTA rail stations, it was necessary to parse the travel data provided by the On-Board Transit Survey in order to extract individual MARTA rail trips. To construct the data-set, first, weekend and weekday trips were merged into a single database. The data file comprised individual records that were identified by a unique identifier. Each identification number was linked with the respondent's information regarding trip origin, boarding ("bus/train-on") location, alighting ("bus/train-off") location, and final destination coordinates as well as household size, income, and vehicle availability. These records were then sorted according to their boarding and alighting coordinates, which were matched with the rail stops' X- and Y-coordinates in order to extract boarding and alighting records. The selection was converted into a separate database that contained both boarding and alighting records that were sorted according to individual rail stops. This newly created file was used to extract walk trips. Based on access and egress modes, riders who have walked at either end of their trips were selected. For access walk trips, if either the origin or boarding location was non-reported, these records were discarded from the walk trip data set. Consistently, for egress walk trips, missing either the destination or alighting coordinates resulted in the elimination of those records from the file. The resultant files were used as actual "walking trips". The airline distances, *d*, were computed for all riders between their origin/destination locations and boarding/alighting stations via the "Great Circle Distance Formula"(Shekar and Xiong, 2008), using decimal degrees, as stated in equation 4 below. Network distance, defined as the actual path traveled along the network, was calculated for all walk trips using ArcView Network Analyst. Since the exact route traveled by

respondents was not reported, walking distances were calculated based on the shortest route possible on the street network.

$$d = 3963.0 \cdot \arccos\left[\sin\left(\frac{lat_1}{180/\pi}\right) \cdot \sin\left(\frac{lat_2}{180/\pi}\right) + \cos\left(\frac{lat_1}{180/\pi}\right) \cdot \cos\left(\frac{lat_2}{180/\pi}\right) \cdot \cos\left(\frac{lon_2 - lon_1}{180/\pi}\right)\right] \qquad (4)$$

where values for latitudes and longitudes are in radians.

Discrepancies in the Data

Total of 4,624 respondents reported walking to/from the station. However, distribution of all walking distances (see figure 8a) demonstrates errors in walk-modes reported. The mean reported walking distance was 3 miles, with maximum distance being over 40 miles. When the distribution of reported walking distances are analyzed for individual stations, it is revealed that stations without feeder bus services, such as Dome, Garnett, and GSU, include the least over-estimated walking distances reported. In fact, the minimum, maximum, average, and standard deviation values of distances claimed walking are within plausible ranges. Table 3 provides statistical information on reported walking distances by individual MARTA rail station.

Table 3. Statistical information on reported walking distances by individual rail station.

Station	n	mean(mi)	min(mi)	max(mi)	std.dev.(mi)
Five Points	3637	2.21	0.01	39.38	4.29
Dome	236	0.56	0.13	1.65	0.45
Vine City	376	1.73	0.06	25.46	3.60
Ashby	486	0.70	0.01	8.34	1.03
Bankhead	1065	5.29	0.11	36.27	6.23
West Lake	528	5.19	0.10	32.09	6.41
HE Holmes	1163	4.72	0.18	42.86	5.31
GSU	429	0.55	0.04	9.05	0.93
King	337	3.31	0.04	26.96	4.67
Inman	301	4.30	0.01	22.49	4.90
Edgewood	191	2.43	0.04	12.76	2.80
East Lake	255	4.15	0.01	25.80	4.78
Decatur	518	3.02	0.00	17.69	3.97
Avondale	866	4.68	0.00	29.99	4.53
Kensington	883	4.52	0.03	34.31	4.87
Indian Creek	702	5.89	0.00	20.76	4.75
Garnett	92	0.62	0.17	1.14	0.24
West End	746	3.23	0.00	22.91	4.25
Oakland	609	3.89	0.11	16.77	3.32
Lakewood	585	5.10	0.22	19.79	3.87
East Point	463	2.97	0.01	26.72	4.44
College	1002	6.36	0.00	34.58	6.51
Peachtree	488	0.91	0.02	33.60	2.52
Civic Center	114	0.62	0.02	1.65	0.45
North Ave.	541	3.38	0.01	24.29	4.88
Midtown	197	2.28	0.05	20.16	3.45
Arts Center	786	2.74	0.00	25.14	4.41
Lindbergh	1081	4.08	0.00	20.99	4.37
Lenox	406	1.44	0.05	19.86	3.20
Brookhaven	397	3.84	0.01	20.01	4.11
Chamblee	400	5.38	0.08	20.15	4.95
Doraville	560	6.26	0.05	25.79	5.53
Buckhead	146	1.50	0.01	18.54	2.97
Medical	198	3.37	0.00	22.59	6.06
Dunwoody	457	3.24	0.02	25.89	4.93
S. Springs	239	3.68	0.06	30.13	6.45
N. Springs	775	7.92	0.09	21.93	6.14

Based on this finding, it can be speculated that the majority of respondents who over-estimated walking distances have in reality walked to a bus stop, in fact choosing bus as their access mode to rail station but reporting walking. In order to account for this mis-reporting, the distribution of reported walking distances was analyzed and 2 miles

was set as a distance threshold to discount all walking that was reportedly over a greater distance. This was based on the assumption that, in reality, walking more than 2 miles would be infeasible. The distribution illustrated in Figure 8b suggests a gamma function would be a good fit to explain the distribution. In transportation-related research gamma distributions are commonly used to mathematically describe distributions which cannot be characterized by either a normal distribution or a negative exponential distribution (Taylor and Young, 1988, Johnson et al., 1994). Indeed, the gamma function fitted to the walking-distance distribution was significant at a 99% level of confidence. Figure 9 shows the probability density function and cumulative distribution function calculated for the fitted gamma distribution.

(a) distribution of distance claimed walking

N=4,624 trips
maximum = 42.86 miles
mean = 3.2 miles
median = 0.93 miles
75th pctile = 4.39 miles

(b) gamma function fitted to the distribution of walking distance, with walking threshold set to 2 miles

N=2,756 trips
maximum = 2.0 miles
mean = 0.53 miles
median = 0.38 miles
75th pctile = 0.70 miles

$\alpha = 1.457$
$\sigma = 0.366$
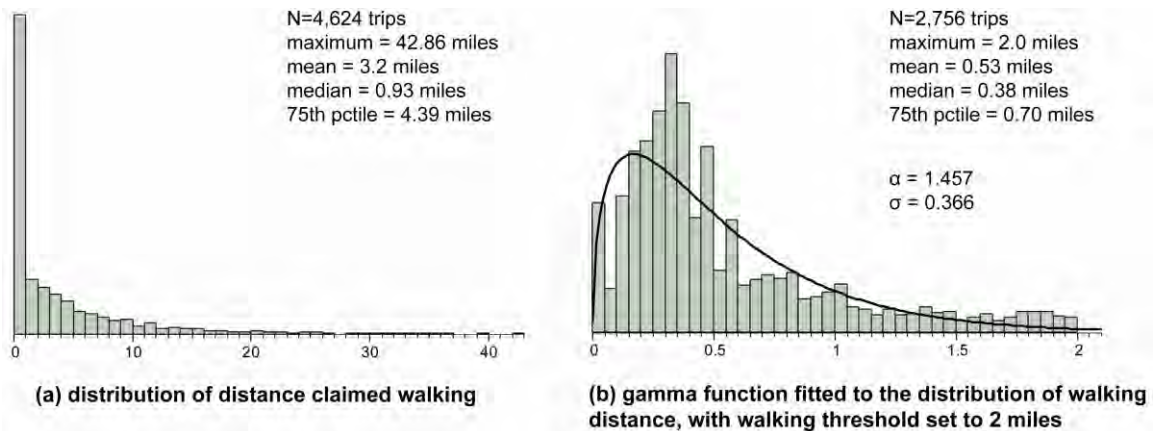
Figure 8. Distribution of walking distances for all claimed walking trips, and for trips under 2 miles.

a. probability density function   b. cumulative distribution function
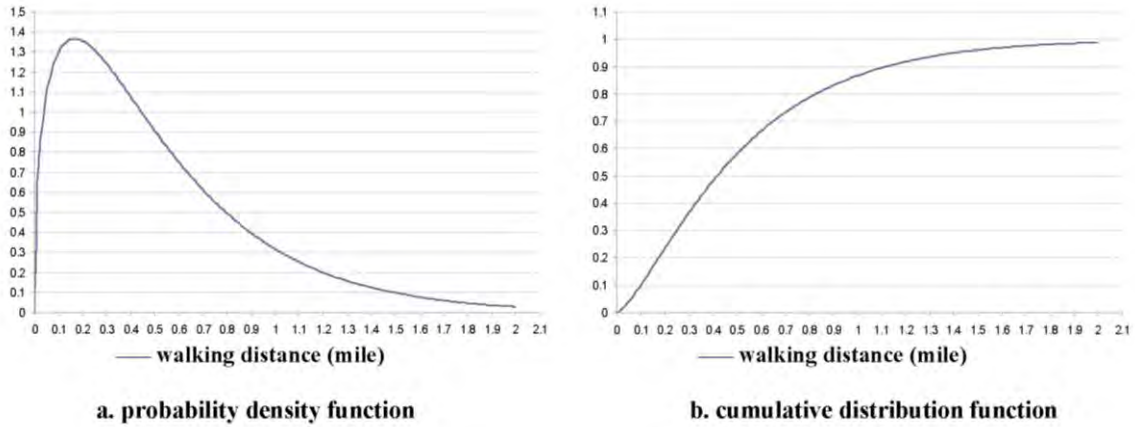
Figure 9. Probability density function and cumulative density function calculated for the gamma distribution.

The distribution of walking distances was elaborated further in an attempt to determine the cut off point for analysis. Bivariate correlations were run between the various moments of walking distances between 1 and 2 miles for 0.1 mile increments, and metric reach at 0.5 and 1 mile buffer ranges. The purpose of these models was to investigate the effect of connectivity variables in explaining the distribution of walking distances. Figure 10 shows that for both ranges the best results are obtained when walking threshold is set to 1.6 miles. The coefficient of determination (r^2) falls steadily after 1.6 miles, which indicates that the strength of the model in estimating walking distances diminishes after this threshold. The cumulative distribution function (Figure 9b) shows that 1.6 miles as the cut off point captures 97% of commuters claimed walking less than 2 miles. Based on these indications, 1.6 miles was regarded as the walking distance threshold in this study, and hence, riders claimed walking over 1.6 miles (2,000 respondents) were discarded from the walking dataset.

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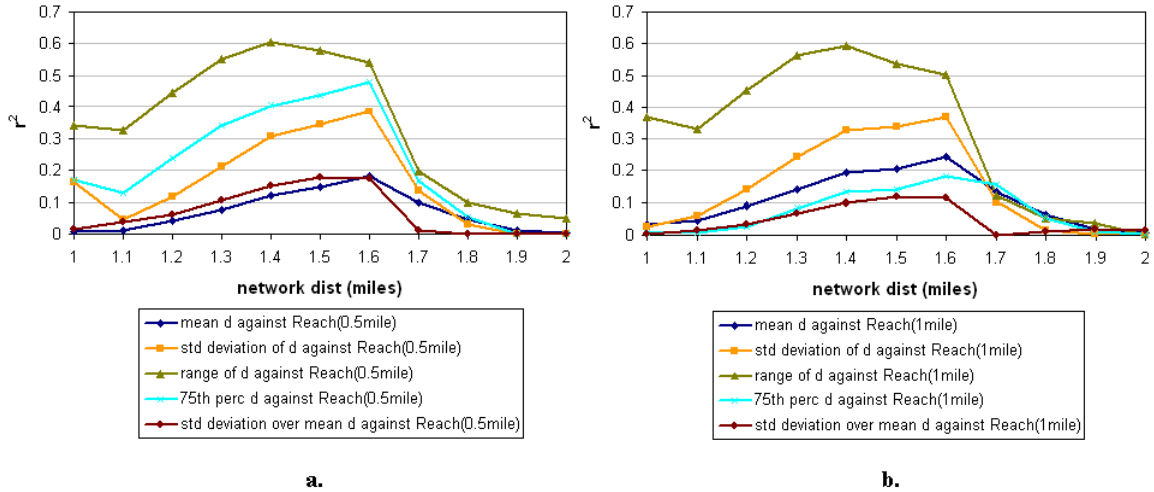
Figure 10. Results of correlations between various moments of walking distances (*d*) for each 0.1 mile increment between 1 and 2 miles and (a) metric reach for 0.5 mile, and (b) metric reach for 1 mile.

Within the database Airport station requires special consideration. The origin and destination locations of 990 people, who claimed walking to/from this station, were geocoded to the same location which pointed to the parking lot of the airport. Considering the fact that there are no destinations (residential and non-residential land-uses) available within 0.25 and 0.5 mile walking ranges around the station, it was assumed that respondents claimed walking apparently walked between the rail stop and the terminal building, which accounted for the walking mode shares at this station. Therefore, the Airport station was excluded from the analysis. Since the refined ridership dataset still includes 13,751 respondents and 37 stations, it is assumed that none of the above-mentioned discrepancies have jeopardized the validity of the results.

CHAPTER 4

SPATIAL TYPOLOGIES OF MARTA RAIL STATIONS ACCORDING TO GIS-BASED ANALYSES

This chapter has two main purposes. The first aim is to define a number of variables with which to characterize the urban form around MARTA rail stations. For this, two criteria are used: first, distance from center, a crude way to differentiate old, dense urban neighborhoods, early suburban areas, and sprawling suburban centers; second, a cluster analysis taking into account population density, land-use mix, and street density, at each of two scales: 1 mile scale (to measure surrounding area characteristics) and 0.25 mile scale (to measure immediate station-area characteristics). The second aim is to arrive at a typology of stations that can be used to empirically study whether the variations within the urban conditions around stations affect walk-mode shares and walking distances to/from stations.

Atlanta was chosen as the case context to empirically study walking behavior. This was partly due to the availability of fairly rich data on land-use characteristics at the parcel level as well as travel data disaggregated according to different modes. Additionally, the fact that Atlanta is not a pedestrian friendly city provides a challenging setting to put the underlying hypotheses of this study regarding street connectivity to a more rigorous test.

With half the population of Washington D.C. and San Francisco, Metropolitan Atlanta is extended over 50 percent more urbanized land (approximately about 1200 square miles), and per capita driving on average is 35 miles daily, which is two and one-

half times more than that of the New York region (Dunphy and Fisher, 1996). The results of an earlier study on urban sprawl and health related issues, where 83 metropolitan areas in the United States were rated in terms of residential density, land-use mix, degree of centering, and street accessibility, have demonstrated that Atlanta sprawls badly in all dimensions (Ewing et al., 2003). FHWA Highway Statistics 2008 (FHWA, 2008) reveals Atlanta's auto-oriented travel behavior. According to urbanized area data statistics Atlanta ranked 9th in terms of daily vehicle miles traveled per capita, which is matched by the annual average daily traffic on freeways (7th in rank). Consistent with its high auto-usage, Atlanta has one of the most extensive freeway infrastructure in the country (measured as the total freeway lane miles), placing the city in the top ten. However; despite its high levels of daily driving, Atlanta also has high levels of transit use. Among densely populated urbanized areas in the country, Atlanta ranked 13th in transit use with a 5.8% rate (Hu and Reuscher, 2005). For comparison purposes, New York's number 1 ranking (24%) was followed by Chicago (11.6%).

This brief overview offers some insights into the travel patterns in Atlanta. As the statistics indicate, Atlanta represents an atypical example; it is a low density city with high levels of transit patronage as well as high levels of highway travel. Based on the research findings reviewed in Chapter 2, it would be expected that transit usage would be low, given low overall densities. One explanation might be that the average values conceal very strong internal differentiation in Atlanta, which in turn may make it an interesting case to study. Another explanation might be that the high vehicle miles per capita are supported by the extensive freeway system, whereas high ridership levels are associated with low-income households with low auto-ownership levels.

The Metropolitan Atlanta Rapid Transit Authority (MARTA) was formed in 1965, and in 1979 the first line started operating between Avondale and Georgia State Stations. It also marked the approved referendum of Fulton and DeKalb Counties to develop an integrated bus and rapid rail system. Atlanta is different in this sense from other rail cities that a single operator manages both the rail and bus systems. The expansion continued through the 90s when MARTA extended crossed beyond the I-285 perimeter with the link between Kensington and Indian Creek Station. By the end of 90s, the North Line spanned for the first time all three jurisdictions, City of Atlanta, Fulton County and DeKalb County. At the beginning of the 21st century, MARTA turned to transit oriented development as an attempt to relieve peak hour congestion and launched a partnership with Bellsouth to create the Lindbergh Transit Oriented Development.

MARTA rail system is cross-shaped with the North-South and East-West Lines intersecting at Five Points Stations at the Central Business District (CBD) in Downtown Atlanta. Figure 11 demonstrates the diagrammatic system map and the distribution of rail stops along the service network. Currently there are a total of 38 rail stations: 11 on the North Line; 4 on the Northeast Line; 9 on the East Line; 7 on the South Line; and 6 on the West Line. Around 40% of transit stops are built at-grade while the remainder is equally underground and elevated. The overall system includes 53 miles of rail transit, and a network of 1,500 route miles of feeder and express bus routes. Even through feeder bus services act as the primary source of access to the rail stations, around 30,000 station parking spaces are provided for park-and-riders since many station-areas are located in low-density neighborhoods with high auto-ownership levels.
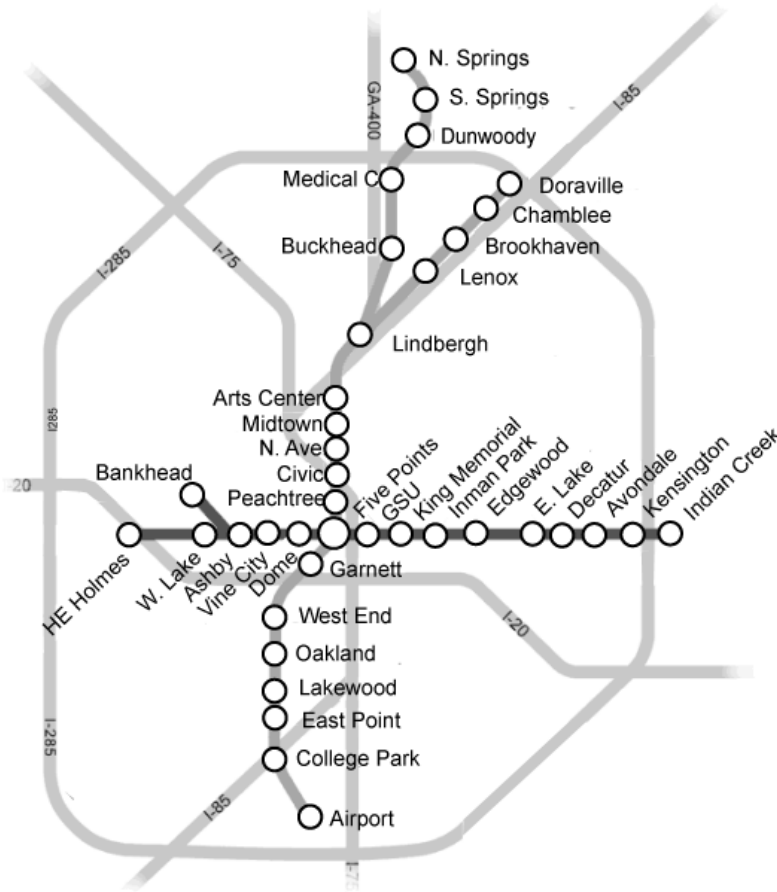
Figure 11. A diagram of MARTA rail system and the distribution of transit stops along the transit service line.

Figure 12 illustrates the geographically accurate representation of MARTA rail system overlaid on the map of Atlanta. As shown, the transit system is bounded within metro Atlanta; only 4 stations, namely Dunwoody, Sandy Springs, North Springs, and Indian Creek, lie beyond I-285.
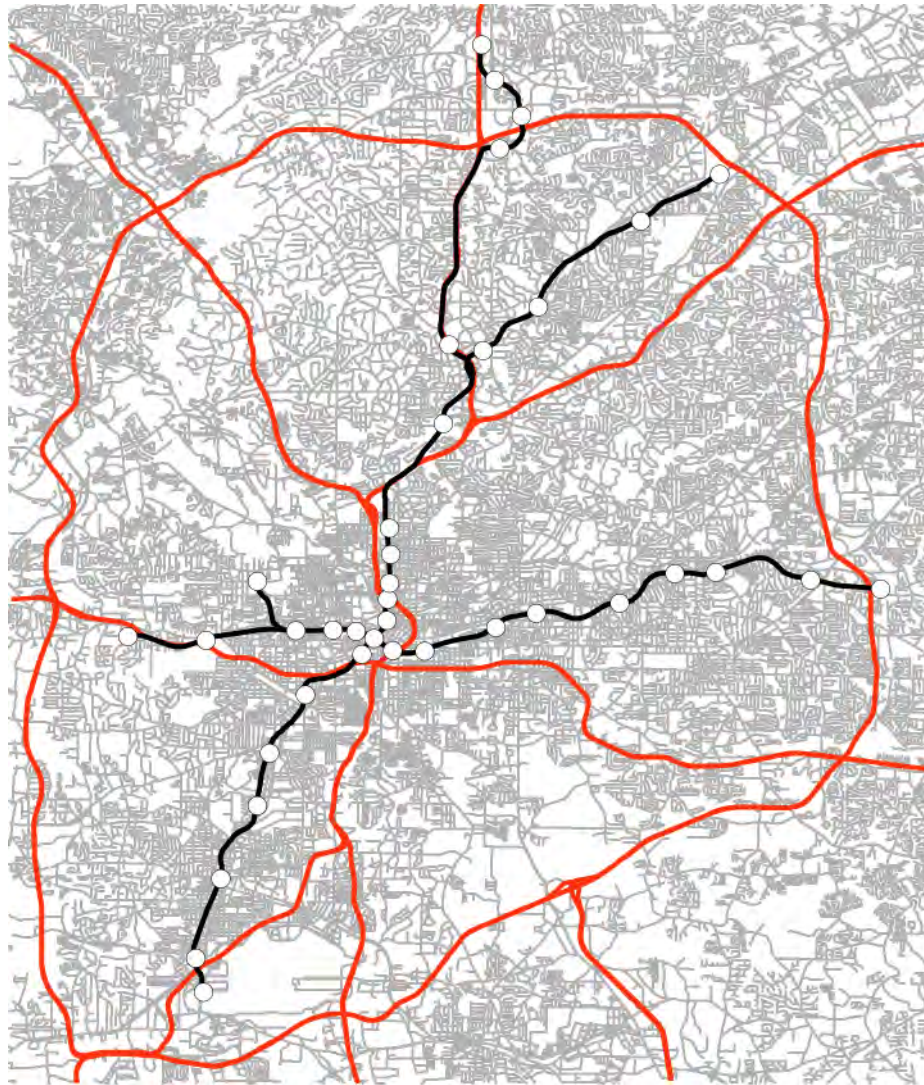
Figure 12. Real geometry of the system overlaid on the map of Atlanta within I-285. The
grey lines represent roads while the red lines denote the freeway system.

Figure 13 illustrates a detailed representation of the geographic location of central
city stations located at the central business district (CBD) in proximity to center (in this
case Five Points station). The surrounding environments of these stations represent the
older and relatively denser areas within the city. As can be seen in the illustration, the

urban form around these centrally located stations can be characterized mainly through high development intensities with fine-meshed urban blocks and denser street networks.
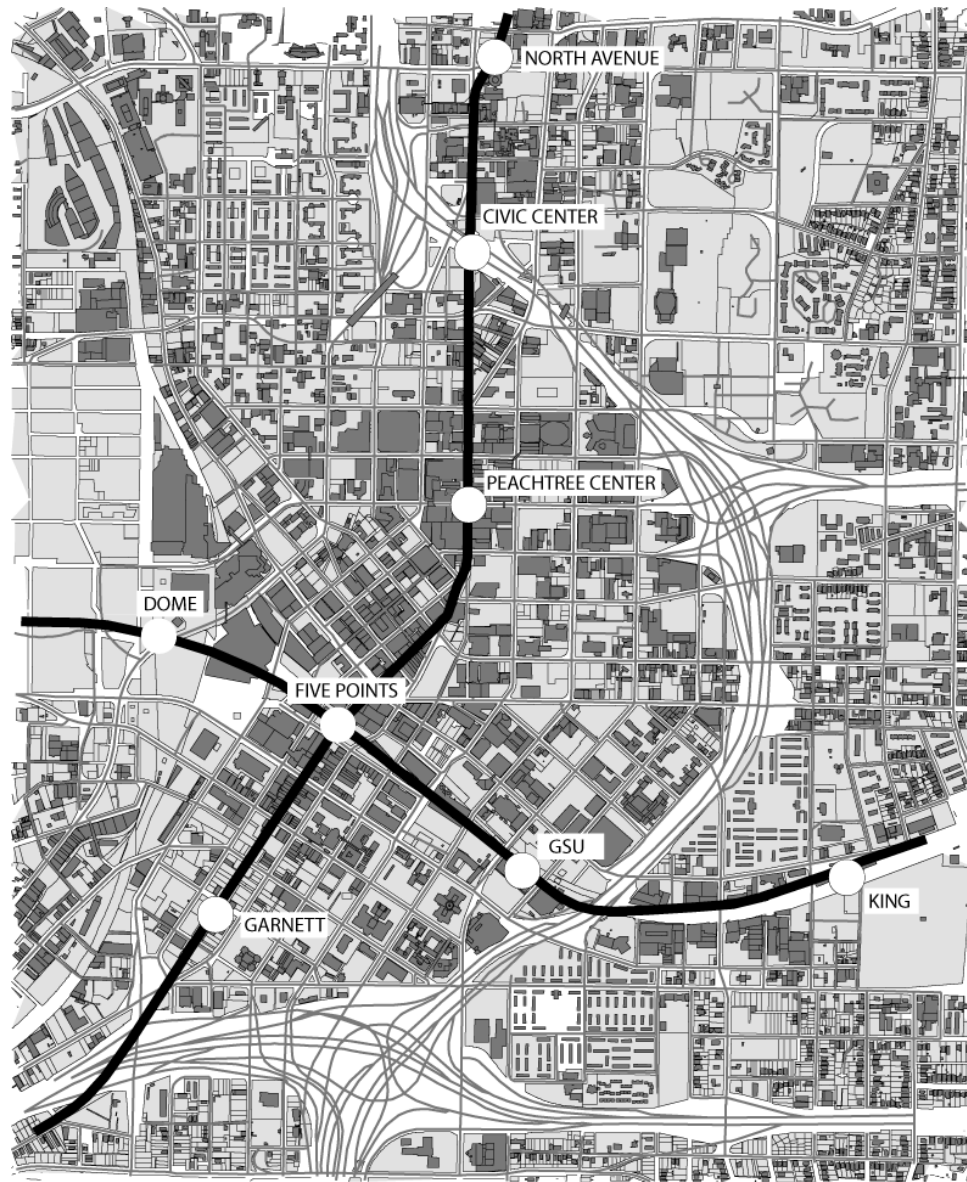
Figure 13. Central city stations shown in context with development densities and street network.

In order to address how station-environments may contribute to culture of walking, it was incumbent to study urban conditions around MARTA rail stations with a view towards drawing typological distinctions regarding the ways in which stations relate to the surrounding street network.

Table 4 describes MARTA rail stations in terms of their transit service features and geographic locations. Distances between the center (Five Points station) and stations are measured using network distance (shortest route along the network), rail distance (rail line miles between stations), and airline distance (crow-fly distance between center and stations). In measuring rail and airline distances, the geocoded locations of rail stations that were obtained from MARTA were used. This shapefile dataset assigned a single point to each transit stop which coincided with a node along the transit service line. In measuring network distance between the stations, the shapefile dataset obtained from Atlanta Regional Commission proved more efficient since it contained geocoded locations of individual station exits. These points were assigned to their corresponding nearest road segments and the network distance between two stations was computed between their nearest exits. Figure 14 shows that the number of station parking spaces increases with higher distance from the center, albeit loosely distributed, while service frequency[8] is clustered around four groups: a first cluster around 42, a second cluster around 35, a third cluster around 21, and a fourth cluster around 18. The graph indicates that service frequency decreases with distance to center but not in a linear way since the trains have to pass through the interior stations due to the geometry of MARTA network.

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[8] Number of inbound trains in am peak hour (7am to 9 am)

Table 4. MARTA rail station transit service levels

MARTA stations		# of parking spaces	service frequency	feeder bus services	station structure	network dist. to five points (miles)	rail dist. to five points (miles)	airline dist. to five points (miles)
	Downtown Hub							
H	Five Points	0	79	Yes	underground	–	–	–
	North Line							
N1	Peachtree Center	0	36	No	underground	0.6	0.5	0.5
N2	Civic Center	0	36	Yes	elevated	1.1	1	1
N3	North Avenue	0	36	Yes	underground	1.9	1.4	1.4
N4	Midtown	0	36	Yes	underground	2.4	2	2
N5	Arts Center	33	36	Yes	underground	2.9	2.5	2.4
N6	Lindbergh Center	2907	36	Yes	at-grade	6.1	5.2	5
N7	Buckhead	0	18	Yes	at-grade	8	7.4	6.7
N8	Medical Center	200	18	Yes	at-grade	13.2	12.1	11.1
N9	Dunwoody	1048	18	Yes	elevated	13.8	13.1	12.4
N10	Sandy Springs	1170	18	Yes	underground	14.7	14.1	12.6
N11	North Springs	2325	18	Yes	elevated	15.4	15	13.7
	South Line							
S1	Garnett	0	36	No	elevated	0.5	0.4	0.4
S2	West End	547	36	Yes	elevated	2.1	1.9	1.8
S3	Oakland	337	36	Yes	at-grade	3.6	3.4	3.2
S4	Lakewood	1134	36	Yes	at-grade	4.8	4.5	4.3
S5	East Point	927	36	Yes	at-grade	6.6	6.4	6
S6	College Park	1971	35	Yes	at-grade	8.6	8.2	7.7
S7	Airport	0	35	Yes	underground	10	9	8.2
	East Line							
E1	Georgia State	0	44	No	elevated	0.8	0.4	0.3
E2	King	0	42	Yes	elevated	1	1.1	0.8
E3	Inman Park	366	42	Yes	at-grade	2.4	2.5	2.1
E4	Edgewood/Candler	679	42	Yes	at-grade	3.2	3.3	2.9
E5	Eastlake	611	21	Yes	at-grade	4.9	5	4.4
E6	Decatur	0	21	Yes	underground	6.3	6.3	5.7
E7	Avondale	823	22	Yes	at-grade	7.1	7.1	6.4
E8	Kensington	1946	22	Yes	at-grade	8.6	9	8
E9	Indian Creek	2350	22	Yes	at-grade	15.1	10.3	9.3
	West Line							
W1	Philips/GWCC/Dome	0	44	No	underground	1	0.4	0.4
W2	Vine City	27	44	Yes	underground	1.2	0.8	0.8
W3	Ashby	161	22	Yes	underground	2	1.5	1.5
W4	West Lake	391	21	Yes	at-grade	4.1	3.2	3.2
W5	H.E. Holmes	1436	21	Yes	elevated	5.7	4.7	4.5
P4	Bankhead	11	22	Yes	elevated	3.6	5.2	2.7
	Northeast Line							
NE7	Lenox	321	18	Yes	at-grade	8.3	7.1	6.8
NE8	Brookhaven	1252	18	Yes	elevated	10	8	8
NE9	Chamblee	1713	18	Yes	elevated	12.6	11	10.4
NE10	Doraville	1070	18	Yes	elevated	15.4	13	12.2
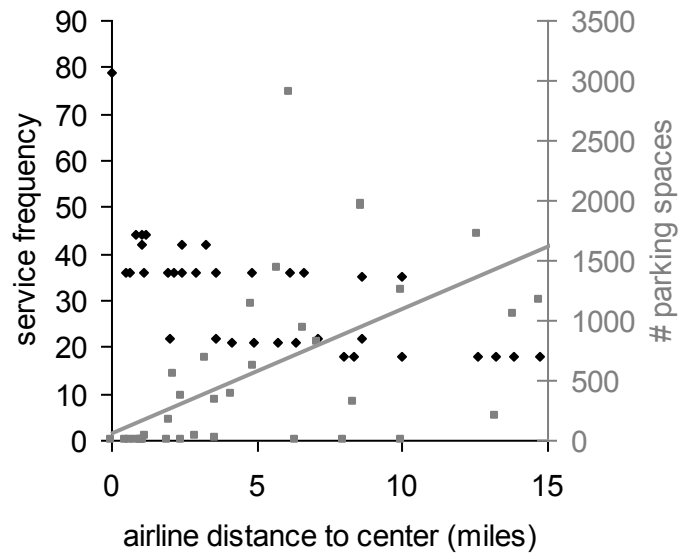
Figure 14. Scatterplot showing the trends of service frequency and number of station

parking spaces by geographic distance from each station to center.

Standard criteria employed to categorize station environments, such as the

classification of stations based on their distance to center, fall short in discriminating

between station-environment characteristics at the local- and meso-scales. Instead, a

typological categorization, which takes into account variations in urban form at differing

scales, is applied using hierarchical clustering method[9]. Figures 15 and 16 show the

results of hierarchical clustering analysis at 1 mile and 0.25 mile buffers respectively.

Results are reported for 1 and 0.25 mile radii in order to demonstrate the differences

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[9] Cluster analysis is a multivariate analysis that assigns objects into subsets (clusters) according to specified criteria so that objects in the same cluster are similar to one another. ROMESBURG, H. 1984. Cluster Analysis for Researchers. *Wadswoth Inc. California*. The aim of this technique is to investigate the association between objects.

between immediate station-area characteristics and station environments at the meso-scale. For the purpose of cluster analysis, the distance between two station environments x and y, D_{xy}, is defined in terms of population density (people in gross acres), mixed-use index (see Equation 1), and metric reach for 1 and 0.25 miles. Ward's minimum variance method, in which the distance between two clusters is defined as the ANOVA sum of squares between the two clusters added up over all the variables, has been applied. Similar results were obtained with average linkage and complete linkage methods. The classification of station-environments at two ranges demonstrates similarities as well as notable differences. At the meso-scale (1 mile range), the clustering of station-areas in the dendogram reveals basic classes of urban patterns. Choosing 1.75 as the cut-off point, four clusters were obtained, as shown in Figure 15.
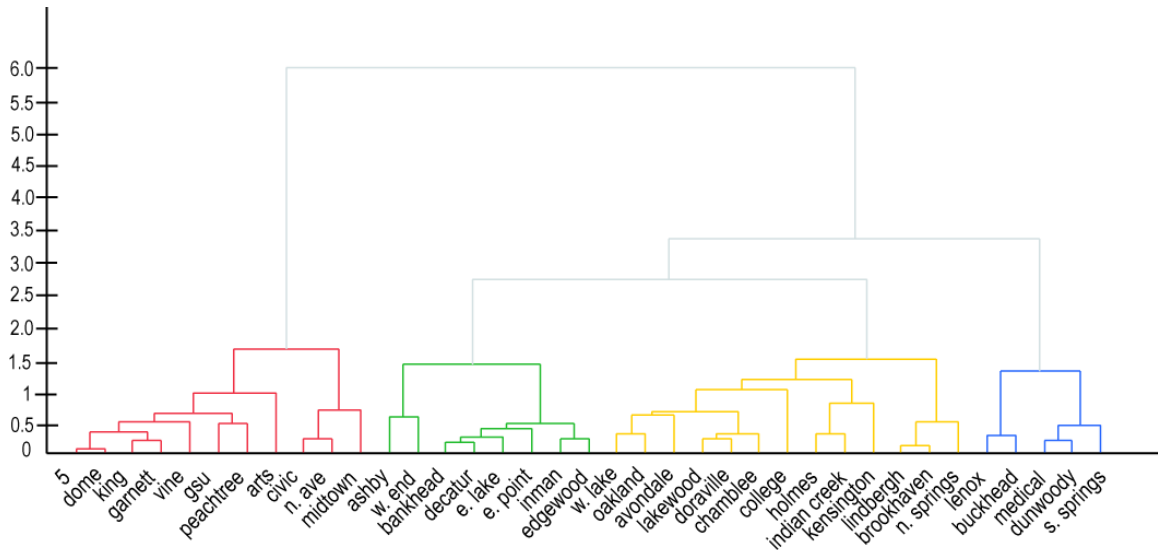
Figure 15. Hierarchical tree (dendogram) based on the 3Ds of urban form: metric reach, population density, and land-use mix index at 1 mile buffer range.
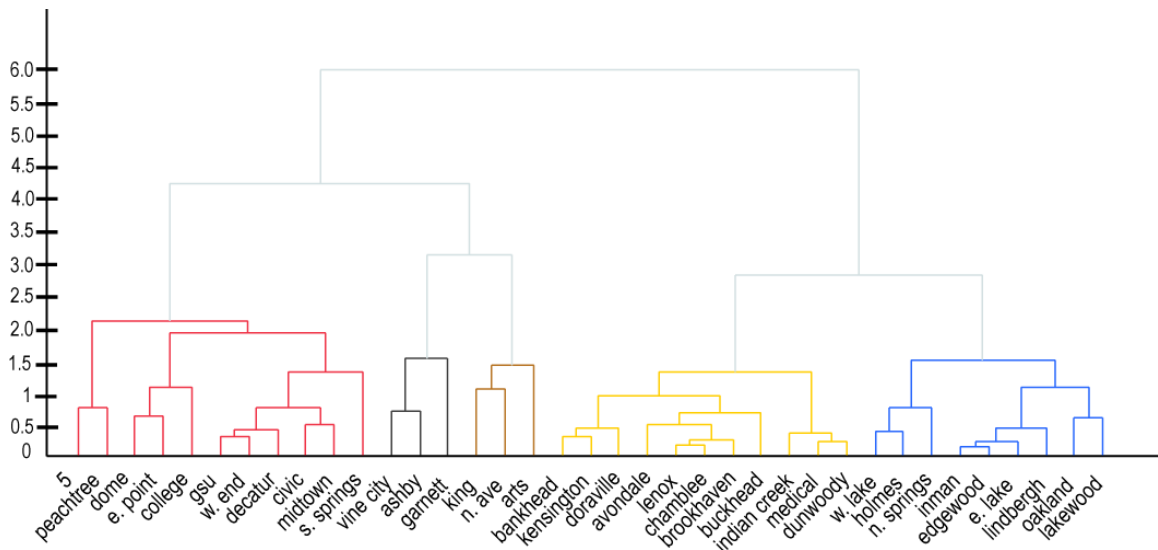
Figure 16. Hierarchical tree (dendogram) based on the 3Ds of urban form: metric reach, population density, and land-use mix index at 0.25 mile buffer range.

A first cluster of CBD stations (in red) from Five Points to Midtown defined by central city stations with high development densities, more grid-like street patterns, and moderate-to-low population densities; a second cluster (in green) from Ashby to Edgewood, representing neighborhood stations of lower mixed-use compositions with high residential building square footage, and relatively dense street networks that include small hubs of high integrators located at the center; a third cluster (in orange) from West Lake to North Springs including in-town suburbs (generally the end stations) with low residential as well as non-residential densities, and sparse street networks with a linear integrator cutting through the area; a last cluster (in blue) from Lenox to Sandy Springs representing emerging business and commercial hubs, once at the edge of developed urban areas, with non-uniform distribution of high development densities and low street connectivity.

The cluster analysis at 0.25 mile range demonstrates some notable differences between the immediate vicinity and larger surroundings of stations, as seen in Figure 16. At the micro-scale, choosing 2.25 as the cut-off point, five clusters were obtained. A first cluster includes local hubs with compact station-area developments of high intensity non-residential uses and street networks; a second cluster, made up of Ashby, Vine City, and Garnett, includes historical mini-downtowns with high population and street network densities; a third cluster, consisting of Arts Center, North Avenue, and GSU, includes central city locations with higher combined population, non-residential land-use, and street density; a fourth cluster includes in-town suburbs with low population densities and connectivity levels; a last cluster capturing commuter stations with high residential densities but low connectivity levels.

Figure 17. Cluster analysis of stations based on population density (persons per gross acre), mixed land-use index, and average metric reach (1 and 0.25 mile) within (a) 1 mile rings and (b) 0.25 mile rings around transit stops.
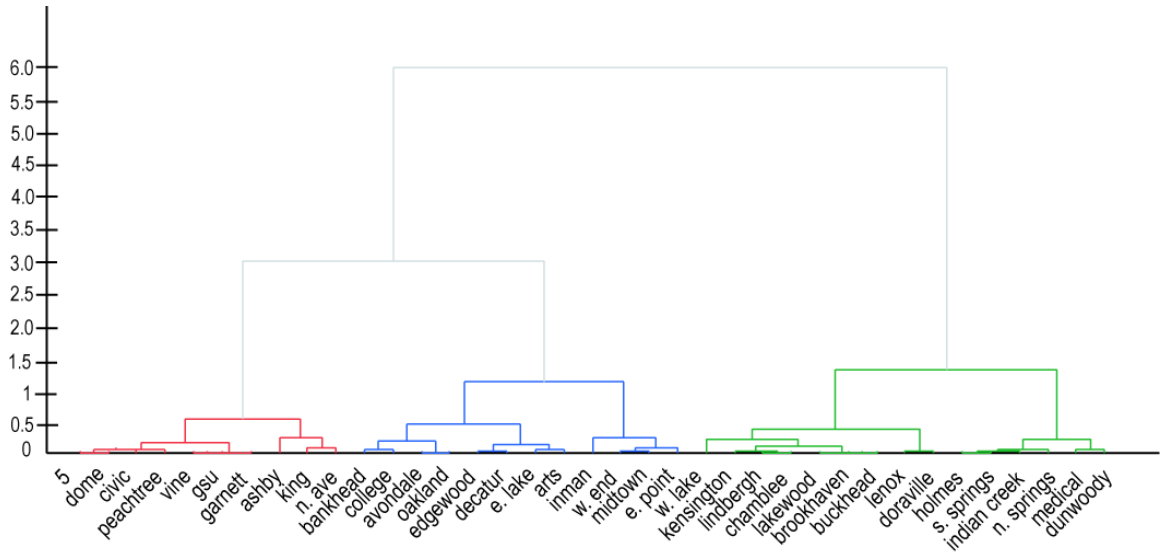
Figure 18. Hierarchical cluster based on average metric reach (1 mile).

(a) Cluster analysis for 1 mile rings around stations

(b) Cluster analysis for 0.25 mile rings around stations
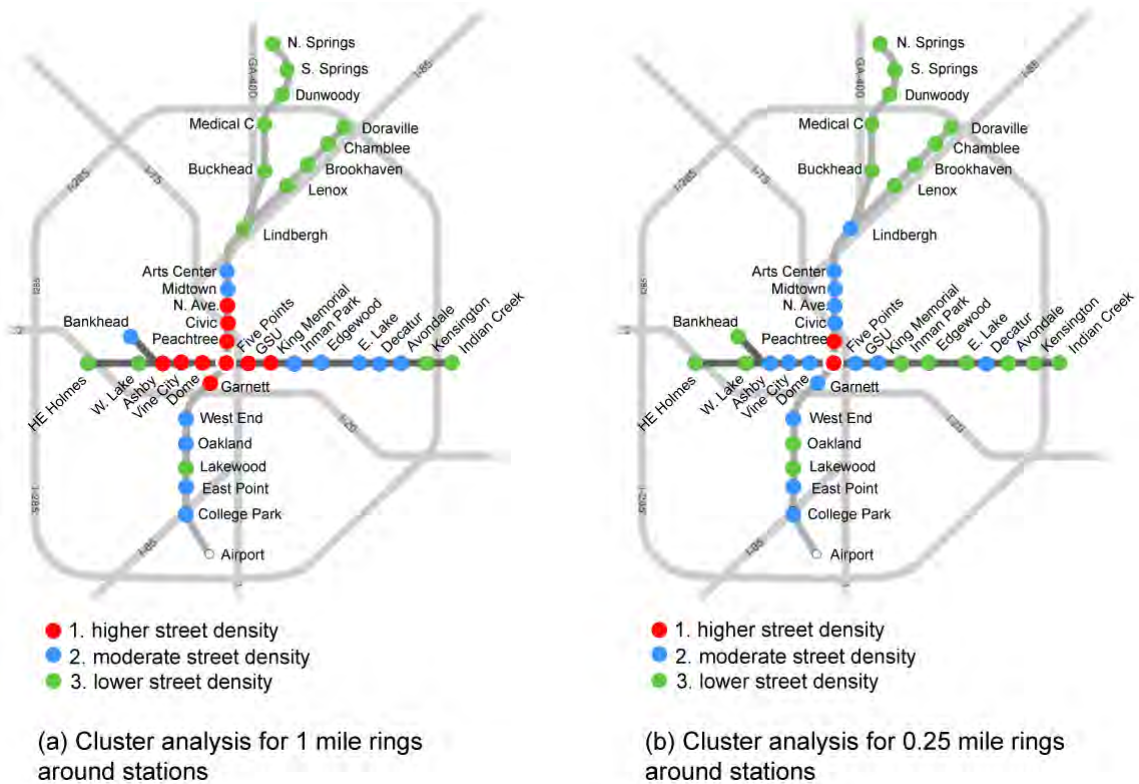
Figure 19. Cluster analysis of stations based on (a) average metric reach (1 mile) and (b) average metric reach (0.25 mile)

Figure 17 color-codes the results of the hierarchical cluster analysis based on three urban form variables for 1 and 0.25 mile rings around stations. Figure 18 shows the dendogram based on average metric reach for 1 mile only, and Figure 19 color-codes the results of hierarchical clustering based on metric reach for 1 and 0.25 mile rings around stations. A variety of cluster analysis based on adding population density and land-use mix to average metric reach in turn is presented in Appendix C (Figures 56-57 and 58-59 respectively). Since the main thrust of this study is to investigate the effect of street network design on travel walking behavior, cluster analysis based on the three urban form variables and street density only are reported here to reveal the strength of metric reach as a spatial descriptor.

Some interesting information can be extracted from the comparisons between the cluster analyses performed based on different sets of variables. For example, at 0.25 mile range East Point and Decatur stations are grouped with high intensity local-hub stations despite their larger distance to the center (Figure 17b). Hierarchical clustering based on metric reach (0.25 mile) only demonstrates that street network density at the local-scale is the primary determinant of this hierarchical grouping (Figure 19b). The relatively dense urban fabric surrounding these stations at both scales is visualized in Figures 21 and 22, which illustrate the density of streets captured within 1 and 0.25 mile buffers respectively. Conversely, Sandy Springs, which has low street density at both scales (Figures 19a-b), is grouped with high-intensity central city stations in the overall model at 0.25 mile range due to its higher land-use diversity (Figure 59b). As such, the hierarchical clustering analysis helps distinguish locally-embedded but globally-segregated station-environments, such as East Point and Decatur, from station-areas that

are embedded (i.e. Peachtree Center, Garnett) or segregated (Indian Creek) at both scales due to their street network patterns. Despite the fact that a number of changes occur in the overall classifications as the (set of) variables entered into the cluster analysis is modified, a certain consistency in the groupings of some stations are well captured through the multiple cluster analyses operated on the urban form variables.
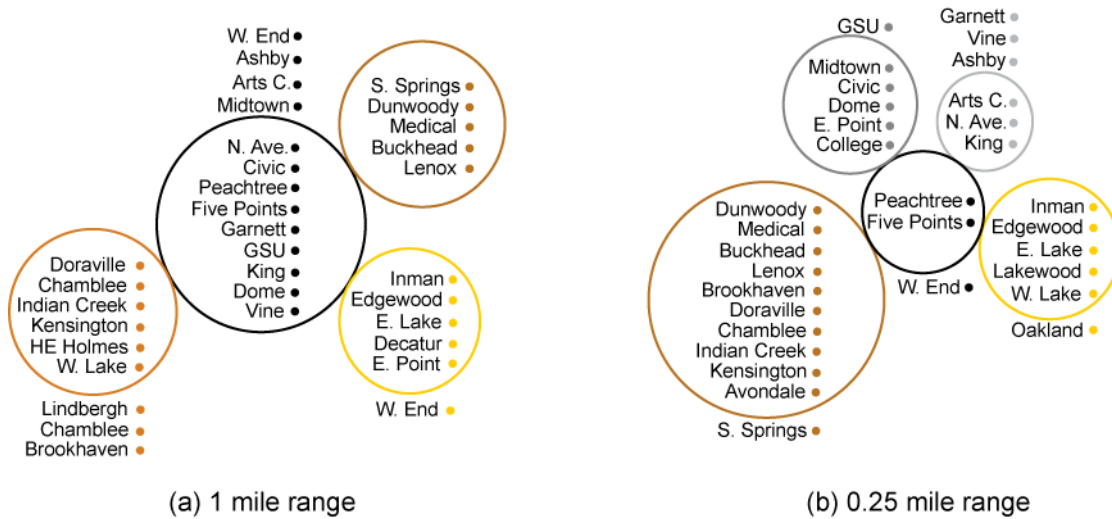
Figure 20. Emerging groupings based on multiple cluster analyses at (a) 1 mile and (b) 0.25 mile range.

Figure 20 visualizes the emerging groupings at 1 and 0.25 mile ranges as a result of multiple cluster analyses based on differing sets of urban form variables. As already indicated by the figure, the identified groups are robust with regard to the number of stations they capture versus the number of stations that remain dangling outside the groups. In both cases, the spatial groupings of stations both differentiate the prominent urban areas –i.e. central areas, early suburbs, emerging centers– based on their distances from the center and capture certain subtleties arising from their spatial qualities, as

discussed above. Hence, cluster analysis based on urban form variables captures the systematic discrimination of urban conditions at different scales and provides fine-grained characterizations of station-areas, which the categorization based on center would overlook. Based on these findings, the classifications of stations obtained by the hierarchical clustering operated on the urban form variables at 1 and 0.25 mile ranges are henceforth adopted as the typologies of MARTA stations.

Tables 5 and 6 provide numerical description of station types based on the cluster analysis at 1 and 0.25 mile range. In both models average block area within the buffers remain constant for all station types. At 1 mile range population and development densities are consistently higher for stations central-city stations which are the high intensity urban nodes, and lower for in-town suburbs which serve mostly as commuter stations. Both central city and edge-city station-areas have similarly high development densities, though with different levels of land-use mix. Street density follows the same order as land-use density. Average metric reach is notably higher at both ranges for central-city and historic mini-downtown stations and lower for edge-city stations. The spatial structure of station-area networks is similar to street density. Average 2-directional reach (10°) steadily decreases from station types 1 and 2 to station types 4 through 5.

Taking into account the varieties in station-area urban conditions presented here, the remainder of the study focuses on understanding whether and how the differences in urban form result in variations in walk-mode shares and walking distances. For this purpose, a more detailed analysis was conducted at the individual station level. The following chapters discuss the modeling framework and the results.
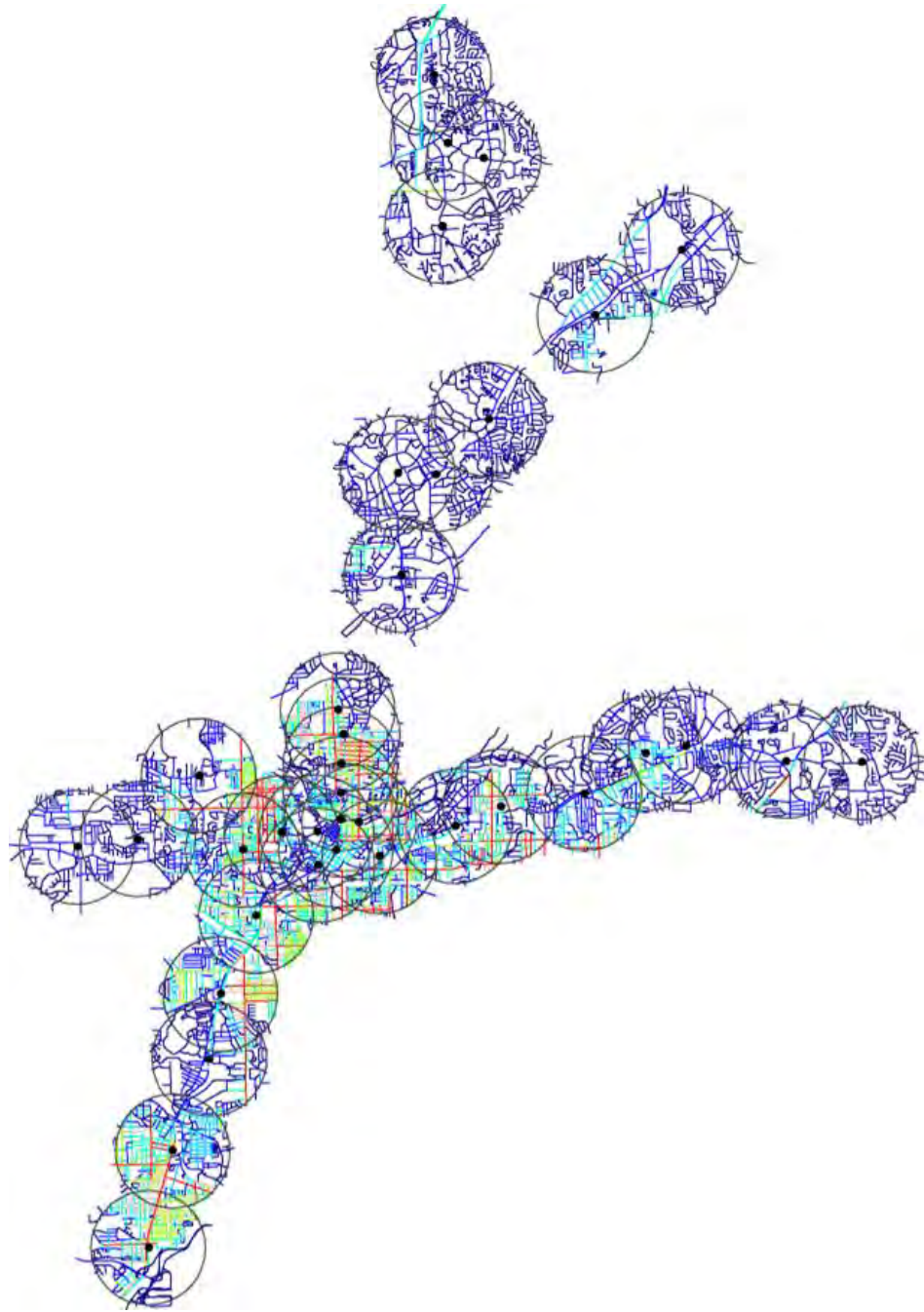
Figure 21. Street networks captured within 1 mile buffers around MARTA rail stations. Streets are color-coded at the same scale according to 2-directional reach (10°). Red reflects higher values, while dark blue shows the lowest. Thus, the colors are based on the ordering of individual streets within the metropolitan network according to their differentiation of internal spatial structures.
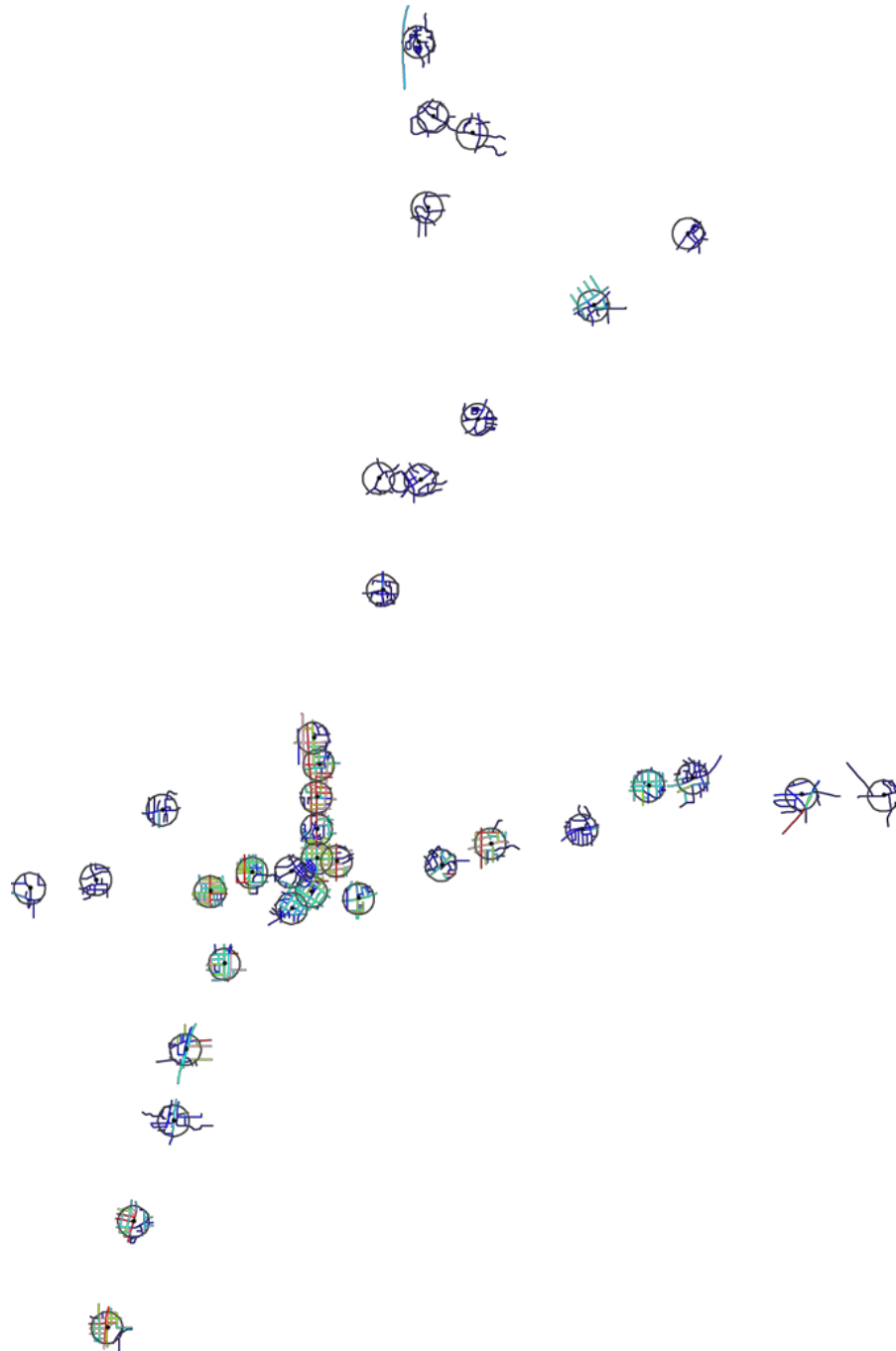
Figure 22. Street networks captured within 0.25 mile buffers around MARTA rail stations. Streets are color-coded at the same scale according to 2-directional reach (10°). Red reflects higher values, while dark blue shows the lowest. Thus, the colors are based on the ordering of individual streets within the metropolitan network according to their differentiation of internal spatial structures.

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Table 5. Spatial Typology of Rail Stations based on the cluster analysis at 1 mile range

Station Types	Type 1	Type 2	Type 3	Type 4
	central city uniform distribution of land-use, high street connectivity	**neighbor-hood** high population	**in-town suburb** mid-to-low densities of population, street network, development	**edge city** non-uniform distribution of development density, low street connectivity
Number of stations	11	8	13	5
Densities of Residential Population and Station boardings				
avg. population/acres	9.85	7.88	5.52	3.66
avg. housing units/acres	4.67	3.34	2.29	2.66
avg. annual boarding	658	503	735	289
Characteristics of Street Connectivity at the buffer scale				
avg. Reach (1mile)	38.85	30.29	18.38	13.84
avg. 2 -directional reach (10°)	8.90	8.01	3.04	0.96
avg. Reach (1mile) / directional distance	8.26	5.85	2.46	1.11
avg. block area in acres	2,009	1,977	2,024	2,061
Land-use Characteristics at the buffer scale				
avg. residential sqft (millions)	3.68	6.99	4.76	4.17
avg. non-residential sqft (millions)	14.38	2.77	2.17	13.30
mixed land-use index	0.81	0.61	0.58	0.73
avg. residential units	9,002	6,763	4,831	4,973

Table 6. Spatial Typology of Rail Stations based on the cluster analysis at 0.25 mile range

Station Types	Type 1	Type 2	Type 3	Type 4	Type 5
	local hub high intensity use and street connectivity	**historic mini-downtown** moderate population density, high connectivity	**central city** high population, high street connectivity	**in-town suburb** high densities of population and development, low street connectivity	**outer city** non-uniform development density, low street connectivity
Number of stations	11	3	3	11	9
Densities of Residential Population and Station boardings					
avg. population/acres	3.30	11.51	15.89	1.13	7.33
avg. housing units/acres	2.32	3.47	8.05	1.12	3.21
avg. annual boarding	798	284	503	730	751
Characteristics of Street Connectivity at the buffer scale					
avg. Reach (0.25mile)	2.44	2.65	2.21	1.16	1.42
avg. 2 -directional reach (10°)	7.88	9.07	10.45	1.28	3.90
avg. Reach (0.25mile) / directional distance	1.04	1.33	1.16	0.41	0.52
avg. block area in acres	130.20	121.70	117.41	122.72	106.96
Land-use Characteristics at the buffer scale					
avg. residential sqft (millions)	0.11	0.23	0.22	0.13	0.28
avg. non-residential sqft (millions)	1.91	0.034	1.35	0.36	0.11
mixed land-use index	0.73	0.79	0.87	0.63	0.57
avg. residential units	227	386	994	77	368

CHAPTER 5

STREET CONNECTIVITY AND WALKING TO/FROM TRANSIT

This chapter discusses the variations in walk-mode shares at individual stations and investigates the urban form factors affecting people's choice of walking as an access/egress mode to transit. The first section disaggregates access/egress trips by mode at the individual station and compares the proportion of walking trips between transit stops. The aim is to consider various factors intrinsic to the transportation system and household characteristics that exert influence on the variations in walking shares. The second section concerns itself with contextual variables and considers to what extent urban form variables affect walking as transit access/egress mode shares. The aim is to develop statistical models for predicting influences of urban form on the variation in walk-mode share.

Walking as transit access/egress mode choice

Figure 23 shows the distributions of mode shares for total transit trips obtained from the travel survey (after removing the discrepant data) as well as access and egress mode shares disaggregated according to walking *from* and *to* station. Transfer from other bus/rail systems –i.e. from CCT (Cobb Community Transit)– has the highest share (%31) for overall mode choice, which is consistent for both access and egress modes. Walking represents slightly less than 20% of all trips, which is comparable to auto share of 23%

on average. This correspondence between walking and auto shares can be partly explained by the lack of auto availability. About one half (47%) of respondents did not have an operable vehicle available for use in their household. However, an examination of the data shows that the availability of feeder bus services also influences riders' choice of commuting to/from public transport nodes. Distributions of all trips by mode for each station are shown in Figure 24. Among the 37 MARTA stations surveyed, the percentage of riders who walked for MARTA varied from 1.8% (N. Springs) to 60% (Peachtree Center). Stations which have more than 40% walk-mode share either no feeder services, i.e. Dome, GSU, Garnett, and Peachtree, or have limited (zero to 4 lines) service, i.e. Ashby, Civic, Midtown. On the other hand, stations at which walk-mode shares are lower than 10%, such as N. Springs, H.E. Holmes, Lindbergh, and Chamblee, receive considerably higher feeder service, ranging from four to fourteen lines per station. The difference between the travel *from* public transport and the travel *to* public transport (Figure 23b and c) reflects mainly the availability of a wider range of options at origins, in particular the option to utilize private vehicle. Nearly two in ten (~18%) accessed public transport terminal by walking while about three in ten (~28%) drove and parked their car. A higher proportion of riders walked (~21%) from rail stations to all destinations than drove (~18%). Table 7 reports transit access/egress mode shares by individual station.
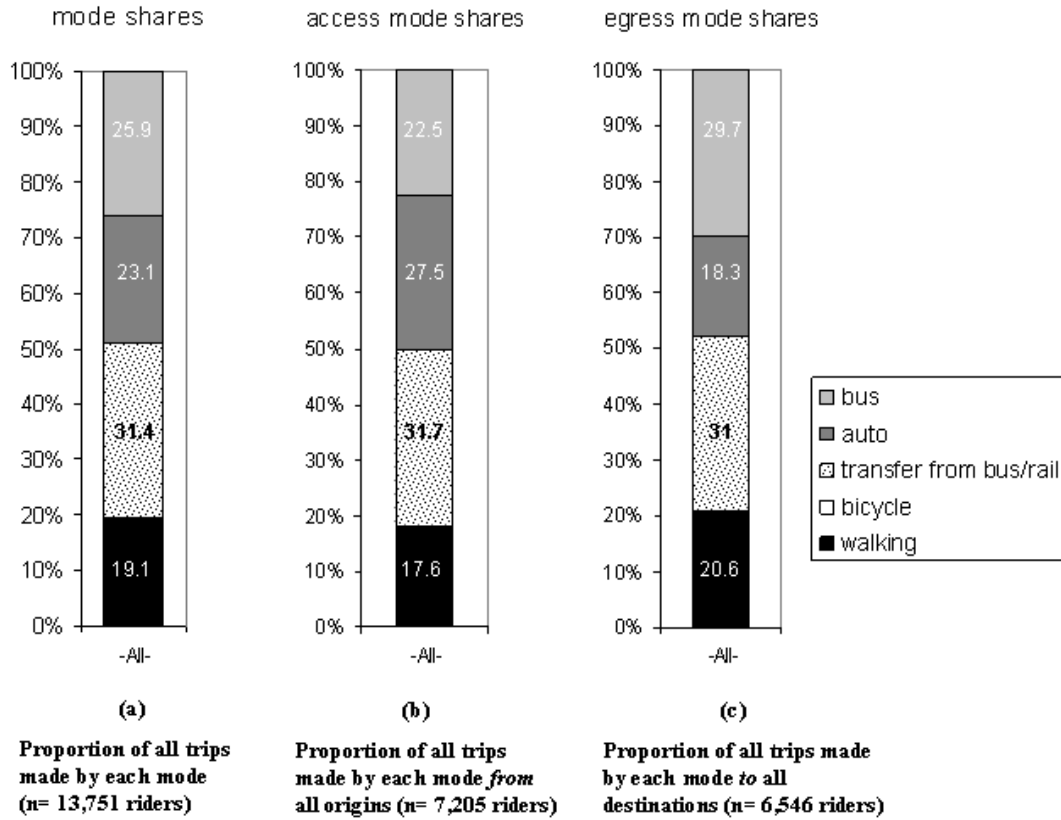
Figure 23. Mode shares for all trips.
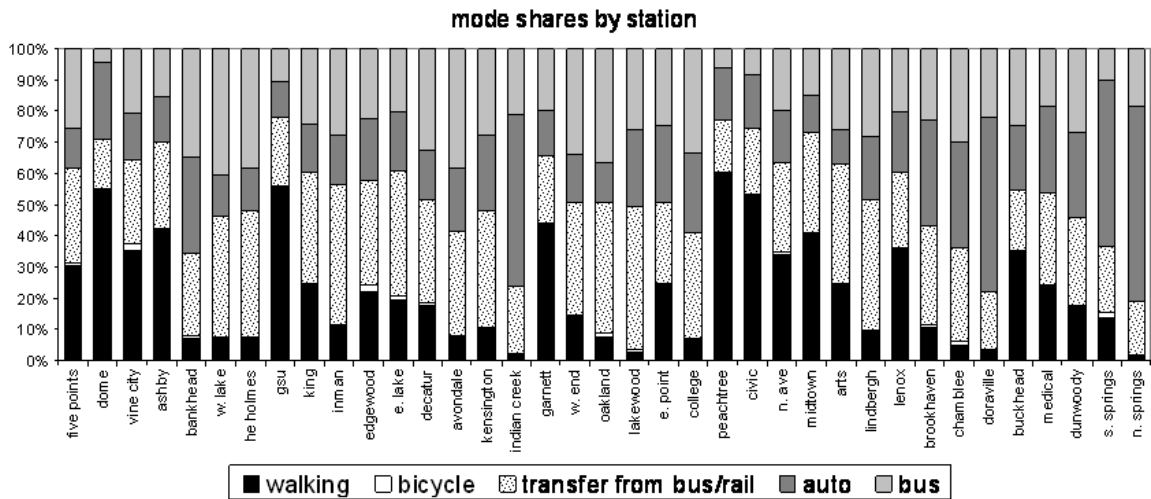
Figure 24. Mode shares for all trips per individual rail station.

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Table 7. Distributions of access/egress trips by mode for the individual station

STATION	walking	bicycle	transfer from bus/rail	car	bus
five points	0.30	0.01	0.31	0.13	0.25
dome	0.55	0.01	0.16	0.25	0.04
vine city	0.35	0.02	0.27	0.15	0.20
ashby	0.42	0.00	0.28	0.15	0.15
bankhead	0.07	0.01	0.26	0.31	0.35
w. lake	0.07	0.00	0.39	0.13	0.40
he holmes	0.07	0.00	0.41	0.13	0.38
gsu	0.56	0.00	0.22	0.12	0.10
king	0.25	0.00	0.36	0.16	0.24
inman	0.11	0.00	0.45	0.16	0.28
edgewood	0.22	0.02	0.34	0.20	0.22
e. lake	0.20	0.01	0.40	0.19	0.20
decatur	0.17	0.01	0.33	0.16	0.32
avondale	0.08	0.01	0.33	0.20	0.39
kensington	0.10	0.01	0.37	0.24	0.28
indian creek	0.02	0.00	0.21	0.55	0.21
garnett	0.44	0.00	0.21	0.15	0.20
w. end	0.14	0.01	0.36	0.16	0.34
oakland	0.08	0.01	0.42	0.13	0.36
lakewood	0.03	0.01	0.46	0.24	0.26
e. point	0.25	0.00	0.26	0.24	0.25
college	0.07	0.00	0.34	0.26	0.33
peachtree	0.60	0.01	0.17	0.17	0.06
civic	0.53	0.00	0.21	0.18	0.08
n. ave	0.34	0.01	0.29	0.17	0.20
midtown	0.41	0.00	0.32	0.12	0.15
arts	0.24	0.00	0.38	0.11	0.26
lindbergh	0.10	0.00	0.42	0.20	0.28
lenox	0.36	0.01	0.24	0.19	0.20
brookhaven	0.11	0.01	0.32	0.34	0.23
chamblee	0.05	0.01	0.30	0.34	0.30
doraville	0.03	0.01	0.18	0.56	0.22
buckhead	0.35	0.00	0.20	0.21	0.25
medical	0.24	0.00	0.30	0.28	0.18
dunwoody	0.17	0.00	0.28	0.28	0.27
s. springs	0.14	0.02	0.21	0.53	0.10
n. springs	0.02	0.00	0.17	0.63	0.18

As noted in Chapter 2, specific types of trips (i.e. shopping, work, recreational, etc.) were shown to influence the choice to walk. In order to better understand walking behavior, walk trips for transit were disaggregated according to origin and destination types. The percent walk trips made from origins *to* transport nodes and *from* transport nodes to destinations are shown in Table 8. Of the total number of trips walked for transit in Atlanta, 14% was made from public transport stops to homes while almost twice as many walk trips (36%) were made from riders' homes to public transport nodes. The difference between walk trips *from* homes and walk trips *to* homes is rather surprising, given the previous finding that a higher proportion of persons chose walking as egress mode overall (Figure 23). This finding indicates that despite the fact that a wider range of commuting options, in particular the option to drive, is available for home-based trips, more riders chose to walk *to* stations from their homes in comparison to those walking *from* stations to their home.

In the case of walking trips not associated with home at either end of the public transport trip, workplaces are the predominant origins and destinations for walking trips to/from public transport. Contrary to home-related walking trips, walk-mode shares are higher at trip-ends rather than at trip-origins, with more riders utilizing other modes of transport such as driving or bus riding at the beginning of their trips from workplaces. Among respondents, nearly four in ten (36%) accessed rail stops by walking from their workplaces while about half of respondents (51%) walked from rail stops to this destination. No other origins or destinations represent more than 12% of walk-mode shares.

Table 8. Proportion of walking trips made from/to rail stations

Destinations	Access-Mode Number of trips from this destination *to* rail stations (per hundred persons) by walking	Egress-Mode Number of trips to this destination *from* rail stations (per hundred persons) by walking
Workplaces	36.39	51.3
Home	35.48	14.14
Shop	4.84	6.73
Restaurants	1.25	0.84
Health services	1.84	3.29
Primary / High school	3.01	2.3
College	8.68	9.4
Social / Personal services	8.51	12
Total	100	100
	n=1,270 riders	n=1,353 riders

Besides these preliminary investigations into the variations in walk-mode shares with regard to the individual station and specific types of trips, a second set of analysis was conducted with the aim to understand how walking shares varied between station types. For this purpose, station types for 1 mile range, as identified by the hierarchical clustering analysis in Chapter 3 were employed. The Student's *t* test ($p<0.05$) was used for comparing the proportion of walking trips between station types. One-way ANOVA was used for comparison of station types. As shown in Figure 25, comparisons between station types, namely central-city, neighborhood, in-town suburb, and edge-city, confirm the considerable range of variation within walk-mode shares at each. The coefficient of determination is 0.64 and it is significant at a 99% level of confidence. Comparison between their means also points to substantial differences in the proportion of walking trips. Results of Student's t test, presented in Table 9, indicate that there is a significant difference between each pair of types, except for types 4 and 2, with regard to their walking shares.

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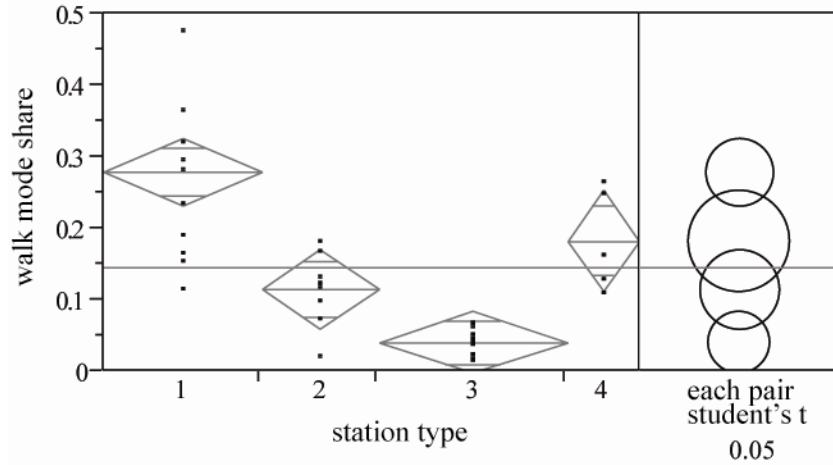
Figure 25. Variations in walk-mode shares between station types as defined by the cluster

analysis.

Table 9. Results of comparisons of means of station types using Student's t test

type	type	difference	std err dif	lower CL	upper CL	p-Value
1	3	0.2376	0.0314	0.1736	0.3015	**0.0000**
1	2	0.1644	0.0356	0.0919	0.2369	**0.0001**
4	3	0.1417	0.0404	0.0596	0.2238	**0.0013**
1	4	0.0959	0.0414	0.0117	0.1800	**0.0268**
2	3	0.0731	0.0345	0.0030	0.1432	**0.0414**
4	2	0.0686	0.0437	-0.0204	0.1575	0.1263

N=37

$R^2 = 0.64$

p-Value=**0.0000**

F ratio=19.92

       Figure 26 shows mode shares for trips at central-city (type 1) and edge-city (type

4) stations separately. The average walking share at central-city stations is 36% while

walking represents 25% of all trips at edge-city stations. This might be partly due to

higher levels of ample parking supply at edge-city stations, which promote driving as

mode of access to/from stations. Probably a more important factor in explaining the walk-

mode rate variation between the two station types is the different urban form

characteristics in terms of land-use mixes and local street connectivity. Central-city station-areas with even distribution of high intensity uses (corner cafes and main street shops) and high densities of street network are likely to influence the decision to walk for transit. The following section moves from these initial assumptions to statistical modeling of walk-mode shares in an attempt to investigate the extent to which street connectivity and land-use diversity explain public transport-related walking.
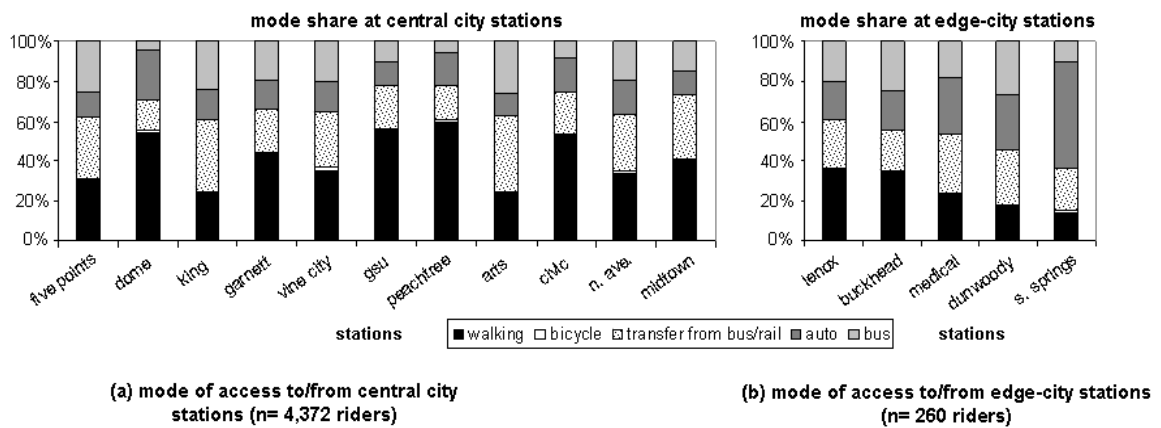
Figure 26. Mode of access to/from central-city versus edge-city stations.

Modeling walking as transit access/egress mode choice

This section examines the following research questions: what are the primary urban form correlates of transit access/egress walk-mode choice? The objective is to identify whether characteristics of station-environments and the location of the station relative to the internal structure of surrounding area are associated with walking shares. This study addresses these research questions in two aspects in an attempt to overcome some of the methodological drawbacks underlined in Chapter 2. First, using multiple regression analyses which control for individual socio-demographic characteristics, all

urban form variables and their interactions with each other are taken into account simultaneously in the specified models. Since a premise of this research is that the configuration of street network has significant associations with walking behavior, the interest is in identifying the relative importance of street layout in explaining the variation in walk-mode shares. Second, the statistical models developed include highly disaggregate data at the segment and parcel level with respect to land-use and street network design data. These smaller units of analysis prevent the unfair advantage of density measures, generally measured at a precise metric scale, over land-use and design measures, measured through coarser indices or dummy variables, and detect walking impacts of urban form more clearly.

The first look at the data involved an overview into the relative increase in magnitudes of travel and urban form variables. Figure 27 illustrates the rates of total ridership, total walking trips, and average population densities (in gross acres) for all rail stations within 0.25, 0.5, 1, and 1.5 mile radii around stations. The plot reveals that walking increases in proportion with the increase in ridership and the increase in population while the radius increases up to 0.5 mile, after which walking levels off. This implies that ½ of a mile is the extent to which the majority of riders in Atlanta are willing to walk. Yet there is still an observable increase in walking rates between 0.5 and 1 mile, though with a relatively less steep slope. The rate of walking to/from stations almost collapses after 1 mile radius. Walking rates are likely to be higher in more pedestrian-friendly station environments and lower in less walkable areas. Yet, the overall plot suggests that in Atlanta, despite high transit patronage levels, public transportation exerts an influence on walk-mode choice only up to ½ a mile of rail stations. Conversely, the

increase in the average station-area densities (people in gross acres) is marginal within ½ of a mile, with 1 mile being the threshold after which the rate of average population density escalates. This implies that the number of people in surrounding areas is not a strong predictor of walk-mode shares, and that other variables, such as density of street network and concentration of mixed-uses, may have a more significant role in explaining pedestrian travel.
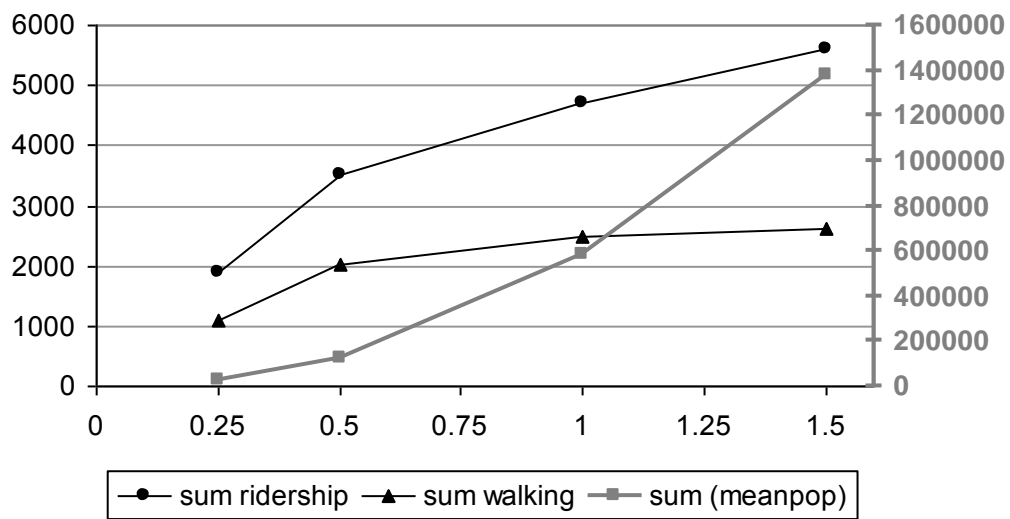
Figure 27. Rates of ridership, walking, and population density within 0.25, 0.5, 1, and 1.5 miles of stations.

Bivariate regression analysis

Preliminary to developing multivariate regression models predicting transit access/egress walk-mode shares, bivariate regressions were estimated in order to compare the explanatory power of the standard measures of connectivity and segment-based connectivity measures applied in this research. For this purpose walk-mode shares were tabulated according to individual stations. For each range, the dependent variable

"proportion of walking" was defined as the ratio of the number of walk-on riders within the specified range to the total ridership for the individual station. When bivariate regression equations were estimated at 1, 0.5, and 0.25 miles separately, the highest coefficient of determination (r^2) was obtained for 1 mile range. As a result, the coefficients of linear models computed at 1 mile range are reported here. A full range of correlations for 0.5 and 0.25 mile ranges are presented in Appendix D.

(a) n=37, r²=0.37, p<0.0001   (b) n=37, r²=0.31, p<0.0003   (c) n=37, r²=0.33, p<0.0002   (d) n=37, r²=0.22, p<0.0035
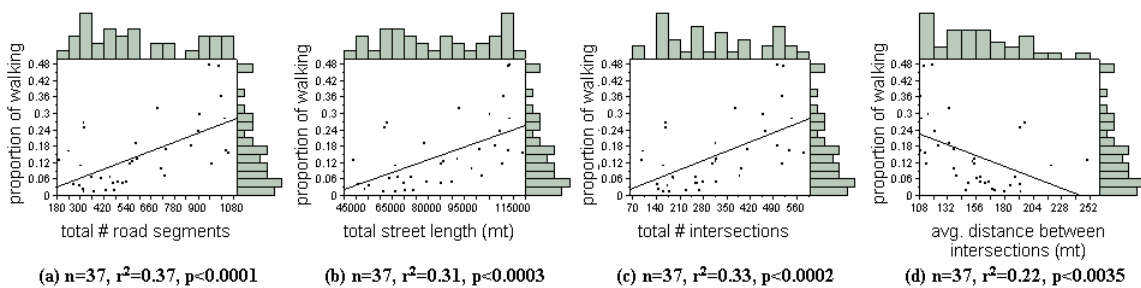
Figure 28. Scatterplots showing the proportion of walking against (a) total number of road segments, (b) total street length (mt), (c) total number of intersections, and (d) average distance between intersections (mt) within 1 mile rings

Figure 28 shows the bivariate regressions between walk-mode shares and standard measures of connectivity calculated based on streets captured within 1 mile radius of stations. While walking shares are positively correlated with the total number of road segments, total street length (mt) and total number of intersections (3- and/or 4-way) captured within the buffers, the coefficient for the average distance between intersections (mt) within catchment areas are negative. This supports the findings of various studies reviewed in Chapter 2 which suggest that shorter distances between street intersections, or smaller blocks, are mode conducive to walking. While all four measures are

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significantly associated with the variation in walk-mode shares (at a 99% level of confidence), total number of road segments produce the highest explanatory power.
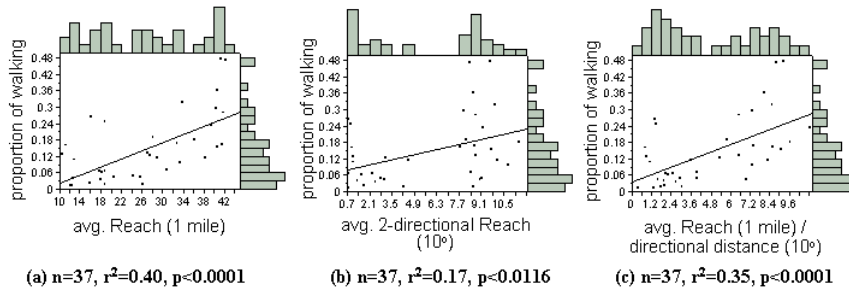
Figure 29. Scatterplots showing the proportion of walking against (a) average Reach (1mile), (b) average 2-directional Reach (10°), (c) average Reach (1mile) divided by the corresponding average directional distance (10°) for 1 mile rings

Figure 29 shows the scatterplots between the proportion of walking trips to/from transit and the segment-based connectivity measures. All measures are positively and significantly associated with walking shares. Comparisons of coefficients of determination indicate that average street density within 1 mile walking radius of stations has the highest explanatory power. For the variables measuring the directional accessibility of areas, while the coefficient of determination for 2-directional Reach (10°) is statistically significant and positive, correlation is best for the composite variable metric reach over directional distance at 1 mile range. This composite variable takes on higher values as the metric reach of a space increases and its directional depth decreases. Put simply, this is equivalent to saying that street networks which give more direct access to more surrounding streets encourage greater numbers of walking trips to/from stations. As seen in the scatterplots, 2-directional reach is underpinned by the polarization of

station-environments in terms of direction changes for 1 mile radius. This finding indicates that directional accessibility as measured by 2-directional reach is not continuously associated with percent walking.

(a) n=37, r²=0.19, p<0.0071   (b) n=37, r²=0.05, p<0.1908   (c) n=37, r²=0.002, p<0.8141
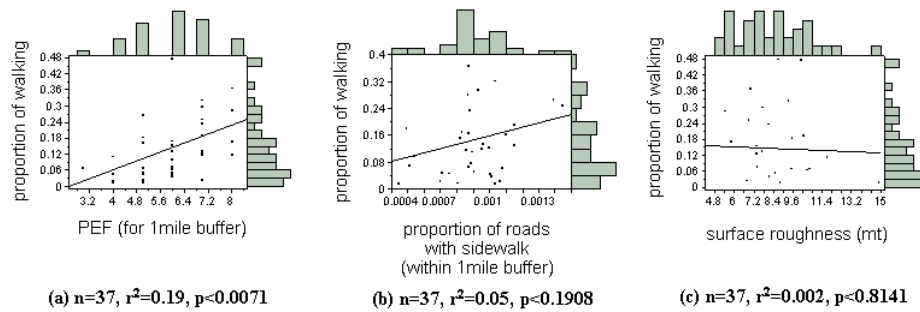
Figure 30. Scatterplots showing the proportion of walking against (a) PEF measure, (b) sidewalk availability, and (c) surface roughness (mt) for 1 mile rings around stations.

Bivariate regressions between walk-mode shares and PEF measure as well as sidewalk availability, and surface roughness calculated for 1 mile range are plotted in Figure 30. As the results indicate, the composite PEF measure yields lower coefficient of determination than those obtained by standard measures of connectivity and segment-based connectivity measures. Since sidewalk availability and surface roughness are not significantly correlated with walk-mode shares, as illustrated in the scatterplots, it can be concluded that the average distance between intersections within catchment areas has the most contribution in explaining the variation in walking shares. However; since the three separate variables are lumped into a single composite measure, the relative impact of each attribute on the decision to walk cannot be assessed.

To this point, the focus has been on the various connectivity measures describing both the average properties and structural differences of street networks within the

surrounding areas of stations. These measures provide a framework through which to test whether and to what extent street network design around stations are related to people's choice to walk to/from transit. In order to explore the effect accruing from the specific location of the station within the buffer (i.e. whether it is situated on denser or less dense part of the grid compared to its surroundings or is located on a linear street segment that acts as a local integrator), a second set of connectivity measures, namely relative measures of connectivity, were developed (see Equation 3). Figure 31 shows the scatterplots between walk-mode shares and the relative measures of connectivity. Based on empirical studies associated with space syntax, as reported in Chapter 2, it was hypothesized that the relative location of the station with respect to the variation in street network pattern would exert influence on walking behavior. Somewhat surprisingly, among the various relative measures of connectivity, only relative metric reach (1 mile) was found to be significantly correlated with the proportion of walking, albeit with only modest predictive power.

(a) n=37, r^2=0.14, p<0.0220   (b) n=37, r^2=0.10, p<0.0616   (b) n=37, r^2=0.008, p<0.6091
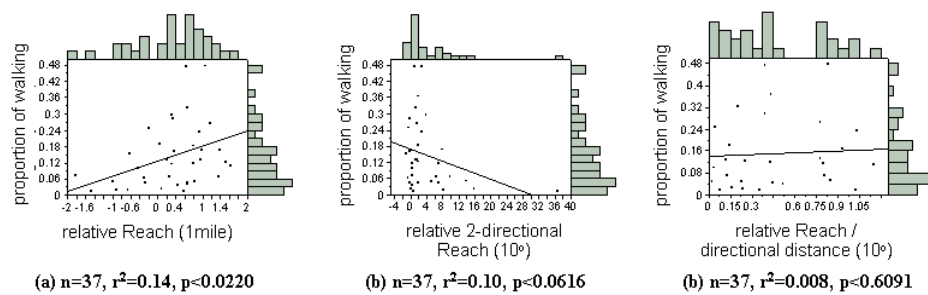
Figure 31. Scatterplots showing the proportion of walking against (a) relative Reach (1 mile), (b) relative 2-directional Reach (10°), and (c) relative Reach (1mile) divided by the corresponding directional distance (10°) for 1 mile rings

Overall, these results are useful to understand the strength and direction of the covariation in the dependant variable (walk-mode share) and the independent variables (street connectivity measures). However; since bivariate regressions are limited in their scope in that they fail to take into account multiple explanatory factors, more comprehensive statistical models were developed in the next step.

Multivariate regression analysis

Following past practice in studies of travel demand, multivariate statistics was used to study the relationship between urban form and walking to/from transit. Multiple regression analysis allows for the simultaneous inclusion of several independent variables to derive at causal explanations while introducing control variables. Thus; it provides the researcher with definitive statements about the observed relationship while revealing the relative effect sizes of each independent variable. The empirical models developed here are based on the hypothesis that environments that are connected so as to support different kinds of walking also support public transportation by encouraging the decision to walk for transit. Hence, the emphasis of this study is not so much on increasing the predictability by developing the best model, but rather on identifying the comparative significance of street network measures in terms of their relative impact on walking, while controlling for individual socio-demographic characteristics and transit service features. JMP statistical software was used to estimate the best fitting linear model using the equation:

$$\hat{Y} = \alpha + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_i \qquad (5)$$

where $\hat{Y}$ is the dependent walking measure, α is the intercept of the model, βi and Xi are coefficient and independent variables respectively, ε_i is the measurement error, and n denotes the number of independent variables. In this section the dependent walking measure is walk-mode share. The walk-mode share data was extracted from the travel data of individual riders (n=13,751). It is the ratio of total walk trips to the total ridership by station. In other words, it represents the percent of walking, including both access and egress walk-mode shares. The independent variables employed in the models were selected from a multitude of factors that were shown to be significantly related to mode choice by the literature, and were grouped into 6 categories. These are:

1. Connectivity: Segment-based measures of connectivity, namely metric reach and metric reach divided by the corresponding average directional distance (10°). Since 2-directional reach did not prove to be as significant a predictor of walk-mode shares as the composite connectivity measure in bivariate correlations, it was decided to include the latter as the connectivity measure in order to evaluate the significance of spatial structure in explaining walk choice. Due to the high multicollinearity between the segment-based connectivity measures, they were not included in the same model. Instead, two sets of models were developed using these two measures separately.

2. Accessibility: Sidewalk availability measuring the percentage of streets with sidewalk that are accessible to pedestrians within walking ranges of stations. Since no direct sidewalk data was included in the existing street network dataset,

sidewalk availability was calculated based on the shape file data obtained from ARC for individual bus stops. This dataset contained a survey of all available bus stops within the region, including information on the presence of sidewalk for the individual road segment on which the bus stop is located at. Sidewalk availability was estimated by calculating the percentage of bus stops with sidewalk systems within the buffers of each rail station, or the percentage of individual road segments with sidewalks, relativized by the total length of streets captured within station-catchment areas. The resulting values were used as a proxy for sidewalk continuity.

3. Density: Population density (people in gross acres) within 1, 0.5, and 0.25 mile radii of stations.

4. Land-Use: Mixed-use entropy index (see Equation 1) measuring the degree of dispersal of uses within the catchment areas of stations.

5. In order to control for the effects of transit service characteristics, four measures of transit features were included. These are type of station structure (underground, elevated, at-grade); service frequency (the number of inbound trains in am peak hours); availability of feeder bus services at station and the number of station-area parking supplies.

6. A composite socio-demographic variable was developed to control for personal and household characteristics. Auto ownership relativized by per-capita income measures the ratio of auto-ownership to per-capita income (annual household income divided by household size). In other words, this composite variable explicitly measures the portion of per-capita income allocated for vehicle

ownership. Thus, this socio-demographic variable allows for more precise estimates of the relationship between income and vehicle ownership (Dargay et al., 2007).

The non-urban form variables were entered into the regression first to allow for the evaluation of urban form variables in context relative to other factors affecting travel behavior. Urban form measures were then added into the model respectively in varying orders to demonstrate the effect of adding each to the model and to infer whether some variables could be eliminated in the final model without noticeably increasing the residual sum of squares.

Tables 10-12 summarize the results of regression models for 1, 0.5, and 0.25 mile radii respectively. This first set of models includes the connectivity measure metric reach as the street connectivity variable. A full set of multivariate regressions with urban form variables introduced to the model at varying sequences are presented in Appendix E (see Tables 36-47). Each column shows, first, the predictability of the model with only the transit service features and individual socio-demographic characteristics, and then, in turn, the effect of adding the connectivity measure, the accessibility measure, the density measure, and the land-use measure to the model.

Table 10. Effect tests for multivariate regressions estimating the proportion of walking within 1

total riders walked / total ridership per station	Controls			+ Land Use			+ Connectivity			+Accessibility			+ Density		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	**0.051**	**8.844**	**0.006**	0.002	0.567	0.458	0.008	2.748	0.109	0.0095	3.0113	0.094	0.0094	2.8784	0.1017
station structure type[b]	0.023	1.994	0.154	0.016	1.931	0.163	0.020	3.220	0.055	0.0199	3.1619	0.0584	0.020	3.030	0.066
service frequency[‡]	0.002	0.395	0.535	0.003	0.805	0.377	**0.031**	**10.215**	**0.003**	**0.032**	**10.168**	**0.0036**	**0.028**	**8.637**	**0.007**
feederbus services (no)	**0.111**	**19.360**	**0.000**	**0.044**	**10.458**	**0.003**	**0.030**	**9.641**	**0.004**	**0.0303**	**9.6295**	**0.0045**	**0.027**	**8.255**	**0.008**
parking supplies	**0.053**	**9.346**	**0.005**	0.009	2.133	0.155	0.000	0.060	0.809	0.000	0.0061	0.9381	0.000	0.008	0.928
mixed-land use index[†]				**0.048**	**11.350**	**0.002**	**0.046**	**14.967**	**0.001**	**0.044**	**13.965**	**0.001**	**0.039**	**11.942**	**0.002**
avg. Reach (1mile)							**0.037**	**12.201**	**0.002**	**0.029**	**9.307**	**0.005**	**0.018**	**5.512**	**0.027**
sidewalk availability[a]										0.001	0.338	0.566	0.001	0.304	0.586
population density: persons per gross acre within 1 mile of station													0.000	0.004	0.949
N=37															
R²	*0.69*			*0.77*			*0.84*			*0.84*			*0.84*		
R² adjusted	*0.62*			*0.72*			*0.80*			*0.79*			*0.78*		
std. error, S_e	*0.08*			*0.07*			*0.06*			*0.06*			*0.06*		
Prob>F													*0.00*		
coefficient of residual variability, V_e													*39.17*		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$\dagger\ Mixed-use\ entropy = -1 \times \left[\frac{\displaystyle\sum_{i=1}^{k} p_i \times \ln(p_i)}{\ln(k)} \right]$$

[b] types of station structure: at-grade, elevated, underground
‡ number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

For 1 mile range (see Table 10 and Tables 36-37), adding metric reach or land-use entropy index first to the controls results in the same level of increase in the predictive power of the model (R^2 change=7%; $p<0.01$). While population density, when added first before the remaining urban from measures, is found to influence percent walking, albeit fairly modestly, it does not add any explanatory power to the model when added in the subsequent stages. Lastly, sidewalk availability is not statistically significant and does not increase the overall predictability. By including land-use mix index in the model, the explanatory role of socio-demographics and parking supply in predicting walking mode choice are attenuated. Interestingly, service frequency variable becomes statistically significant with the inclusion of average Reach.

Looking at the models for 0.5 mile range (see Table11 and Tables 38-39), while adding land-use mix index increases the explanatory power of the model moderately (R^2 change=11%; $p<0.01$), the inclusion of metric reach adds an inconsequential increase of 2-4% ($p<0.05$). It is noteworthy that average Reach becomes significant only when land-use mix is entered into the model. It appears that land-use, which over time became tuned to spatial structure of urban networks, out-performs the effects of street density at 0.5 mile range.

For 0.25 mile (see Table 12 and Tables 40-41), the only significant increase in the predictive power of the model is observed when metric Reach is added to the model (R^2 change=9-13%; $p=0.001$). At this range the connectivity measure is the only urban form variable significantly associated with the proportion of walking.

Table 11. Effect tests for multivariate regressions estimating the proportion of walking within 0.5

11. Effect tests for multivariate regressions estimating the proportion of walking within 0.5 mile

total riders walked within 0.5 mile / total ridership per station	Controls			+ Land Use			+ Connectivity			+ Accessibility			+ Density		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	**0.022**	**7.159**	**0.012**	0.000	0.075	0.786	0.000	0.033	0.857	1E-06	0.0007	0.979	3.4E-08	2E-05	0.997
station structure type■	0.004	1.277	0.267	0.002	0.673	0.418	0.001	0.271	0.606	0.0009	0.4051	0.53	0.001	0.329	0.571
service frequency‡	0.001	0.370	0.547	0.000	0.040	0.842	0.005	2.375	0.134	0.0052	2.4647	0.128	0.005	2.452	0.129
feederbus services (no)	**0.098**	**32.156**	**0.000**	**0.020**	**8.554**	**0.007**	**0.010**	**4.667**	**0.039**	**0.0096**	**4.5464**	**0.042**	**0.009**	**3.971**	**0.056**
parking supplies	**0.013**	**4.351**	**0.045**	0.002	1.018	0.321	0.000	0.006	0.940	0.0006	0.2939	0.592	0.001	0.285	0.598
mixed-land use index†				**0.024**	**10.414**	**0.003**	**0.028**	**13.514**	**0.001**	**0.028**	**13.059**	**0.001**	**0.027**	**12.522**	**0.001**
avg. Reach (0.5mile)							**0.009**	**4.259**	**0.048**	**0.011**	**5.072**	**0.032**	**0.010**	**4.555**	**0.042**
sidewalk availability■										0.002	0.874	0.358	0.002	0.865	0.361
population density: persons per gross acre within 0.5 mile of station													0.000	0.069	0.794
N=37															
R²		**0.65**			**0.74**			**0.77**			**0.78**			**0.78**	
R² adjusted		**0.59**			**0.69**			**0.72**			**0.72**			**0.71**	
std. error, Se		**0.06**			**0.05**			**0.05**			**0.05**			**0.05**	
Prob>F														**0.00**	
coefficient of residual variability, Ve														**50.99**	

Numbers in bold = p< 0.05, numbers in italics = p<0.10

Notes:

■ proportion of roads with sidewalk

$$\dagger Mixed-use\ entropy = -1 \times \left[\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right]$$

■ types of station structure: at-grade, elevated, underground

‡ number of inbound trains in am peak hour (7am-9am)

* ratio of average auto-ownership to average per-capita income calculated per station

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Table 12. Effect tests for multivariate regressions estimating the proportion of walking

Effect tests for multivariate regressions estimating the proportion of walking within

total riders walked within 0.25 mile / total ridership per station	Controls			+ Land Use			+ Connectivity			+ Accessibility			+ Density		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	**0.006**	**9.977**	**0.004**	**0.005**	**8.097**	**0.008**	**0.005**	**12.318**	**0.002**	**0.0037**	**9.3133**	**0.0051**	**0.0037**	**9.0441**	**0.0058**
station structure type^b	**0.007**	**6.378**	**0.005**	**0.005**	**4.310**	**0.023**	0.002	2.798	0.078	0.0016	2.0471	0.1487	0.001	1.729	0.197
service frequency^‡	0.001	2.256	0.144	0.001	2.243	0.145	**0.006**	**14.539**	**0.001**	**0.0059**	**14.823**	**0.0007**	**0.005**	**12.373**	**0.002**
feederbus services (no)	**0.007**	**11.790**	**0.002**	**0.006**	**9.574**	**0.004**	**0.004**	**9.327**	**0.005**	**0.0027**	**6.7148**	**0.0152**	**0.002**	**5.347**	**0.029**
parking supplies	0.000	0.557	0.461	0.000	0.473	0.497	0.000	0.027	0.870	6E-08	0.0001	0.9905	3.3E-06	0.008	0.929
mixed-land use index^†				0.000	0.170	0.683	0.000	0.972	0.333	0.001	1.584	0.219	0.001	1.465	0.237
avg. Reach (0.25mile)							**0.006**	**14.232**	**0.001**	**0.006**	**14.290**	**0.001**	**0.006**	**13.933**	**0.001**
sidewalk availability^■										0.000	0.912	0.348	0.000	0.745	0.396
population density: persons per gross acre within 0.25 mile of station													0.000	0.187	0.669
N=37															
R^2	**0.61**			**0.61**			**0.74**			**0.75**			**0.75**		
R2 adjusted	**0.53**			**0.52**			**0.67**			**0.67**			**0.66**		
std. error, S_e	**0.02**			**0.02**			**0.02**			**0.02**			**0.02**		
Prob>F													**0.00**		
coefficient of residual variability, V_e													**58.62**		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:

■ proportion of roads with sidewalk

$$\dagger \; Mixed - use \; entropy = -1 \times \left(\frac{\left| \sum_{i=1}^{k} p_i \times \ln(p_i) \right|}{\ln(k)} \right)$$

b types of station structure: at-grade, elevated, underground

‡ number of inbound trains in am peak hour (7am–9am)

* ratio of average auto-ownership to average per-capita income calculated per station

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Table 13. Parameter estimates and residual plots for "reduced" models estimating the proportion of walking

Reduced Model

total riders walked / total ridership per station	B	t	std β
constant		-0.936	
station structure type[b] (elevated)	-0.031	-2.254	-0.214
service frequency[‡]	-0.003	-2.882	-0.324
feederbus services (no)	0.052	2.725	0.235
mixed-land use index[†]	0.765	6.365	0.599
avg. Reach (1mile)	0.005	3.480	0.457
N	37		
R²	0.83		
R² adjusted	0.79		
std. error, Se	0.06		
Prob>F	0.00		

Reduced Model

total riders walked within 0.5 mile/total ridership per station	B	t	std β
constant		-0.389	
feederbus services (no)	0.043	2.621	0.278
mixed-land use index[†]	0.398	5.741	0.583
avg. Reach (0.5mile)	0.006	2.059	0.202
N	37		
R²	0.75		
R² adjusted	0.73		
std. error, Se	0.05		
Prob>F	0.00		

Reduced Model

total riders walked within 0.25 mile/total ridership per station	B	t	std β
constant		3.906	
auto ownership relativized by per-capita income*	-0.117	-3.859	-0.408
service frequency	-0.001	-3.526	-0.495
feederbus services (no)	0.022	3.185	0.355
avg. Reach (0.25mile)	0.036	5.142	0.751
N	37		
R²	0.67		
R² adjusted	0.63		
std. error, Se	0.02		
Prob>F	0.00		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

These multivariate regressions proved useful in determining the statistically insignificant variables or those without any contribution to the overall predictability to be omitted in the final model, without leading to biased parameter results. The variables not significant at 5% level were eliminated one at a time to produce a "reduced" model. Table 13 shows the effect levels of statistically significant variables included in the "reduced" models for three ranges. The results suggest that density of streets over a given area is significantly associated with the choice to walk. In all models, the standardized coefficient (stdβ) for metric reach is positive and statistically significant (at a 99% level of confidence). This suggests that even after controlling for density, land-use, transit features, and socio-demographics, street layout acts as a significant inducement to riders' propensity to walk. Figure 32, which shows the prediction profiler plots for each variable in the "reduced" model for 1 mile range, illustrates the significance levels and effect sizes of each independent variable. Figure 33 reports the scatterplot showing the proportion of walking to/from stations as affected by the variables in the "reduced" model.
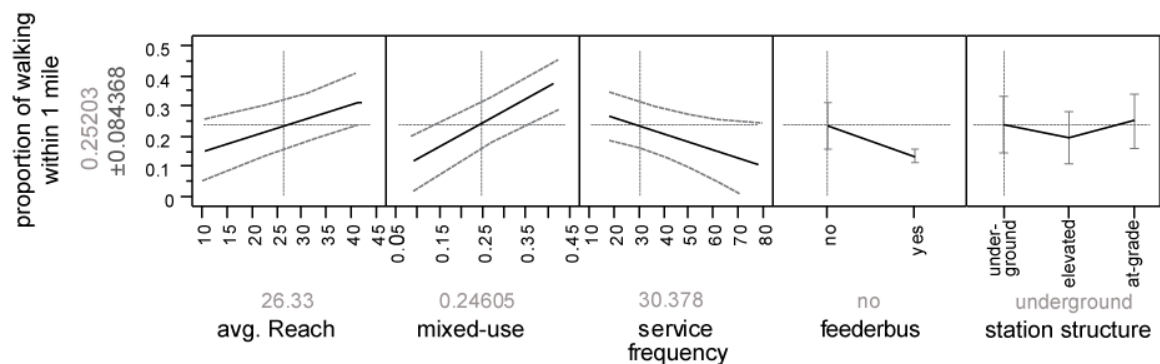
Figure 32. Prediction profiler plots for the variables in "reduced" model for 1 mile.
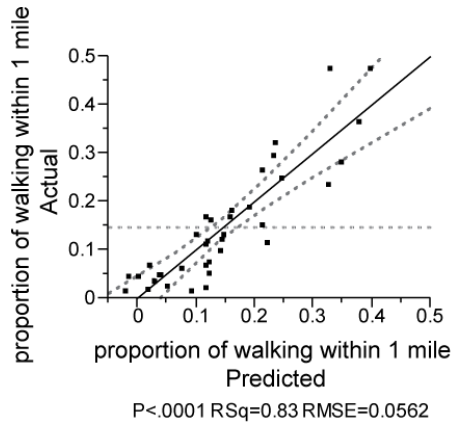
Figure 33. Scatterplot showing the proportion of walking to/from stations within 1 mile by the "reduced" model.

Comparisons of coefficients between the "reduced" models provide useful insights about the individual contribution of urban form measures. From the relative effect sizes it is clear that the primary factors in explaining predictability are metric reach and land-use mix. While metric reach is statistically significant across all models, the highest standardized coefficient is obtained for 0.25 mile range. By contrast, land-use mix does not enter the "reduced" model as a significant variable at this range. It seems that ¼ of a mile is an overly limited radius which fails to capture the impacts of land-use mix on walking. At meso-scale (greater than ½ of a mile) metric reach still continues to be a reasonably significant predictor, but land-use mix appears to be the most powerful variable in explaining the variation in proportion of walking. Higher correlation coefficients of mixed-use entropy index and metric reach within 0.5 and 1 mile buffers suggest that the decision to walk to/from transit is significantly associated with these two urban form dimensions, namely the density of available streets and mixing of land-uses, within a larger surrounding context of stations. Lastly, the population density coefficient

is positive but not significant in any of the three models. Based on the findings of earlier studies it can be hypothesized that the relationship between population density and mode choice is non-linear (Frank and Pivo, 1994). An alternative explanation may be based on the argument, underlined in Chapter 2, that employment densities exert a stronger influence on mode choice than population densities. Including employment density levels in the model might capture a truer relation between walk-mode shares and station-area densities.

Statistical models also point to statistically significant associations between non-urban variables and walking shares. Consistent with theory, ridership levels are sensitive to transit service levels and personal attributes. The coefficient on the feeder bus variable indicates that the availability of feeder bus services at stations is negatively associated with the proportion of walking, with more people choosing to ride the bus to/from stations than to walk. Contrary to expectation, service frequency is negatively correlated with percent walking. It may be suggested that during peak hours, in competition with walking, other modes, most notably bus ridership, are more attractive. The statistical significance and direction on the socio-demographic variable is as expected. This confirms that percent walking increases with decreasing levels of per-capita income allocated for auto ownership. However; since the effect size of this non-urban variable is low in the overall models, it does not stand out as a major contributor to walk-mode choice. Lastly, the coefficient of elevated station structure type is negative and statistically significant at 1 mile range. Since elevated stations, such as Holmes, Chamblee, and Doraville, are generally located in relatively sparse urban grids, this

finding might be suggestive of a covert implication regarding the role of local urban grids in explaining walking behavior.

Multivariate regression models estimated by including the composite connectivity measure, metric reach divided by the corresponding average directional distance based on metric reach (10°), follow similar patterns with the earlier models including metric reach. Tables 14-16 report the results of regression models for 1, 0.5, and 0.25 mile radii respectively. Table 15 summarizes the "reduced" models for 3 ranges. A full set of multivariate regressions with urban form variables introduced to the model at varying sequences is presented in Appendix F (see Tables 42-47). Results reveal that aside from street density and land-use mix, spatial structure of urban areas also mattered. In all ranges, the standardized coefficient for the composite connectivity measure is positive and statistically significant. The sign and significance of the coefficient remains consistent even after the inclusion of other urban form measures, controlling for non-urban form factors. In fact, the relative effect size (stdβ) of the composite connectivity measure in the "reduced" model (Table 17) is comparable to that of metric reach at both 0.5 and 1 mile ranges. This indicates that the configuration of street networks at the scale of an individual area is a reasonably significant predictor of the variation in walk-mode shares at stations. More particularly, the composite connectivity measure, which takes into account both street density and the shape and alignment of streets as indexed by the direction changes needed to navigate the system, is clearly associated with riders' choice to walk for transit.

Table 14. Effect tests for multivariate regressions estimating the proportion of walking within 1

total riders walked / total ridership per station	Controls			+ Land Use			+ Connectivity			+ Accessibility			+ Density		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.051	8.844	0.006	0.002	0.567	0.458	0.007	2.359	0.136	0.0067	2.287	0.142	0.0066	2.157	0.154
station entrance type[b]	0.023	1.994	0.154	0.016	1.931	0.163	0.018	3.173	0.057	0.0184	3.117	0.061	0.018	3.010	0.067
service frequency[‡]	0.002	0.395	0.535	0.003	0.805	0.377	0.030	10.410	0.003	0.03	10.19	0.004	0.028	9.310	0.005
Feederbus services (no)	0.111	19.360	0.000	0.044	10.458	0.003	0.047	16.561	0.000	0.0472	16.03	4E-04	0.047	15.462	0.001
parking supplies	0.053	9.346	0.005	0.009	2.133	0.155	0.001	0.363	0.552	0.0012	0.423	0.521	0.001	0.414	0.526
mixed-land use index[†]				0.048	11.350	0.002	0.047	16.437	0.000	0.042	14.318	0.001	0.036	11.691	0.002
avg.metric reach(1 mile) / directional distance (10^x)							0.043	15.241	0.001	0.035	11.723	0.002	0.023	7.687	0.010
sidewalk availability[a]										0.000	0.108	0.745	0.000	0.044	0.835
population density: persons per gross acre within 1 mile of station													0.000	0.064	0.802
N=37															
R²	0.69			0.77			0.85			0.85			0.85		
R² adjusted	0.62			0.72			0.81			0.81			0.80		
std. error, Se	0.08			0.07			0.05			0.05			0.05		
Prob>F													0.00		
coefficient of residual variability, Ve													37.89		

Numbers in bold = p< 0.05, numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$Mixed - use\ entropy = -1 \times \left[\frac{\sum_{i=1}^{k} p_i \times \ln(p_i)}{\ln(k)} \right]$$

[b] types of station entrances: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

Table 15. Effect tests for multivariate regressions estimating the proportion of walking within 0.5

Effect tests for multivariate regressions estimating the proportion of walking within 0.5

total riders walked within 0.5 mile / total ridership per station	Controls			+ Land Use			+ Connectivity			+ Accessibility			+ Density		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	**0.022**	**7.159**	**0.012**	0.000	0.075	0.786	0.000	0.023	0.882	1E-07	6E-05	0.994	2E-09	9E-07	0.999
station entrance type[b]	0.004	1.277	0.267	0.002	0.673	0.418	0.001	0.260	0.614	0.0008	0.352	0.558	0.001	0.311	0.581
service frequency[‡]	0.001	0.370	0.547	0.000	0.040	0.842	0.003	1.417	0.244	0.0025	1.152	0.292	0.003	1.118	0.300
Feederbus services (no)	**0.098**	**32.156**	**0.000**	**0.020**	**8.554**	**0.007**	**0.016**	**7.698**	**0.010**	**0.0172**	**7.919**	**0.009**	**0.017**	**7.493**	**0.011**
parking supplies	**0.013**	**4.351**	**0.045**	0.002	1.018	0.321	0.000	0.091	0.765	5E-06	0.002	0.961	0.000	0.001	0.970
mixed-land use index[†]				**0.024**	**10.414**	**0.003**	**0.028**	**13.249**	**0.001**	**0.027**	**12.667**	**0.001**	**0.027**	**12.164**	**0.002**
avg.metric reach(0.5mile)/ directional distance (10^x)							**0.008**	**3.836**	**0.060**	**0.009**	**4.237**	**0.049**	0.008	3.691	0.065
sidewalk availability[a]										0.001	0.507	0.482	0.001	0.488	0.491
population density: persons per gross acre within 0.5 mile of station													0.000	0.010	0.922
N=37															
R²	0.65			0.74			0.77			0.77			0.77		
R² adjusted	0.59			0.69			0.71			0.71			0.70		
std. error, S_e	0.09			0.05			0.05			0.05			0.05		
Prob>F													0.00		
coefficient of residual variability, V_e													52.44		

Numbers in bold = p< 0.05, numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$^{†}Mixed-use\ entropy = -1 \times \left\{ \frac{\left[\sum_{i=1}^{k} p_i \times \ln(p_i) \right]}{\ln(k)} \right\}$$

[b] types of station entrances: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

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Table 16. Effect tests for multivariate regressions estimating the proportion of walking within

	Controls			+ Land Use			+ Connectivity			+ Accesibility			+ Density		
total riders walked within 0.25 mile / total ridership per station	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	**0.007**	**10.785**	**0.003**	**0.004**	**6.377**	**0.017**	**0.005**	**8.754**	**0.006**	**0.0044**	**7.838**	**0.009**	**0.0045**	**7.972**	**0.009**
station entrance type[b] (at-grade)	**0.003**	**5.272**	**0.029**	**0.003**	**5.705**	**0.023**	**0.003**	**4.805**	**0.037**	**0.0026**	**4.678**	**0.039**	**0.002**	**4.293**	**0.048**
service frequency[‡]	0.000	0.624	0.436	0.001	1.164	0.289	**0.002**	**4.246**	**0.048**	0.0022	3.966	0.056	0.002	2.979	0.096
Feeder bus services (no)	**0.010**	**14.605**	**0.001**	**0.006**	**9.761**	**0.004**	**0.006**	**11.273**	**0.002**	**0.0058**	**10.43**	**0.003**	**0.005**	**8.230**	**0.008**
parking supplies	0.000	0.613	0.439	0.000	0.090	0.766	0.000	0.024	0.877	2E-05	0.031	0.862	0.000	0.000	0.982
mixed-land use index[†]				*0.002*	*3.721*	*0.063*	0.001	2.490	0.125	0.001	2.381	0.134	0.001	2.016	0.167
avg.metric reach (0.25mile)/ directional distance (10⁵)							**0.003**	**4.684**	**0.039**	**0.002**	**4.364**	**0.046**	**0.003**	**4.689**	**0.039**
sidewalk availability[a]										0.000	0.048	0.829	0.000	0.003	0.957
population density: persons per gross acre within 0.25 mile of station													0.000	0.641	0.430
N=37															
R²	0.53			0.58			0.64			0.64			0.65		
R² adjusted	0.45			0.49			0.55			0.53			0.53		
std. error, S_e	0.03			0.02			0.02			0.02			0.02		
Prob>F													0.00		
coefficient of residual variability, V_e													69.99		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$\dagger Mixed-use\ entropy = -1 \times \left[\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right]$$

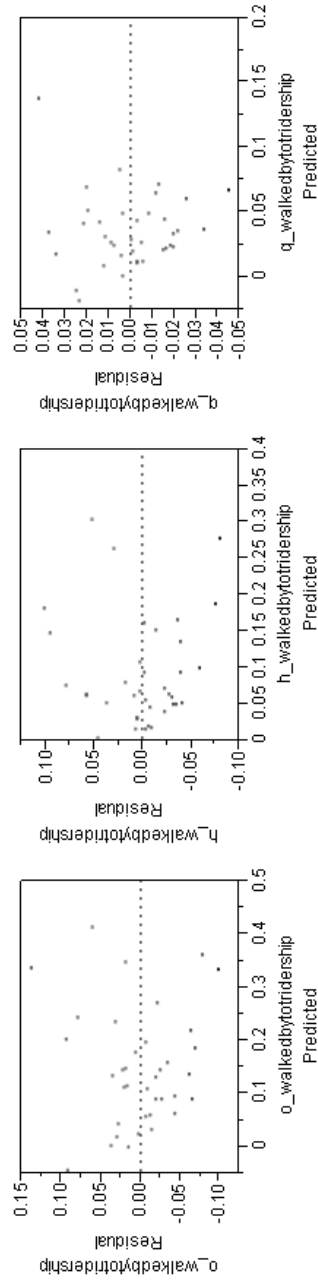[b] types of station entrances: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

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Table 17. Parameter estimates and residual plots for "reduced" models estimating the proportion of

Reduced Model

total riders walked / total ridership per station	B	t	std β
constant		0.15	
service frequency ‡	-0.002	-2.471	-0.256
Feederbus services (no)	0.062	3.334	0.280
mixed-land use index †	0.773	6.800	0.605
avg.metric reach(1mile)/ directional distance(10°)	0.016	3.908	0.421
N		37	
R²		0.81	
R² adjusted		0.79	
std. error, S_e		0.06	
Prob>F		0.00	

Reduced Model

total riders walked within 0.5 mile/total ridership per station	B	t	std β
constant		0.22	
Feederbus services (no)	0.049	3.156	0.317
mixed-land use index †	0.404	5.915	0.592
avg.metric reach(0.5mile)/ directional distance(10°)	0.014	2.214	0.197
N		37	
R²		0.75	
R² adjusted		0.73	
std. error, S_e		0.040	
Prob>F		0.000	

Reduced Model

total riders walked within 0.25 mile/total ridership per station	B	t	std β
constant		4.20	
auto ownership relativized by per-capita income	-0.127	-3.480	-0.442
Feederbus services (no)	0.027	3.299	0.429
avg.metric reach(0.25mile)/ directional distance(10°)	0.025	2.361	0.304
N		37	
R²		0.49	
R² adjusted		0.44	
std. error, S_e		0.03	
Prob>F		0.00	

Numbers in bold = p< 0.05; numbers in italics = p<0.10

It should be noted that bivariate regressions reported previously in this section indicated some degree of skewness in the distributions of the dependent variable (proportion of walking) for 3 ranges. This is a common issue in many fields, such as bio-informatics (Bennett and Riley, 1992) and econometrics (Fox, 1997). A common approach in tackling with skewed dataset is to ignore the skewness and use normal distribution methods of analysis, i.e. standard linear models (McGuinness et al., 1997). The underlying argument is that due to the Central Limit Theorem[10] (CLT) of statistics (Rice, 1995) normal distribution methods may still result in viable conclusions regarding the significance levels. Yet, certain transformations might be applied to such data to reduce or remove skewness. The most common approach is logarithmic transformation. In order to ensure the validity of results obtained from the multivariate regression models developed, logarithmic transformation was applied to the dependent data, which resulted in a more parsimonious model. The new results were then compared with the previous findings to arrive at definitive conclusions.

In general, results are similar for models with logarithmic transformation presented in Tables 18-21. A comparison between the two sets of models indicates that accounting for skewness by re-calibrating the initial models through log-transformation enhances the significance of street network design and land-use mix. When the log-transformed models developed with the inclusion of metric reach are examined (Table 18), metric reach and land-use mix variables remain positively and statistically significant for 3 ranges. In terms of standardized coefficients, the results for these two urban form

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[10] In probability theory, the CLT states that the mean of a population data, regardless of its distribution, will approach to normal distribution when repeated randomly.

variables (Table 19) are comparable to those in the initial models (Table 13). The only observed differences between the two sets of models are related to the significance of transit service features. The feeder bus coefficient still produces the expected positive sign, but it is no longer significant in the logarithmic models. Similarly, while service frequency enters the transformed model as a significant variable at 1 mile range, its significance level and effect size drops considerably for 0.25 mile radius. Conversely, there is also evidence that effect size of a variable increases with logarithmic transformation. Sidewalk availability measure becomes significant for 0.5 mile range, albeit fairly modestly and at a 90% confidence interval.

Table 18. Effect tests for log-transformed models estimating the proportion of walking within 1, 0.5, and 0.25 mile

Final Model

log of (total riders walked / total ridership per station)	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.277	0.936	0.342
station entrance type[b]	1.726	2.948	0.072
service frequency[‡]	1.288	4.356	0.047
Feederbus services (no)	0.119	0.402	0.531
parking supplies	0.074	0.251	0.621
avg. Reach (1mile)	1.675	5.666	0.025
sidewalk availability[a]	0.002	0.005	0.942
population density: persons per gross acre within 1 mile of station	0.22	0.76	0.39
mixed-land use index[†]	2.312	7.817	0.010
N	37		
R²	0.78		
R² adjusted	0.70		
std. error, Se	0.54		
Prob>F	0.00		
coefficient of residual variability, Ve	23.4		

Final Model

log of (total riders walked within 0.5 mile / total ridership per station)	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.048	0.113	0.739
station entrance type[b]	0.390	0.920	0.346
service frequency[‡]	0.624	1.474	0.235
Feederbus services (no)	0.037	0.088	0.769
parking supplies	0.172	0.405	0.530
avg. Reach (0.5mile)	3.241	7.653	0.010
sidewalk availability[a]	1.67	3.94	0.06
population density: persons per gross acre within 0.5 mile of station	0.065	0.152	0.699
mixed-land use index[†]	3.058	7.221	0.012
N	37		
R²	0.72		
R² adjusted	0.62		
std. error, Se	0.65		
Prob>F	0.00		
coefficient of residual variability, Ve	22.8		

Final Model

log of (total riders walked within 0.25 mile / total ridership per station)	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	3.479	4.548	0.042
station entrance type[b]	2.169	2.836	0.104
service frequency[‡]	1.077	1.408	0.246
Feederbus services (no)	0.687	0.898	0.352
parking supplies	0.031	0.040	0.843
avg. Reach (0.25mile)	3.107	4.062	0.054
sidewalk availability[a]	0.533	0.696	0.411
population density: persons per gross acre within 0.25 mile of station	0.042	0.055	0.816
mixed-land use index[†]	2.041	2.668	0.114
N	37		
R²	0.57		
R² adjusted	0.43		
std. error, Se	0.87		
Prob>F	0.00		
coefficient of residual variability, Ve	22.4		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$Mixed-use\ entropy = -1 \times \left\{ \frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right\}$$[†]

[b] types of station entrances: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

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19. Parameter estimates and residual plots for "reduced" log-transformed models estimating the

ster estimates and residual plots for "reduced" log-transformed models estimating the proportion of

Reduced Model

log of (total riders walked / total ridership per station)	B	t	std β
constant		-13.34	
station entrance type (elevated)	-0.294	-2.304	-0.251
service frequency‡	-0.022	-2.174	-0.281
avg. Reach (1mile)	0.049	3.539	0.516
mixed-land use index†	6.515	5.952	0.631
N	37		
R^2	0.76		
R^2 adjusted	0.72		
std. error, S_e	0.52		
Prob>F	0.00		

Reduced Model

log of (total riders walked within 0.5 mile / total ridership per station)	B	t	std β
constant		-11.24	
avg. Reach (0.5mile)	0.179	3.965	0.465
sidewalk availability[a]	207.6	2.08	0.23
mixed-land use index†	4.372	4.652	0.522
N	37		
R^2	0.69		
R^2 adjusted	0.66		
std. error, S_e	0.62		
Prob>F	0.00		

Reduced Model

log of (total riders walked within 0.25 mile / total ridership per station)	B	t	std β
constant		-2.64	
auto ownership relativized by per-capita income*	-3.644	-2.835	-0.380
avg. Reach (0.25mile)	0.730	1.397	0.455
N	37		
R^2	0.40		
R^2 adjusted	0.37		
std. error, S_e	0.92		
Prob>F	0.00		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Residual plot (y-axis: Residual, log_o_walkbyriders; x-axis: log_o_walkbyriders Predicted)

Residual plot (y-axis: Residual, log_h_walkbyriders; x-axis: log_h_walkbyriders Predicted)

Residual plot (y-axis: Residual, log_q_walkbyriders; x-axis: log_q_walkbyriders Predicted)

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The logarithmic models estimated by including the composite connectivity measure follow similar patterns with those including metric reach. Tables 20 and 21 reveal that connectivity and land-use are associated with the increase in the proportion of walking; whereas the evidence relating non-urban form factors to walking is inconclusive. The most consistent association is between higher values of connectivity measure and mixed-land-use index and more walk-mode shares. Stations with higher directional accessibility and maximally mixed uses within their catchment areas attract more walk-on riders, even when controlling for other factors. Somewhat surprisingly, at 0.25 mile range only auto-ownership relativized by per-capita income enters as a significant variable. Connectivity and land-use measures fail to correlate with the proportion of walking. The interpretation for the lack of correlation might be that within 0.25 mile distance from a station people are inclined to walk for transit irrespective of the urban form characteristics of the station area. As the distance to station increases the spatial structure of street networks and the distribution of development densities appear to induce the decision to walk. In fact, street network begins to overpower the effects of socio-demographic characteristics and transit features. Therefore it would appear that in addition to street density, spatial structure based on directional bias is indeed implicated in the way in which street networks function to support walking.

Table 20. Effect tests for log-transformed models estimating the proportion of walking within 1, 0.5, and 0.25

20. Effect tests for log-transformed models estimating the proportion of walking within 1, 0.5, and 0.25 mile

Final Model

log of (total riders walked / total ridership per station)

	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.098	0.379	0.544
station entrance type[b]	*1.645*	*3.113*	*0.061*
service frequency‡	**1.259**	**4.853**	**0.037**
Feederbus services (no)	0.541	2.086	0.161
parking supplies	0.408	1.573	0.221
avg.metric reach(1mile) / directional distance(10")	**2.640**	**10.176**	**0.004**
sidewalk availability[a]	0.042	0.161	0.692
population density: persons per gross acre within 1 mile of station	0.15	0.58	0.45
mixed-land use index†	**2.246**	**8.656**	**0.007**
N	37		
R^2	0.81		
R^2 adjusted	0.74		
std. error, S_e	0.51		
Prob>F	0.00		
coefficient of residual variability, V_e	21.9		

Final Model

log of (total riders walked within 0.5 mile / total ridership per station)

	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.046	0.107	0.746
station entrance type[b]	0.369	0.848	0.365
service frequency‡	0.099	0.227	0.638
Feederbus services (no)	0.551	1.266	0.270
parking supplies	0.000	0.001	0.978
avg.metric reach(0.5mile)/ directional distance(10")	**2.916**	**6.695**	**0.015**
sidewalk availability[a]	*1.32*	*3.03*	*0.09*
population density: persons per gross acre within 0.5 mile of station	0.020	0.045	0.833
mixed-land use index†	**3.075**	**7.061**	**0.013**
N	37		
R^2	0.71		
R^2 adjusted	0.61		
std. error, S_e	0.66		
Prob>F	0.00		
coefficient of residual variability, V_e	23.1		

Final Model

log of (total riders walked within 0.25 mile / total ridership per station)

	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	**5.840**	**6.416**	**0.018**
station entrance type[b]	1.371	0.753	0.481
service frequency‡	0.606	0.666	0.422
Feederbus services (no)	1.511	1.660	0.209
parking supplies	0.280	0.308	0.584
avg.metric reach(0.25mile)/ directional distance(10")	1.182	1.298	0.265
sidewalk availability[a]	0.002	0.002	0.963
population density: persons per gross acre within 0.25 mile of station	0.045	0.049	0.826
mixed-land use index†	0.660	0.725	0.402
N	37		
R^2	0.51		
R^2 adjusted	0.32		
std. error, S_e	0.95		
Prob>F	0.01		
coefficient of residual variability, V_e	24.5		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$Mixed - use\ entropy = -1 \times \left[\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right]$$

[b] types of station entrances: at-grade, elevated, underground
‡ number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

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Table 21. Parameter estimates and residual plots for "reduced" log-transformed models estimating the proportion of walking ... parameter estimates and residual plots for "reduced" log-transformed models estimating the proportion of walking

Reduced Model

log of (total riders walked / total ridership per station)	B	t	std β
constant		-13.35	
station entrance type (elevated)	-0.243	-1.925	-0.207
service frequency‡	-0.020	-2.092	-0.249
avg.metric reach(1mile) / directional distance (10^x)	0.161	3.775	0.516
mixed-land use index†	7.008	6.639	0.679
N		37	
R^2		0.77	
R^2 adjusted		0.73	
std. error, S_e		0.51	
Prob>F		0.00	

Reduced Model

log of (total riders walked within 0.5 mile / total ridership per station)	B	t	std β
constant		-11.96	
sidewalk availability^a	190.3	1.94	0.21
avg. metric reach(0.5mile)/ directional distance (10^x)	0.387	3.951	0.437
mixed-land use index†	4.974	5.642	0.594
N		37	
R^2		0.69	
R^2 adjusted		0.66	
std. error, S_e		0.62	
Prob>F		0.00	

Reduced Model

log of (total riders walked within 0.25 mile / total ridership per station)	B	t	std β
constant		-0.93	
auto ownership relativized by per-capita income*	-4.295	-2.964	-0.448
N		37	
R^2		0.20	
R^2 adjusted		0.18	
std. error, S_e		1.05	
Prob>F		0.01	

Numbers in bold = p< 0.05, numbers in italics = p<0.10

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In conclusion, multivariate regression models were successful in providing a description of the relationship between the primary urban form factors –density, land-use, and street layout– and walking for transit. The coefficient of residual variability (V_e) reported for all complete models indicate typical-to-good levels of fit. The residual plots for "reduced" models illustrate that points are not evenly distributed about the x-axis. This indicates that there might be additional variables impacting the dependent variable, which need to be included in the statistical models. These can be addressed through future research. However, the results of bivariate and multivariate regressions estimated show that the connectivity measures are significantly associated with walk-mode shares; adding other urban form and non-urban form variables to the model does not reduce the effect levels and significance levels of these measures. Hence, adding additional variables to the models is not likely to affect the significance of the connectivity measures noticeably. At this stage no cross-effects are considered. Arguably, the overall coefficient of determination can be increased by a model that includes the cross-effects. However, the intention of this study is to primarily examine the comparative significance of variables derived from connectivity networks, not so much to develop the best model.

The findings presented in this chapter confirm the hypothesis that urban form characteristics of station-environments are significantly associated with increased transit access/egress walk-mode shares. No conclusive evidence was found regarding the role of the location of the station within the surrounding area. Tables 22 and 23 present an overview of the results with respect to the "reduced" models and the "reduced" log-transformed models estimating transit access/egress walk-mode shares at 1 and 0.25 mile radii. From the standardized coefficients, it is clear that measures of street network design

and land-use mix are most strongly associated with walking shares, with signs matching expectations. The relative effect size of metric reach and metric reach over directional distance is systematically high within all buffers even after control variables are introduced. Mixed-use entropy index has slightly higher positive standardized coefficients than connectivity measures at 0.5 and 1 mile ranges, but fails to enter the models at 0.25 mile range.

Importantly, the results of the multivariate regression models point to the importance of station-environment at 1 mile radius in affecting the proportion of walking trips to/from transit. As seen from the "reduced" models, the coefficient of determination is considerably higher for 1 mile range. Even though the relative effect size of metric reach is consistent across ranges, ¼ of a mile appears to be an overly limited distance threshold since it fails to capture the effects of land-use mix. Thus, based on these inferences it can be argued that 1 mile should be promoted both as the distance to model pedestrian context around stations and as metric threshold for calculation of Reach in the characterization of street networks with the particular aim to influence the decision to walk for transit.

(a) Reduced Model

total riders walked / total ridership per station	B	t	std β
constant		-0.94	
station structure type[b] (elevated)	-0.03	-2.25	-0.21
service frequency‡	0.00	-2.88	-0.32
feederbus services (no)	0.05	2.72	0.24
mixed-land use index†	0.77	6.36	0.60
avg. Reach (1mile)	0.01	3.48	0.46
N	37		
R²	0.83		
R² adjusted	0.79		
std. error, Se	0.06		
Prob>F	0.00		

(b) Reduced Model

total riders walked within 0.25 mile/total ridership per station	B	t	std β
constant		3.91	
auto ownership relativized by per-capita income*	-0.12	-3.87	-0.41
service frequency‡	0.00	-3.53	-0.50
feederbus services (no)	0.02	3.18	0.36
avg. Reach (0.25mile)	0.04	5.14	0.75
N	37		
R²	0.67		
R² adjusted	0.63		
std. error, Se	0.02		
Prob>F	0.00		

(c) Reduced Model

log of (total riders walked / total ridership per station)	B	t	std β
constant		-13.34	
station structure type[b] (elevated)	-0.29	-2.30	-0.25
service frequency‡	-0.02	-2.17	-0.28
avg. Reach (1mile)	0.05	3.54	0.52
mixed-land use index†	6.51	5.95	0.63
N	37		
R²	0.76		
R² adjusted	0.72		
std. error, Se	0.52		
Prob>F	0.00		

(d) Reduced Model

log of (total riders walked within 0.25 mile / total ridership per station)	B	t	std β
constant		-2.64	
auto ownership relativized by per-capita income*	-3.64	-2.84	-0.38
avg. Reach (0.25mile)	0.73	3.40	0.46
N	37		
R²	0.40		
R² adjusted	0.37		
std. error, Se	0.92		
Prob>F	0.00		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Table 23. "Reduced" models of walking shares estimated with the inclusion of metric reach over directional "Reduced" models of walking shares estimated with the inclusion of metric reach over directional distance for (a) models of walking shares estimated with the inclusion of metric reach over directional distance... model... mile and

total riders walked / total ridership per station	B	t	std β
constant		0.15	
service frequency‡	0.00	-2.47	-0.26
feederbus services (no)	0.06	3.33	0.28
mixed-land use index†	0.77	6.80	0.51
avg.metric reach(1mile)/ directional distance(10^x)	0.02	3.91	0.42
N	37		
R²	0.81		
R² adjusted	0.79		
std. error, Se	0.06		
Prob>F	0.00		

total riders walked within 0.25 mile/total ridership per station	B	t	std β
constant		4.20	
auto ownership relativized by per-capita income*	-0.13	-3.48	-0.44
feederbus services (no)	0.03	3.30	0.43
avg.metric reach(0.25mile)/ directional distance(10^x)	0.03	2.36	0.30
N	37		
R²	0.49		
R² adjusted	0.44		
std. error, Se	0.03		
Prob>F	0.00		

log of (total riders walked / total ridership per station)	B	t	std β
constant		-13.35	
station structure type[b] (elevated)	-0.24	-1.93	-0.21
service frequency‡	-0.02	-2.09	-0.25
avg.metric reach(1mile) / directional distance (10^x)	0.16	3.78	0.52
mixed-land use index†	7.01	6.64	0.68
N	37		
R²	0.77		
R² adjusted	0.73		
std. error, Se	0.51		
Prob>F	0.00		

log of (total riders walked within 0.25 mile / total ridership per station)	B	t	std β
constant		-0.93	
auto ownership relativized by per-capita income*	-4.30	-2.96	-0.45
N	37		
R²	0.20		
R² adjusted	0.18		
std. error, Se	1.05		
Prob>F	0.01		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

One practical application of the findings presented here is in forecasting the travel impacts of transit-oriented development (TOD) scenarios and in evaluating planning guidelines and urban design decisions regarding proposals for new developments that would be served by transit. Traditional models of travel behavior do not take into account the interaction between street networks and land-uses, or as shown here, the spatial structure of urban form. Integrating measures of street density and measures of configurational variables can lead to enhanced models of urban form and function. The enhanced models of walking can provide policy-makers and planners with informed decisions on where to invest their efforts in creating transit-oriented and pedestrian-friendly environments. For ease of interpretation, the coefficients estimated in the initial set of models (non-transformed models) are used as a framework to translate the theoretical implications of these results into practice. The results reported in Table 13 reveal that one standard deviation increase in the average density of street connections (metric reach) within 1 mile of a mile around rail stations in Atlanta is associated with approximately a half standard deviation increase in the percent of people walking for transit. This accounts approximately for 34% of the predicted variable. Looking at the unstandardized coefficients (B) for metric reach across all models, it can be inferred that all else being equal, raising the average metric reach of the street network within 1, ½, and ¼ mile of a station by 10 miles increases the ratio of walking by 0.05, 0.06, and 0.36 percentage points respectively. For the sake of comparisons, the conditions within 1 mile buffers of Inman and Dunwoody MARTA stations could be represented by infinite square grids that have the same reach values. Based on the average metric reach (for 1 mile threshold) values associated with each station-environment, the existing

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approximate block face length was calculated as 200 meters and 550 meters for Inman and Dunwoody respectively. These comparative urban block dimensions clearly indicate that Inman neighborhood, which is the first planned suburb in Atlanta[11], has a considerably denser urban mesh than that of Dunwoody, which represents one of the emerging business poly-centers within the city. In real terms, a 10 miles of increase in the average metric reach values within 1 mile buffers around both stations is associated with 50 meters and 250 meters of decrease in the block face lengths of Inman and Dunwoody station-areas respectively[12].
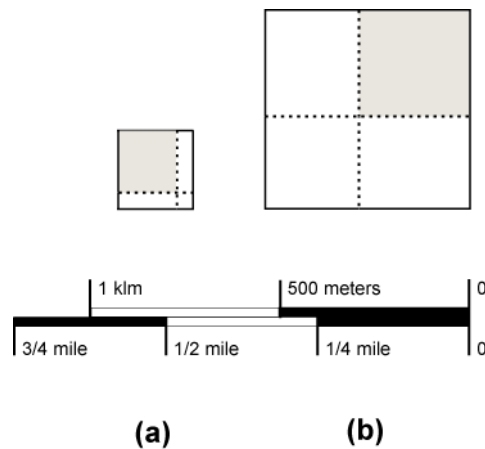
Figure 34. Visualization of the change in the block size within 1 mile buffers of (a) Inman MARTA station and (b) Dunwoody MARTA station that would be needed to bring about a 0.05 increase in the ratio of walking. The visualization is based on hypothetical square grids with the same reach values, actual and desired.

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[11] Inman Park Neighborhood Association; http://www.inmanpark.org/ (Accessed: May 24 2010)
[12] Numbers are based on the calculations proposed by Peponis et al. (2008)

As seen in Figure 34, increasing the average metric reach of station-areas within 1 mile of station is a fairly feasible investment decision which promotes sustainable forms of urbanization responsive to transportation proposals. These results are useful to understand the expected long-term impacts of urban design and urban master planning decisions aimed at creating walkable neighborhoods. The percentages estimated are indicative and depend in part on the variables included in the case context. Nevertheless, these results suggest that street connectivity measured at the appropriate range can add explanatory power for accurate forecasting models.

CHAPTER 6

STREET CONNECTIVITY AND DISTANCES WALKED TO/FROM TRANSIT

This chapter examines the following research question: are there significant variations in the distances walked to/from MARTA stations, and if so, are they associated with the surrounding urban form? Based on ARC's 2001-2002 Regional On-Board Transit Survey the first section presents detailed information on the distances walked for MARTA rail stations and studies the variations between station types. The second section develops statistical models to analyze the relationship between urban form and distances riders walk for transit.

Trip Distances

The distributions of distances traveled on foot for all trips and for work- and home-related trips are shown in Figures 35 and 36 respectively. Among the various functions fitted to the walking distance distributions, gamma function was best fitted to the distributions. Cramer-von Mises tests, which examine the goodness-of-fit, demonstrate that walking distances are well explained by gamma functions. The distributions of distances for all walk trips and work trips are at 99% and 95% confidence intervals respectively. Even in the case of home trips, which have a small number of observations that is likely to diverge from the gamma distribution, gamma function still fits the distribution well (at a 90% confidence interval). For the full group of respondents

(Figure 35), the mean distance walked was 0.47 miles (756 mt). The analysis of data

demonstrates that a quarter of riders walked less than $\frac{1}{5}$ of a mile (25th pctile=0.20 mi); a

second quarter of people walked between $\frac{1}{5}$ of a mile and $\frac{3}{8}$ of a mile (50th pctile=0.38

mi); a third quarter reported walking between $\frac{3}{8}$ of a mile and $\frac{5}{8}$ of a mile (75th

pctile=0.64 mi); and the last quarter walked more than $\frac{5}{8}$ of a mile.
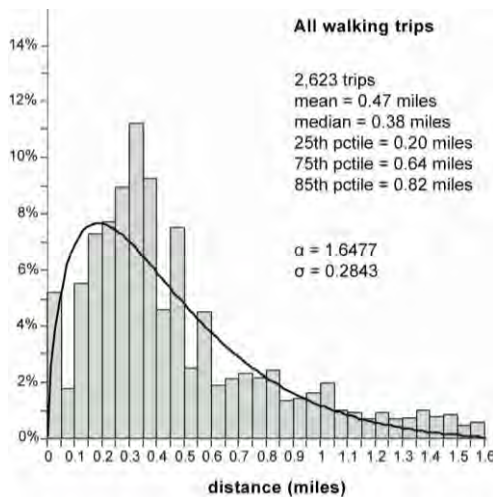
Figure 35. Distances walked to/from all rail stations. Gamma function was fitted to the

distribution.
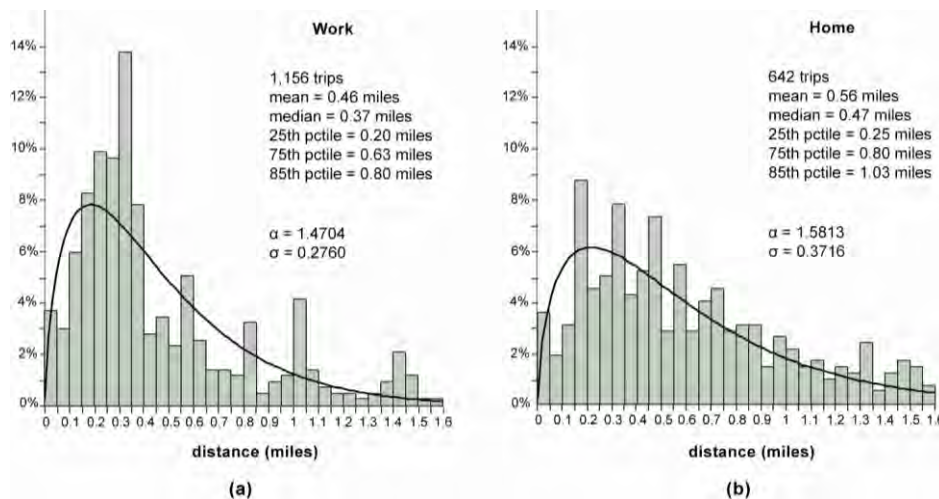
Figure 36. Distances walked between rail stations and (a) work and (b) home nodes.

Gamma functions were fitted to the distributions.

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The most common origins-destination nodes for walking trips were work places (44%) and homes (24.5%). Figure 36, which shows the distributions of self-reported walking distances between these nodes and stations, reveals that riders walked, on average, further for home-related trips. Mean, median, and 85th percentile walking distances are higher between home and station than between workplaces and transit stop. As reviewed in Chapter 2, earlier studies on walking distances to/from rapid rail stations for US travelers determined distances well under half a mile. Average walking distance to/from public transport was found to be 0.29 miles in Orange County (Hsiao et al., 1997); the median distance traveled for light rail was about 0.20 miles in Calgary, Canada (O'Sullivan and Morrall, 1996). Based on these surveys and more, walking distance guidelines adopted by transport and urban planners typically specify distances between 0.25 mile (400 mt) and 0.5 mile (800 mt) for the maximum range of traveling on foot for rail stops. The findings of this study reflect a different outcome than this 'rule of thumb'. Figure 37, which shows the cumulative distribution function calculated for the fitted gamma distribution to all walk trips, indicates that 36% of MARTA riders walked further than 0.5 miles. This result is in line with recent studies which report greater walking distances than are generally considered to be the accepted norm (Agrawal et al., 2008, Burke and Brown, 2007, Olszewski and Wibowo, 2005). The analysis presented here shows that in Atlanta riders are willing to walk considerably longer distances for transport than they may have previously assumed. Distances walked to/from stations are much farther than the ¼ to ½ of a mile range promoted. From a planning point of view this indicates that planners and designers should re-consider the walking distance guidelines when designing TODs, taking into account larger trip distances.

cumulative distributions of walking distance to rail stops
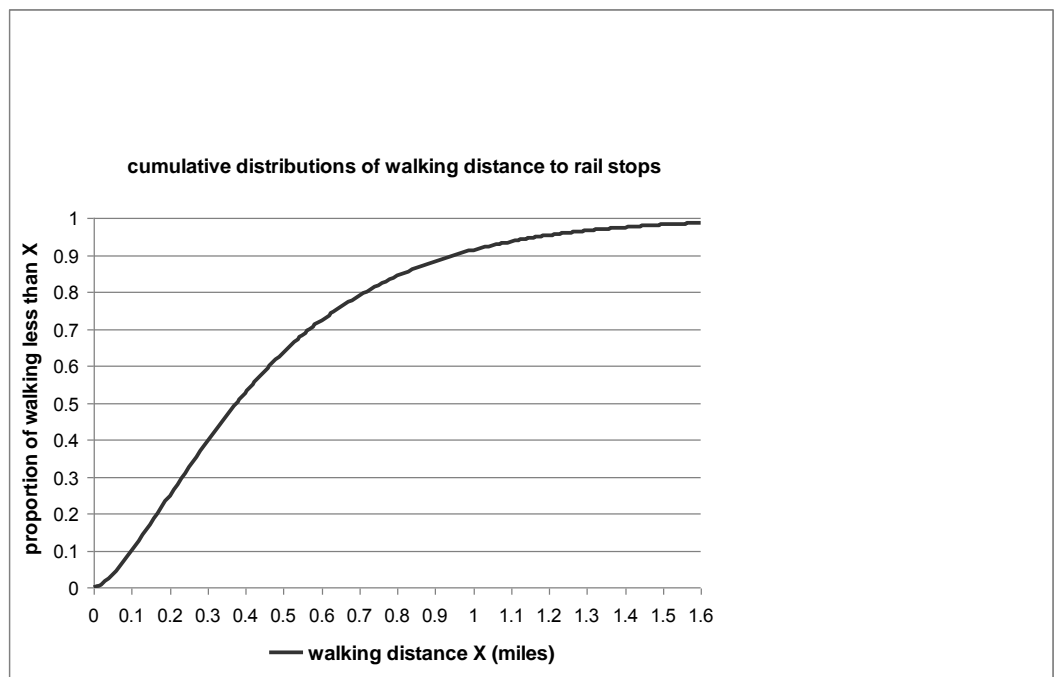
Figure 37. Cumulative distribution of walking distance to all rail stations.

Distances walked for individual rail stops and street network characteristics within 1 mile buffers of stations are summarized in Table 24. Comparisons across station-environments demonstrate notable differences in their street network designs. Comparisons between walking distances point to substantial variations in distances walked for individual stations. The average network walking distance per station ranges from 0.19 miles (Sandy Springs) to 0.67 miles (Midtown). Interestingly, stations such as Doraville and Chamblee, which have low-to-medium average metric reach values, share high average walking distances of 0.67 and 0.66 miles respectively. However; the differences between stations are captured better by studying the standard deviations for walking distances. The higher-end values capture the central city stations, such as Midtown, Ashby, Civic Center and Dome; whereas the lower-ends point to stations located within emerging urban centers at the edge of the city, namely Sandy Springs, Lenox, Dunwoody and Medical Center. These differentiations would appear to parallel the variations in land-use compositions as well as street network layouts in station-

environments. Centrally located stations are characterized by higher concentrations of retail and commercial activities near residences and denser local networks within their surroundings. On the contrary, edge-city station-areas have uneven distribution of development densities along with low-to-moderate street density levels.

In order to account for the variations between walking distances, The Student's t test ($p<0.05$) was used to compare the average and standard deviation of distances between station types, consistent with the analysis run in Chapter 5. For this purpose, station types for 1 mile range, as identified by the hierarchical clustering analysis in Chapter 3 were employed. As shown in Figure 38, comparisons between station types, namely central-city (type1), neighborhood (type2), in-town suburb (type3), and edge-city (type4), confirm the significant range of variation in the distances walked ($p<0.0024$). Results of Student's t test, presented in Table 25, indicate that there is a significant difference between station types 1-4, 2-4, and 3-4 while types 1-3, 2-3, and 1-2 are not statistically different with regard to their average walking distances.

Table 24. Descriptive statistics for network walking distances and network connectivity measures for rail stations

	network walking distance (in miles)					measures of connectivity (for 1mile buffer)			
	mean	std. dev.	median	25th pctile	85th pctile	avg. Reach (1mile)	avg. 2-directional reach (10°)	total street length(mi)	total # inter-sections
All stations	0.47	0.31	0.37	0.23	0.82	26.43	7.75	52.03	316
Five Points	0.40	0.30	0.33	0.21	0.60	41.55	8.74	70.34	536
Dome	0.52	0.41	0.28	0.28	1.08	41.66	9.67	70.69	543
Vine City	0.61	0.27	0.55	0.43	0.91	40.52	11.42	74.04	582
Ashby	0.50	0.45	0.38	0.13	1.10	36.06	8.56	66.73	501
Bankhead	0.39	0.22	0.32	0.22	0.69	26.09	2.99	43.58	270
West Lake	0.59	0.28	0.57	0.34	0.92	20.49	1.29	43.22	261
HE Holmes	0.41	0.17	0.40	0.29	0.64	12.69	8.59	31.73	141
GSU	0.44	0.31	0.36	0.32	0.59	40.56	10.09	69.03	516
King	0.58	0.38	0.54	0.26	1.08	38.26	8.42	68.74	516
Inman	0.62	0.33	0.65	0.31	0.90	30.79	8.70	63.29	389
Edgewood	0.56	0.37	0.46	0.25	0.89	27.08	4.49	57.05	319
East Lake	0.66	0.38	0.69	0.42	1.07	28.80	3.10	53.08	308
Decatur	0.38	0.36	0.27	0.14	0.70	27.44	2.75	53.47	317
Avondale	0.61	0.39	0.58	0.22	0.97	24.16	2.23	49.20	279
Kensington	0.39	0.30	0.39	0.17	0.58	17.80	0.75	41.77	188
Indian Creek	0.47	0.38	0.48	0.01	0.84	12.43	7.99	38.07	162
Garnett	0.62	0.24	0.70	0.41	0.81	40.40	10.75	65.39	458
West End	0.65	0.39	0.69	0.39	1.07	33.33	9.07	60.74	393
Oakland	0.45	0.25	0.42	0.27	0.72	24.26	4.24	55.65	319
Lakewood	0.46	0.18	0.50	0.29	0.68	18.81	8.66	45.68	229
East Point	0.59	0.40	0.47	0.25	1.14	32.70	8.96	62.66	412
College	0.44	0.27	0.49	0.23	0.66	25.57	8.30	52.74	256
Peachtree	0.45	0.37	0.31	0.19	0.94	42.06	9.63	70.27	519
Civic	0.60	0.43	0.41	0.29	1.23	41.15	9.19	70.62	503
N. Avenue	0.59	0.40	0.47	0.28	1.16	39.34	9.91	67.92	466
Midtown	0.67	0.45	0.55	0.25	1.16	33.81	8.07	57.41	375
Arts Center	0.55	0.35	0.51	0.31	0.83	28.07	1.61	48.63	316
Lindbergh	0.31	0.29	0.17	0.12	0.58	18.11	0.81	39.60	190
Lenox	0.35	0.14	0.31	0.31	0.46	16.10	0.78	39.01	167
Brookhaven	0.38	0.29	0.28	0.18	0.83	18.69	2.42	45.08	255
Chamblee	0.66	0.33	0.72	0.44	1.01	17.99	1.72	34.31	172
Doraville	0.67	0.39	0.74	0.37	1.06	15.90	0.95	33.28	145
Buckhead	0.43	0.25	0.51	0.23	0.64	18.75	0.97	38.50	169
Medical	0.30	0.15	0.37	0.22	0.37	11.19	1.03	31.10	98
Dunwoody	0.36	0.15	0.35	0.28	0.50	10.48	1.01	30.30	97
S. Springs	0.19	0.08	0.19	0.10	0.26	12.70	0.76	41.17	160
N. Springs	0.34	0.19	0.33	0.15	0.63	12.05	7.75	41.13	177
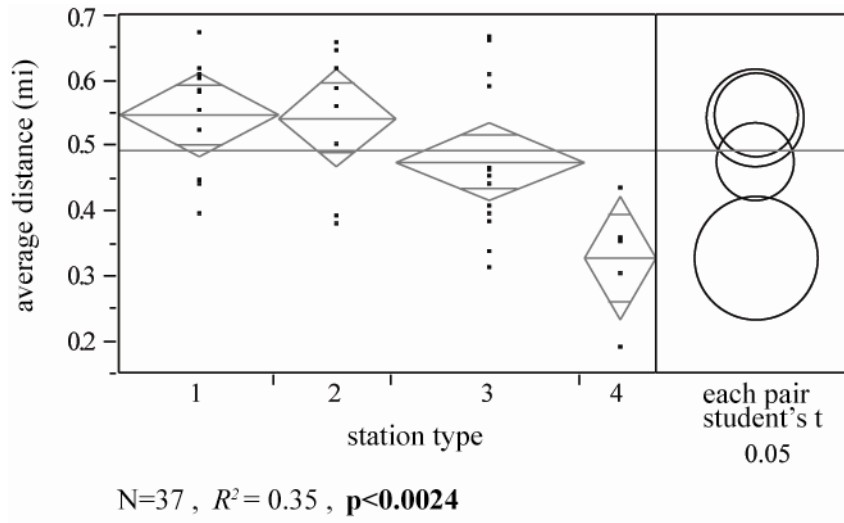
Figure 38. Variations in mean walking distances between station types as defined by the cluster analysis.

Table 25. Results of comparisons of means of average distances between station types using Student's t test

type	type	difference	std err dif	lower CL	upper CL	p-Value
1	4	0.2208	0.0565	0.1059	0.3357	**0.0004**
2	4	0.2153	0.0597	0.0938	0.3367	**0.0010**
3	4	0.1474	0.0551	0.0353	0.2595	**0.0115**
1	3	0.0734	0.0429	-0.0139	0.1606	0.0966
2	3	0.0678	0.0471	-0.0279	0.1636	0.1588
1	2	0.0055	0.0487	-0.0935	0.1045	0.9102

N=37

Figure 39 compares the distributions of average distances walked for transit between central-city and edge-city stations. Contrary to previous findings, which reported much shorter walking distances at CBD stations than distances at suburban ones (O'Sullivan and Morrall, 1996), the distributions illustrate that MARTA riders walked higher on average between stations and origin-destination nodes at central-city stations

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than at edge-city stations. The average walking distance of 4,372 pedestrian trips observed at central-city stations is 0.45 miles while the average distance walked at edge-city stations is 0.34 miles for a total of 260 trips. However; since there is relatively a small number of riders walking at edge-city stations, long walking distances exert a stronger influence on the average walking distance. Thus, in addition to mean values, a comparison of the dispersion of distances would suggest additional insight into walking behavior at varying urban conditions.
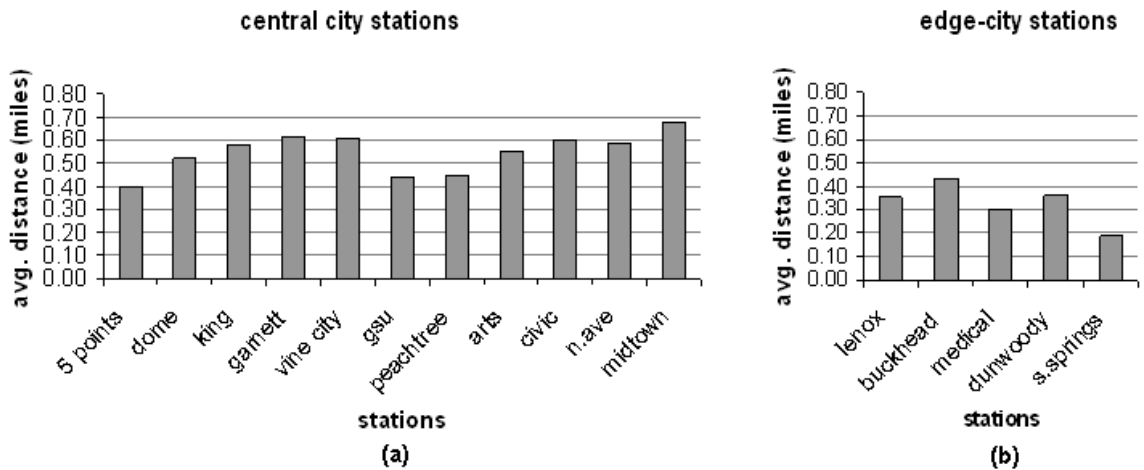
Figure 39. Average walking distances at (a) central-city stations and (b) edge-city stations.

Figure 40 shows that there is a more pronounced difference between station types in terms of the standard deviation of walking distances (p<0.0001). Results of Student's t test presented in Table 26 point also to significant differences between each pair of station types, with the exception of types 2 and 1, in the dispersion of distances.
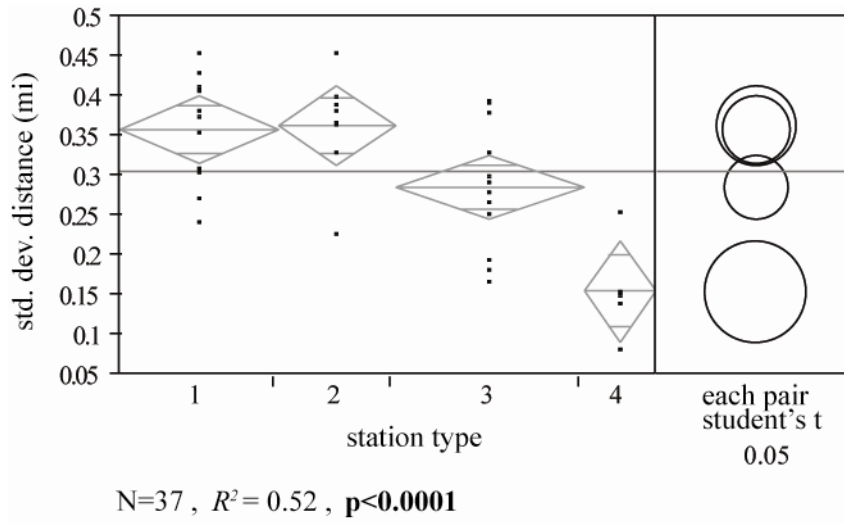
Figure 40. Variations in standard deviation of walking distances between station types as defined by the cluster analysis.

Table 26. Results of comparisons of means of standard deviations of distances between station types using Student's t test

type	type	difference	std err dif	lower CL	upper CL	p-Value
2	4	0.2081	0.0399	0.1269	0.2893	**0.0000**
1	4	0.2023	0.0378	0.1255	0.2792	**0.0000**
3	4	0.1299	0.0368	0.0549	0.2049	**0.0013**
2	3	0.0782	0.0315	0.0142	0.1422	**0.0182**
1	3	0.0724	0.0287	0.0141	0.1308	**0.0166**
2	1	0.0058	0.0325	-0.0604	0.0720	0.8606

N=37

Figure 41 compares the distributions of standard deviations of distances walked for transit between central-city and edge-city stations. The distributions indicate a larger variability among distances walked at central-city stations. Standard deviations for walking distances are 0.34 and 0.17 miles for central-city and edge-city stations respectively.

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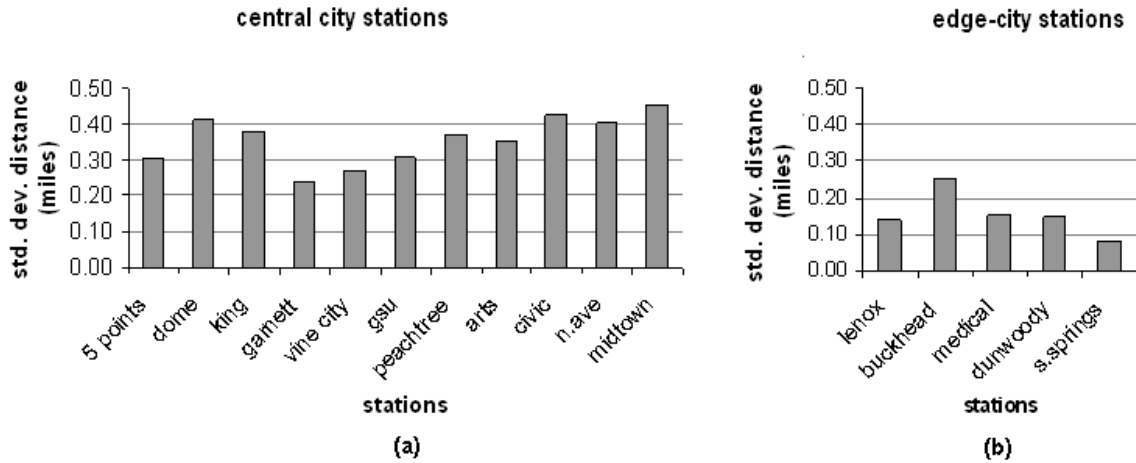
Figure 41. Standard deviation of walking distances (a) central-city stations and (b) edge-city stations.

Based on these initial results, the characteristics of station-environments –density, land-use, and street network– are hypothesized to significantly affect the differences in walking distances. Higher densities of streets and development within the surrounding areas of central-city stations provide commuters with a higher number of potential destinations and the ability to connect to a multitude of attractors. On the contrary, at edge-city stations, poor walking environments due to the paucity of direct and dense connections between activities (i.e. between residential and commercial/retail uses) along with the uneven distribution of land-uses act as an impediment to walking, in terms of both walking trips and walking distances.

Modeling walking distances

This section tests the hypothesis that urban conditions around stations and the location of the station relative to the internal structure of these areas affect the distances walked for transit by developing statistical models predicting the influences of urban form on walking distances. This contributes to the literature reviewed in Chapter 2 by determining the urban form correlates of convenient distance thresholds and investigating to what extent these determinants help extend acceptable walking distances.

Bivariate regression analysis

In order to compare the explanatory power of the standard measures of connectivity and segment-based connectivity measures in explaining distances walked, bivariate regressions were estimated for 1 mile range. This is consistent with the analysis run in Chapter 5. For this purpose walking trips and the associated distances were tabulated according to individual stations.

Figure 42 shows that the standard connectivity measures are significantly correlated with the average walking distances (at a 95% and 99% level of confidence). Total number of road segments, total street length (mt) and total number of intersections (3- and/or 4-way) within 1 mile of stations have positive correlations and produce similar levels of coefficients of determination. The average distance between intersections (mt), or the block face length, has a higher explanatory value with a negative relationship.

(a) n=37, r²=0.17, p<0.0116   (b) n=37, r²=0.17, p<0.0104   (c) n=37, r²=0.19, p<0.0068   (d) n=37, r²=0.27, p<0.0010
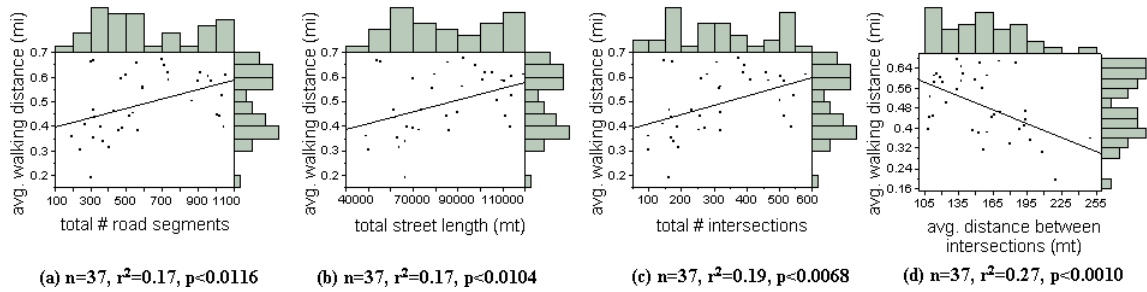
Figure 42. Scatterplot showing average walking distance by station against (a) total number of road segments, (b) total street length (mt), (c) total number of intersections, and (d) average distance between intersections (mt) within 1 mile rings

Figure 43 shows bivariate regressions between the segment-based connectivity measures and the average walking distances. The scatterplots demonstrate that both metric accessibility and directional accessibility are positive and statistically significant (at a 99% level of confidence). The coefficients of determination for all three measures are comparable to that of block face length.

(a) n=37, r²=0.24, p<0.0008   (b) n=37, r²=0.26, p<0.0014   (c) n=37, r²=0.24, p<0.0031
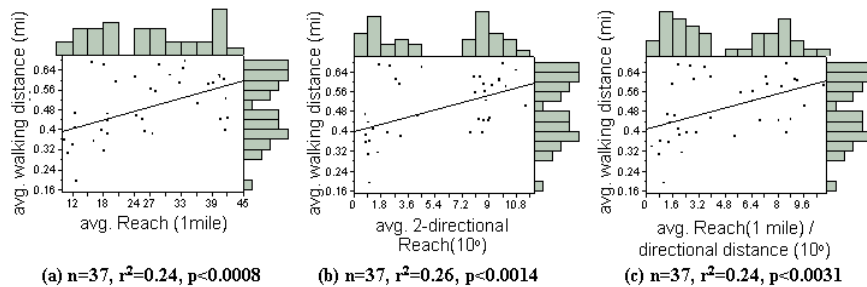
Figure 43. Scatterplots showing average walking distance by station against (a) average Reach (1mile), (b) average 2-directional Reach (10°), and (c) average Reach (1mile) divided by the corresponding average directional distance (10°) for 1 mile rings

In addition to analyzing the average distances, bivariate regressions were estimated for the standard deviation of walking distances in order to understand the urban form factors affecting the variation in distances walked to/from stations[13]. The underlying hypothesis is that distances walked would be more spread in more connected and well-designed station-areas.

Figure 44 shows that standard measures of connectivity are significantly correlated with the standard deviation of distances (at a 99% level of confidence). All four indices have comparable coefficients of determination.

(a) n=37, r²=0.30, p<0.0005   (b) n=37, r²=0.31, p<0.0003   (c) n=37, r²=0.33, p<0.0002   (d) n=37, r²=0.42, p<0.0001
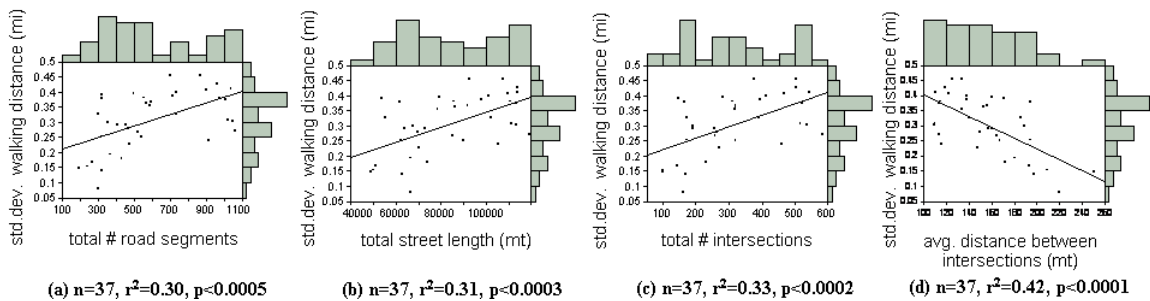
Figure 44. Scatterplot showing the standard deviation of walking distance by station against (a) total number of road segments, (b) total street length (mt), (c) total number of intersections, and (d) average distance between intersections (mt) within 1 mile rings

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[13] Bivariate regressions were also estimated for the index of dispersion (*D*) of walking distances to compare the dispersion of distances walked at stations using a normalized measure of dispersion. This index measures the ratio of the variance (σ^2) to the mean (μ). A full range of correlations are presented in Appendix F (Figures 66-69). The results indicate that measures of connectivity produce marginally higher correlations with standard deviation of distances as compared to the index of dispersion.

Figure 45 demonstrates that segment-based connectivity measures have comparable significance levels and explanatory power to standard measures of connectivity.
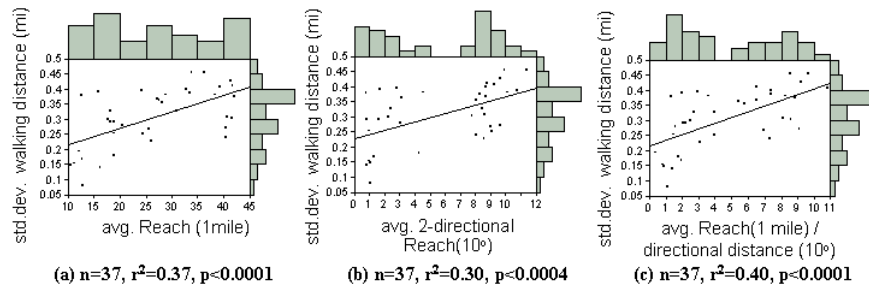
Figure 45. Scatterplots showing the standard deviation of walking distance by station against (a) average Reach (1mile), (b) average 2-directional Reach (10°), and (c) average Reach (1mile) divided by the corresponding average directional distance (10°) for 1 mile rings

Overall, these results indicate that local street network layout within 1 mile of stations has significant associations with walking thresholds. Station-environments with relatively smaller urban blocks, higher densities of available streets and street connections appear to encourage higher average walking distances. This contradicts some of the literature reviewed in Chapter 2 (Handy, 1992). These preliminary results also demonstrate that urban areas with increased potentiality in terms of higher street density and directional distance tend to support a higher variability in distances walked. More important is the finding that apart from density of streets and street intersections, walking distances are strongly correlated with the spatial structure of local street networks. 2-directional reach and the composite connectivity variable, which takes into account the

structural order of accessible streets with regard to direction changes, are significantly associated with both the average walking distances and the dispersion within the distances walked to/from stations. This implies that directional accessibility is as important as metric accessibility in describing street connectivity and the ways in which it helps extend acceptable walking thresholds.

Consistent with the analysis of walk-modes shares reported in Chapter 5, bivariate regressions were estimated between the PEF measure and walking distances. Equally consistent with the previous results is the rather poor ability of the composite factor to explain the variations in both the average distances and variability of distances. Figure 46 demonstrates that correlations are significant only at a 90% level of confidence, with low resultant coefficients of determination.

(a) n=37, r^2=0.09, p<0.0673   (b) n=37, r^2=0.15, p<0.0189
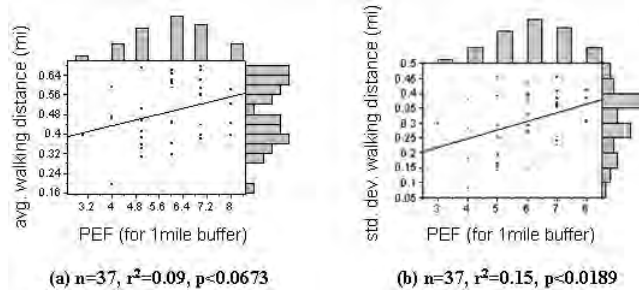
Figure 46. Scatterplots showing the PEF measure calculated for 1 mile range against (a) the average walking distance, and (b) the standard deviation of walking distance by station within 1 mile rings

Apart from the properties of street networks within the surrounding areas of stations, the location of the station relative to the internal structure of these areas was also investigated to identify whether the differentiation between well and less well connected road segments and streets within a given area affected distances walked. Figures 47 and

48 demonstrate the scatterplots showing the relative measures of connectivity against the average and standard deviation of walking distances respectively. Against expectations, the measures did not produce any statistically significant correlations between walking distance indices. This finding further corroborates earlier results on walk-mode shares. Therefore, the evidence relating the relative significance of the station's location within the buffer to walking behavior was deemed not to affect the distance walked.

(a) n=37, r^2=0.01, p<0.4990   (b) n=37, r^2=0.02, p<0.4050   (c) n=37, r^2=0.000, p<0.9890
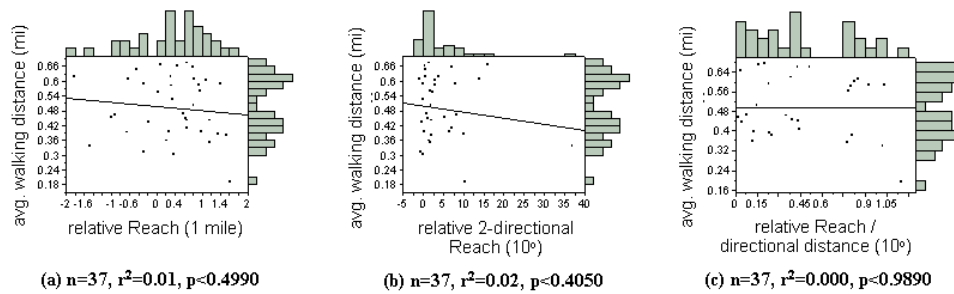
Figure 47. Scatterplots showing average walking distance by station against (a) relative Reach (1mile), (b) relative 2-directional Reach (10°) for 1 mile rings, and (c) relative Reach (1 mile) divided by the corresponding directional distance (10°) for 1 mile rings

(a) n=37, r^2=0.04, p<0.2459   (b) n=37, r^2=0.03, p<0.2919   (c) n=37, r^2=0.001, p<0.8922
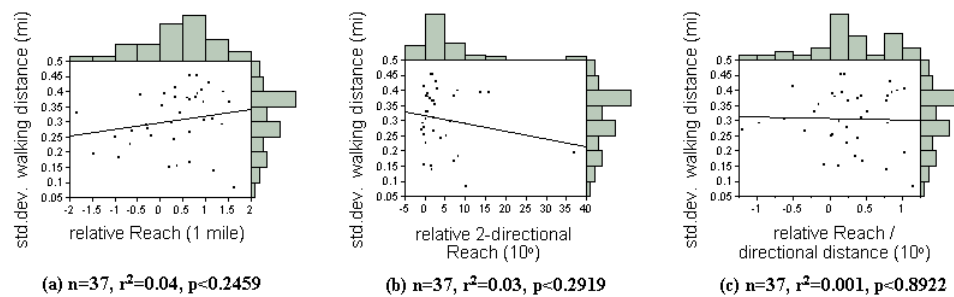
Figure 48. Scatterplots showing the standard deviation of walking distance by station against (a) relative Reach (1mile), (b) relative 2-directional Reach (10°) for 1 mile rings, and (c) relative Reach (1 mile) divided by the corresponding directional distance (10°) for 1 mile rings

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Stepwise and Multivariate regression analysis

Additional analysis examining the link between urban form and walking distances help further clarify the relationship identified between urban form and distances walked for transit. When stepwise regressions based on the forward selection method were estimated for different walking distance indices controlling for transit service characteristics and socio-demographic attributes, two of the urban form variables, namely street connectivity and population density, entered the models as most significant predictors. In the models developed for predicting the average walking distances, shown in Tables 27 and 28, connectivity measures were found to be the most statistically significant variables. Although the coefficients for metric reach (1 mile) and metric reach (1 mile) divided by directional distance (10°) are positive, the composite connectivity measure has a lower significance level than metric reach. In the stepwise regression model estimated with the inclusion of metric reach (Table 27), the coefficients for mixed-land-use index and feederbus services are marginally significant (at a 90% confidence level). Surprisingly, the sign of land-use mix is negative, which is contrary to a priori expectations and earlier results. The computation of land-use mix entropy is based on six different categories, as explained earlier. It can be speculated that while entropy is an efficient indicator of spatial inter-mixing among land-use categories within an area, it might not yield a better understanding of walking distance analysis. This suggests that categorizing land-uses with different categories, such as only considering residential and non-residential uses, might be a better approach. Clearly, the inclusion of subsequent variables into both models enhanced the overall predictability.

Table 27. Parameter estimates for step-wise regression model estimating average walking distance to/from stations

average walking distance by station	B	F	prob>F	B	F	prob>F	B	F	prob>F	B	F	prob>F
avg. Reach (1mile)	**0.006**	**11.28**	**0.002**	**0.008**	**17.32**	**0.000**	**0.009**	**21.28**	**0.000**	**0.012**	**21.46**	**0.000**
mixed-land use index[†]				*-0.454*	*4.837*	*0.035*	*-0.384*	*3.529*	*0.069*	*-0.379*	*3.61*	*0.067*
Feederbus services (0=no, 1=yes)							*-0.060*	*3.03*	*0.091*	*-0.06*	*3.606*	*0.067*
service frequency[‡]										*-0.003*	*2.42*	*0.130*
N=37												
R²		0.24			0.34			0.39			0.44	
std. error		0.01			0.01			0.01			0.01	

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:

$$^†Mixed-use\ entropy = -1 \times \left(\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right)$$

[‡] number of inbound trains in am peak hour (7am-9am)

Table 28. Parameter estimates for step-wise regression model estimating average walking distance to/from stations

average walking distance by station	B	F	prob>F	B	F	prob>F	B	F	prob>F	B	F	prob>F
avg. metric reach(1mile) / directional reach (10°)	**0.018**	**9.59**	**0.004**	**0.022**	**13.11**	**0.001**	0.014	2.40	0.131	*0.018*	*3.93*	*0.056*
mixed-land use index[†]				*-0.362*	*3.01*	*0.092*	*-0.414*	*3.86*	*0.058*	-0.303	2.01	0.166
population density: persons per gross acre within 1 mile of station							0.014	1.61	0.213	0.018	2.87	0.100
station structure type[ᵇ]										0.018	2.16	0.132
N=37												
R²		0.22			0.28			0.31			0.40	
std. error		0.01			0.01			0.01			0.01	

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:

$$^†Mixed-use\ entropy = -1 \times \left(\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right)$$

[ᵇ] types of station structure: at-grade, elevated, underground

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While stepwise methods are helpful in sorting out the most significant measures from a large number of potential explanatory variables, without appreciably increasing the residual sum of squares, they have been criticized for overfitting the data and for being biased towards yielding high coefficients (Draper and Smith, 1981). Hence, the findings of the stepwise regressions were tested against a multivariate regression model in which all variables were entered simultaneously. Table 29 presents the multivariate model predicting average walking distance. As parameter estimates indicate the resultant coefficient of determination is higher than of the stepwise model, and while there is a decrease in the significance level of metric reach, this measure still proves to be the only significant variable in the model (at a 99% confidence level).

By contrast, connectivity measures did not prove as powerful in explaining the dispersion of walking distances, and thus did not enter the models predicting the standard deviation of distances. Stepwise regression model produced for predicting the range of variation in the walking distances (Table 30) shows population density within 1 mile of stations alone explained 45% of the standard deviation[14]. Inclusion of the subsequent variables improved the predictive power of the model, albeit modestly. Among the variables entered into the model the most statistically significant variable is population density (at a 99% confidence level). While land-use mix is significant at a 95% level of confidence, it has a counterintuitive sign. The coefficient for metric reach is marginally significant (at a 90% confidence level).

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[14] Stepwise and multivariate regression models were also estimated for the index of dispersion (D) of walking distances to compare the dispersion of distances walked at stations using a normalized measure of dispersion. The model results are presented in Appendix F (Tables 48-49). The results suggest that population density is the only significant variable in the models.

Table 29. Parameter estimates and residual plot for the multivariate regression model estimating average distances walked to/from stations

Multivariate Regression Model

average walking distance by station	β	t	prob>|t|
constant		1.030	
auto ownership relativized by per-capita income*	-0.082	-0.346	0.732
station structure type[■] (underground)	-0.055	-1.683	0.104
station structure type[■] (elevated)	0.033	1.295	0.207
station structure type[■] (at-grade)	0.022	0.779	0.443
service frequency[‡]	-0.003	-1.314	0.200
feederbus services (0=no, 1=yes)	0.050	1.200	0.241
parking supplies (0=no, 1=yes)	0.015	0.445	0.660
avg. Reach (1mile)	**0.012**	**2.826**	**0.009**
sidewalk availability[■]	13.770	0.100	0.921
population density: persons per gross acre within 1 mile of station	0.009	0.680	0.502
mixed-land use index[†]	-0.323	-0.939	0.356
N		37	
R^2		0.50	
R^2 adjusted		0.31	
std. error, S_e		0.11	
Prob>F		0.022	
coefficient of residual variability, V_e		21.0	

Numbers in bold = p< 0.01; numbers in italics = p<0.05
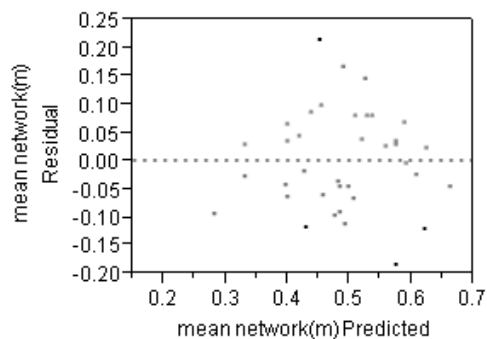
Notes:
[■] proportion of roads with sidewalk

$$^{†}Mixed-use\ entropy = -1 \times \left(\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right)$$

[■] types of station structure: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

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Table 30. Parameter estimates for step-wise regression model estimating standard deviation of walking distances to/from stations

standard deviation of walking distance by station	B	F	prob>F	B	F	prob>F	B	F	prob>F
population density: persons per gross acre within 1 mile of station	**0.024**	**28.31**	**0.000**	**0.028**	**34.22**	**0.000**	**0.020**	**8.74**	**0.006**
mixed-land use index[†]				*-0.27*	*3.99*	*0.054*	**-0.33**	**5.86**	**0.021**
avg. Reach (1 mile)							*0.00*	*3.02*	*0.092*
N=37									
R²		0.45			0.51			0.55	
std. error		0.01			0.01			0.01	

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:

$$^{†}Mixed-use\ entropy = -1 \times \left(\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right)$$

When the findings of the stepwise regression are tested against a multivariate model (Table 31), it is found that the overall coefficient of determination is comparable to the one produced by the stepwise model, but there is a noticeable decrease in the significance levels of the coefficients. While metric reach and population density is marginally significant (at a 90% confidence level), land-use mix is no longer statistically significant. Based on the comparative results of stepwise and multivariate regression models, it can be argued that station-environments with higher population densities within 1 mile of their radii promote wider range of distances walked for transit.

Table 31. Parameter estimates and residual plot for the multivariate regression model estimating the standard deviation of distances walked to/from stations

Multivariate Regression Model

standard deviation of walking distance by station	β	t	prob>|t|
constant		2.507	
auto ownership relativized by per-capita income*	-0.224	-1.361	0.185
station structure type[■] (underground)	-0.011	-0.469	0.643
station structure type[■] (elevated)	-0.006	-0.344	0.734
station structure type[■] (at-grade)	0.017	0.860	0.398
service frequency[‡]	-0.002	-1.542	0.135
feederbus services (0=no, 1=yes)	-0.016	-0.567	0.576
parking supplies (0=no, 1=yes)	-0.003	-0.140	0.890
avg. Reach (1mile)	*0.006*	*1.898*	*0.069*
sidewalk availability[■]	-98.557	-1.041	0.307
population density: persons per gross acre within 1 mile of station	*0.015*	*1.723*	*0.097*
mixed-land use index[†]	-0.338	-1.427	0.165

N	37
R²	**0.61**
R² adjusted	**0.46**
std. error, S_e	**0.07**
Prob>F	**0.002**
coefficient of residual variability, V_e	**23.3**

Numbers in bold = p< 0.05; numbers in italics = p<0.10
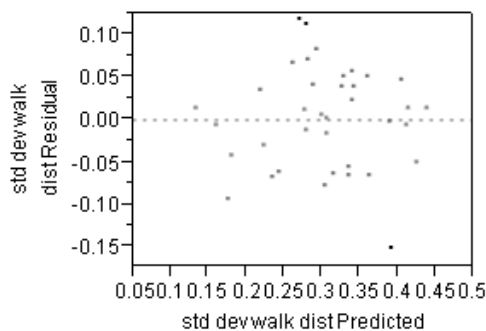
Notes:
[■] proportion of roads with sidewalk

$$^{†}Mixed-use\ entropy = -1 \times \left(\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right)$$

[■] types of station structure: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

To conclude this section, the results of stepwise and multivariate regression models confirm the findings of bivariate regression analyses that street network layout is the primary determinant of average distances walked for transit, over and above other determinants included in this study. Both metric and directional accessibility play a major role in extending acceptable distance thresholds. Increasing the density of streets and reducing direction changes within 1 mile of stations results in higher average walking distances to/from MARTA rail stations. The models also suggest that controlling for non-urban form attributes, population density within walking distance of stations exert the strongest influence on the dispersion of walking distances. The importance of population density may lie in its role as a surrogate for perceived factors, such as the increased sense of safety due to higher number of people within the surrounding areas. Overall, stepwise and multivariate regression analyses were useful in examining the significance of variables derived from connectivity networks. However; the residual plots for multivariate regression models illustrate that points are not evenly distributed about the x-axis. This suggests that a host of other variables, such as the ease of street crossings, attractive landscaping, traffic signaling, and the availability of other pedestrian amenities, might enhance the overall predictability as well as the distribution of residuals obtained from the models. Considering the complexity of modeling walking behavior, the variables to be included in such models would vary from case to case. These can be addressed through future research. However, the results of stepwise and multivariate regressions estimated show that the connectivity measures are significantly associated with walk-mode shares. Thus, adding additional variables to the models is not likely to affect the significance of the connectivity measures noticeably.

Lastly, combining the results from the analysis of walk-mode shares and walk trip distances, the reciprocal influence between the proportion of walking and distances walked were addressed. Simple bivariate regressions, estimated between the proportion of walking trips and walking distances, aggregated at the station level, reveal some informative patterns. Figure 49, which shows the pairwise scatterplots, indicates that walk-mode shares have a statistically significant association with the variations in walk trip distances. Correlations point to an increase in percent walking with an increase in both the average walking distances (Figure 49a), and the dispersion of distances walked (Figure 49b). This point holds significance for policy makers and transportation, planning, and public health investigators in understanding whether the two policy components –energy saving and public health– have concomitant positive health effects on travelers as well as transportation benefits. Consequently, these findings can provide a useful basis for assessing the extent to which a policy aimed at increasing public transportation and thus reducing energy consumption can also directly impact on health targets.
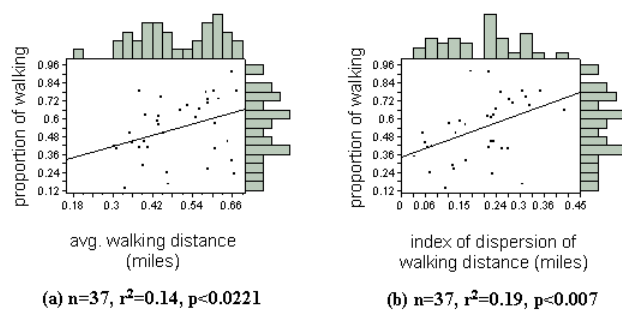
Figure 49. Scatterplots showing walk-mode shares by station against (a) average walking distance, and (b) index of dispersion of walking distance

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CHAPTER 7

CONCLUSIONS AND FUTURE DIRECTIONS

Outline of findings

In this research, linear models were developed to determine whether urban form variables are significantly associated with different walking behaviors, namely transit walk-mode shares and walking distances to/from stations, while controlling for individual socio-demographic characteristics and transit service features. Overall, the analyses presented here confirm the hypothesis that local conditions around MARTA rail stations are significantly related to riders' choice to walk to/from transit. Of course, these relationships do not necessarily indicate causality.

The three dimensions of urban form do not all matter equally. While mixed-use neighborhoods around stations increase the odds of walking to/from transit, higher station-area population densities promote a wider range of distances walked to/from stations. More significantly, street networks with denser and more direct connections are associated with higher proportion of walking shares among station patrons as well as longer average walking distances.

The findings of this research lend specific support for three main conclusions that have significant implications for urban planning and urban design decisions aimed to reduce automobile dependence and induce non-auto commuting. These will be summarized under four headings: surrounding street connectivity, station location, walking distances, land-use and population density.

Surrounding street connectivity

The results of this study emphasize the importance of including measures of street connectivity in transit-oriented studies. It is shown that street connectivity is strongly associated with walk-mode shares when controlling for transit service characteristics as well as population density, land-use mix and personal attributes in buffers of 1, 0.5, and 0.25 mile radius around the stations.

Street connectivity was measured using standard planning measures (total street length, total number of intersections, total number of road segments, average distance between intersections), and more recent road-segment-based measures, metric reach and directional reach. The density of street intersections has an impact on transit walk-mode shares as well as distances walked. However, the results presented here also underscore the significance of the spatial structure of street networks, specifically the alignment of streets and the directional distance hierarchy engendered by the street network. Directional accessibility plays as significant a role as metric accessibility in affecting the proportion of riders walking for transit. But the strongest correlations are obtained when considering metric and directional accessibility in conjunction, by taking the ratio of metric reach over directional distance.

Station location

The segment-based connectivity measures also allowed testing a subtler hypothesis that the location of a station relative to the street hierarchy of the surrounding area plays a role in affecting the proportion of riders walking for transit or the distance walked. The hypothesis was rejected. The results of linear models predicting walk-mode

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shares and walking distances showed that the specific location of the station within the surrounding area did not matter as did the average properties of street layout around transit.

This is in apparent contrast with earlier findings reported in Chapter 2 demonstrating that spatial hierarchy of street networks tend to be directly related to the distribution of pedestrian movement (Hillier et al., 1987, Ozbil and Peponis, 2007, Peponis et al., 1989). The convergence of higher densities of movement on particular streets, however, probably expresses a number of underlying trends: first, more paths linking a variety of origins and destinations go through the most integrated streets; second, the most integrated streets attract uses which are dependent upon pedestrian movement, such as street-front retail; third, integrated streets register more prominently in the cognitive maps of areas. As these factors work together, it is natural that streets which are better integrated into their surroundings will attract more movement. Walking to the station, on the other hand, is a purposeful kind of movement, directed towards distinct destinations. The fact that the likelihood of walking to the station is not affected by the relative location of the station within the local spatial structure of an area is, with hindsight, not surprising: people are likely to be able to learn the way to the station even if the station is not located on the most prominent streets; they are likely to use the station even when it is not adjacent to other attractors such as shops; and the use of the station is not likely to be affected by whether the station lies on the way to other destinations.

Thus, the rejection of the original hypothesis does not challenge previous syntactic findings in any fundamental way. Rather, it suggests a need to sharpen some distinctions within the theory of space syntax. First, the distinction between the

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characteristics of areas which encourage movement in general, and the characteristics of areas in which movement is directed to particular destinations. Second, the distinction between the kinds of movement which benefit from the synergies that come together on the most integrated spaces (cognitive prominence, convergence of a variety of paths, attraction of pedestrian friendly land-uses), and the kinds of movement that are directed to specific points of attraction, such as transit stations, independent of such synergies.

Walking distances

Walking for transit emerges as an important component of travel in the Atlanta Metropolitan Area. Based on the detailed information presented on the distances walked for rail stops, it is shown that riders are willing to walk substantial distances for transport. The mean and median distances riders walked to/from rail stations were 0.47 and 0.38 miles respectively, while 85th percentile walking distance was 0.82 miles. These numbers are in contrast with the findings of previous studies relating to US riders reviewed in Chapter 2 and the conventional wisdom among planners which suggests ¼ to ½ of a mile as walking distance threshold.

Cumulative distribution of distances walked to/from stations indicates that half of the walk-on riders walk over 10 minutes[15]. This corresponds to a significant portion of the recommended levels of minimum 30 minutes of physical activity daily (U.S. Department of Health and Human Services, 1996, Pate et al., 1995). Moreover, the findings suggest that 15% of the walk-on riders walk 20-32 minutes, which almost meets the outlined recommendation. Research to date has demonstrated a strong link between

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[15] Based on an average pedestrian walking speed of 3 miles an hour.

the built environment and obesity (Ewing et al., 2003, Saelens et al., 2003, Frank et al., 2003). The findings reported here clearly indicate congruence between the aim of fighting obesity and the aim of increasing transit mode-share. They also implies that planners and designers developing neighborhoods that would be served by transit should re-consider walking distance guidelines based on larger walk trip distances than are generally the norm. The same is true for transportation modelers who have tended to assume shorter walking distances in the models.

More important, the results of analyses for walk trip distances indicate that changes in local urban conditions around stations affect the distance riders are willing to walk. Specifically, the models point to the fact that street network configuration is a primary determinant of the variation in average walking distances, controlling for urban form and non-urban form factors. Both metric accessibility and directional accessibility play a major role in extending acceptable distance thresholds. Based on the effect levels and significance levels of both measures, it can be concluded that increasing density of available streets and reducing direction changes within 1 mile of stations results in higher average walking distances to/from rail stations. To date, research on factors influencing distances people walk for transit have turned to perceptual qualities of environments, such as street crossings, attractive landscaping, tree covers, and signalization (Agrawal et al., 2008, Cao et al., 2007). However; there has been little information regarding the role of street configuration on distances walked. The results of this study confirm the premise that station-area characteristics affect convenient distance thresholds and that walkable environments encourage higher average walking distances by creating vibrant and safe urban conditions. The empirical findings presented here can provide researchers and

planners with specific tools to design urban environments that would induce riders to walk more often and for greater distances.

Land-use and population density

The spatial structure of street network does not work independently of land-use. On the contrary, based on the standardized coefficients estimated in regression models, street network and land-use mix have comparably high positive impacts on transit walk-mode shares. The findings suggest that higher levels of land-use mix encourage people to walk for transit when analyzed at 0.5 and 1 mile ranges. In addition, once other urban form variables are controlled for, population density has no statistical significance in explaining percent walking. This might be supportive of the argument that employment density exerts a stronger influence on the variation in mode choice for walking (Frank and Pivo, 1994), and that combined population and employment densities has a greater degree of explanatory power over mode shares (Parsons Brinkerhoff Quade and Douglas Inc., 1996a). Thus, future research should take into account employment density in addition to population density.

Besides these primary findings, this research also suggests additional insights meriting further study. The analyses indicate that urban form measured at a smaller geographic unit, such as neighborhood scale and road segment level, might more clearly detect the impacts of neighborhood-scale initiatives –i.e. TODs– on non-motorized travel patterns. Finer grain research, including parcel information on land-use as well as detailed information on walk trips are needed to inform specific design and planning decisions aimed at increasing the likelihood of transit use and walking through the

creation of lively walkable environments around transit stations. This finer grain research would require a very generous budget to collect rich parcel-level land-use data and to obtain more detailed information on walk trips than is generally available from regional travel surveys. Based on the evidence presented in this study, these types of finer-grained design rules can enhance smart growth's design scenarios.

Limitations

The study also has limitations that must be clearly acknowledged. One concern is that some potentially critical variables were not explicitly considered, due to the limitations of the available data. For example, it is hard to separate the influences of urban form from those of self-selection. It is probable that individuals choosing to walk or to ride transit will choose neighborhoods supportive of these preferences. Past research has shown self-selection to be significantly associated with travel behavior (Kitamura et al., 1997, Krizek, 2003). In this study, the individual and household preferences were to some extent controlled for indirectly, through the inclusion of socio-demographic measures that are likely to impact preferences. Future work that uses attitude surveys along with travel diaries would arrive at more definitive conclusions with regard to the possible causal relationship between urban form and non-motorized travel.

Another example of a potentially confounding variable is age. It is possible that areas with similar street connectivity characteristics, and even similar population densities and land-use-mix characteristics will be associated with different walking behaviors if they are characterized by different age pyramids: older people may be less able to walk than younger one, for example. The lack of an age variable in the survey did

not allow explicit control for this variable. This is yet another reason why no causality should be uncritically inferred from the statistically significant associations reported in this thesis.

Another component missing in the study design is related to the design of stations, which captures micro-scale design elements –i.e. characteristics of station entrances– indicating how well stations are embedded within their local urban environments. It is highly probable that stations which are immediately connected to the street-level would be more attractive to pedestrians than stations which are surrounded by parking. In this study, the physical design aspect of the rail station was to some extent controlled for indirectly, through the inclusion of a "station structure" variable (i.e. at-grade, elevated, underground). However, investigation into the individual components of station design would require comparisons of stations with similar socio-demographics as well as street network layout. The limited number of stations available in the current data-set did not allow explicit control for this measure. Future work that encompasses a larger set of transit nodes would shed light to the association between station design and walking behavior.

A different concern with the results presented is whether they can be generalized to other areas or cities. As acknowledged in Chapter 4, Atlanta represents an extreme case in the spectrum of urban conditions in the US –a low density city with high levels of highway travel as well as transit patronage. Hence; the results from a study of Atlanta are not intended for drawing generalizable conclusions but rather as contributions to the future development of a particular kind of environment. A logical extension of the work presented in this study would be to expand the case studies to validate further or falsify

the findings of this research. These caveats notwithstanding, the findings presented in this research support the hypothesis that environments are not isotropic. Some are more conducive to walking due to different density of interface generated by connectivity patterns and local spatial structure of street networks, as well as diverse land-use patterns.

Implications

Apart from theory building, this research also holds validity for more practical implications. The findings confirm the hypothesis that well structured and differentiated street networks affect not only transit access/egress walk-mode shares but also the distance people are willing to walk to/from a station. These results are not intended as contributions to the development of transportation models, even though they might point to a possible revision of assumptions regarding walking distances, as noted above. Rather, they are likely to guide future efforts to integrate subdivision provisions and regulations with zoning regulations in developing currently sparse suburban areas towards dense transit-oriented urban hubs.

Traditional models estimating development impacts are based on the consideration of socio-demographic factors and transit service related features, but they do not take into account the structural qualities of street networks. The evidence in this study confirms the premise that the demand for public transport-related walking is significantly influenced by the configuration of street layout. In fact, a comparison of standardized coefficients in the models reveals that connectivity measures have larger effect sizes than those of socio-demographic attributes and transit-related variables. Thus, incorporating measures of street density and measures of directional accessibility in

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transit-oriented studies can lead to enhanced models of urban form and function, which, in return, can inform specific urban design and urban master planning decisions.

Other potential implications can best be drawn when this study is considered in the context of the larger literature on the syntactic analysis of cities reviewed in Chapter 2, as well as the work presented in the appendices. Street classification systems, particularly as they inform street section design, could be informed by the fact that the connectivity of street networks, including their internal structure and hierarchy, plays a role in distributing pedestrian movement and in influencing acceptable walking distances. For example, the provision of more generous sidewalks on spatially more prominent streets would make good sense in the light of the association between measures of street connectivity and densities of walking (Appendix B). Also, extensive sidewalks should be a higher priority in areas which have denser street intersections and a clearer internal hierarchy of access based on directional distances.

The findings outlined above and the discussion of their limitations and possible extensions converge onto one main idea. There are good reasons why transit planning, street network design and street design must be reintegrated, both in practice and in the knowledge that supports practice. From the viewpoint of walking to the station, the spatial configuration of the network is an integral part of the transit system on a scale considerably larger than the immediate vicinity of the station. In fact, a well-designed street systems help augment (positive side effects for public health) and spread (increasing walking distance thresholds) the value of a station making it more attractive. This study is a contribution to better understanding the synergies between street network design, transit planning and station design.

APPENDIX A

The Effects of Street Configuration on Transit Ridership

Empirical research dealing with how built environments can influence travel behavior has been framed around three properties of environment: density, land-use and the design of street network. There is a substantial amount of literature that has acknowledged density as a significant predictor of travel choice (Badoe and Miller, 2000, Marshall and Grady, 2005, Pushkarev and Zupan, 1977, Smith, 1984). A plethora of recent studies have suggested that compact developments with higher densities generate fewer vehicle trips and encourage non-motorized travel by reducing the distance between origins and destinations; by offering a wider variety of choices for commuting and a better quality of transit services; and by triggering changes in the overall travel pattern of households (Cervero and Kockelman, 1997, Ewing et al., 1994, Holtzclaw, 1994, Krizek, 2003). A number of empirical studies have identified threshold densities to give planners a sense of whether there is a reasonable possibility for transit to work in different settings. Newman and Kenworthy (1999) recommend densities above 30 to 40 persons per hectare (12 to 16 persons per acre) for public transit-oriented urban developments.

Studies regarding the measurable impacts of land-use characteristics on transit use and mode of access to transit have verified that high land-use mix at the trip origins and destinations yield in increase in transit shares and non-auto commuting (Cervero, 1996, Cervero, 2006, Holtzclaw, 1994) and induce walking (Cervero, 1988, Frank and Pivo, 1994). The general inferences that can be drawn from these studies are that the characteristics of areas around stations strongly influence the ways in which patrons travel to and from transit: in employment centers land-use mix is found to contribute to increasing use of transit; while, in residential neighborhoods urban design that supports pedestrians is shown to influence the mode of access to transit, that is whether people

walk or drive to the station. Pedestrian-friendly neighborhoods are claimed to be more congenial to transit use as well as to walking.

Empirical investigations evaluating how the built environment shapes travel choices have mainly focused on road network designs, characterized by local street connectivity, block sizes, the density and pattern of intersections and block face lengths among other factors (Boarnet and Crane, 2001, Cervero and Kockelman, 1997, Siksna, 1997, Southworth and Owens, 1993). Pertinent analysis has computed higher NA (neighborhood accessibility) levels for communities with higher street intersection densities or lower average block areas (Krizek, 2000, Krizek, 2003). A common theme of this body of research is that inordinate size of street blocks or the lack of a fine-grained urban network of densely interconnected streets fails to promote walking (Ewing et al., 2003, Hess et al., 1999).

In spite of the plethora of studies on the influences of land-use, density, and urban form on transit use, no conclusions emerge on the relationships between street networks and travel. A limitation of these studies is the difficulty to develop well-specified statistical models that allow researchers to accurately evaluate the individual effect of street network. Part of the reason is due to collinearity between density, land-use mix and urban form. Fairly compact neighborhoods in US cities generally have more varied land-uses, on average shorter block lengths with more grid-like street patterns. Thus, the effect of street network design on overall travel remains unclear.

The connectivity measures used in this research (Peponis et al., 2008) offer a systematic framework for evaluating impacts of the layout of streets on ridership, controlling for the multi-collinearity caused by various other aspects of the built

environment. The analysis is based on standard GIS-based representations of street networks according to street center-lines. The unit of analysis is the road segment. Road segments extend between choice nodes, or street intersections at which movement can proceed in two or more alternative directions. Road segments may contain one or more line segments. A line segment is the basic unit of the map drawn and is always defined as a single straight line. Thus, unlike the axial line map, this analysis treats the unit of analysis (the road segment, for which the individual values are computed) and the unit of computation (the line segment which provides the base metric for values) as different entities. Figure 1 illustrates the new unit of analysis by clarifying the difference between road segments and line segments.

Analysis is based on finding the subset of street center-lines and parts of lines that can be reached subject to some limitation. When the limitation is metric distance, the total length of street reached is called metric reach, Rv, and the set of segments Sv. When the limitation is a number of permissible direction changes, the total length of streets reached is called directional reach, Ru, and the set of street segments Su.

a: urban area   b: nodes
                ○ line node
                ● road node

c: network   d: road segments
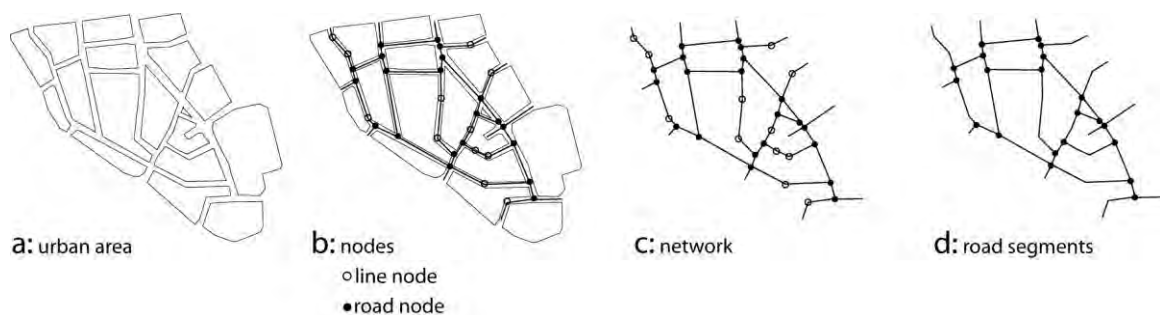
Figure 50. Definition of Road Segments.

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We analyzed average annual daily station boardings for the year 2007 per transit station in Chicago (CTA), Dallas (DART), and Atlanta (MARTA). In order to judge how the radius distance for the analysis affects results, all areas were analyzed at 0.25, 0.5 and 1 mile radii. Similarly, we established population densities for the same surrounding areas using US 2000 census data. We measured street connectivity using metric and directional reach based on ESRI Streetmap 2003 maps. We also factored in transit service features, namely supply of park-and-ride facilities, availability of feederbus services, and service potential that is the number of intersecting rail routes at each station. When multivariate regressions are run for 3 ranges separately, street connectivity is found to be a rather significant predictor of ridership levels in all three catchment areas when controlling for population density and transit station measures. However, the best results are obtained for the 0.5 mile range. This supports the findings of various studies which suggest that within short distances people will walk to transit regardless of local street connectivity (Cervero, 1993, Lund et al., 2004). In other words, people residing within 0.25 mile distance from a station are inclined to use transit irrespective of the street connectivity levels of the station area. Higher correlation coefficients within the 0.5 mile buffer suggest that the decision to walk a slightly longer but still very manageable distance is strongly affected by the density of street connections. The effect becomes weaker when we look at 1 mile radius, because the extra effort to walk a considerably longer distance begins to overpower the positive influence of connectivity.

We then produced "standard", "urban form", and "reduced" models for average annual daily boardings for 0.5 mile wide ring to identify the statistical significance levels of all variables and to capture the unique contributions of connectivity measures to the

overall model. The "standard" model includes control variables, which are the city variable, distance to CBD from each station, transit service features, and station-area population densities. The "urban form" model is constructed by the inclusion of connectivity measures, metric reach (avg Reach) and 2-directional reach (avg R_2), in addition to controls. The "reduced" model shows the extracted measures which are statistically significant at the 0.01 level in the "urban form" model. Table 32 presents the results of effect tests for the three models. Consistent with theory, ridership levels are sensitive to the population density around stations. However; the high positive coefficients on the park-and-ride and service potential variables support the argument that residential density thresholds are interrelated with various factors such as measures of transit operational levels and the supply and price of parking (Parsons Brinkerhoff Quade and Douglas Inc., 1996a, Pushkarev and Zupan, 1982). When we introduce control variables, 31% of the variation in transit ridership is explained. When the "urban form" model is examined, connectivity measures, metric reach and 2-directional reach, add moderate explanatory power of 5% point to the "standard" model. However; for the "urban form" model only metric reach entered as a significant connectivity measure. There was no significant correlation between ridership levels and 2-directional reach. This somewhat surprising finding suggests that even though direction changes appear to have significant impact on movement within an urban environment as suggested by standard syntax theory, decision to use transit does not depend on them. The explanation may be quite simple. We can distinguish between two kinds of walking. Directed walking aimed at moving from a familiar origin to a known destination, and walking which involves different degrees of exploration (looking for something to buy in a familiar area

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or exploring an unfamiliar area) or different degrees on wandering (recreational walking). Direction changes are a cognitive variable and are likely to influence the latter kind of walking which involves cognitive decisions, overt or latent. Directed walking is likely to follow an established route without much ongoing cognitive effort and can thus be independent of directional reach or traditional syntactic integration.

Table 33 shows the effect levels of statistically significant variables included in the "reduced" model. The signs of control variables are consistent with a priori expectations; for example, boarding levels increase with the availability of parking. The model shows that ridership levels are most sensitive to service potential of a station along with the city variable that captures the variations in-between cities. Figure 51, which shows the prediction equations for each variable in the model, clearly demonstrates the variations between 3 cities. Figure 52 illustrates the scatter plot showing the natural log of annual average daily station boardings as affected by variables in the "reduced" model. Metric reach appears to be a reasonably significant predictor of transit ridership. In fact, the model suggests that density of street connectivity impacts the probability of using transit more than population density within 0.5 mile of transit.

Table 32. Effect tests for multivariate regressions estimating natural log of annual average daily station boardings

Dependent variable: natural log of annual average daily station boardings

	standard model			urban form model			reduced model		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
Explanatory variables									
City*	**20.225**	**19.175**	**0.000**	**22.727**	**22.619**	**0.000**	**30.907**	**30.210**	**0.000**
Distance to CBD†: miles between station and center	1.665	3.158	0.077	0.321	0.640	0.425	—	—	—
Park-and-ride (no, yes)	1.915	3.630	0.058	**4.513**	**8.984**	**0.003**	**5.429**	**10.613**	**0.001**
Feederbus services (no, yes)	1.564	2.965	0.087	*2.916*	*5.805*	*0.017*	—	—	—
Service potential: number of intersecting rail routes at station	**16.259**	**30.830**	**0.000**	**13.460**	**26.792**	**0.000**	**13.572**	**26.533**	**0.000**
Population density: persons per gross acre within 0.5 mile of station	*2.602*	*4.934*	*0.027*	**3.919**	**7.802**	**0.006**	*2.682*	*5.244*	*0.023*
avg R_2‡				0.742	1.478	0.226	—	—	—
avg Reach				**5.791**	**11.528**	**0.001**	**6.668**	**13.035**	**0.000**
Number of cases	219			219			219		
R squared	**0.31**			**0.35**			**0.33**		

Note: Numbers in bold = p< 0.01; numbers in italics = p<0.05

* City was entered as a categorical variable into the equation to capture the differences that are due to cities.

† Measures the crow-fly distance between transit station and city center in CBD.

‡ Average 2-directional reach expresses the average length of streets within 0.5 mile radius of station that is up to 2 direction changes away from the station.

Table 33. Parameter estimates for multivariate regressions estimating natural log of annual average daily station boardings

Dependent variable: natural log of annual average daily station boardings			
	Reduced model		
	B	t	std β
Explanatory variables			
constant		0.000	
city [atlanta]	**0.791**	**0.000**	**0.518**
city [chicago]	**-0.267**	**0.008**	**-0.233**
city [dallas]	**-0.523**	**0.000**	**-0. 325**
Park-and-ride (no)	**-0.238**	**0.001**	**-0.241**
Park-and-ride (yes)	**0.238**	**0.001**	**0.241**
Service potential: number of intersecting rail routes at station	**0.235**	**0.000**	**0.329**
Population density: persons per gross acre within 0.5 mile of station	*0.010*	*0.023*	*0.166*
avg Reach	**0.078**	**0.000**	**0.291**
Number of cases		219	
R squared		**0.33**	

Note: Numbers in bold = p< 0.01; numbers in italics = p<0.05
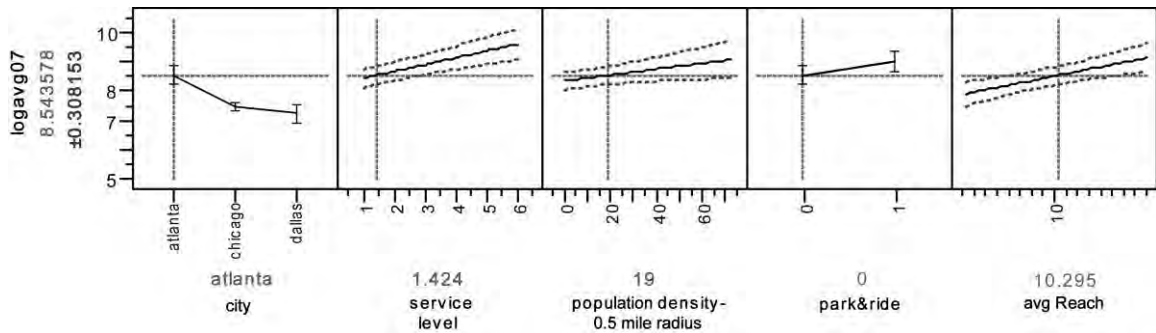
Figure 51. Prediction equations for the variables in "reduced" model.
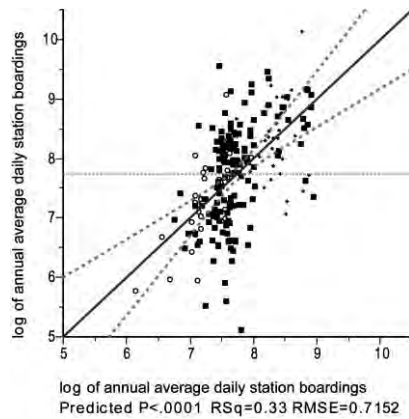
Figure 52. Scatter plot showing the natural log of annual average daily station boardings by the "reduced" model.

Our work is still in progress and conclusions are, at this stage, tentative. We have not considered any cross-effects. Even though the correlations between our effect variables are low; arguably the overall co-efficient of determination could be increased by a model that includes the cross-effects. However, our intention here was to primarily examine the comparative significance of variables derived from connectivity networks, not so much to develop the best model. The variables to be included in such models would vary from case to case. To the extent that the results of this study hold more generally, we confirm the importance of including the density of street connections in transit-oriented studies. The empirical model developed in this research is based on the hypothesis that environments that are connected so as to support different kinds of walking also support public transportation. Within this framework our study shows that street connectivity has significant effects on transit ridership when controlling for population density, transit service features, and distance to CBD. The high positive standardized coefficient of metric reach is systematically high in all 3 catchment areas

when control variables are introduced. Consistent with studies (Bernick and Cervero, 1997, Pettinga, 1992, Untermann and Lewicki, 1984) that consistently report exponential decline in transit patronage with distance from a station, correlations appear to diminish starting from 0.5 mile buffer range. In other words, while configuration of street network within 0.25 and 0.5 mile radius of rail stations acts as an incentive to transit riding, between a distance of 0.5 and 1 mile, the proportion of transit riders who walk to or from transit steadily decreases. These results suggest that street connectivity measured at the appropriate range can add explanatory power for accurate forecasting models.

Our research supports the previous finding that increased transit patronage is provided by higher population densities within walkable rings around stations. The impact of population density is fairly consistent within all buffers. However; our estimated linear model demonstrates that population densities of station catchment areas have less impact on ridership than street connectivity at the 0.5 mile radius. Importantly, when distance between station and CBD is excluded from the equation, significance of population density is reduced notably. Moreover, consistent with theory, the service potential of stations and the supply of park-and-ride proved to be the most significant correlates of ridership. Thus, it seems imperative that conclusions regarding the effects of density should be considered in conjunction with the degree to which stations are differentiated according to their service features.

Besides these primary findings, we gained several additional insights through this research. Our analysis indicates that there is noteworthy variation among the cities selected. Particularly, Atlanta is significantly different from Dallas and Chicago. Partly,

this is due to the fact that station area densities in Atlanta vary in a rather small range*. This much smaller variation among population densities of station catchment areas obliterated the predictive advantage of this variable in the case for Atlanta.

Lastly, the absence of land-use data at the road segment scale was a limitation of this analysis. While we currently have land-use data at the parcel level for Atlanta, we lack access to similar data for other cities. More work is needed to determine if land-use can be suitably incorporated in the model at this stage. The US census contains information on population densities, housing, and socio-demographic characteristics at the tract-level and the census block-group level. Very little information is available on specific land-use compositions. This is a significant barrier to carrying out small scale studies at the neighborhood level on how the design of street network shapes non-motorized travel.

In conclusion we note that our results, at this stage, largely confirm and complement existing models that have been reviewed above. Finer grain research, including parcel information on land-use as well as field studies of pedestrian movement are needed before we can inform design and planning decisions aimed at increasing the likelihood of transit usage through the creation of lively walkable environments around transit stations. This indicates that further research that focuses on measures of land-use mix and walking at a smaller geographic unit of analyses (i.e. road segment scale) might more clearly detect relationships with transit riding. This finer grain research would require a very generous budget to collect rich parcel-level land-use data and to obtain

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* Minimum and maximum population densities within 0.5 mile of station are 0.8 and 15 persons per gross acre respectively.

more detailed information on pedestrian movement than is generally available from regional travel surveys. Based on the presented evidence in our study, we believe such research refinements to be worthwhile pursuing. We hope to incorporate such data in our future prospective work to complement our model.

APPENDIX B

Modeling street connectivity and pedestrian movement according to standard GIS street network representations

Can alternative measures of street connectivity be used to express hypotheses on the theory of natural movement?

The relationship between the distribution of pedestrian movement and the spatial structure of street layouts is well established (Hillier et al., 1987, Hillier and Iida, 2005, Hillier et al., 1993, Penn et al., 1998, Peponis et al., 1989). The most cited pioneering studies have relied on "axial maps" of street networks drawn by the researchers. Here we discuss how far the correlation can also be replicated based on new measures of street connectivity (Peponis et al., 2008). The new measures have been developed to allow the analysis of standard GIS-based representations of street networks according to street center-lines.

The unit of analysis is the road segment rather than the axial line. Road segments extend between choice nodes, or street intersections at which movement can proceed in two or more alternative directions. No equivalent of the axial line is constructed. Figure 1 illustrates the new unit of analysis by clarifying the difference between road segments and street segments.

a: urban area
b: nodes
 o line node
 • road node
C: network
d: road segments
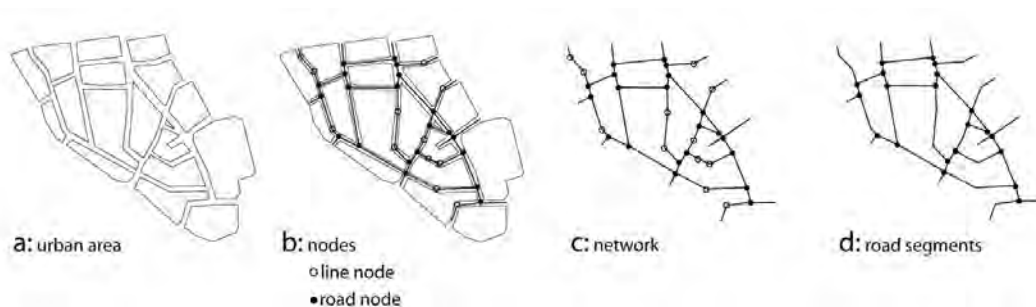
Figure 53. Definition of road segments.

Analysis is based on finding the subset of street center-lines and parts of lines that can be reached subject to some limitation. When the limitation is metric distance, the total length of street reached is called Metric Reach, Rv, and the set of street segments Sv. When the limitation is a number of permissible direction changes, the total length of streets reached is called Directional Reach, Ru, and the set of street segments Su. When combined metric and direction-change thresholds are applied, the total length of street reached is called Metric-Directional Reach, Rw, and the set of street segments Sw. Given some measure of reach, analysis proceeds by computing the average number of direction changes needed to get to the average portion of street length in the corresponding subset of street center-lines and parts of center-lines. Direction changes are simply added up, same as with the calculation of depth according to axial maps. However, a direction change is defined as a rotation of the center-line of movement by more than a specified angle. Thus, unlike traditional axial map analysis, we are dealing with a parametric definition of what counts as a direction change. A second parametric variable, "the very small street segment threshold", specifies the very small street segments as a proportion of the average road segment. When the computation reaches any sequence of very small segments, the associated angles of direction changes are added instead of being considered one at a time. A direction change is identified when the sum of consecutive angles crosses the set threshold. Depending on whether the number of direction changes for the average accessible unit of street length is based on Rv, Ru or Rw, we symbolize the mean directional distance associated with a road segment by Dv, Du or Dw.

At this stage we report results based on the following measures: first, Rv for 1 mile, Dv for 1mile, 10° angle threshold and 0.10 very small segment threshold; second,

Ru for 0 direction changes, 10° angle threshold and 0.20 very small segment threshold. This is equivalent to measuring the length of the axial line that covers the center of a road segment, except that our computation of what we call "directional elements" allows that a directional element bifurcates at very small angles and thus includes street lengths branching at very small angles from a common point of origin; third, Ru for 2 direction changes, 10o angle threshold and 0.20 very small segment threshold, as well as Du for the same parameters.

Various quantitative measures have been introduced in the literature to evaluate pedestrian accessibility and measure street connectivity. The distance between origins and destinations for walking and the total length of streets covering an area have been suggested by some authors (Aultman-Hall et al., 1997) to describe how the character of streets differs at neighborhood and regional levels. Pedestrian Route Directness, which measures the ratio between a chosen pedestrian route distance and the 'crow-fly' distance to a particular destination, has been studied (Hess, 1997, Randall and Baetz, 2001) as an indicator of how accessible a neighborhood is to the pedestrians. Some researchers have chosen to calculate the density and pattern of intersections, average block areas and block face lengths per unit area to capture the degree of network connectivity (Cervero and Kockelman, 1997, Krizek, 2003, Siksna, 1997, Southworth and Owens, 1993). Each of these measures is aimed to explain a (slightly or considerably) different aspect of connectivity pertinent to pedestrian accessibility. However, most of the analyses mentioned here do not involve extensive data collection on actual densities of pedestrian movement. Thus, space syntax still represents a rare attempt to develop an empirically

tested model of the distribution of pedestrian movement according to the configuration of streets.

Three areas in Atlanta

Atlanta is not a pedestrian friendly city. With half the population of Washington D.C. and San Francisco, Metropolitan Atlanta is extended over 50 percent more urbanized land (approximately about 1200 square miles), and per capita driving on average is 35 miles daily, which is two and one-half times more than that of the New York region (Dunphy and Fisher, 1996). Bearing these extremities in mind, we have chosen to study three areas in particular. The first area, which had been previously studied in the 1990s (Peponis et al., 1997), is Downtown Atlanta (average block area 1.7 hectares), that includes some of the most densely populated road segments within the city. The second area is Midtown (average block area 3.04 hectares), which has recently experienced very rapid mixed-use growth with explicit attempts by the city of Atlanta and Midtown Coalition to encourage walking through the provision of remodeled sidewalks. The third study area is the Virginia Highland neighborhood (average block area 7.5 hectares), developed in the early 1900s, which remains a pedestrian oriented environment attracting visitors to its shops, restaurants and bars. Our expectation, based on our everyday experience of the neighborhood, was that pedestrian movement, while of low intensity, would be better distributed than in other areas. We have not, at this point, completed our study of Buckhead, a post 1960s "edge city" which was previously studied in the 1990s. Population densities calculated according to the 2000 US census for the three areas investigated here are 2603, 2726 and 1608 per square kilometer respectively.

These figures do not include estimates of the people who work in each area and commute in daily.

Figure 54a shows the 3 areas and marks the observation sets for each area. In the cases of Downtown and Midtown, we followed the method of the moving observer; while in the case of Virginia Highland, we followed the method of gate counts. We completed 20 rounds of observation during working hours in Downtown and Midtown, and 20 minutes of observation for each gate in Virginia Highland, distributed over 10 different periods including evening hours when the area attracts more visitors. Figure 54b shows graphically the distribution of movement densities using different line thicknesses for Downtown and Midtown, and circles of different diameters for Virginia Highland. Figure 55 provides statistical information on pedestrian densities.
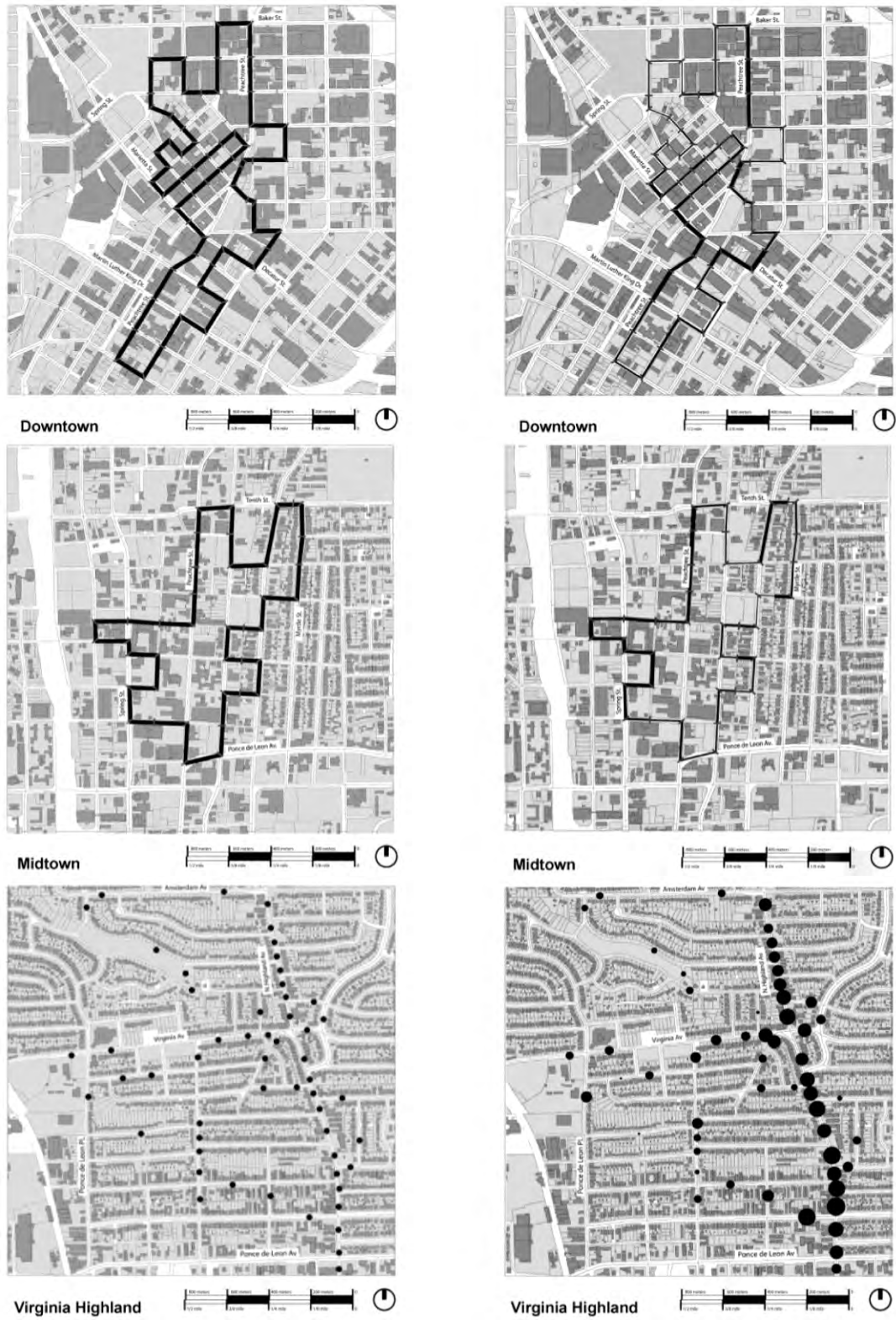
Figure 54. (a) Location of pedestrian observations, (b) Graphic representation of
observed pedestrian densities.

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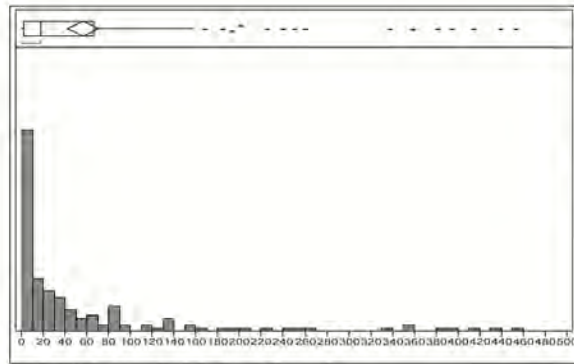
moving/100m or moving/minute, all observations

Quantiles			Moments	
100.0%	maximum	453.48	Mean	56.767302
99.5%		453.48	Std Dev	95.243727
97.5%		394.87	Std Err Mean	7.5533189
90.0%		168.33	upper 95% Mean	71.685802
75.0%	quartile	86.67	lower 95% Mean	41.848801
50.0%	median	17.91	N	159
25.0%	quartile	1.80	Sum Wgt	159
10.0%		0.35	Sum	9026.0009
2.5%		0.10	Variance	9071.3676
0.5%		0.00	Skewness	2.5455764
0.0%	minimum	0.00	Kurtosis	6.3119343
			CV	167.77921
			N Missing	0
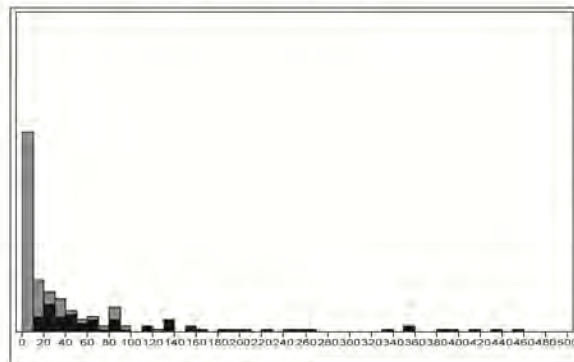
moving/100m Downtown observations (in black)

Quantiles			Moments	
100.0%	maximum	453.48	Mean	122.89509
99.5%		453.48	Std Dev	123.41183
97.5%		445.55	Std Err Mean	15.673318
90.0%		359.33	upper 95% Mean	154.23582
75.0%	quartile	172.47	lower 95% Mean	91.554353
50.0%	median	68.65	N	62
25.0%	quartile	31.11	Sum Wgt	62
10.0%		20.79	Sum	7619.4955
2.5%		14.07	Variance	15230.479
0.5%		11.48	Skewness	1.3719168
0.0%	minimum	11.48	Kurtosis	0.807935
			CV	100.42047
			N Missing	0
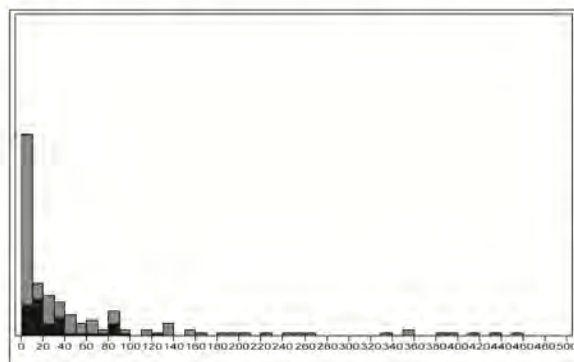
moving/100m Midtown observations (in black)

Quantiles			Moments	
100.0%	maximum	125.00	Mean	31.762034
99.5%		125.00	Std Dev	30.301974
97.5%		122.48	Std Err Mean	4.6756962
90.0%		84.28	upper 95% Mean	41.204794
75.0%	quartile	39.20	lower 95% Mean	22.319274
50.0%	median	18.92	N	42
25.0%	quartile	10.49	Sum Wgt	42
10.0%		6.45	Sum	1334.0054
2.5%		4.93	Variance	918.20966
0.5%		4.93	Skewness	1.4126729
0.0%	minimum	4.93	Kurtosis	1.1407022
			CV	95.403129
			N Missing	0
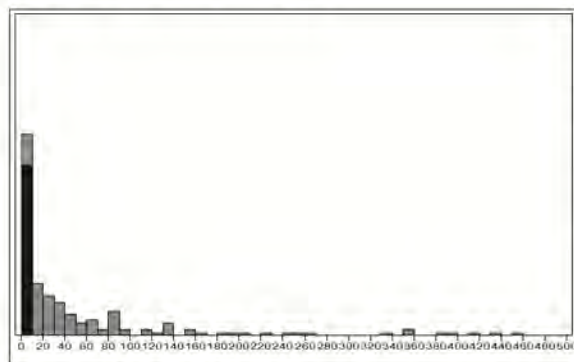
moving/minute Virginia Highland (in black)

Quantiles			Moments	
100.0%	maximum	5.9000	Mean	1.3181818
99.5%		5.9000	Std Dev	1.2698922
97.5%		5.5200	Std Err Mean	0.1712322
90.0%		2.9300	upper 95% Mean	1.6614818
75.0%	quartile	1.9500	lower 95% Mean	0.9748819
50.0%	median	0.8000	N	55
25.0%	quartile	0.3000	Sum Wgt	55
10.0%		0.1500	Sum	72.5
2.5%		0.0200	Variance	1.6126263
0.5%		0.0000	Skewness	1.5179056
0.0%	minimum	0.0000	Kurtosis	2.6519158
			CV	96.336652
			N Missing	0

Figure 55. Statistical profile of observed pedestrian densities.

We observed 62 road segments in Downtown and 42 in Midtown. When observations are aggregated and averaged by axial line, our observations cover 33 axial lines in Downtown and 18 in Midtown. In Virginia Highland we observed 55 gates. When gates on the same axial line are added and averaged, our observations cover 25 axial lines. Thus we have observed a total of 159 road segments and can characterize movement for 76 axial lines.

Figure 55 shows how strongly the three areas differ. The median density of moving pedestrians per 100 meters or per minute is 68.7, 18.9 and 0.9 for Downtown, Midtown and Virginia Highland respectively, while the corresponding means are 122.9, 31.8 and 1.3.

The distribution of pedestrian movement densities as a function of axial integration

Each observation area was analyzed based on a standard axial map drawn to cover the surroundings in such a way that computations of Integration Radius 3 for observed lines would not suffer any edge effects. In all cases, axial maps cover areas at least as large as 3 miles x 3 miles. In order to replicate methodologies used in the past, when several observation segments or gates were found on the same axial line, values were averaged as appropriate so that each line was associated with one estimate of pedestrian density only. The results of the correlation analysis (Linear Pearson correlations) are shown in Table 34.

Table 34. Correlations between axial integration and pedestrian movement densities

	Correlation (r) between LogMov/100meters or LogMov/min and axial Integration	Correlation (r) between LogMov/100meters or LogMov/min and axial Integration radius 3
Downtown Atlanta	0.57 (p<0.0005)	0.28 (p<0.1126)
Midtown Atlanta	0.05 (p<0.8538)	0.01 (p<0.9766)
Virginia-Highland	0.57 (p<0.0030)	0.73 (p<0.0001)
All observations	0.92 (p<0.0001)	0.53 (p<0.0001)

The correlations for all observed lines are not to be discussed much, because they correspond to a very polarized scatter-plot due to the fact that Virginia Highland has much lower pedestrian densities and much lower Integration values as compared to the other two areas. We note that the correlation between pedestrian movement and Integration for Downtown is almost identical to the one reported in the earlier study, r value of 0.55, (Peponis et al., 1997) even though the observation spaces are not identical. However, the earlier study showed a higher correlation for Integration Radius 3, namely 0.39, as compared to the new value of 0.28. To interpret this difference we notice that our new study encompasses a greater number of sub-areas that appear distinct from a land-use point of view (intensive high rise developments, the old low rise Poplar district, and sparsely developed blocks south of the Peachtree-Marietta intersection). The inclusion of sub-areas, which may be characterized by a different orientation of pedestrian movement with respect to the local street system, can account for the lower correlation to Integration

Radius 3 that we obtained. However, in both studies, Integration proves to offer stronger post-diction of pedestrian movement than Integration Radius 3.

Midtown strikingly fails to show any correlation between syntactic structure and pedestrian movement. Our findings suggest that the pedestrians observed in the area do not orient their movement according to the syntactic structure of the surrounding street fabric. This is surprising given the deliberate policies to create a pedestrian friendly mixed-use environment. We interpret the result to imply that pedestrian movement is oriented to local attractors, whether high rise residential buildings or the various restaurants and bars (all mostly along Peachtree Street with only occasional emphasis on West Peachtree, Spring Street or the transverse streets) and has not yet become tuned to the larger surrounding fabric.

The correlations for Virginia Highland are high, as would be expected, with a particularly strong correlation of movement densities to Integration Radius 3. Thus, while movement in Downtown appears to be distributed according to a global rather than a local scale or syntactic integration, movement in Virginia Highland is even more strongly distributed according to a local scale.

When Midtown is excluded from the data set, our results indicate that syntactic variables account for 30 to 50 percent of the variation of pedestrian movement densities. While this is a high proportion, our results also point to the possible effect of other factors. We speculate that these factors include not only the variation of land development by parcel, but also the location of parking facilities. Much movement occurs between a parking facility and a particular destination. This contributes to the fragmentary overall nature of movement. With the exception of some areas in

Downtown, there appears to be little causal, exploratory, distributed movement around the three areas.

The distribution of pedestrian movement densities as a function of the new measures of street connectivity

We now turn to the analysis of the same observations according to the existing GIS representations of street-center lines and the new variables introduced earlier. For the purposes of this particular analysis we have excluded freeways (Interstates) since they do not factor in pedestrian movement. The results (linear Pearson correlations) are presented in Table 35.

Table 35. Correlations between measures of street connectivity and pedestrian movement densities

	Correlation (r) between LogMov/100m or LogMov/min and Rv(1mile)	Correlation (r) between LogMov/100m or LogMov/min and Dv(1mile,10°,0.10)	Correlation (r) between LogMov/100m or LogMov/min and Rv(1mile)/ Dv(1mile,10o,0.10)	Correlation (r) between LogMov/100m or LogMov/min and Ru(0d, 10°,0.20)	Correlation (r) between LogMov/100m or LogMov/min and Ru(2d, 10°,0.20)	Correlation (r) between LogMov/100m or LogMov/min and Du(2d,10°,0.20)	Correlation (r) between LogMov/100m or LogMov/min and Ru(2d, 10°,0.20)/ Du(2d,10°,0.20)
Downtown Atlanta	0.27 (p<0.03)	-0.43 (p<0.00)	0.51 (p<0.00)	0.14 (p<0.27)	0.08 (p<0.56)	0.21 (p<0.10)	0.07 (p<0.58)
Midtown Atlanta	0.17 (p<0.29)	0.30 (p<0.05)	-0.19 (p<0.24)	0.07 (p<0.63)	0.08 (p<0.62)	0.38 (p<0.01)	0.12 (p<0.46)
Virginia-Highland	0.63 (p<0.00)	-0.53 (p<0.00)	0.73 (p<0.00)	0.45 (p<0.00)	0.54 (p<0.00)	0.19 (p<0.16)	0.53 (p<0.00)
All observations	0.90 (p<0.00)	-0.37 (p<0.00)	0.76 (p<0.00)	0.04 (p<0.59)	0.22 (p<0.00)	0.45 (p<0.00)	0.20 (p<0.01)

Results obtained for all observations considered as a single set are based on a polarized scatter-plot and consequently will not be discussed as indicative of a trend. This is consistent with the standard syntactic analysis reported earlier. Equally consistent with the previous results is the rather poor ability of the new measures to post-dict movement densities in Midtown. The only significant correlation is between movement density and Directional Reach computed for two direction changes subject to a 10° threshold angle and a 0.20 very small segment threshold (7th column). Even this correlation, however, is based on a scatter-plot which is dominated by outliers. When we consider Midtown and Downtown, the best correlations are obtained when we divide Metric Reach for 1 mile radius by Directional Distance based on metric reach, subject to a 10o threshold angle and a 0.20 very small segment threshold. This composite variable takes on higher values as the metric reach of a space increases and its directional depth decreases. In simple English, this is equivalent to saying that road segments from which more street length is accessible within 1 mile walking radius, taking fewer turns to get everywhere, draw greater volumes of pedestrians.

The correlation for Downtown (0.51) is very close to the best correlation previously obtained with syntactic Integration (0.57). In the case of Virginia Highland, the correlation (0.73) is exactly as strong as the one obtained with syntactic Integration radius 3.

Discussion

Our work is still in progress and conclusions are, at this stage, tentative. First, our observation data in Atlanta yields less strong correlations than those previously obtained

by similar studies in London (Hillier et al., 1993) or in some Greek cities (Peponis et al., 1989). In Atlanta, pedestrian movement is less tuned to the spatial structure of streets and may be affected more strongly by other factors, including the juxtaposition of drastically different development densities and the distribution of parking. Second, the new measures seem to work as well as the standard syntactic measures in modeling the manner in which the street network affects pedestrian flows. This merits further discussion.

Both standard syntactic measures and the new measures are sensitive to direction changes, in other words to the underlying topology of streets. In standard syntactic analysis direction changes are not defined parametrically. This, of course, has changed when angular analysis and fractional analysis have been introduced (Dalton, 2001). The new measures used in this paper are inherently parametric, in that one can vary what counts as a direction change. At the same time our measures are not sensitive to the magnitude of a direction change as is angular analysis. There is, however, general agreement in principle that direction changes are important in determining how likely it is that a given space will attract greater flows of movement as compared to its surroundings. This is true whether we give a non parametric (standard syntax) or a parametric (new measures) definition of what counts as a direction change, or whether we decide to measure the magnitude of all direction changes and define angular distances (angular analysis). The common underlying hypothesis is that direction changes do matter, because they impose a cognitive load on navigation and the processes of cognitive mapping that are associated with navigation.

Standard space syntax, however, does less to express street connectivity in terms of density. Here we use the term density to refer to the amount of street which is available within a given metric range. The syntactic measure of connectivity (the number of street intersections per line) could be construed as a measure of density had it been explicitly relativized by line length. In standard syntax, however, metric properties are not emphasized as much as topological ones. In making these comments we do not underestimate the continuous preoccupation with metric properties in the work of Hillier since 1999. On the contrary, we converge with a main thrust of this work, namely that metric properties have to be introduced at the foundations of the theory of syntax. Consistent with this our new measures express the density of street connectivity directly. Our results indicate that a measure of density (Metric Reach) plays as important a role in the distribution of movement as a measure of direction changes (Directional Distance).

Finally, we note that the new measure that was aimed at emulating Integration Radius 3, in other words the average directional distance to all spaces that can be reached within up to two direction changes, did not contribute much to our modeling of pedestrian movement. The same negative finding seems to apply to our measures of directional reach, whether at zero direction changes (conceptually equivalent to measuring the length of axial lines, but with parametric twists), or at 2 direction changes. We think that too strong an interpretation of these results is premature. At this stage, it is important to acknowledge that our new measures allow us to draw a distinction between street connectivity as measured subject to metric thresholds and street connectivity as measured subject to directional thresholds. As our data base and our analyses expand, we might be able to throw more light on the interplay between measures of direction change

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and measures of the density of connections as determinants of pedestrian flows. For now, we hypothesize that we are dealing with the interplay between potentiality (density) and structure (directional bias based on configuration).

APPENDIX C

Varieties of cluster analyses of station-environments based on average metric reach, population density, and mixed-land-use for 1 and 0.25 mile radii.
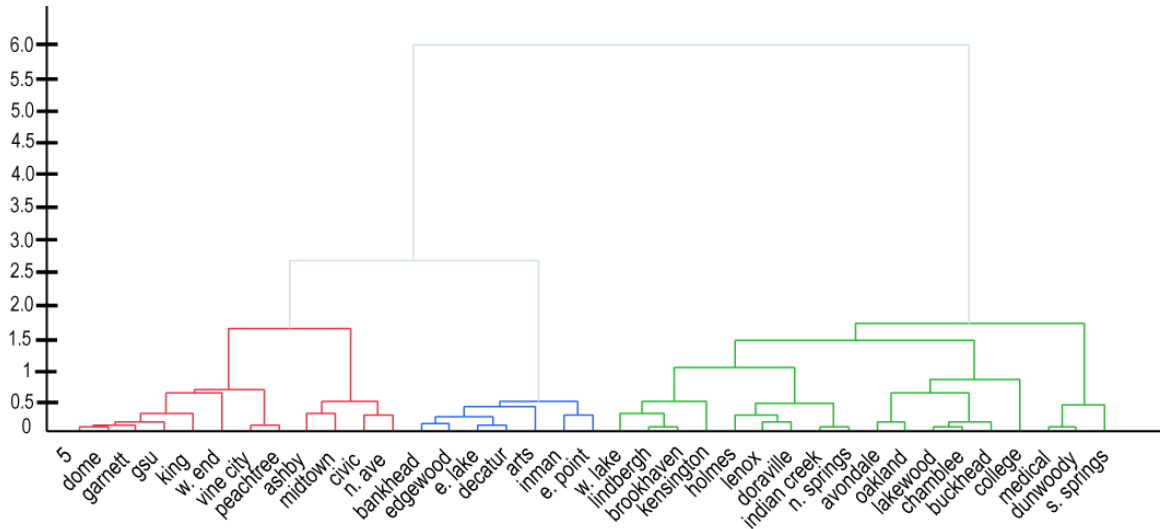
Figure 56. Hierarchical cluster based on average metric reach (1 mile) and population

densities within 1 mile rings around transit stops.
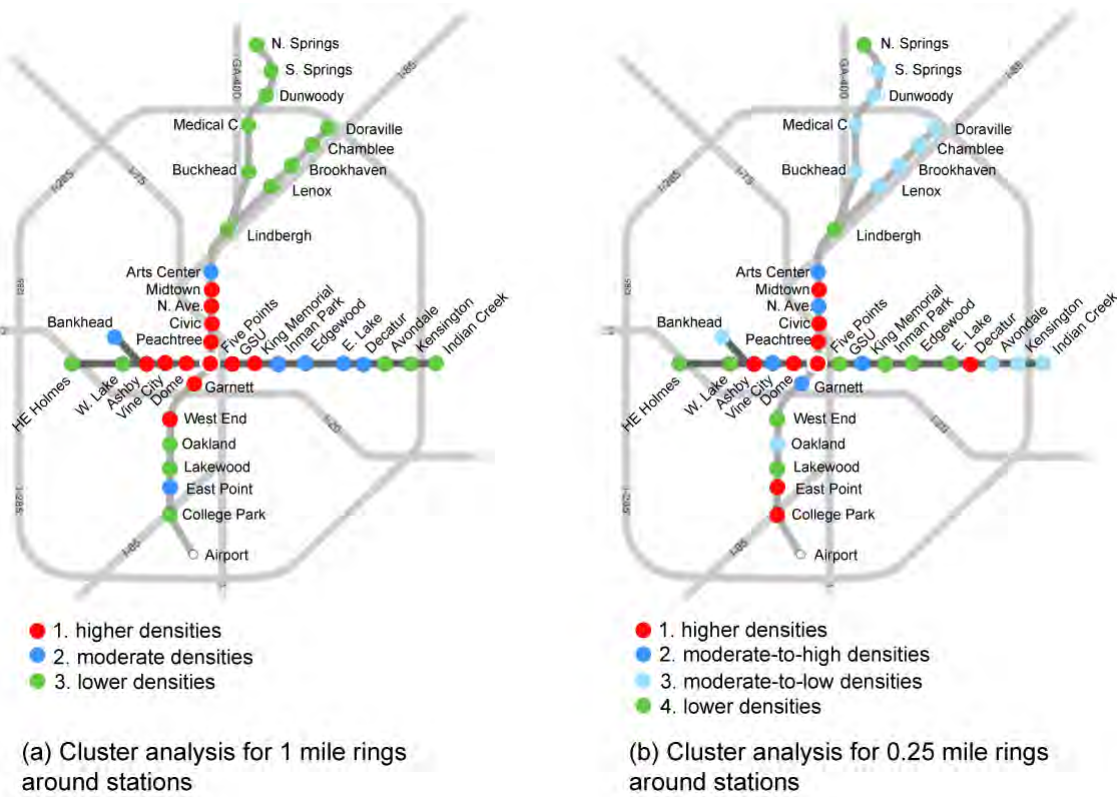
Figure 57. Cluster analysis of stations based on average metric reach (1 and 0.25 mile)

and population densities (persons per gross acre) within 1 and 0.25 mile rings around
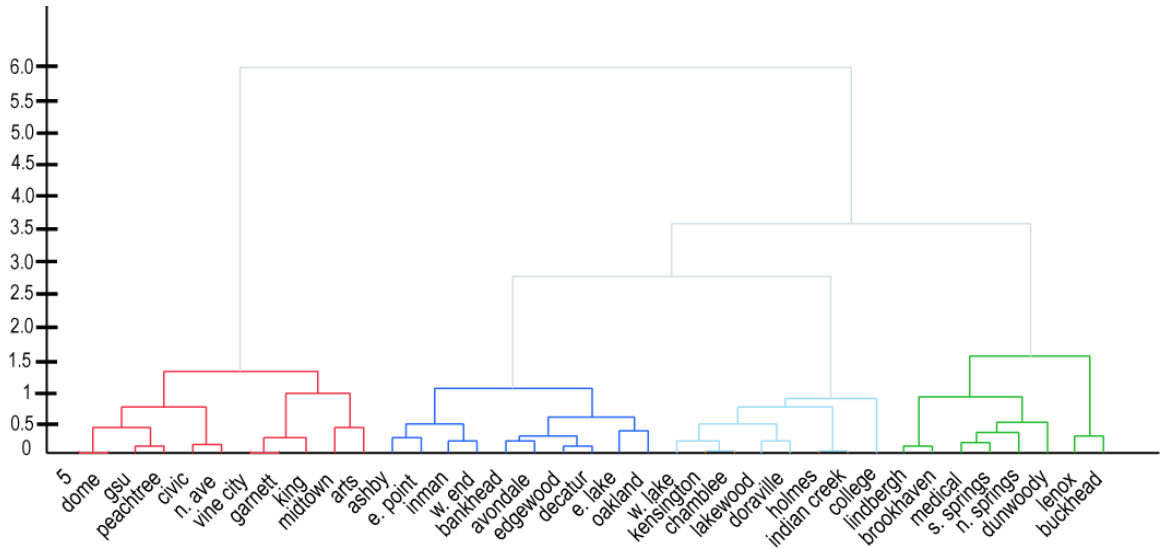
transit stops.

Figure 58. Hierarchical cluster based on average metric reach (1 mile) and mixed land-use index within 1 mile rings around transit stops.
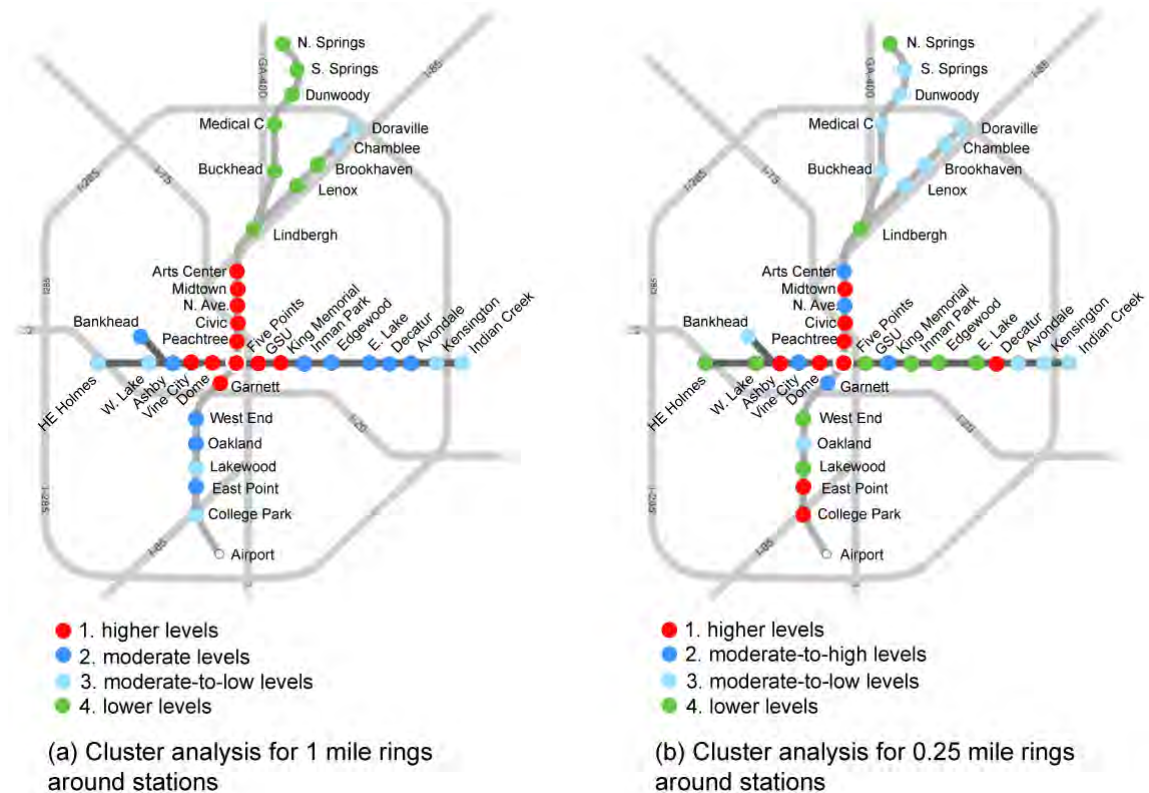
Figure 59. Cluster analyses of stations based on average metric reach (1 and 0.25 mile) and mixed land-use index within 1 and 0.25 mile rings around transit stops.

APPENDIX D

Results of bivariate regressions between walk-mode shares at MARTA

rail stations and street connectivity measures for 0.5 and 0.25 mile radii.

(a) n=37, r²=0.24, p<0.0023   (b) n=37, r²=0.23, p<0.0027   (c) n=37, r²=0.20, p<0.0052   (d) n=37, r²=0.02, p<0.4472
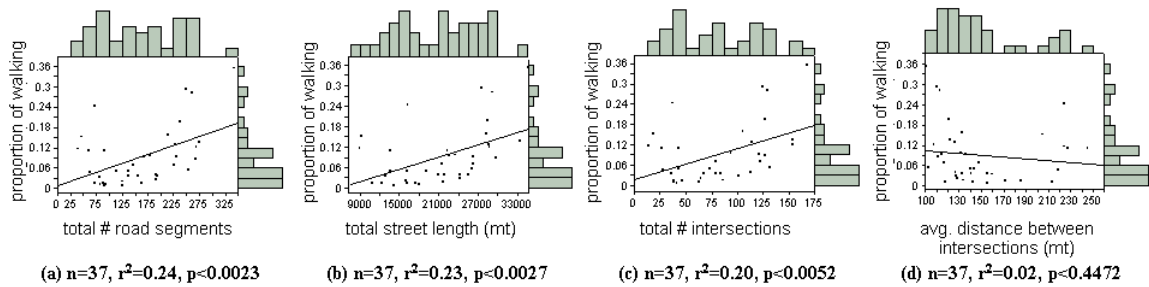
Figure 60. Scatterplots showing the proportion of walking against (a) total number of road segments, (b) total street length (mt), (c) total number of intersections, and (d) average distance between intersections (mt) within ½ mile rings

(a) n=37, r²=0.28, p<0.0008   (b) n=37, r²=0.07, p<0.1190   (c) n=37, r²=0.16, p<0.0154
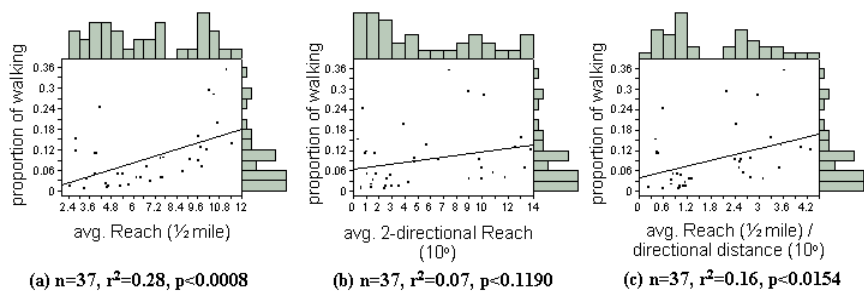
Figure 61. Scatterplots showing the proportion of walking against (a) average Reach (½ mile), (b) average 2-directional Reach (10°), and (c) average Reach (½ mile) divided by the corresponding average directional distance (10°) for ½ mile rings

(d) n=37, r²=0.08, p<0.0865   (b) n=37, r²=0.12, p<0.04   (b) n=37, r²=0.002, p<0.7922
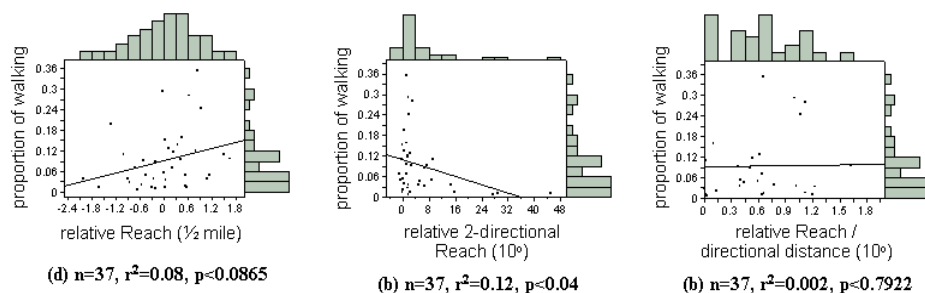
Figure 62. Scatterplots showing the proportion of walking against (a) relative Reach (½ mile), (b) relative 2-directional Reach (10°), and (c) relative Reach (½ mile) divided by the corresponding average directional distance (10°) for ½ mile rings

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(a) n=37, r²=0.25, p<0.0017 **(b) n=37, r²=0.25, p<0.0016** **(c) n=37, r²=0.22, p<0.0036** **(d) n=37, r²=0.05, p<0.1963**
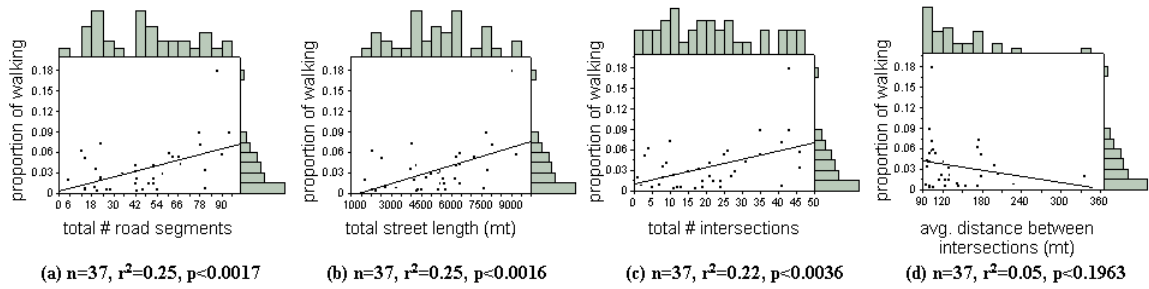
Figure 63. Scatterplots showing the proportion of walking against (a) total number of road segments, (b) total street length (mt), (c) total number of intersections, and (d) average distance between intersections (mt) within ¼ mile rings

(a) n=37, r²=0.35, p<0.0001 **(b) n=37, r²=0.09, p<0.0674** **(c) n=37, r²=0.18, p<0.0084**
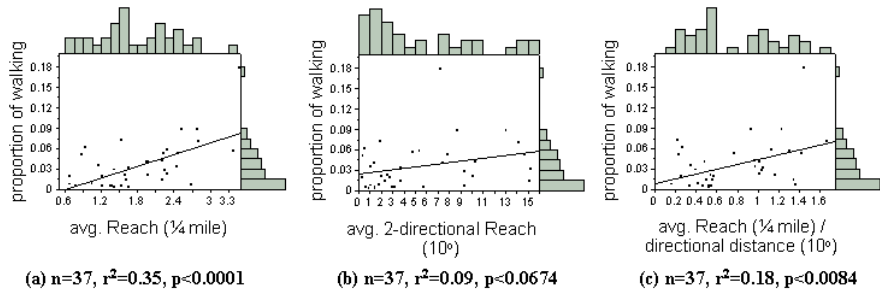
Figure 64. Scatterplots showing the proportion of walking against (a) average Reach (¼ mile), (b) average 2-directional Reach (10°), and (c) average Reach (¼ mile) divided by the corresponding average directional distance (10°) for ¼ mile rings

(d) n=37, r²=0.007, p<0.6346 **(b) n=37, r²=0.09, p<0.0734** **(b) n=37, r²=0.007, p<0.6212**
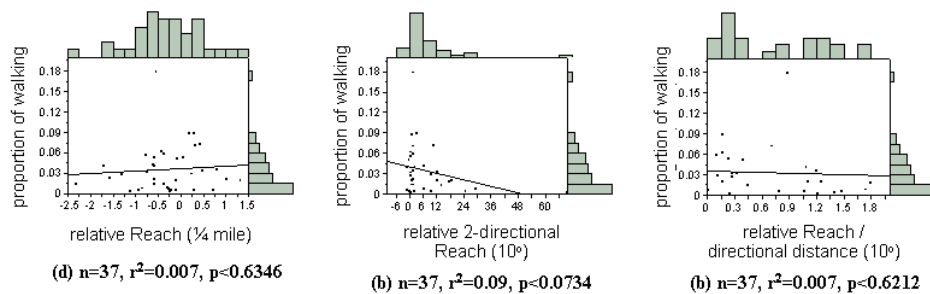
Figure 65. Scatterplots showing the proportion of walking against (a) relative Reach (¼ mile), (b) relative 2-directional Reach (10°), and (c) relative Reach (¼ mile) divided by the corresponding directional distance (10°) for ¼ mile rings

APPENDIX E

Results of multivariate regression analysis predicting walk-mode shares at MARTA rail stations using urban form measures as independent variables, and non-urban form measures as statistical controls for 1, 0.5 and 0.25 mile radii.

Table 36. Effect tests for multivariate regressions estimating the proportion of walking

Effect tests for multivariate regressions estimating the proportion of walking within 1

total riders walked / total ridership per station	Controls			+ Connectivity			+ Accessibility			+Density			+ Land-use		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.051	8.844	0.006	0.072	15.946	0.000	0.032	7.024	0.013	0.0244	5.3185	0.029	0.0094	2.8784	0.1017
station structure type[b]	0.023	1.994	0.154	0.021	2.358	0.112	0.022	2.410	0.108	0.018	1.9642	0.1598	0.020	3.030	0.066
service frequency[‡]	0.002	0.395	0.535	0.030	6.621	0.015	0.029	6.312	0.018	0.0189	4.1209	0.052	0.028	8.637	0.007
feeder/bus services (no)	0.111	19.360	0.000	0.080	17.606	0.000	0.068	14.780	0.001	0.0726	15.827	0.0005	0.027	8.255	0.008
parking supplies	0.053	9.346	0.005	0.007	1.440	0.240	0.003	0.556	0.462	0.0037	0.8177	0.3739	0.000	0.008	0.928
avg. Reach (1 mile)				0.040	8.752	0.006	0.043	9.315	0.005	0.013	2.792	0.106	0.018	5.512	0.027
sidewalk availability[a]							0.003	0.674	0.419	0.005	1.133	0.297	0.001	0.304	0.586
population density: persons per gross acre within 1 mile of station										0.005	1.076	0.309	0.000	0.004	0.949
mixed-land use index[†]													0.039	11.942	0.002
N=37															
R^2	0.69			0.76			0.76			0.77			0.84		
R^2 adjusted	0.52			0.70			0.70			0.70			0.78		
std. error, S_e	0.08			0.07			0.07			0.07			0.06		
Prob>F													0.00		
coefficient of residual variability, V_e													39.17		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$†Mixed-use\ entropy = -1 \times \left(\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right)$$

[b] types of station structure: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

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Table 37. Effect tests for multivariate regressions estimating the proportion of walking within 1

total riders walked / total ridership per station	Controls			+ Density			+ Land Use			+ Accessibility			+ Connectivity		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.051	8.844	0.006	0.058	11.925	0.002	0.005	1.450	0.239	0.0063	1.6633	0.208	0.0094	2.8784	0.1017
station structure type[b]	0.023	1.994	0.154	0.014	1.443	0.253	0.014	1.835	0.178	0.014	1.8391	0.1783	0.020	3.030	0.066
service frequency[‡]	0.002	0.395	0.535	0.010	2.092	0.159	0.010	2.675	0.113	0.0109	2.8532	0.1027	0.028	8.637	0.007
feederbus services (no)	0.111	19.360	0.000	0.116	23.937	0.000	0.051	13.756	0.001	0.05	13.144	0.0012	0.027	8.255	0.008
parking supplies	0.053	9.346	0.005	0.037	7.596	0.010	0.007	1.799	0.191	0.007	1.932	0.1759	0.000	0.008	0.928
population density: persons per gross acre within 1 mile of station				0.031	6.314	0.018	0.020	5.278	0.029	0.011	2.961	0.097	0.000	0.004	0.949
mixed-land use index[†]							0.037	10.024	0.004	0.034	8.872	0.006	0.039	11.942	0.002
sidewalk availability[a]										0.001	0.253	0.619	0.001	0.304	0.586
avg. Reach (1 mile)													0.018	5.512	0.027
N=37															
R²	0.69			0.74			0.81			0.81			0.84		
R² adjusted	0.62			0.68			0.76			0.75			0.78		
std. error, Se	0.08			0.07			0.06			0.06			0.06		
Prob>F													0.00		
coefficient of residual variability, Ve													39.17		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
a proportion of roads with sidewalk

$$\dagger Mixed-use\ entropy = -1 \times \left[\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right]$$

b types of station structure: at-grade, elevated, underground

‡ number of inbound trains in am peak hour (7am-9am)

* ratio of average auto-ownership to average per-capita income calculated per station

Table 38. Effect tests for multivariate regressions estimating the proportion of walking within 0.5

	Controls			+ Connectivity			+ Accessibility			+ Density			+ Land Use		
total riders walked within 0.5 mile / total ridership per station	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.022	7.159	0.012	0.023	7.707	0.009	0.016	5.422	0.027	0.0165	5.3462	0.028	3.4E-08	2E-05	0.997
station structure type[b]	0.004	1.277	0.267	0.003	0.908	0.348	0.003	1.125	0.298	0.0029	0.936	0.342	0.001	0.329	0.571
service frequency[‡]	0.001	0.370	0.547	0.005	1.730	0.198	0.005	1.810	0.189	0.0057	1.859	0.184	0.005	2.452	0.129
feederbus services (no)	0.098	32.156	0.000	0.074	24.790	0.000	0.071	23.853	0.000	0.0619	20.032	1E-04	0.009	3.971	0.056
parking supplies	0.013	4.351	0.045	0.005	1.599	0.216	0.001	0.274	0.604	0.0008	0.2602	0.614	0.00062	0.2846	0.598
avg. Reach(0.5mile)				0.005	1.616	0.213	0.007	2.476	0.126	0.007	2.426	0.131	0.010	4.555	0.042
sidewalk availability[a]							0.003	0.897	0.351	0.003	0.897	0.352	0.002	0.865	0.361
population density: persons per gross acre within 0.5 mile of station										0.000	0.122	0.730	0.000	0.069	0.794
mixed-land use index[†]													0.027	12.522	0.001
N=37															
R²	0.65			0.67			0.68			0.68			0.78		
R² adjusted	0.59			0.60			0.60			0.59			0.71		
std. error, S_e	0.06			0.05			0.05			0.06			0.05		
Prob>F													0.00		
coefficient of residual variability, V_e													50.99		

Numbers in **bold** = p< 0.05; numbers in italics = p<0.10

Notes:

[a] proportion of roads with sidewalk

$$\dagger\ Mixed-use\ entropy = -1 \times \left[\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right]$$

[b] types of station structure: at-grade, elevated, underground

[‡] number of inbound trains in am peak hour (7am-9am)

* ratio of average auto-ownership to average per-capita income calculated per station

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Table 39. Effect tests for multivariate regressions estimating the proportion of walking within 0.5 mile

total riders walked within 0.5 mile / total ridership per station	Controls			+ Density			+ Land Use			+ Accessibility			+ Connectivity		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	**0.022**	**7.159**	**0.012**	0.021	6.848	0.014	0.000	0.040	0.842	0.0001	0.0435	0.836	3.4E-08	2E-05	0.997
station entrance type■	0.004	1.277	0.267	0.004	1.288	0.265	0.002	0.751	0.393	0.0016	0.6665	0.421	0.001	0.329	0.571
service frequency‡	0.001	0.370	0.547	0.001	0.413	0.526	0.000	0.101	0.753	0.0003	0.103	0.751	0.005	2.452	0.129
feederbus services (no)	**0.098**	**32.156**	**0.000**	**0.097**	**30.969**	**0.000**	**0.020**	**8.545**	**0.007**	**0.0196**	**7.9351**	**0.009**	*0.009*	*3.971*	*0.056*
parking supplies	**0.013**	**4.351**	**0.045**	0.012	3.736	0.063	0.002	0.641	0.430	0.0015	0.5895	0.449	0.001	0.285	0.598
population density: persons per gross acre within 0.5 mile of station				0.000	0.073	0.789	0.001	0.414	0.525	0.001	0.371	0.548	0.000	0.069	0.794
mixed-land use index†							**0.025**	**10.529**	**0.003**	**0.025**	**10.108**	**0.004**	**0.027**	**12.522**	**0.001**
sidewalk availability■										0.000	0.006	0.937	0.002	0.865	0.361
avg. Reach (0.5mile)													**0.010**	**4.555**	**0.042**
N=37															
R^2	0.65			0.65			0.74			0.74			0.78		
R^2 adjusted	0.59			0.58			0.68			0.67			0.71		
std. error, S_e	0.06			0.05			0.05			0.05			0.05		
Prob>F													0.00		
coefficient of residual variability, V_e													50.99		

Numbers in bold = p< 0.05, numbers in italics = p<0.10

Notes:

■ proportion of roads with sidewalk

$$ † \ Mixed - use \ entropy = -1 \times \left[\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right] $$

■ types of station structure at-grade, elevated, underground

‡ number of inbound trains in am peak hour (7am-9am)

* ratio of average auto-ownership to average per-capita income calculated per station

Table 40. Effect tests for multivariate regressions estimating the proportion of walking within 0.25 mile

total riders walked within 0.25 mile / total ridership per station	Controls			+ Connectivity			+ Accessibility			+ Density			+ Land Use		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.006	9.977	0.004	0.006	14.491	0.001	0.005	12.843	0.001	0.0055	12.748	0.0013	0.0037	9.0441	0.0058
station structure type[a]	0.007	6.378	0.005	0.001	3.244	0.082	0.001	3.087	0.089	0.0012	2.8409	0.103	0.001	1.729	0.197
service frequency[‡]	0.001	2.256	0.144	0.005	11.623	0.002	0.005	11.903	0.002	0.0041	9.5767	0.0044	0.005	12.373	0.002
feederbus services (no)	0.007	11.790	0.002	0.005	12.423	0.001	0.005	10.878	0.003	0.0035	8.0805	0.0083	0.002	5.347	0.029
parking supplies	0.000	0.557	0.461	0.000	0.027	0.870	0.000	0.055	0.816	2E-06	0.0041	0.9491	0.000	0.008	0.929
avg. Reach (0.25mile)	0.008	18.223	0.000	0.008	18.223	0.000	0.007	17.307	0.000	0.007	17.332	0.000	0.006	13.933	0.001
sidewalk availability[a]							0.000	0.876	0.357	0.000	0.566	0.458	0.000	0.745	0.396
population density: persons per gross acre within 0.25 mile of station										0.000	0.797	0.380	0.000	0.187	0.669
mixed-land use index[†]													0.001	1.465	0.237
N=37															
R²	0.61			0.70			0.71			0.72			0.75		
R2 adjusted	0.53			0.65			0.64			0.64			0.66		
std. error, S_e	0.02			0.02			0.02			0.02			0.02		
Prob>F													0.00		
coefficient of residual variability, V_e													58.62		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:

[a] proportion of roads with sidewalk

[†] $Mixed-use\ entropy = -1 \times \left[\dfrac{\displaystyle\sum_{i=1}^{k} p_i \times \ln(p_i)}{\ln(k)} \right]$

[a] types of station structure: at-grade, elevated, underground

[‡] number of inbound trains in am peak hour (7am-9am)

[*] ratio of average auto-ownership to average per-capita income calculated per station

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Table 41. Effect tests for multivariate regressions estimating the proportion of walking within 0.25

41. Effect tests for multivariate regressions estimating the proportion of walking within 0.25 mile

total riders walked within 0.25 mile / total ridership per station	Controls			+ Density			+ Land Use			+ Accessibility			+ Connectivity		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.006	9.977	0.004	0.006	9.571	0.004	0.005	7.771	0.009	0.005	8.2449	0.0079	0.0037	9.0441	0.0058
station structure type[b]	0.007	6.378	0.005	0.007	6.036	0.006	0.005	4.058	0.028	0.0048	3.9842	0.0305	0.001	1.729	0.197
service frequency[‡]	0.001	2.256	0.144	0.001	1.642	0.210	0.001	1.641	0.211	0.0012	1.99	0.1698	0.005	12.373	0.002
feederbus services (no)	0.007	11.790	0.002	0.006	9.524	0.004	0.005	7.945	0.009	0.005	8.296	0.0077	0.002	5.347	0.029
parking supplies	0.000	0.557	0.461	0.000	0.561	0.460	0.000	0.477	0.496	0.0003	0.5708	0.4565	0.000	0.008	0.929
population density: persons per gross acre within 0.25 mile of station				0.000	0.023	0.882	0.000	0.019	0.890	0.000	0.077	0.783	0.000	0.187	0.669
mixed-land use index[†]							0.000	0.161	0.691	0.000	0.030	0.864	0.001	1.465	0.237
sidewalk availability[■]										0.000	0.589	0.450	0.000	0.745	0.396
avg. Reach (0.25mile)													0.006	13.933	0.001
N=37															
R²	0.61			0.61			0.61			0.62			0.75		
R2 adjusted	0.53			0.52			0.50			0.49			0.66		
std. error, S_e	0.02						0.02			0.02			0.02		
Prob>F													0.00		
coefficient of residual variability, V_e													58.62		

Numbers in bold = p< 0.05, numbers in italics = p<0.10

Notes:

■ proportion of roads with sidewalk

$$Mixed-use\ entropy = -1 \times \left[\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right]$$

[b] types of station structure: at-grade, elevated, underground

[‡] number of inbound trains in am peak hour (7am-9am)

* ratio of average auto-ownership to average per-capita income calculated per station

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Table 42. Effect tests for multivariate regressions estimating the proportion of walking within 1

total riders walked / total ridership per station	Controls sum of squares	F ratio	prob>F	+ Connectivity sum of squares	F ratio	prob>F	+ Accessibility sum of squares	F ratio	prob>F	+ Density sum of squares	F ratio	prob>F	+ Land Use sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.051	8.844	0.006	0.068	15.569	0.000	0.025	5.754	0.023	0.0201	4.722	0.039	0.0066	2.157	0.154
station entrance type[b]	0.023	1.994	0.154	0.017	1.976	0.157	0.017	1.934	0.163	0.0161	1.886	0.171	0.018	3.010	0.067
service frequency[‡]	0.002	0.395	0.535	0.027	6.281	0.018	0.025	5.806	0.023	0.0215	5.047	0.033	0.028	9.310	0.005
Feederbus services (no)	0.111	19.360	0.000	0.115	26.218	0.000	0.103	23.609	0.000	0.1025	24.06	4E-05	0.047	15.462	0.001
parking supplies	0.053	9.346	0.005	0.022	5.080	0.032	0.012	2.659	0.114	0.0098	2.304	0.141	0.001	0.414	0.526
avg.metric reach(1mile) / directional distance (10^x)				0.045	10.264	0.003	0.050	11.459	0.002	0.022	5.061	0.033	0.023	7.687	0.010
sidewalk availability[a]							0.005	1.154	0.292	0.008	1.841	0.186	0.000	0.044	0.835
population density: persons per gross acre within 1 mile of station										0.007	1.572	0.221	0.000	0.064	0.802
mixed-land use index[†]													0.036	11.691	0.002
N=37															
R^2	0.69			0.77			0.78			0.79			0.85		
R^2 adjusted	0.62			0.71			0.71			0.72			0.80		
std. error, S_e	0.08			0.07			0.07			0.07			0.06		
Prob>F													0.00		
coefficient of residual variability, V_e													37.89		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$\dagger \; Mixed-use\; entropy = -1 \times \left[\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right]$$

[b] types of station entrances: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

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Table 43. Effect tests for multivariate regressions estimating the proportion of walking

Effect tests for multivariate regressions estimating the proportion of walking within 1

total riders walked / total ridership per station	Controls			+ Density			+ Land Use			+ Accessibility			+ Connectivity		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	**0.051**	**8.844**	**0.006**	**0.058**	**11.925**	**0.002**	0.005	1.450	0.239	0.0063	1.663	0.208	0.0066	2.157	0.154
station entrance type [b]	0.023	1.994	0.154	0.014	1.443	0.253	0.014	1.835	0.178	0.014	1.839	0.178	*0.018*	*3.010*	*0.067*
service frequency[‡]	0.002	0.395	0.535	0.010	2.092	0.159	0.010	2.675	0.113	0.0109	2.853	0.103	**0.028**	**9.310**	**0.005**
Feederbus services (no)	**0.111**	**19.360**	**0.000**	**0.116**	**23.937**	**0.000**	**0.051**	**13.756**	**0.001**	**0.05**	**13.14**	**0.001**	**0.047**	**15.462**	**0.001**
parking supplies	**0.053**	**9.346**	**0.005**	**0.037**	**7.596**	**0.010**	0.007	1.799	0.191	0.0074	1.932	0.176	0.001	0.414	0.526
population density: persons per gross acre within 1 mile of station				**0.031**	**6.314**	**0.018**	**0.020**	**5.278**	**0.029**	*0.011*	*2.961*	*0.097*	0.000	0.064	0.802
mixed-land use index[†]							**0.037**	**10.024**	**0.004**	**0.034**	**8.872**	**0.006**	**0.036**	**11.691**	**0.002**
sidewalk availability[a]										0.001	0.253	0.619	0.000	0.044	0.835
avg.metric reach(1mile) / directional distance(10")													**0.023**	**7.687**	**0.010**
N=37															
R²	**0.69**			**0.74**			**0.81**			**0.81**			**0.85**		
R2 adjusted	**0.62**			**0.68**			**0.76**			**0.75**			**0.80**		
std. error, S_e	**0.08**			**0.07**			**0.06**			**0.06**			**0.06**		
Prob>F													**0.00**		
coefficient of residual variability, V_e													37.89		

Numbers in bold = $p < 0.05$; numbers in italics = $p < 0.10$

Notes:
[a] proportion of roads with sidewalk

$$mixed - use\ entropy = -1 \times \left(\frac{\sum_{i=1}^{k} p_i \times \ln(p_i)}{\ln(k)} \right)$$

[b] types of station entrances: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

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Table 44. Effect tests for multivariate regressions estimating the proportion of

Effect tests for multivariate regressions estimating the proportion of walking

tests for multivariate regressions estimating the proportion of walking within

total riders walked within 0.5 mile / total ridership per station	Controls			+ Connectivity			+ Accessibility			+ Density			+ Land Use		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.022	7.159	0.012	0.023	7.501	0.010	0.016	5.415	0.027	0.0166	5.281	0.029	2E-09	9E-07	0.999
station entrance type[b]	0.004	1.277	0.267	0.003	0.896	0.351	0.003	1.059	0.312	0.0029	0.918	0.346	0.001	0.311	0.581
service frequency[‡]	0.001	0.370	0.547	0.004	1.320	0.260	0.003	1.046	0.315	0.0032	1.027	0.32	0.003	1.118	0.300
Feederbus services (no)	0.098	32.156	0.000	0.096	31.961	0.000	0.098	32.117	0.000	0.0934	29.68	8E-06	0.017	7.493	0.011
parking supplies	0.013	4.351	0.045	0.008	2.597	0.118	0.003	1.012	0.323	0.0032	1.011	0.323	0.000	0.001	0.970
avg.metric reach(0.5mile)/ directional reach (10⁴)				0.004	1.410	0.244	0.006	1.976	0.170	0.006	1.863	0.183	0.008	3.691	0.065
sidewalk availability[a]							0.002	0.616	0.439	0.002	0.593	0.448	0.001	0.488	0.491
population density: persons per gross acre within 0.5 mile of station										0.000	0.046	0.832	0.000	0.010	0.922
mixed-land use index[†]													0.027	12.164	0.002
N=37															
R^2	0.65			0.66			0.67			0.67			0.77		
R^2 adjusted	0.59			0.60			0.60			0.58			0.70		
std. error, S_e	0.09			0.05			0.05			0.06			0.05		
Prob>F													0.00		
coefficient of residual variability, V_e													52.44		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$Mixed-use\ entropy = -1 \times \left\{ \frac{\left[\sum_{i=1}^{k} P_i \times \ln(P_i) \right]}{\ln(k)} \right\}$$

[b] types of station entrances: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

Table 45. Effect tests for multivariate regressions estimating the proportion of walking within 0.5

total riders walked within 0.5 mile / total ridership per station	Controls			+ Density			+ Land Use			+ Accessibility			+ Connectivity		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	0.022	7.159	0.012	0.021	6.848	0.014	0.000	0.040	0.842	0.0001	0.044	0.836	2E-09	9E-07	0.999
station entrance type[b]	0.004	1.277	0.267	0.004	1.288	0.265	0.002	0.751	0.393	0.0016	0.666	0.421	0.001	0.311	0.581
service frequency[‡]	0.001	0.370	0.547	0.001	0.413	0.526	0.000	0.101	0.753	0.0003	0.103	0.751	0.003	1.118	0.300
Feederbus services (no)	0.098	32.156	0.000	0.097	30.969	0.000	0.020	8.545	0.007	0.0196	7.935	0.009	0.017	7.493	0.011
parking supplies	0.013	4.351	0.045	0.012	3.736	0.063	0.002	0.641	0.430	0.0015	0.589	0.449	0.000	0.001	0.970
population density: persons per gross acre within 0.5 mile of station				0.000	0.073	0.789	0.001	0.414	0.525	0.001	0.371	0.548	0.000	0.010	0.922
mixed-land use index[†]							0.025	10.529	0.003	0.025	10.108	0.004	0.027	12.164	0.002
sidewalk availability[a]										0.000	0.006	0.937	0.001	0.488	0.491
avg.metric reach(0.5mile)/ directional distance(10°)													0.008	3.691	0.065
N=37															
R^2	0.65			0.65			0.74			0.74			0.77		
R^2 adjusted	0.59			0.58			0.68			0.67			0.70		
std. error, S_e	0.09			0.06			0.05			0.05			0.05		
Prob>F													0.00		
coefficient of residual variability, V_e													52.44		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$Mixed-use\ entropy = -1 \times \left[\frac{\sum_{i=1}^{k} P_i \times \ln(P_i)}{\ln(k)} \right]$$

[b] types of station entrances: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

Table 46. Effect tests for multivariate regressions estimating the proportion of

Effect tests for multivariate regressions estimating the proportion of walking

tests for multivariate regressions estimating the proportion of walking within

total riders walked within 0.25 mile / total ridership per station	Controls			+ Connectivity			+ Accessibility			+ Density			+ Land Use		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	**0.007**	**10.785**	**0.003**	**0.008**	**13.860**	**0.001**	**0.008**	**13.495**	**0.001**	**0.0079**	**13.52**	**1E-03**	**0.0045**	**7.972**	**0.009**
station entrance type^b	**0.003**	**5.272**	**0.029**	**0.003**	**4.415**	**0.044**	**0.002**	**4.240**	**0.049**	*0.0023*	*3.888*	*0.059*	**0.002**	**4.293**	**0.048**
service frequency^‡	0.000	0.624	0.436	*0.002*	*3.928*	*0.057*	*0.002*	*3.875*	*0.059*	0.0016	2.799	0.105	*0.002*	*2.979*	*0.096*
Feederbus services (no)	**0.010**	**14.605**	**0.001**	**0.009**	**16.039**	**0.000**	**0.009**	**15.608**	**0.000**	**0.0068**	**11.61**	**0.002**	**0.005**	**8.230**	**0.008**
parking supplies	0.000	0.613	0.439	0.000	0.026	0.874	0.000	0.028	0.869	6E-05	0.103	0.751	0.000	0.000	0.982
avg.metric reach (0.25mile) / directional distance (10^x)				**0.003**	**6.071**	**0.020**	**0.003**	**4.705**	**0.038**	**0.003**	**5.161**	**0.031**	**0.003**	**4.689**	**0.039**
sidewalk availability^a							0.000	0.071	0.792	0.000	0.180	0.675	0.000	0.003	0.957
population density: persons per gross acre within 0.25 mile of station										0.001	0.942	0.340	0.000	0.641	0.430
mixed-land use index^†													0.001	2.016	0.167
N=37															
R^2	**0.53**			**0.61**			**0.61**			**0.62**			**0.65**		
R^2 adjusted	*0.45*			*0.53*			*0.51*			*0.51*			*0.53*		
std. error, S_e	0.03			0.02			0.02			0.02			0.02		
Prob>F coefficient of residual variability, V_e													0.00 69.99		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
^a proportion of roads with sidewalk

$$Mixed-use\ entropy = -1 \times \left[\frac{\left(\sum_{i=1}^{k} P_i \times \ln(P_i) \right)}{\ln(k)} \right]$$

^b types of station entrances: at-grade, elevated, underground
^‡ number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

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Table 47. Effect tests for multivariate regressions estimating the proportion of walking within

total riders walked within 0.25 mile / total ridership per station	Controls			+ Density			+ Land Use			+ Accessibility			+ Connectivity		
	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F	sum of squares	F ratio	prob>F
auto ownership relativized by per-capita income*	**0.007**	**10.785**	**0.003**	**0.007**	**10.424**	**0.003**	**0.004**	**6.167**	**0.019**	**0.004**	**6.297**	**0.018**	**0.0045**	**7.972**	**0.009**
station entrance type[b]	**0.003**	**5.272**	**0.029**	**0.003**	**5.036**	**0.032**	**0.003**	**5.450**	**0.027**	**0.0032**	**5.021**	**0.033**	**0.002**	**4.293**	**0.048**
service frequency[‡]	0.000	0.624	0.436	0.000	0.322	0.575	0.000	0.710	0.406	0.0005	0.838	0.368	0.002	2.979	0.096
Feeder/bus services (no)	**0.010**	**14.605**	**0.001**	**0.008**	**11.873**	**0.002**	**0.005**	**8.030**	**0.008**	**0.0051**	**8.018**	**0.008**	**0.005**	**8.230**	**0.008**
parking supplies	0.000	0.613	0.439	0.000	0.701	0.409	0.000	0.133	0.718	0.0001	0.161	0.691	0.000	0.000	0.982
population density: persons per gross acre within 0.25 mile of station				0.000	0.156	0.696	0.000	0.131	0.720	0.000	0.230	0.635	0.000	0.641	0.430
mixed-land use index[†]							*0.002*	*3.576*	*0.069*	0.002	2.364	0.135	0.001	2.016	0.167
sidewalk availability[a]										0.000	0.288	0.595	0.000	0.003	0.957
avg.metric reach (0.25mile)/ directional distance (10^n)													**0.003**	**4.689**	**0.039**
N=37															
R²	0.53			0.53			0.58			0.58			0.65		
R² adjusted	0.45			0.43			0.48			0.46			0.53		
std. error, S_e	0.03			0.03			0.02			0.03			0.02		
Prob>F													0.00		
coefficient of residual variability, V_e													69.99		

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$Mixed-use\ entropy = -1 \times \left\{ \frac{\left(\sum_{i=1}^{k} P_i \times \ln(P_i) \right)}{\ln(k)} \right\}$$

[b] types of station entrances: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

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APPENDIX F

Results of bivariate, stepwise and multivariate regression analysis predicting the index of dispersion (*D*) of walking distances at MARTA rail stations using urban form measures as independent variables, and non-urban form measures as statistical controls for 1 mile radii.

(a) n=37, r²=0.25, p<0.0016   **(b)** n=37, r²=0.26, p<0.0014   **(c)** n=37, r²=0.27, p<0.0010   **(d)** n=37, r²=0.33, p<0.0002
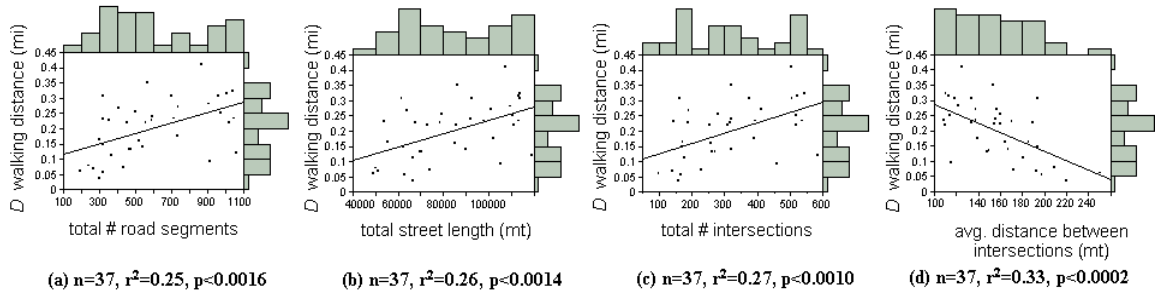
Figure 66. Scatterplot showing the index of dispersion of walking distance by station against (a) total number of road segments, (b) total street length (mt), (c) total number of intersections, and (d) average distance between intersections (mt) within 1 mile rings

(a) n=37, r²=0.28, p<0.0007   **(b)** n=37, r²=0.18, p<0.0080   **(c)** n=37, r²=0.34, p<0.0002

Figure 67. Scatterplots showing the index of dispersion of walking distance by station against (a) average Reach (1mile), (b) average 2-directional Reach (10°), and (c) average Reach (1mile) divided by the corresponding average directional distance (10°) for 1 mile rings

(b) n=37, r²=0.10, p<0.0548

Figure 68. Scatterplots showing the index of dispersion of walking distance by station against the PEF measure calculated for 1 mile rings

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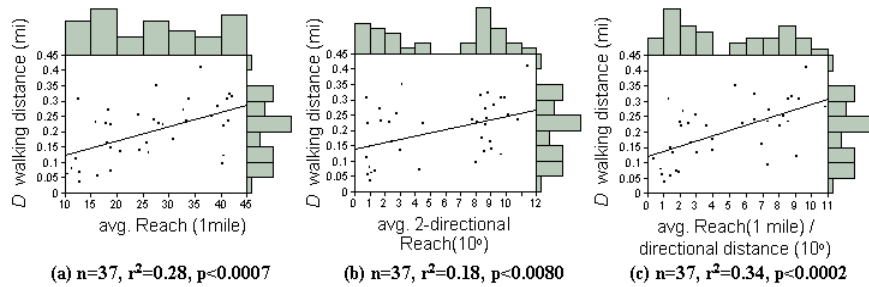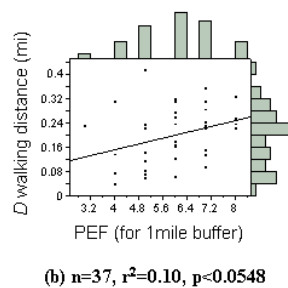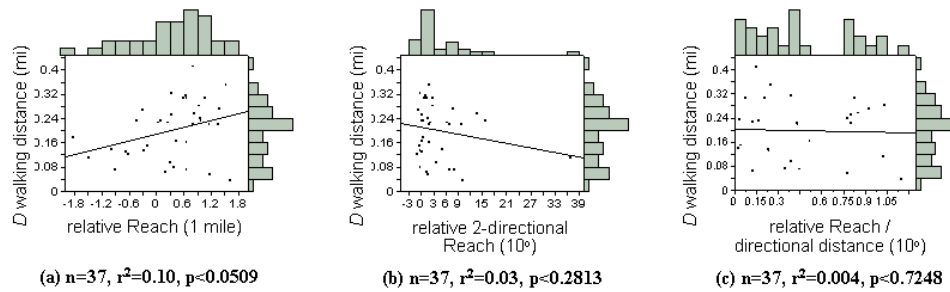| | | (a) n=37, r²=0.10, p<0.0509 | | (b) n=37, r²=0.03, p<0.2813 | | (c) n=37, r²=0.004, p<0.7248 |

Figure 69. Scatterplots showing the index of dispersion walking distance by station against (a) relative Reach (1mile), (b) relative 2-directional Reach (10°) for 1 mile rings, and (c) relative Reach (1 mile) divided by the corresponding average directional distance (10°) for 1 mile rings

Table 48. Parameter estimates for step-wise regression model estimating index of dispersion of walking distances to/from stations

index of dispersion of walking distance by station	B	F	prob>F	B	F	prob>F	B	F	prob>F	B	F	prob>F
population density: persons per gross acre within 1 mile of station	0.022	24.43	0.000	0.020	19.13	0.000	0.015	7.53	0.010	0.019	9.09	0.005
sidewalk availability[a]				-106.94	3.42	0.073	-137.82	4.99	0.032	-76.55	0.93	0.341
parking supplies (0=no, 1=yes)							-0.02	1.77	0.192	-0.032	3.13	0.086
mixed-land use index[†]										-0.263	1.49	0.231
N=37												
R²		0.41			0.47			0.49			0.51	
std. error		0.01			0.01			0.01			0.01	

Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
[a] proportion of roads with sidewalk

$$^{\dagger}Mixed-use\ entropy = -1 \times \left(\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right)$$

Table 49. Parameter estimates for the multivariate regression model estimating the index of dispersion of distances walked to/from stations

Multivariate Regression Model

index of dispersion of walking distance by station	β	t	prob>|t|
constant		1.257	
auto ownership relativized by per-capita income*	-0.231	-1.414	0.169
station structure type[■] (underground)	0.015	0.659	0.516
station structure type[■] (elevated)	-0.024	-1.395	0.175
station structure type[■] (at-grade)	0.010	0.505	0.618
service frequency[‡]	-0.001	-0.997	0.327
feederbus services (0=no, 1=yes)	-0.042	1.398	0.174
parking supplies (0=no, 1=yes)	-0.014	0.582	0.565
avg. Reach (1mile)	0.002	0.515	0.610
sidewalk availability[■]	-120.403	-1.273	0.214
population density: persons per gross acre within 1 mile of station	*0.018*	*2.100*	*0.045*
mixed-land use index[†]	-0.350	-1.472	0.153
N		37	
R²		**0.57**	
R² adjusted		**0.43**	
std. error, Sₑ		**0.07**	
Prob>F		**0.003**	
coefficient of residual variability, Vₑ		**35.6**	

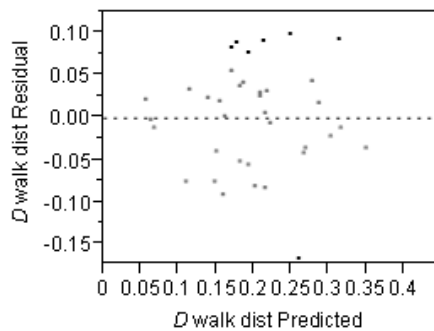Numbers in bold = p< 0.05; numbers in italics = p<0.10

Notes:
[■] proportion of roads with sidewalk

$$\text{Mixed} - \text{use entropy} = -1 \times \left(\frac{\left(\sum_{i=1}^{k} p_i \times \ln(p_i) \right)}{\ln(k)} \right)$$

[■] types of station structure: at-grade, elevated, underground
[‡] number of inbound trains in am peak hour (7am-9am)
* ratio of average auto-ownership to average per-capita income calculated per station

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