PhD DISSERTATION

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Title: Path and Place: A Study of Urban Geometry and Retail Activity in Cambridge and Somerville, MA.

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Abstract

This dissertation investigates retail location patterns in urban settings – a domain that has received relatively little attention in recent decades. We analyze which land use, urban form, and agglomeration factors explain observed retail patterns in an empirical case study of Cambridge and Somerville, MA. We are particularly interested in whether and how the distribution of retailers is affected by the spatial configuration of the built environment – the physical pattern of urban infrastructure, the spacing and sizes of buildings, and the geometry of circulation routes. We argue that understanding retail location patterns in urban settings is not only important for improving retail location theory, but also essential for designing economically, socially, and environmentally sustainable urban neighborhoods.

The dissertation proposes a novel graph-analysis framework in which retail location patterns can be represented under realistic constraints of urban geometry, land use distribution, and travel behavior. A series of spatial accessibility metrics, which we hypothesize to affect retail location choices, are introduced and applied in this framework using individual buildings as units of analysis. In order to test the statistical significance of these different metrics on retail location choices, we adopt the strategic interaction methodology from spatial econometrics and apply it for the first time in the context of location studies. We specify a linear probability model with a binary dependent variable and estimate how buildings' probabilities to accommodate retail establishments relate endogenously to other retailers' location choices and exogenously to both land use and urban form characteristics around each building. We apply the model to all retail and food-service establishments as a group and to different three-digit NAICS establishment categories individually.

The results confirm that retail location choices in our study area are significantly related to both other retailers' endogenous location choices and exogenous land use characteristics around each building. However, controlling for both of these factors, we find that the spatial distribution of retail activity is also significantly related to the geometry of the built environment. By setting constraints on accessibility, visibility, adjacency, and density, the geometry of the built environment produces a rich landscape of information that appears to guide opportunities for business from building to building.

The findings inform economists and planners about factors that attract retailers in urban settings, and urban designers about how the seemingly basic act of laying out streets, parcels and buildings can affect the location choices retail and service land uses, thereby shaping the economic structure of the city in important ways.

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This dissertation talks about the importance of physical places, but it is also itself very much a product of an extraordinary place — MIT. The brilliant people, ideas, and opportunities connected through a web of infinite paths around this Institute have played a central role in the development of this research. The idea to study the influence of urban geometry on land use locations choices using both retail location theory and configurational studies of the built environment is probably partly due to the close spatial connectivity between the various departments of this campus. But it is undoubtedly the gifted faculty and colleagues around the Institute who have helped me grow this idea into a dissertation.

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Introduction

1.1 Background of the problem

Understanding the relationship between the spatial structure of human settlements and the social life of their inhabitants is one of the central challenges of city planning. Yet despite extensive investigation to date, the relationship between the spatial configuration of cities and social processes that take place in them has proven to be a topic of extraordinary complexity, with only modest advances available to illuminate a dissertation on the matter. The importance of built geometry in the ancient monastic societies of the Middle- and Far-East, and South America went beyond symbolic significance, affecting numerous procedures of daily life (Lynch 1984). Studies of indigenous cultures in the American Amazon have suggested that the geometry of settlement patterns was of vital importance in preserving social organization and kinship hierarchies (Lévi-Strauss 1963). There is little consensus, however, over the significance of urban form in contemporary societies.

Making reference to life sciences, Jane Jacobs has described cities as problems of *organized complexity*, which not only contain a large number of variables, but also challenge an analyst with countless interrelationships between the variables (Jacobs 1961: 428). Indeed, the state of knowledge of the form-process dialectic suggests that general questions such as 'what is the influence of urban configuration on social life?' are defeated at the outset, since more interactions are found than a single answer could possibly suggest. Perhaps more important, the notion of complexity evoked in Jacobs' reading of cities, also suggests that any particular interaction between form and use is likely to be neither unique nor deterministic. Instead, the argument suggests, the relationship can take many forms and depend on a range of additional factors that affect people's use of space beyond spatial form. Using an example of city parks, Jacobs argues:

"How much a park is used depends, in part, upon the park's own design. But even this partial influence of the park's design upon the park's use depends, in turn, on who is around to use the park, and when, and this in turn depends on the uses of the city outside the park itself. Furthermore, the influence of these uses on the park is only partly a matter of how each affects the park independently of the others; it is also partly a matter of how they affect the park in combination

with one another, for certain combinations stimulate the degree of the influence from one another among their components… No matter what you try to do to it, a city park behaves as a problem in organized complexity, and that is what it is. " (Jacobs 1961: 433)

Jacobs' remarks came at a time when architectural intervention was still widely regarded as the primary tool for addressing the social and economic ills of cities. Jacobs invited architects to investigate the complex interaction between form and use and cautioned designers and policy makers to recognize the limits of spatial design and to refrain from inferring strong causal relationships without the support of evidence.

Vigilant against 'spatial determinism', a number of urban sociologists have drawn a similar critique, alerting urban designers to remain wary of what Webber has called "*some deep-seated doctrine that seeks order in some simple mappable patterns, when it is really hiding in extremely complex social organization instead* " (Webber 1963). These arguments developed largely in response to a series of large-scale urban renewal projects across the U.S. and Europe that had addressed acute poverty in distressed urban areas using urban design as the primary tool. These projects produced disastrous consequences. Though it can be argued that these consequences were the result of a limited social and economic scope of the interventions, the critique also pointed out the insufficiency of a historic and deeply-rooted tradition of city planning that, until then, had been principally dominated by architects (Howard 1902; Garnier 1939; LeCorbusier 1967; Fourier 1971), and which had come to exhibit its limits in dealing with complex social and economic problems in postwar cities. The critics contended that a deeper understanding of the relationship between spatial and social processes was needed before urban design could be taken as a fix to any of the latter.

While it is now generally accepted that urban design is not the only — nor by any means the dominant — force acting upon the social life of cities, urban designers' response to the Webberian criticism has proven difficult and slow. This shortcoming has gradually pushed the field of urban design towards the margins of the contemporary theory of urban studies and planning. Within these confines, important theoretical developments in urban design have indeed occurred. Neo-Marxist planning theory, for instance, has offered a view of urban development that acknowledges the diverse actors and institutions affecting the spatial structure of cities, in which urban design holds a modest but important position (Harvey 1973; Lefebvre 1974; Gottdiener 1985). Christopher Alexander, Leslie Martin, Kevin Lynch, John Habraken, Konstantinos Doxiadis, and others have searched vigorously for plausible propositions that would link physical configuration with the qualities of cities (Alexander 1964; Doxiades 1968; Martin and March 1972; Lynch 1984; Habraken and Teicher 1998). Yet skepticism and pressure still loom over urban design scholars, whose theoretical foundations for the social value of spatial design still remain fragile. *"Maybe Team X and Archigram",* writes Koolhaas, *"were, in the sixties, the last real 'movements' in urbanism, the last ones to propose with conviction new ideas and concepts for the organization of urban life"* (Koolhaas 2001).

The general view of urban design within the larger field of city planning today has come to the point where it is no longer a question of whether there are additional influences on social behavior beyond spatial configuration, as an 18th- or 19th-century architect might have conceded, but rather if spatial configuration has *any* importance at all for the social processes of the city (Talen and Ellis 2002). This dissertation is largely motivated by a conviction that this view is problematic on several fronts. First, as a growing proportion of human activities take place in cities (UnitedNations 2007), it becomes increasingly important to understand how the physical environment of the city affects, and desirably benefits, the activities of its users. Most daily activities of city dwellers are constrained, to a greater or lesser degree, by the configuration of the built environment — the physical pattern of urban infrastructure, the geometry of built form and its circulation routes, the shape of public space and paths that connect them. The basic social significance of urban form thus emerges through the mere fact of its ubiquitous use. The growth and change of cities at an unprecedented rate demands attention to form and more empirical research, not neglect. The consequences of disregarding spatial configuration and geometry in the contemporary planning of cities could be as grave as their excessive emphasis in the mid-century urban renewals.

Second, despite the inadequacy of professional knowledge concerning the ingredients of 'good city form', a layperson's attraction towards delightful urban environments, such as Paris, Porto, or Hong Kong, provides testimony to the important role that urban geometry plays in shaping our attitudes towards cities. Rather than assigning the emotions triggered by delightful urban environments to the realm of the metaphysical, we might attempt to understand them with methodological rigor. Learning from precedent is of course a central component of a designer's education, but the attempts to capture the positive qualities of past precedents often seem to lead to mimicry and kitsch, instead of constructive knowledge for intelligent, context-appropriate design. In order to venture towards a better understanding of the social significance of environmental geometry, precedents need to be examined not only through plans, but also through observation, user accounts, and other forms of social, economic, and environmental data.

Third, important developments in configurational studies have occurred since the writing of Lynch and others, creating new opportunities for empirical research on city form. Among these, the ubiquity of computers and the availability of data that describe both static and dynamic components of the city have dramatically improved an analyst's capacity to study complex relationships between built form and its occupancy patterns. Tools like geographic information systems (GIS), computer-aided design (CAD), digital databases, and statistical software, largely unavailable a decade ago, have now become widely available to urban designers. Furthermore, geographically-referenced digital data describing the built, social, and economic environment of the city have become accessible for research during the same period. These developments have opened up various new directions for theoretical and empirical propositions about city form and initiated an active area of urban design research[1].

Taking advantage of some of these developments, this dissertation introduces an alternative view of urban design than architects would typically express. It focuses on a configurational view of urban design — the study of how the geometric layout of streets, parcels, and buildings can affect the perceived value and patterns of use of different locations within a city. Rather than centering on the qualities of buildings and streets themselves, this dissertation focuses predominantly on the spatial interdependence between these elements of the city. This view of urban design under emphasizes many important sensory characteristics of

[1] The contemporary centers of research include the Santa Fe Institute, the Center of Advanced Spatial Analysis (CASA) and the Space Syntax group in London, the Human Space Lab in Milan, the UPC Barcelona, l'Institut Français d'Urbanisme, and the city design and development and urban information systems groups at MIT, to name a few.

the built environment that contribute to our daily appreciation of cities — the identity, the aesthetic quality, and the meaning of buildings, streets, and public spaces. In fact, in the following analysis, we alter our field of vision so that we may perceive the invisible aspects of city design that cannot be seen through the eyes of an observer at any single location in the city. Instead, we attempt to capture the dynamics that emerge as people travel through streets, moving from one building to another, collectively producing the patterns of flow and encounter that make different locations within the network of city streets more or less amenable for different activities. In this respect, some might argue that this study does not even deal with urban design or architecture, since "Architecture begins where engineering ends", as Walter Gropius said. Yet the practice of urban design shows that the functional prerequisites that good architecture relies upon are poorly attended to in practice and insufficiently addressed in academia. Compared to the capacity to produce individual buildings of architectural quality, contemporary urbanism appears less able to capitalize on what Jan Gehl calls the *life between buildings*[2]: the social and economic linkages and movement patterns that result from inter-relationships between buildings and which each building in turn contributes to. Even the most outstanding individual buildings or public spaces can fail to be appropriated by their users if the spatial configuration around the projects disincentivizes their workings[3]. We shall thus argue that, despite the narrow focus that a configurational view of urban design offers, the spatial configuration of the built environment can produce important effects for the social use of buildings — effects, which may at times outweigh the sensory qualities of buildings and public spaces themselves. In the long run, a better understanding of the configurational qualities of place may also lead us to a better understanding of the fundamental interactions that link qualities of urban structure to the qualities of meaning and identity in architecture (Lynch 1996: 252).

Research on different aspects of the social significance of urban form has not only been criticized outside of the urban design field, but also within. It is often urban designers, architects, and planners themselves who dispute the existence of any systematic relationships between spatial and social structure. Claims towards such a relationship appear to challenge a deep-rooted conviction that the creative human agency that guides city development makes each piece of a city so unique as to render any systematic analysis meaningless. Even if systematic relationships are found, the critics argue, they have limited value in normative situations because creativity and unorthodox solutions can always displace historic conventions of development. Researching the relationship between spatial form and social behavior thus appears to challenge the agency of a designer. This sort of criticism stems from a perceived difference between practical knowledge (Schön 1983), embodied in a designer on the one hand, and codifiable and explicit knowledge that is produced in research, on the other. We do not challenge the central importance of implicit practical knowledge or *Metis*, a Greek term derived from the Goddess of the same name who personified wisdom (Scott 1999), in the design process. Rather, the spatial research developed in this dissertation explores how research findings, obtained by analyzing large amounts of data, could supplement the diverse arsenal of knowledge used by design professionals in practice. Beyond practical applicability,

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[2] See Gehl, J. (1987). Life between buildings : using public space. New York, Van Nostrand Reinhold.

[3] One of many well-known examples is the Constitution Plaza in Hartford, CT by another modernist designer Victor Gruen.

however, we also remain hopeful that a stronger appreciation for research might help the field of urban design reclaim its theoretical position in the larger field of urban studies and planning.

1.2 Statement of the problem

This dissertation focuses on a particular aspect of the urban form-process relationship. The social process we examine is the choice of location for operating one's business in an urban environment. The central question of the dissertation is the following: *Does the spatial configuration of the built environment affect location choices of retail and food service establishments?*

By 'spatial configuration' we refer to the relationships of adjacency and connectivity that result from the geometric layout of buildings and public spaces and the circulation routes that connect them. We are interested in exploring whether the spatial patterns of access and encounter that result from the particular way these elements of the city are laid out may generate economic incentives for locating one's business in one location rather than another. Put alternatively, we investigate whether physical design is significantly related to the distribution of retail activities in a city. Confirming a plausible relationship with evidence could shed new light on the social significance of urban design, a topic that remains widely disputed in mainstream planning theory. The findings could also lead to practically valuable knowledge regarding the effects of urban form on location and land use.

The relationship between retail location choices and the spatial configuration of a city has been subject to some study, but a good deal more assertion. New Urbanists' claims, among others, about the importance of density and accessibility for sustaining retail and service establishments in town centers have produced surprisingly little empirical research (Duany, Plater-Zyberk et al. 1991). Scholars using graph theory metrics on urban form, on the other hand, have produced numerous studies on the subject, but shortcomings in methodological rigor have rendered their results too porous to be taken seriously in the planning and economic research community (Hillier 1996; Porta, Crucitti et al. 2005). Our understanding of the role of urban spatial configuration on land use location choices thus remains contested.

Unlike most past retail location studies that operate at a district or town resolution (Berry, 1967, Eppli and Shilling, 1996), inside shopping centers (Brueckner, 1993, Carter and Vandell, 2005, Miceli et al., 1998), or at street level (Porta, Strano et al. 2009),we model our analysis at a fine spatial resolution across a large and relatively dense urban area, using individual buildings as units of analysis. Retail location studies at this level of detail have been rare in the literature. Using novel data and exploratory econometric methods, we thus chart a relatively unknown territory. However, building upon previous conventions of representation allows us to employ familiar graph theory-type metrics to quantify the attributes of urban form around each building under the realistic constraints of the street network and built fabric.

The location values that emerge from the spatial configuration of the built environment are of course also related to the human activities that take place therein. Thus, in addressing how environmental geometry may induce or curb spatial accessibility at different locations within the built environment, we also need to consider the extents and types of activities that take place in the various buildings that are being accessed. We argue, however, that it is important to distinguish attributes of accessibility that result from urban form from those that result from land use attractions. Doing so allows us to investigate whether and how strongly location choices are affected by each type of variable individually. A clear distinction of factors allows us to estimate whether retailers cluster in popular locations, such as Central Square in Cambridge, because of an endogenous attraction to other retailers, to other land uses and transit stations, to advantageous configuration of urban form, or to a combination of any of these factors.

We center the analysis on one family of economic activities: retail establishments. Retail establishments offer an interesting case because their attraction to highly accessible locations is well documented in retail location literature. This allows us to embark on the analysis with a clear set of hypotheses and expectations. At the same time, we also aim to address important shortcomings in retail location theory, which is relatively advanced in explaining location patterns in shopping malls, but remarkably less advanced in explaining retail patterns in urban settings. The bulk of retail location research of the recent decades has developed using empirical data from privately- and centrally-managed shopping malls. We do not know whether location patterns encountered in shopping malls are transferable to retail agglomerations encountered in dense urban environments.

Second, retail location theory has primarily focused on the spatial inter-dependencies between retailers. Neo-classical retail location theory, particularly, centers on inter-store externalities, explaining how the location and characteristics of one store may affect the operations of another store. The state of knowledge on how exogenous location factors like spatial accessibility and land use attractions may influence retail location decisions is less good. Focusing exclusively on endogenous location factors and explaining one store's location choices with other stores' location choices overlooks one of the most interesting questions in economic geography: why do agglomerations form at certain locations in the first place? Explaining why urban centers in general — and retail agglomeration in particular — emerge at particular locations in a city remains a glaring shortcoming of economic geography. We suspect that the role of environmental geometry in this question is central, but poorly understood.

However, the primary purpose of this study is not to improve retail location theory. Instead, the subject matter explored in this dissertation is foremost driven by the practical necessity to improve our ability first to comprehend and then to design vibrant and sustainable urban neighborhoods. Nurturing commercial land uses that support daily retail and service needs at the neighborhood level has become an important goal in planning environmentally, socially, and economically sustainable urban areas worldwide. Several recent studies have found that the availability of mixed land uses near one's place of residence is key to achieving these goals. A higher concentration of commercial land uses within walking distance reduces people's reliance on private automobiles and decreases vehicle miles travelled (Frank and Pivo 1994; Krizek 2003; Zegras 2004), decreases urban energy consumption (Newman and Kenworthy 1999), produces better health indicators among residents (Hoehner, Ramirez et al. 2005; Rundle, Roux et al. Forthcoming), and fosters social cohesion (Jacobs 1961; Pendola and Gen 2008). From an economic viewpoint, we now know that clusters of small entrepreneurial businesses produce important agglomeration efficiencies (Krugman 1991; WorldBank 2009). A diverse set of small establishments tends to generate higher employment growth and stronger resilience to economic fluctuations and externals shocks than a small set of large establishments (Glaeser, Kerr et al. 2009). But, despite the abundant evidence on the social, environmental, and economic efficiencies that commercial establishments within walking range generate, we are astonishingly incapable of explaining how such land use mixes work, what we can do to sustain them, and how we could stimulate their development in the countless growing cities around the globe. Even modest insights into the spatial economic workings of urban retail operations could produce great value for the contemporary practice of urban design and planning. Analytic methods that are systematic and replicable in many different urban environments could turn this current shortcoming into a strength. This dissertation aims to introduce methods of spatial analysis that are easily replicable in the rapidly urbanizing cities around the World. Taking advantage of recent computational developments, we propose a systematic approach for detecting location choice preferences that, we hope, will contribute to urban designers' arsenal of knowledge for creating vibrant and sustainable urban environments.

1.3 Scope of the study

Our research is grounded in two existing bodies of theory: urban economics and configurational studies of the built environment. Both configurational studies of the built environment and urban economics have developed important explanations of the spatial distribution of urban land uses. However, mutual adoption of methods and joint modeling remain lacking between these two fields. Built-form studies have produced practical methods for measuring socially meaningful properties of the built environment, but their measures remain largely unused in urban economics. Urban economics, on the other hand, has produced deep insights into the production functions, linkages and location decisions of households and firms, but these insights remain underutilized by scholars of city form. This dissertation investigates whether a joint application of both types of measures could produce a better explanation of the observed pattern of retailers in a city.

Many attributes of urban form may affect retail location choices. The geometry of an individual building, for instance, can influence the building's use — an activity of a certain type and size requires an appropriate spatial shell. A comfortable fit with the layout of the building may well be a decisive criterion for a particular use. A space that is either too large or small, a disposition of rooms that does not satisfy desired adjacencies, a circulation system that impedes daily business are but a few instances of spatial misfit that demonstrate why form needs to follow function.

There is also an aesthetic dimension to urban form. Retailers of a certain type may prefer to locate in buildings, streets, or neighborhoods that satisfy desired aesthetic standards. Antique dealers, for instance, might prefer architectural Baroque or Neo-classicism, while art dealers might instead value industrial structures. Aesthetic qualities of the built environment can sometimes be important factors for location choices.

Another important quality of urban form for retail location choices is the capacity of the chosen environment to accommodate growth and change. A business owner who foresees considerable growth over time might desire a location that can accommodate growth with the least friction possible. Such retailers might value neighborhoods that are growing or witnessing considerable change. Flexibility towards future uncertainty can play a decisive role in some stores location decisions.

The analysis presented in this dissertation will, however, not address these attributes of urban form. A thorough study of ways in which these qualities of urban form affect retail location choices would require several dissertations. Instead, we will focus on the spatial accessibility of a location: the geometric layout of building footprints and public spaces and the circulation routes that connect them. The geometric and topological relationships that emerge from these patterns arrange establishments and people in space by locating them in relation to each other, at either a greater or lesser degree of agglomeration and separation. The geometric order of the built environment can thereby engender patterns of movement and encounter that may incentivize or disincentivize a retail operation. The distribution of land uses, on the other hand, determines the character of these movements and encounters. The relationship between the configurational qualities of the built environment and retail location choices seems to provide ample subject matter for a dissertation, allowing us to develop a more focused investigation than a broader exploration of multiple, simultaneous, urban form qualities would permit.

The present analysis does not focus on the decision-making process of business-owners who are about to establish new or move existing stores. Instead, we focus on the 'revealed' location choices, where economic activities have already been located, based on past decisions. We use the observed distribution of economic establishments and a series of attributes of the built environment to infer which factors have played a significant role in their location choices in the past.

It is important to note that using cross-sectional data in statistical analysis limits our ability to distinguish causal relationships from mere correlations. We can therefore only speculate whether causality is present in any of the spatial and social relationships we find. More reliable causal inference could be developed in future research using longitudinal data and natural experiments.

1.4 Summary of chapters

The next chapter reviews the literature on retail location choices as well as the configurational studies of the built environment. Discussing both bodies of theory successively, we describe which problems have been addressed in the past, which aspects of retail location choices remain poorly understood and outline the areas of overlap that could potentially take both fields in new directions. Chapter Three first introduces a novel representational framework using graphs, where factors of urban form, land use, and travel behavior can be jointly depicted. This framework allows us to represent the problem of location choices, and to measure detailed attributes of spatial accessibility in our study area. We then introduce our case study area of Cambridge and Somerville MA, and describe the various predictors of retail location choices that were captured for the analysis that follows. The second half of the chapter introduces the empirical estimation methodology. An innovative spatial econometric model is proposed, where three types of important effects on retail location choices can be jointly estimated. First, the methodology includes a strategic interaction component that allows us to evaluate the degree to which location choices depend endogenously on other establishments' presence in the neighborhood. Second, the methodology includes a set of exogenous variables that predict how the spatial and economic characteristics around each location may affect retail location choices. And third, the methodology addresses the hazard of omitted variables that are often found in spatial location choice studies. Having introduced the methodology, Chapter Four will turn to the results of our case study analysis. It will first present our findings for all retailers as an aggregated group, and then turn to individual types of retailers, discussing the particular factors related to location choices of disaggregated retail categories. Chapter Five concludes and discusses some directions for future research.

2

Review and synthesis of literature

A field of configurational studies of the built environment developed among architects, planners, and transportation researchers in the 1960s and 70s. The work is characterized by attempts to understand the societal forces that shape settlement patterns and to develop analytic methods that outline meaningful properties of environmental geometry (See March and Steadman 1971; Martin and March 1972; Anderson 1978; Hillier and Hanson 1984; Habraken and Teicher 1998; Porta, Crucitti et al. 2005). This work has also investigated effects that environmental geometry might have on the performance and quality of cities (Weeks 1960; Proshansky, Ittelson et al. 1970; Tabor 1976; Lynch 1984; Ellingham and Fawcett 2006) by analyzing the relationship between social behavior and spatial configuration using both quantitative and qualitative methods, which range from mathematical geometry and graph theory to ethnographic surveys and comparative analysis. Scholars of this field have a deep understanding of environmental geometry and are primarily interested in understanding or measuring the social significance of architectural and urban form.

Around the same time, land use location theory, a different field, but equally concerned with urban space, emerged in economics. The scholars of location theory focus on the spatial distribution of land uses, firm location choices, and land values (Lösch 1954; Isard 1956; Alonso 1964; Mills 1967; DiPasquale and Wheaton 1996). They seek to understand how various individuals and groups with different interests and requirements compete for locations and produce the observed urban land use pattern. Whereas configurational studies are predominantly concerned with the geometry of the environment, urban economics centers on the efficiencies that result from a spatial interaction between land uses. Configuration of the environment is of interest to urban economics insofar as it constitutes the spatial stage where market competition occurs, imposing transportation and time costs for interaction. Details of spatial configuration have typically been of minor interest in the these studies: "*The city is viewed as if it were located on a featureless plain, on which all land is of equal quality, ready for use without further improvements, and freely bought and sold*"

(Alonso 1964). Newer land use and accessibility models often operate implicitly within the actual geometry of the street network, representing spatial relationship between locations by a time or distance cost along shortest-travel paths (Wyatt 1997; Bhat, Handy et al. 2002; Waddell and Ulfarsson 2003). However, the interaction between the distribution of land uses and the configuration of city form has not been an explicit area of research in urban economics. Understanding this interaction is important for planners. How are firm location decisions affected by advantages in accessibility set by environmental geometry? How is the spatial configuration of the city in turn affected by the requirements posed by urban land uses? What land use attractions and configurational characteristics of locations make them more or less suitable for certain types of uses? The relationship between urban economics and urban design is generally under-examined and little understood, making desirable even modest advances in unbundling the social and economic significance of city form.

This dissertation aims to overlap a detailed configurational study of urban form with an economic analysis of location choices. Both configurational studies of the built environment and urban economics have developed important explanations about the spatial distribution of land uses. But a mutual adoption of methods and joint modeling remains lacking. Built-form studies have resulted in practical methods for measuring socially meaningful properties of the built environment (March and Steadman 1971; Martin and March 1972; Anderson 1978; Steadman 1983; Hillier and Hanson 1984), but their measures remain largely unused in urban economics. Urban economics, on the other hand, has evaluated location choices with respect to production functions and economic linkages to suppliers or customers, largely ignoring environmental geometry (Huff 1963; Waddell and Ulfarsson 2003; Huang and Levinson 2008). Earlier writings of Proudfoot and Hurd have explicitly commented on the configurational aspects of location at neighborhood scale (Hurd 1903; Proudfoot 1937), and configurational questions are implicit in some scholars' research on location choices (Carter and Vandell 2005), but an explicit focus on the effects of environmental geometry on location values has not been central in either field. Empirical research presented in this dissertation moves towards a joint approach, where spatial attributes of the built environment are evaluated from an economic perspective of land use location choices. We conjecture that a joint usage of both types of measures could produce a better explanation of the observed urban structure, and we hypothesize that environmental geometry could be an important determinant of economic location choices.

2.1 Classical retail location theory

The spatial distribution of retailers has been widely studied by scholars of the city. Already in 1916 Robert Park noted that "*There is now a class of experts, whose sole occupation is to discover and locate, with something like scientific accuracy, taking account of the changes which present tendencies seem likely to bring about, restaurants, cigar stores, drug-stores, and other small retail business units whose success depends largely on location. Real estate men are not infrequently willing to finance a local business of this sort in locations which they believe will not be profitable, accepting as their rent a percentage of the profits*" (Park 1916: 95). Proudfoot categorized the principle spatial patterns of retailers of early 20th-century American cities into five groups according to commodities sold, concentration or dispersal of outlets, and customer type: (1) the central business district; (2) the outlying business center; (3) the principal business thoroughfare; (4) the neighborhood business street; and (5) the isolated store cluster (Proudfoot 1937). These five patterns of retailing continue to this day, with a few additions. Over the course of the 20th-century the car-oriented shopping mall, which is somewhat analogous to Proudfoot's outlying business center, has become one of the most important retail typologies of our time. Much of retail location literature has come to focus on this typology. An isolated general store, big enough to supply all quotidian merchandise, the strip-mall, which resembles Proudfoot's principal business thoroughfare, but serves a predominantly vehicular clientele, and the non-store retailer (i.e. catalogue, phone or internet order) might also be added to the list of prominent 20th-century retail typologies.

Several economic forces that shape the densities and location patterns of retailers have found an explaination since Park's and Proudfoot's writing. Previous comprehensive reviews of retail store location theories have been given by Isard, Berry, Stahl, Vandell and carter, and Eppli and Benjamin among others (Isard 1956; Berry 1967; Stahl 1987; Vandell and Carter 1993; Eppli and Benjamin 1994). A review of different mathematical models for predicting potential store locations are given by Huff, O'Kelley, Achabal, Gorr, and others (Huff 1963; O'Kelly 1981; Achabal, Gorr et al. 1982; Ghosh, Craig et al. 1984). Popular sources of recent publications include: The Journal of Retailing, The Journal of Real Estate Research, and Journal of Real Estate Literature.

A typical retail location model postulates that store owners are expected to locate at points of maximal demand, "as closely as possible to the consumers demanding their commodity bundle; and to retailers who, by supplying complementary commodity bundles, attract the desired clientele" (Stahl 1987: 759). Location decisions also need to account for direct competitors, by balancing the potential of higher demand that results from clustering with competitors against the monopolistic advantages of increased market area that result from locating in isolation. The choice of location thus directly affects the patronage and revenues of retail establishments and constitutes an important part of a retailer's production function[1].

2.1.1 A one-dimensional model

DiPasquale and Wheaton illustrate a simple classical model, where store location choices happen on a one-dimensional straight line (DiPasquale and Wheaton 1996). The model starts with the point of view of consumers, whose shopping frequencies collectively constitute the aggregate demand for retailers. Consumers' decisions of shopping frequency are viewed as a cost-minimization problem. Total costs in this scenario signify the combined costs of purchase prices and transportation costs, as well as inventory costs to store merchandise at home. Shopping frequency thus depends on the type of commodity bought, the frequency of its use, and the transportation costs of delivering it. The total annual cost (C) of consuming a good is given by the annual purchase price of the units Pu (unit price P times the amount purchased annually u), the annual transportation costs for delivering the good kv (transportation costs per trip k times trip

[1] Retailers also compete for customers through prices and choice of merchandise.

frequency v), and the inventory costs: storage cost per year i times the purchase value of the average inventory between two shopping trips $Pu/2v$ (DiPasquale and Wheaton 1996: 132):

$$C = Pu + kv + i\left(\frac{Pu}{2v}\right)$$

Equation 1

Consumers are thought to adjust their shopping frequency so as to minimize their total costs C. This minimization problem is solved by equating the first-order derivative of Equation 1with respect to v to zero, which leads to an optimal purchase frequency v^*:

$$v^* = \left(\frac{iPu}{2k}\right)^{\frac{1}{2}}$$

Equation 2

The inspection of the optimal purchase frequency (v^*) in Equation 2 is telling with regard to consumer shopping behavior. If transportation costs (k) are higher, then all else equal, shopping frequency (v^*) is lower. If storage costs (i) are higher, as is the case with perishable goods for instance, then shopping frequency is higher. Similarly, if the amount consumed annually rises, then all else equal, purchase frequency rises. Items that rarely amortize or perish and those that are hard to store (e.g. furniture items) are purchased at a lower frequency. Retailers selling infrequently-purchased goods are thus expected to locate at larger intervals and to draw customers from larger market areas than neighborhood grocery stores. However, the exact spacing of different types of retailers also depends on the fixed costs of establishing and running a business and the pricing policy of competitive retailers. Lower prices can compensate customers for longer trips.

A given purchase frequency leads to a model that explains store-owners location decisions. This model estimates the expected density of retail facilities as a function of four parameters:

v: frequency of purchase trips
k: costs of travel per mile
C: fixed cost for a retail facility
F: buyer density in a given linear radius

Customers are assumed to be uniformly distributed along a horizontal line, as shown in Figure 3. The model assumes that all retailers offer identical products. Consumers are expected to shop at the retailer whose total delivered price for the good is lowest. The total delivered price of an item is the sum of the purchase price P and the travel cost kD (travel cost per mile times distance). In equilibrium, each store has identical sales prices[2] and an equal-size double-sided market area ($2T$), inside of which it offers the lowest delivered price for consumers located within that zone (DiPasquale and Wheaton 1996: 136). The market area between two stores is defined as the point where the total delivered cost is equal between two stores

[2] Reaching identical prices in equilibrium is just one theory according to Tirole, J. (1988). Theory of Industrial Organization. Cambridge, MIT Press.

(*P*+*kT*). Beyond that point, transportation costs make the total price of the delivered good lower in a neighboring store.

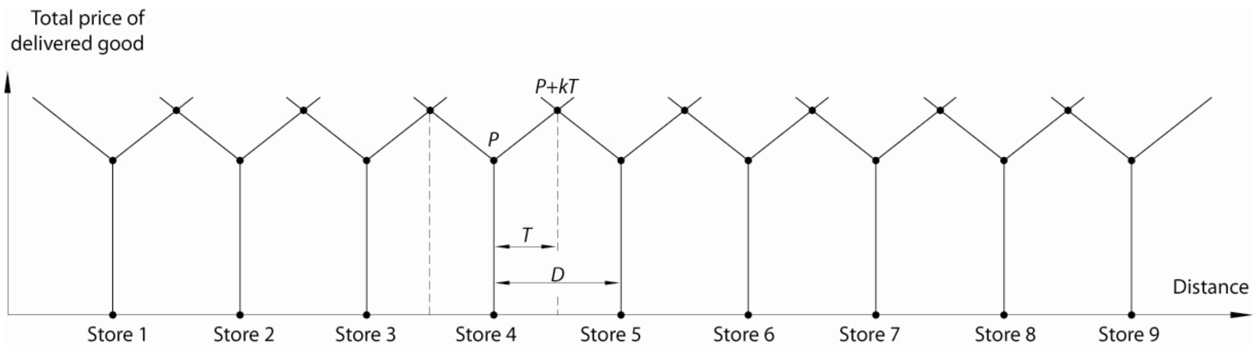

Figure 1 Retail market areas of nine stores in a linear space.

The long-run equilibrium distance (*D*) between stores is given as follows[3]:

$$D = \left(\frac{C}{kvF} \right)^{\frac{1}{2}}$$

Equation 3

Equation 3 suggests that retailers distribute themselves evenly along the line, each one being distance D apart from the neighboring stores. This distance D is given as a function of fixed costs of a retail facility (C), transportation costs (k), purchase frequency (v), and buyer density (F). Descriptive statistics of the equation suggest that if the frequency of trips (v) increases, then the distance between facilities (D) decreases and the density of facilities is higher. If the fixed costs of setting up a facility (C) rise, then the distance between facilities also rises, and density decreases. As the density of customers (F) goes up, the density of facilities also goes up. We thus expect to find higher densities of retailers that sell frequently purchased goods, such as food and drinks, clothes, and accessories, than infrequently-purchased goods, such as building materials or automobiles.

2.1.2 A two-dimensional model

A general two-dimensional model of retail distribution was formulated by Christaller and Lösch in Central Place Theory (CPT) (Christaller 1933; Lösch 1954). Analogous to the one-dimensional example of Figure 1, identical stores have identical two-dimensional market areas in equilibrium. The size of market areas and the distance between stores are ultimately determined by two fundamental inputs to the model: *range*, which denotes the maximum distance a consumer will travel to purchase a good; and *threshold*, the

[3] A full explanation of how we arrive at this solution is given in DiPasquale, D. and W. C. Wheaton (1996). Urban economics and real estate markets. Englewood Cliffs, NJ, Prentice Hall.
p. 136

minimum demand necessary for a store to stay in business. Christaller and Lösch illustrate how the combination of range and threshold leads to a regular hexagonal pattern of stores, where the size of the hexagons is determined by the maximum range of customers and the minimum threshold of the store. Identical stores divide the market areas evenly, with each store being equidistant from neighboring stores selling the same goods, as shown in Figure 2.

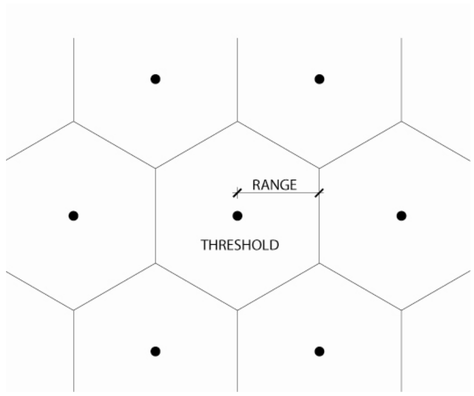

Figure 2 Market areas of identical stores in Central Place Theory .

Similar stores have similar market areas, but stores offering different goods can have different market areas. As bread, for instance, is bought frequently, a relatively small market area will generate enough demand for a bread store to remain viable. Furniture, on the other hand, is bought rarely, and so market areas of furniture stores must be correspondingly large. Smaller retailers, which attract more frequent purchase patterns, can thus emerge at the boundaries of larger retail market areas. For a single region, there might be several bread stores and only one (or no) furniture stores. These differences lead to overlapping market areas, where hexagons of higher-order goods, which are rarely bought or otherwise require large market areas to remain viable, reach across market areas of lower-order goods, as illustrated in Figure 3. Higher-order centers combine a wider variety of different stores, while lower-order centers only offer goods that can be supported by a smaller market area.

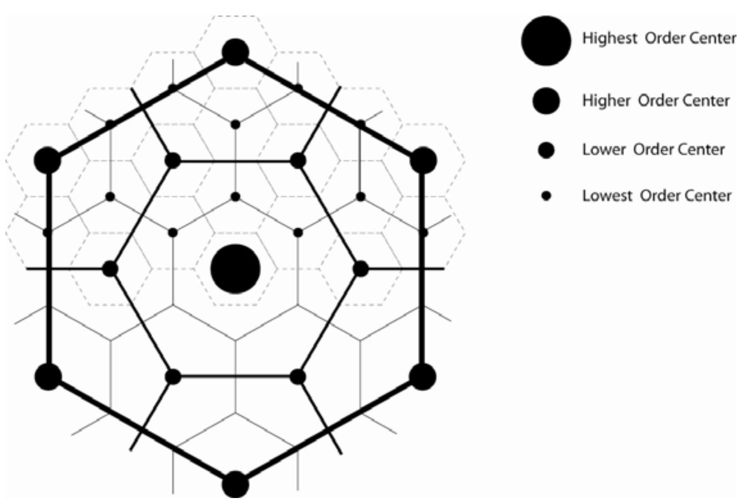

Figure 3 Overlapping market areas of hierarchical centers in Central Place Theory

The hexagonal pattern of centers in Figure 3 describes the most economic pattern of development that can serve an even distribution of customers with a minimum number of centers. But it is important to note that the emergence of hexagonal market areas assumes a spatial environment that resembles a featureless plain, on which all land is of equal quality, ready for use without further improvements. Consumers are assumed to obtain a particular good only from the nearest center and to make a separate trip for each type of merchandise. Customers are assumed to approach centers along straight-line travel paths from any point in the region.

The absence of a spatial transportation network in CPT leads to a spatial puzzle. If one were to commute between higher- and lower-order centers in the hexagonal pattern of Figure 3, a fundamental transportation inefficiency would appear: routes connecting two higher order centers, passing through lower order centers, would be crooked, not straight, as transportation economies would suggest. Christaller acknowledged the issue by evoking Kohl's *traffic principle* (Kohl 1850), according to which travel routes are expected to follow most economical paths between centers:

"One sees immediately that if the central places are distributed according to the traffic principle, a considerably higher number of central places of each type will be necessary in order to supply the region with central goods of a particular range. This contrasts with the marketing principle, which economizes on the number of central places required to supply the whole land. Both principles are theoretically correct, as both are, in a certain sense of the word, of the highest rationality. But there can be only one possibility with the highest economic rationality. Which possibility it is will depend upon the concrete circumstances. Either the traffic principle has such a weight that it outweighs the marketing principle, advantage for advantage, or the marketing principle is the stronger one, or finally, the most favorable system is obtained through a combination of both principles, i.e., through a compromise". (Christaller and Baskin 1966: 74)

However, he later concluded that "*Since the marketing principle is clearly dominant in determining the distribution of the central places in Southern Germany, we may say, generally then, that the marketing principle is the primary and chief law of distribution of the central places. The traffic and the separation principles are only secondary laws causing deviations; these laws are effective in practice only under certain conditions*." (Christaller and Baskin 1966: 192)

The *marketing principle* of CPT, which suggests the most economical hexagonal pattern of centers, and Kohl's *traffic principle*, which emphasizes the economies of travel routes, thus produces a theoretical dichotomy: is the spatial evolution of the pattern driven by an efficient allocation of centers or by efficient commuting between centers? The resolution is not essential to CPT, since inter-center commuting in general and multipurpose shopping in particular are not addressed in the theory. Similar to the one-dimensional market area analysis of the preceding section, CPT assumes that consumers make a separate trip for each good and always shop at the nearest center. Goods offered in different centers are thus assumed to be acquired on different trips, and inter-center transportation inefficiencies therefore do not affect the model.

CPT has propagated a great deal of empirical research. Christaller produced the first assessment of Central Places in Southern Germany in his original publication (Christaller 1933). Similar findings were contemporaneously produced in Estonia by Edgar Kant (Kant 1933; Kant 1935). Evidence of Central Places in the United States is given by Berry, who used data from rural Iowa and urban Chicago (Berry 1967).

2.1.3 Effects of an irregular environment and exogenous agglomeration

Both the one-dimensional retail store location model, presented in section 2.1.1, and the two-dimensional model of Central Place Theory rely on an important assumption regarding the environment that the models operate in. Both models assume a spatial environment that resembles a featureless plain, on which all land is of equal quality, ready for use without further improvements. This assumption allows the spatial distribution of centers to become perfectly uniform across space. Stores selling the same goods divide the market areas evenly, with each store obtaining an identical market area, and each store being equidistant from similar neighboring stores (See Figure 1and Figure 2).

The homogenous environment assumption is, of course, a coarse simplification that clarifies the analysis and produces a more parsimonious model. It eliminates the role of transportation networks and urban form from the analysis, allowing location patterns to emerge in response to marketing forces that can flow freely across space in any geographic direction. A consumer is expected to patronize the closest center using a straight-line route from his or her location of origin.

The reality of built environments is more complex. The homogenous environment assumption is especially problematic when analyzing land use location patterns within a city — which is the central concern of the present study. Physical travel in a city follows streets, turns when routes intersect, and chooses among many alternative paths. The geometric configuration of the urban street network and transit system generates an uneven level of accessibility throughout a city, limiting access to opportunities in some places, while favoring it in others. We hypothesize that the geometric configuration of the built environment can thus exert an important influence on the spatial distribution of centers in intra-urban settings.

Take for example the linear model presented in Figure 1. Though this one-dimensional model does not explicitly describe how retail densities are affected by the spatial configuration of the environment, some effects of urban form are implicit in the model. One parameter of Equation 3 is particularly tied to urban form: F, the buyer density in a given linear radius[4]. The density of customers is affected by building

[4] In fact, C, the fixed costs involved in setting up a store, is also strongly affected by urban configuration. Urban form can affect the fixed costs involved in setting up a store by influencing the ease with which ground-floor units in buildings can be converted into retail uses. A series of other factors, such as labor costs and zoning regulations, play an important role in costs as well. However, all else equal, if the structure and circulation of a building typology allow ground-floor units to be converted into shops at a lower cost, then the presence of such buildings can increase the density of retailers. Medieval merchant houses of old European centers, many of which now accommodate ground-floor businesses, offer a good example. The twentieth-century prefabricated apartment blocks, on the other hand, exemplify a typology where the conversion of ground-floor units is complicated by structural and configurational factors. Using load-bearing façade panels prohibits the addition of new doors and windows. A common stairwell serving multiple units can create conflicts between residential and commercial circulation inside the building. A ground floor that is raised by a flight of stairs creates privacy for residential units, but complicates both visual and physical access to potential retail units. Establishing retail outlets in neighborhoods of prefabricated apartment blocks thus often requires entirely new buildings, elevating construction and administrative costs of setting up shop. According to Equation 3, we would expect higher retail densities in neighborhoods where building typologies facilitate the conversion of ground floors for retailing.

heights and the floor area ratio (FAR) of a neighborhood. Buildings with double the heights, all else equal, can house double the customers for retailers. Neighborhoods where higher residential densities are achieved with taller structures are thus expected to have a higher density of retailers.[5] The relationship between retail density and customer density is not linear however. Plotting the relationship between F and D from Equation 3, reveals a curvilinear and diminishing relationship between customer density and distances between stores (Figure 4). This implies that doubling the population density of an area reduces the distance between retailers by *less* than half. Larger increases in retail density[6] appear at the lower end of the population density spectrum, and smaller increases at the higher end of the population density spectrum. Keeping the average floor area per person constant, we thus expect retail density to increase at a diminishing rate as the amount of built floor area increases per unit area of land.

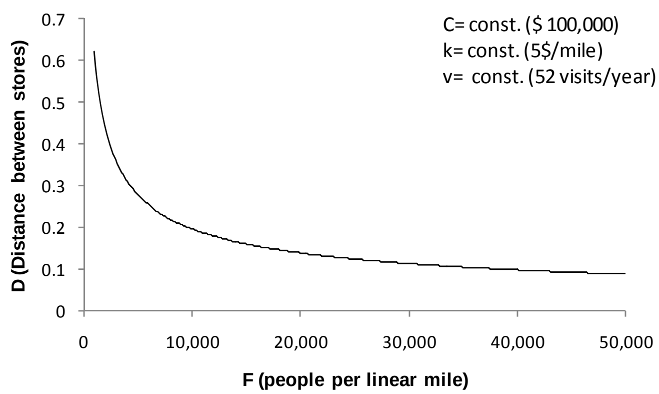

Figure 4 A bivariate graph showing the relationship between F and D from Equation 3, keeping other inputs constant.

Beyond the simple effect of building heights, other geometric changes in the plan configuration of the street network also add interesting effects to buyer density *F* in Equation 3. In the linear model of Figure 1 the number of visitors at each store (*2TF*) is found by multiplying the store's market area (*2T*) by the linear density of customers in the market area (*F*). If we rearrange the nine stores of Figure 1 into a different linear configuration, a cross for instance, keeping the linear length of streets constant, as shown in Figure 5, then different locations within the network face different access to customers. Assuming that travel can only occur along the linear lines that form the cross (e.g. city streets), a store at the center would have four times the access reach of stores at the far ends of the cross arms. An equilibrium, where all stores' market areas are equal, as in Figure 1, would require that distances between stores be shorter around the center — the most accessible location in the layout (Figure 5). This is because the advantageous market area

[5] In the urban area of Hong Kong, for instance, which has an average floor area ration of about nine, and a population density of 44,000 per square kilometer, there are 711 Seven-Eleven convenience stores: one store per every 0.0745 square kilometers. Source: ccNg, E. Designing high-density cities for social and environmental sustainability. London ; Sterling, VA, Earthscan
Source: http://www.demographia.com/db-hkuza1.htm, accessed July 5, 2010.
Source: http://en.wikipedia.org/wiki/7-Eleven, accessed July 5, 2010.
[6] Figure 4 illustrates the relationship with distance, not density. The effects on store density are found by taking the inverse of the distance between stores.

at the center would, in the long run, be reduced by stores moving closer to the center until all store's market areas are equal. Keeping the total number of stores constant, this would lead to a higher density of stores around the center of the cross than in the outlying areas. The geometry of the environment thus generates shorter distances between stores at more accessible locations.

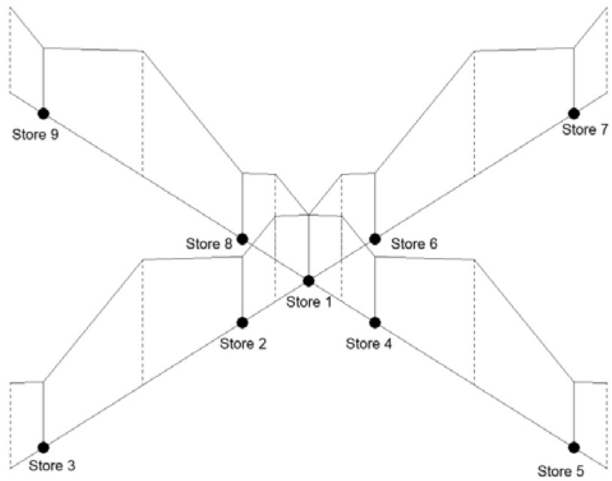

Figure 5 Equal-size retail market areas of nine stores on a cruciform linear network.

Environmental geometry can further augment store density as localized levels of accessibility increase. Unusually high levels of accessibility, which could result from an atypical intersection of numerous streets or the presence of a subway stop, could lead to the emergence of clusters of competitive stores. Additional retailers would be expected to join the cluster until profits resulting from advantageous accessibility are dampened though competition. The cluster would stop growing when enough retailers have entered a cluster to lower profits to the same level as the next best alternative location. The scenario thus illustrates an exogenous agglomeration process, whereby retailers do not agglomerate because of mutual complementarily or because of proximity to suppliers, but rather because the spatial configuration of the environment supplies certain locations with better access to customers.

Analogous effects of environmental geometry on retail location choices are typically missing from economic location studies. This might be partially explained by the complexity that spatial irregularities introduce to the models, and/or the lack of established conventions for measuring spatial configuration. The analysis of location patterns on networks has, however, recently become graspable with the aid of computers. GIS Network Analyst[7], TransCAD[8], SANET[9], GeoDaNet[10], NetworkX[11], and UCL DepthMap[12] currently offer some of the most popular software platforms for spatial network analysis, making the laborious task of computing location attributes on a network manageable. Meanwhile, research

[7] http://www.esri.com/software/arcgis/extensions/networkanalyst/index.html (Accessed February 17, 2010)
[8] http://www.caliper.com/tcovu.htm (Accessed February 17, 2010)
[9] http://sanet.csis.u-tokyo.ac.jp/ (Accessed February 17, 2010)
[10] http://geodacenter.asu.edu/software (Accessed February 17, 2010)
[11] http://networkx.lanl.gov/ (Accessed February 17, 2010)
[12] http://www.vr.ucl.ac.uk/depthmap/ (Accessed February 17, 2010)

on configurational studies of city form has made significant theoretical progress in proposing appropriate measures to describe variations in accessibility that result from urban form. We shall review some of these techniques in greater detail later in this chapter.

2.2 Neo-classical Retail Location Theory and Endogenous Agglomeration

The last section presented an example of *exogenous clustering*, where the density of competitive stores increased in the part of a network where spatial access was geometrically favorable. We call such clustering exogenous since it is attributable to an external resource, which all retailers are attracted to. However, retail agglomeration can also arise from *endogenous* factors: externalities between retailers that make it inherently beneficial for stores to locate in close proximity to each other. These externalities form the central focus of neo-classical retail location theory.

2.2.1 Transportation Savings and the Clustering of Complementary Stores

Empirical studies of retail distribution over the 20th-century have increasingly accumulated evidence that challenges the predictions of Central Place Theory. The single-purpose, nearest-center patronage assumption of CPT has attracted most criticism. Multiple empirical studies have shown that people do not always choose the closest shopping venues and that they often shop at multiple stores on the same trip. Using data similar to Berry's, Rushton, Golledge, and their colleagues showed that only 35% of a rural Iowa population shopped at the nearest center (Rushton, Golledge et al. 1967). Clarke, using data from New Zealand, showed that the nearest-center patronage assumption becomes less tenable as the size of the destination center increases (Clark 1968). Whereas 63-83% of trips to small shopping centers patronized the nearest destinations, only half of the trips led to the closest destination among largest centers. The difference is explained, the authors argue, by transportation savings achieved by multipurpose shopping at the larger centers. Hanson studied explicitly whether shopping trips are multipurpose and found that 61% of all trips in his sample were multipurpose (Hanson 1980). Similarly, O'Kelly found that 63% of grocery shopping trips and 74% of non-grocery trips were multipurpose (O'Kelly 1981).

Multipurpose shopping introduces inter-store externalities to a retail location model, challenging the store distribution predictions of CPT. Transportation savings that arise in multipurpose shopping bias consumers in favor of larger centers. If a similar bundle of goods can be acquired by either patronizing disparate small stores on multiple trips or a large and heterogeneous cluster on a single trip, then the latter option often leads to a lower total cost due to savings in transportation.[13] As a larger variety of goods draw a larger pool of customers, a positive feedback loop incentivizes stores to cluster in even larger

[13] This is of course ignoring other potentially important factors of destination choice, such as emotional pleasure, which could lead to the patronage of multiple isolated small stores despite the additional transportation cost.

heterogeneous centers (Bacon 1971; Mullingan 1987). Eaton and Lipsey have shown how multipurpose shopping on the part of consumers and profit maximizing locational choice on the part of firms can lead to a higher concentration of clusters than predicted in CPT (Eaton and Lipsey 1982). West, Hohenbalken, and others have corroborated this effect using empirical evidence from Edmonton, Alberta:

"Our tests support the hypothesis of a hierarchy of shopping centres with properties that are more closely aligned to an Eaton and Lipsey than a Christaller-type hierarchy. In particular, we found that our shopping centre hierarchy has one important characteristic that is consistent with the predictions of the Eaton and Lipsey model, but not Christaller's, namely the replication of stores of the same type in the same shopping centre. We would expect such replications to arise naturally from the profit maximising locational behaviour of firms confronted with comparison and multipurpose shopping behaviour on the part of consumers (behaviour that is outside the Christaller model, but within those developed by Eaton and Lipsey)". (West, Hohenbalken et al. 1985: 116).

Though multipurpose shopping has mainly been used to explain the success of shopping malls, its underlying advantages are equally applicable to traditional retail clusters in urban settings. A variety of individual stores located in close proximity allows customers to bundle multiple shopping trips into one, reducing total transportation costs for patrons and increasing demand for retailers (Figure 6). Empirical research on malls has shown that the size of a shopping center is, in fact, a considerably stronger predictor of patronage than distance to the center (Eppli and Shilling 1996). Since vehicular transportation costs associated with malls are much lower on a per mile basis than pedestrian transportation costs, we should expect a different balance of factors in urban settings where shops are often accessed on foot. Higher transportation costs make people more sensitive to distances required to reach larger centers, leading to a stronger patronage of closer and smaller stores.

Figure 6 A small cluster of complementary retailers on Highland Avenue near Davis Square in Somerville MA. The adjacent individual stores include a set of complementary establishments: a dessert store, a dairy shop, a bread store, a restaurant, and a service/catering company (Photo: Andres Sevtsuk, April 2009).

Neo-classical retail location theory suggests that multipurpose shopping also introduces a second, related effect to explain the clustering of heterogeneous and complementary stores: demand externalities. Demand externalities refer to customer spillovers that one store can produce for other stores. Given conveniently small distances between stores, customer traffic attracted to higher-order retailers can increase traffic in lower-order retailers. Unlike the transportation effect in multi-purpose shopping, where heterogeneous clusters enable customers to purchase a set of *planned* goods at lower total costs, demand externalities produce additional *unplanned* purchases in lower-order stores. A customer visiting a department store in a mall, for instance, might pay a visit to a newspaper kiosk in the same mall, thus making a purchase that he or she would avoid if a separate trip to a newspaper kiosk were required. Demand externalities are generally thought to flow in one direction — from more popular to less popular stores or from anchor stores to non-anchor stores.

Brueckner has provided a model that demonstrates how a careful manipulation of the size of stores in a shopping center, according to their level of demand externalities and their impact on the center as a whole, can maximize shopping center revenues (Brueckner 1993). In his model, the sales volume of a store i, denoted as R_i, depends on the amount of space S_i that the store occupies[14]. In the presence of inter-store externalities, R_i also depends on the amount of space allocated to other stores in the center. Store i's sales are thus given as a function of all stores' areas in the center:

$R_i = R^i\,(S_1, S_2, \ldots, S_n)$, *where*

$$\frac{\partial R_i}{\partial S_i} > 0 \; and \; \frac{\partial R_i}{\partial S_j} \geq 0, \qquad i \neq j$$

Equation 4

Equation 4 shows that as store *i's* own space rises, then sales at store *i* are also expected to rise. However, if a nearby store j produces positive demand externalities for store i, then store *i's* sales can also rise as store *j's* floor area increases. If no externalities exist between i and j, then the marginal effect of store *j's* space increase on store *i's* sales can also be zero. However, if a center contains multiple stores of a given type, then competition between stores might reverse this effect. For instance, if store i and j are both shoe stores, then $\partial R_i/\partial S_j$ and $\partial R_j/\partial S_i$ could both be negative as an increase in the size of store i reduces the sales of the competing store j and vice versa. Brueckner goes on to show how a careful and coordinated manipulation of complementary store sizes can lead mall-owners to optimal profits for the center as a whole.

A large body of empirical research has studied demand externalities in shopping malls. Anikeeff provides an overview of previous attempts to measure the degree of spillovers, or ''retail compatibility,'' across different types of non-anchor stores (Anikeeff 1996). Nelson classified stores into five categories according to the percentage of customers who visit a given pair of stores (Nelson 1958). More recently, Eppli and Shilling used a new dataset and enhanced methods to re-estimate the degree of retail compatibility for a sample of stores in fifty-four regional shopping centers in the United States (Eppli and Shilling 1993).

[14] Space is used as a proxy variable for capturing the choice of merchandise at the sore.

They found that regional shopping centers with greater quantities of space devoted to anchor tenants have higher non-anchor tenant sales for eight out of nine merchandise types.

Theories on profitable mixing of tenants in planned shopping malls have also led numerous researchers to look for implicit evidence of demand externalities embodied in tenants' rent contracts. In a widely popular practice, mall owners charge a discriminatory percentage of rent from tenants, depending on their impact on not only their own revenues, but also on the revenues of the mall as a whole[15]. Stores that constitute the primary motivation for customers' trips to the center (i.e. department stores), generally pay low or no rent, while odd specialty stores that are not on the list of many shoppers pay high rents, as most of their traffic comes from nearby stores. This difference in rents is seen as implicit evidence of demand externalities that anchor stores generate for non-anchor stores. Empirical evidence of differential rents is given by (Benjamin, Boyle et al. 1990; Benjamin, Boyle et al. 1992).

Centrally-managed private shopping centers offer cheaper percentage rent contracts as an incentive to attract big anchor stores to the center. The positive demand externalities that such stores create for other stores are thereby returned in the form of cheaper rent payments. Eppli and Benjamin have shown that the image and fame of anchor stores (i.e. brands) play an important part in customer draw, often increasing the customers willingness to patronize otherwise distant locations (Figure 7) (Eppli and Benjamin 1994).

Figure 7 Porter Square Mall in Porter Square, Cambridge MA. A careful manipulation of demand externalities and rent contracts allows mall owner to maximize profits by orchestrating an optimal tenant mix. The part of the mall on the image contains only well-known brand stores: a *Dunkin' Donuts* coffee shop, a *Mexican Grill* restaurant, a *RadioShack* electronics store, a *Liquor World* alcohol store, and a *Zoots* drycleaner.(Photo: Andres Sevtsuk, April 2009)

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15 There is a debate over the question of whether these discriminatory rents favor mall owners or mall tenants. See Wheaton, W. C. (2000). "Percentage Rent in Retail Leasing: The Alignment of Landlord--Tenant Interests." Real Estate Economics **28**(2): 185-204.

It is generally agreed in retail location literature that a profitable orchestration of complementary stores in planned shopping malls, coupled with discriminatory rent contracts that attract anchor stores to the center, is the primary reason why shopping malls have managed to eclipse other traditional forms of retailing in the US in the course of the 20th-century. Unlike main streets and neighborhood retailers, private shopping malls purposefully coordinate the tenant mix, prohibiting 'unwanted' store entry to the center and optimizing the performance of the cluster as a whole. A central management system allows owners to choose only stores that increase mall revenues by either attracting additional customers or paying higher rents for positive demand externalities, so that the positive externalities produced by higher-order stores are perfectly balanced by lower rents per square foot, thus providing all stores an equal incentive to join the center. Without subsidized rent contracts, anchor stores would face a disincentive to locate in shopping malls, since their customer draw would generate positive externalities for other stores with no compensation for the favor. Such is the case, however, in uncoordinated urban retail clusters (i.e. main streets, neighborhood centers, etc)[16]. This suggests that we should not expect the store clusters and agglomeration patterns found in shopping malls to appear analogous in urban settings. Instead, we expect clustering preferences to vary among different types and sizes of retailers. Non-anchor stores, such as small retailers who offer a limited choice of infrequently purchased merchandise, are more likely to value heterogeneous cluster locations, because the availability of complementary stores in a cluster enables customers to acquire a larger assortment of products from a single location, saving transportation costs and offering an incentive to visit the cluster. Large anchor stores, on the other hand, do not benefit from urban cluster locations in the same way that they do in malls. By attracting a large customer pool, they generate positive externalities for lower-order stores, without receiving rent subsidies or other types of return for the deed. We suspect that this might lead some anchor-stores to avoid cluster locations.

Retail location literature has been relatively silent on un-coordinated retail clusters[17]. The literature on demand externalities is especially vague about externalities in urban settings. Anecdotal evidence suggests that large anchor stores, such as supermarkets, are found equally often in free-standing locations as in neighborhood retail clusters. It is unclear if choosing a free-standing location is a result of an endogenous repellent force that drives large stores away from clusters or simply an exogenous attraction towards different types of locations, such as locations that are closer to people's homes. Since demand externalities do not explicitly damage retailers' own revenues, but rather just spill customers over to other stores, there is little reason to believe that a repellent force is at work. Rather, faced with a lack of rent incentives at a cluster location, anchor stores might simply drift to locations that are advantageous for exogenous reasons, such as better access to customers. At the same time, a large enough group of non-anchor stores at a cluster location could *collectively* produce enough positive externalities to attract a large anchor into a cluster. Such a *collective* positive externality challenges the currently popular assumption that demand externalities flow in only one way: from anchors to non-anchors. It is easy to conceive how the dynamics between an anchor

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[16] From an urban planning perspective, the efficiency of the planned shopping center model suggests that in order to support traditional forms of street retailing, merchant associations and other forms of collaborative action might aid clusters of small stores in a competition against large shopping malls.

[17] An exception is offered by Stahl, K. (1987). Theories of Urban Business Location. Handbook of Regional and Urban Economics. E. S. Mills. Amsterdam: North-Holland. **2:** 760-820.

store and a large set of non-anchor stores can indeed collectively produce two-way demand externalities that benefit all stores. Given the lack of theory on uncoordinated clusters, we shall try to address some of these questions empirically in Chapters Four and Five.

Another important factor that explains uncoordinated clusters is information spillovers. Caplin and Leahy have developed a search-theoretic model that explains how some potentially advantageous locations for urban retailing can remain underutilized for considerable time periods due to risk and information spillovers (Caplin and Leahy 1998). The first store that makes the decision to locate at a new location with little or no previous retail establishments must do so by internalizing a considerable risk. Should the location prove to be poor, then the penalties are carried by the risk taker alone. Should the location prove to be successful, however, then the payoffs are not only internalized by the risk taker, but will also help reveal the value of a location to potential competitors who have waited. The authors use their model to explain why Lower Sixth Avenue in New York City remained inactive among retailers for years, but witnessed a rapid turnaround after a Bed Bath & Beyond store opened shop there in 1992. Bed Bath & Beyond internalized the first mover's risk by making a considerable investment in an uncertain location. The apparent success of the store quickly assured other retailers of the location value and resulted in a rapid retail revitalization of the area. Caplin and Leahy's model can help us explain why some locations that appear promising due to their exogenous accessibility characteristics might remain under-utilized by retailers in our case study area.

2.2.2 Comparison Shopping and the Clustering of Homogenous Stores

The review of classical and neo-classical retail location theory thus far has addressed the distribution of individual stores and discussed the theory behind clustering of complementary stores. Complementary agglomerations were explained by two important phenomena: customer savings in transportation costs and demand externalities with customer spillovers between retailers. However, a daily experience of cities also shows that homogenous retailers sometimes agglomerate in clusters of stores selling almost identical goods. Anecdotal data suggests that competitive clustering is commonplace among book stores, restaurants, clothing stores, accessory stores, and occasionally even competitors whose merchandise is virtually identical, as in the case of gas stations. The arguments so far have not addressed why competitive retailers might also desire to locate in close proximity to each other. According to Central Place Theory, competitive sellers should locate at even distances from each other, with each Central Place containing only a single store of a certain kind. Why then would competitive stores decide to collocate?

We suggested one explanation in section 2.1.3, where we illustrated how geographic irregularities in spatial accessibility can lead to higher concentrations of competitive stores around the most accessible locations. The argument proposed that a significant node in the urban street network, where multiple highly-trafficked roads meet, leads to better access to customers and therefore higher store density (See Figure 5). Variable accessibility to buildings and transit stations could explain at least some competitive clustering. Retail location theory has traditionally paid little attention to such exogenous factors, a shortcoming we attempt to address in the course of this dissertation.

Neo-classical retail location theory also offers endogenous reasons that could lead competing stores to cluster. One of the earliest explanations for competitive clustering was given by Harold Hotelling in his 1929 paper, *Stability in Competition* (Hotelling 1929). Hotelling provided an example of two sellers on a linear line (i.e main street), facing perfectly inelastic demand, and demonstrated how competitive price and location games between the sellers can produce an equilibrium solution where both sellers are spatially clustered at the center of the line. Hotelling showed that even though the socially optimal solution would predict that two retailers divide up a market equally, uncertainty about competitors' location and price adjustments can incentivize retailers to cluster next to each other (Webber 1972). He argued that such clustering is socially suboptimal, because it demands exceedingly high travel costs from consumers. Consumers would be better off if the sellers located at the 1/4th and 3/4^{ths} points of the line, which would still yield identical revenue for both vendors.

Hotelling's work has inspired a large amount of theoretical and empirical research on competitive clustering throughout the 20th-century. Critics have shown that Hotelling's theory doesn't always hold and that there are other explanations behind competitive clustering. Smithies, and Lerner and Singer have shown that if the number of firms in Hotelling's one-dimensional line were increased, then firms would never group in clusters greater than two, and clustering could only occur at the periphery of the market. If demand is responsive to delivered price, that is, if demand is elastic and customers are sensitive to transportation costs, then firms on the one-dimensional line will be equally spaced instead of clustered (Lerner and Singer 1937; Smithies 1941). Hotelling's theory of Stability in Competition provides only a partial explanation of why competing retailers might choose to agglomerate.

Neo-classical retail location literature suggests that another endogenous reason, one indicative of people's shopping behavior, is also at stake. This endogenous reason is related to shopper's desire to compare similar items of merchandise before purchasing a particular item. Eaton and Lipsey have developed a model that explains clustering of homogenous firms as a cost-saving mechanism for clients whose purchase decisions are led by a desire to compare prices and products (Eaton and Lipsey 1975). Whereas Hotelling regarded competitive clustering as socially 'wasteful', Eaton and Lipsey's theory suggests that clustering is in fact useful for consumers because it saves them search costs that would otherwise accrue by visiting multiple competitive stores at disparate locations.

Though effectively useful for customers who like to compare prices and similar products, competitive clustering still produces two important negative effects for retailers. First, customers will have to be split between competitors. If a market area can only support a certain number of customers — just enough to keep one seller in business — then the addition of another identical seller can lead to the ruin of both, producing a strong disincentive to cluster. Second, competition over customers between homogenous firms will also reduce revenues by forcing stores to engage in a Cournot competition that lowers prices (Cournot 1838). Isolated retailers always possess a certain degree of monopoly power in their market area. When firms are spatially dispersed, then reasonable mark-ups in prices can increase profits without chasing away customers whose next best alternative is inconveniently far. In fact, free-standing retailers can theoretically increase the prices of goods of inelastic demand so high that the delivered price (including transportation costs) for customers, who come from nearby locations, remains just below the delivered price of the next best alternative. Such monopoly power disappears when retailers face direct competitors next door. Two competitive retailers can of course engage in a duopoly, both raising prices as they perceive that doing so makes both stores better off, but such understandings between competitors are notoriously fragile. The chances of inflated oligopoly prices sharply decrease as more firms are added to the game. How, then, is the clustering dilemma resolved for competitive retailers?

Economists have argued that, despite the negative externalities of competitive clustering, allowing customers to engage in price and product comparisons (and thereby lowering customers' search costs), can increase demand by attracting more customers to competitive clusters. Dudey has provided an important model that accounts for both negative Cournot competition effects described above and the positive additional demand effects. His model shows that an equilibrium solution can be reached where competitive clustering can still be a reasonable outcome due to savings in customer search costs (Dudey 1990). Homogenous competitive clustering occurs if the positive externalities of agglomeration outweigh the negative effects of competition. If the increased customer flow due to clustering exceeds the loss of customers in competition, then retailers are expected to cluster.

The tradeoffs that influence a retailer's decision to join competitive clusters are explained in the following simple model provided by (DiPasquale and Wheaton 1996). The inputs of the model are:

v: expected number of visits to each store if the store was located in an isolated place.
s: expected number of visits to each store if the store was located in a cluster.
n: the total number of retailers in a cluster.
α: extra customer attraction factor that results from clustering ($\alpha \geq 0$).
β: degree of complementarity or competitiveness among retailers ($0 \leq \beta \leq 1$) If β=0, then retailers are entirely complementary to each other, and if β=1, then retailers are entirely competitive.

Total visits to the cluster are given by the sum of individual visits to individual retailers as if they were isolated (vn) and some additional visits that result from the attraction factor (α) of the cluster as a whole: vn^{α}. How the total number of customers who come to the cluster as a whole is shared between individual retailers depends on the degree of complementarity or competition among retailers. If a retailer purely complements other retailers, then it faces no direct competition and clearly benefits from clustering. If several retailers offer similar products, however, then they act as competitors against each other. The probability of customers visiting a single retailer is given as: $1/n^{\beta}$. This means that if a retailer is a pure complement to other retailers, then $\beta = 0$ and the probability of this retailer being visited by a customer who comes to the cluster to purchase a particular good sold by this retailer is one[18]. If all retailers in the cluster sell the exact same products, however, then $\beta = 1$ and the probability of a retailer being visited by a customer who comes to the cluster is divided between all stores: 1/n. Competition therefore produces a negative force for clustering decisions. The total expected visits to a particular store in the cluster (s) is

[18] If β =0, then $1/n^{\beta} = 1/n^{0}=1$

determined by the tradeoff between the additional customer attraction factor that results from clustering (α) and the negative externalities of competition (β) :

$$s = vn^{(\alpha-\beta)}$$

Equation 5

Competitive retailers are expected to cluster if the increased customer flow due to clustering exceeds the negative externalities of competition, that is if $\alpha > \beta$. Neo-classical retail location theory suggests that an important factor — and one that increases α from the customers' perspective — is the diminished search cost at centers where prices and products can readily be compared. Note that unlike demand externalities, which primarily spill customers from anchor stores to non-anchor stores, producing only one-way benefits (in favor of non-anchor stores), a demand increase that results from comparison shopping generally benefits both stores.

It follows from the theory that not all stores are equally likely to value competitive clusters. Competitive clustering should be more pronounced for *search goods* for which price and product comparison is important and practically feasible only by visiting retailers in person, not via remote communication channels, such as telephone or Internet. Sellers of *search goods* have a greater proclivity toward agglomeration than sellers of *convenience goods* (Dudey 1993). While in liquor stores, for instance, a tactile comparison of one merchant's bottles with another merchant's bottles might create little added value, trying on shoes at a shoe store and evaluating the fit in person, can be an important step before spending. This difference explains why shoe stores are expected to cluster, but liquor stores are not. Dudey points out that this was already suggested by Scitovsky in 1952, who observed that:

"*[w]hen the majority of buyers are experts, who insist on inspecting and comparing alternative offers before every purchase, then it is in the sellers' interest to facilitate such comparisons. For example, if a buyer has to choose among five alternatives of which four are easily comparable but the fifth is not, he will concentrate on comparing and choosing among the four and may ignore the fifth altogether. Hence the desire of every seller who faces expert buyers to be near his competitors and render his wares easily comparable to theirs*." (Scitovsky 1952)

The role of comparison shopping in influencing competitive clustering has also been validated by empirical evidence. Nevin and Houston found that the variety of retail merchandise for comparison shopping is a strong predictor of shopping-center sales (Nevin and Houston 1980). Hise and Kelly found that the number of competitive retailers at a shopping center is significantly correlated with the income of the center (Hise and Kelly 1983). Ingene has shown that the level of assortment of similar merchandise can be one of the strongest predictors for customers' choice of shopping destinations (Ingene 1984). In a survey of 1,200 individuals in six malls in the U.S., Bloch and his colleagues found that visits to shopping areas without buying plans, together with visits to look at goods that might be bought in the future, constituted 62% of all trips (Bloch, Ridgeway et al. 1991).

Empirical evidence that demonstrates differences in attitudes towards competitive clustering of different types of retailers, such as shoe stores or liquor stores, is scarce. Empirical attempts to analyze competitive clustering in uncoordinated urban centers (i.e. main streets) have been especially hampered by the lack of data and difficulties of filtering out endogenous and exogenous factors that affect clustering. Do coffee shops cluster at locations like Central Square in Cambridge, MA because of endogenous reasons that attract more customers or exogenous reasons — such as accessibility — that make Central Square attractive to multiple stores despite competition? Both explanations are theoretically plausible, and we shall leave it for empirical analysis to sort out the answer in Chapter Four.

2.2.3 Summary

The theory of retail location choices has witnessed a considerable evolution in the course of the 20th-century. Christaller's and Lösch's Central Place Theory, developed in the 1930s, provided a major milestone towards a schematic model that could explain the observed distribution patterns of retail centers. Though the model was far from complete and relied on a series of simplifying assumptions regarding consumer behavior, it provided a foundation for a rapid evolution of theory to follow. The ambiguous assumptions of CPT, such as the nearest-center/single-purpose postulate (See 2.1.1and 2.1.2), were gradually overcome by incorporating multi-purpose shopping and consumer transportation savings into the theory. Fitting multi-purpose shopping into theory provided a more realistic view of observed shopping behavior and led to more accurate spatial predictions that could explain a higher degree of complementary clustering between retailers than foreseen by CPT. The explanation of competitive clustering, on the other hand, turned out to be more challenging and remains an active area of research to this day. Hotelling's *Principle of Minimum Differentiation*[19] provided a partial explanation of the agglomeration of similar stores as early as 1929, but it was not until comparison shopping and consumer search costs were formally integrated into the theory that competitive clustering was convincingly addressed (Dudey 1990).

Much of retail location literature has focused on malls and other planned shopping centers. While malls constitute an important part of the contemporary retail landscape, especially in the US, we find too little literature on traditional un-coordinated retail location choices. The focus on shopping malls has even produced an impression amongst some non-economists that the theory of retail location choices has taken a normative approach, arguing for the economic superiority of malls. This is a disturbing finding for urban planners who have engaged in revitalizing economic development in dense urban areas in the recent decade. The lack of theoretical research on urban retailing is perhaps partially explained by the historic data scarcity on individual business establishments. The central ownership and management system of shopping malls has made data gathering much easier in malls than in uncoordinated urban settings. Public data on individual business establishments, released at five year intervals by the Economic Census (formerly known as the Census of Retail Trade)[20], has shown statistical information only at the zip code level, without disclosing locations of individual retailers. However, individual business establishment data has recently become

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[19] Eppli has pointed out that this term was actually first used by Boulding to describe Hotelling's insights of *Stability in Competition:* Boulding, K. E. (1966). Economic Analysis. New York, Harper and Row.

, Eppli, M. and J. Benjamin (1994). "The Evolutionof Shopping Center Research." Journal of Real Estate Research **Vol. 9**(1): pp. 5-32

[20] http://www.census.gov/econ/census02/ (Accessed February 18, 2010)

available through private sources, such as InfoUSA[21], Dun & Bradstreet[22], and Yellow Page listings[23], making urban retail studies technically feasible.

The review of literature suggests that location choices can substantially differ in coordinated (e.g. malls) and uncoordinated settings (e.g. main streets). Unlike shopping malls, uncoordinated urban retailers generally cannot cooperate to optimize store mix and store sizes to maximize the revenues of the cluster as a whole[24]. Consequently, urban retail clusters usually cannot offer rent subsidies comparable to malls to attract certain types of stores (i.e. anchor stores) to locate in clusters. The store mix of uncoordinated clusters could thus substantially deviate from the store mix of coordinated clusters.

Besides the *planned* versus *unplanned* difference, neighborhood retail location choices are also more sensitive to exogenous location factors than malls. Both classical and neo-classical literatures on retail location have typically paid little attention to exogenous factors, particularly the configurational details of environmental geometry[25]. Most retail location models described above operate in an idealized homogenous environment, where space is treated as a featureless plain. This makes some sense when studying the locations of malls, which are often found in relatively isolated settings, where owners have great control over adjacencies, access, and looks. Stores within a typical shopping mall all rely on vehicular access and therefore face a similar accessibility[26]. Urban retailing, on the other hand, generally occurs in relatively small buildings, located within a network of streets, buildings, and adjacent land uses, where different parcels or streets can face vastly different levels of accessibility. We shall illustrate these differences using empirical data in Chapter Three of the dissertation. We argued above (Section 2.1.3) that advantageous accessibility can not only incentivize individual retailers to prefer highly connected locations, but also produce higher aggregate store densities at such locations in equilibrium. The built environment — the geometry of roads, the density of building stock and the distribution of land uses — could therefore produce a significant exogenous influence on intra-urban retail location choices that has remained relatively under-examined so far.

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[21] http://www.infousa.com/ (Accessed February 18, 2010)

[22] http://www.dnb.com/ (Accessed February 18, 2010)

[23] http://www.yellowpages.com/ (Accessed February 18, 2010)

[24] We should note that such cooperative behavior could nonetheless occur implicitly on a non-contractual basis or in some instances explicitly via local merchant associations.

[25] An exception is given by Carter and Vandell, who studied location choices and rent patterns inside the spatial structures of shopping centers stores (Carter and Vandell 2005). They found that central locations in malls are commonly occupied by small and highly profitable stores, and peripheral locations by large anchor stores. The authors concluded that the spatial patterns of rent inside malls follow the predictions of bid-rent theory (Alonso 1964), according to which rent in the center is highest due to savings in transportation costs. However, an important aspect distinguishes foot-traffic patterns between stores from a Alonso's bid-rent model: the value of the central location in a mall does not arise from routine centrifugal trips from the periphery to the center, but from foot traffic that leads from one peripheral anchor to another. In other words the value of central locations in malls lies in the fact that these locations are between other stores and can be visited unplanned, with little extra effort. Whereas Alonso's value of centrality lies in the ease of access from all surrounding locations, the value of betweenness derives from the frequency at which a location is passed during other trips in the network. In simple spatial structures of malls the betweenness and centrality of a location often coincide. However, in a more complex network of city streets, the two qualities of location can and do significantly diverge. We shall return to this distinction with more detail in the next part of this chapter, where we introduce graph theory measures that capture both kinds of qualities of a location.

[26] Access to the mall becomes mentally interchangeable with access to the individual stores inside the mall.

Disentangling exogenous location influences from endogenous location influences presents significant methodological difficulties for empirical research. When spatial clustering is observed among retailers, how could one know whether the clustering is attributable to some exogenous location factors, such as proximity to a subway stop, or an endogenous agglomeration factor, such as demand externalities? Even carefully controlling for exogenous location variables, countless unobserved spatial qualities of a location can easily remain unnoticed. Distinguishing the two types of effects is essential if empirical evidence is to be used to test theoretical predictions. In Chapter Three, we introduce an innovative methodology that directly addresses this challenge.

Overall, we anticipate a heightened interest in *urban* retail location studies in the years to come, using the newly available data sources and methods of analysis. This dissertation hopes to stimulate further research in this area. Centering our focus on urban settings, we also hope to better align economic research with the contemporary aspirations of urban planning concerning urban revitalization and sustainable city design. We thereby not only hope to better explain the distribution of urban retailing, but also to contribute to knowledge that would allow this form of retailing to flourish in future cities. Auguste Lösch once wrote: *"The real duty of the economist is not to explain our sorry reality, but to improve it*." (Auguste Losch, 1954:4, 508)

2.3 Configurational studies of the built environment

Integration of space into economic models was a major development in the 20th-century, which led economists to tackle questions of location, agglomeration, congestion, and the formation of cities. Though far from complete (Krugman 1998), economics of space now constitutes several important subfields of mainstream economic theory. The retail location models described above are but one specific example of spatial economics. Yet, the notion of space included in these models leaves urban planners and architects both short of satisfied, pondering whether the two-dimensional Euclidian plane, topographically even and planimetrically uninterrupted, does justice to the way urban space is used and perceived in the physical environment of a city. A patron who walks to a store from his house is forced to follow a network of streets, take turns when routes intersect, and choose a path among multiple competing alternatives, many of which lead to the same place at the end. For an urban designer, these spatial intricacies, which distinguish the city from a featureless plane, accumulate and amount to a whole called *urban form*. It is this difference between a featureless plane and the form of a city that constitutes the subject matter of urban design. Thus a designer will not question whether accounting for urban form in an analysis of location is worth the effort.

However, for economists this is not an obvious tack. Following the path set out by von Thünen, economic theory of space makes almost no reference to urban form (Thünen 1826). William Alonso's work showed that when activity locations are accounted for with their actual land area, as opposed to infinitesimal featureless points, then important phenomena, such as the flight to suburbia in mid-century America, can suddenly be explained on economic grounds (Alonso 1970). Still, accounting for parcel sizes is far short of accounting for a sufficiently realistic picture of urban form. Representing space on geometric networks is mathematically far more challenging than representing space on an unobstructed vector field. For an economist, the gains in explanatory power must be high enough to balance the added complexity of configurational analysis. It is the role of empirical research to demonstrate the magnitude of these gains.

Empirical research in urban and regional economics has recently turned to experimenting with greater spatial detail. One particular motivation for this was given by New Urbanists, who claimed that neo-traditional, mixed-use, and walkable neighborhoods generate higher socio-economic benefits than typical suburbs. Empirical research using hedonic price models and detailed accessibility calculations has determined experimentally that the economic value of New Urbanist neighborhoods has indeed been capitalized in higher residential property values, at least in the Portland area (Song and Knaap 2003). However, a typical problem an empiricist faces is the lack of established and reliable metrics that capture meaningful properties of urban form. How exactly do suburbs differ from dense urban neighborhoods? What are the principal metrics that differentiate the two? For empirical analysis, it is more often the difficulty of capturing sensible metrics of urban form, than a lack of interest in form, that appears to limit research. This problem is well known among architects, planners, and transportation researchers. Configurational study of the built environment is a growing field that has attracted considerable research in the latter half of the 20th-century.

Providing a coherent review of configurational studies of the built environment is rather challenging, as the material leaps over the disciplinary boundaries of several fields, including architecture, planning, environmental cognition, transportation research, and urban geography. Considerable advances have been made towards meaningful descriptive methods of the built environment in all of these fields, and the area is active in contemporary planning literature, with much remaining to be done. Some of the research that has been produced to date remains poorly integrated across disciplines. Knaap, Song, and their colleagues have described the study of urban form as a blind man's investigation of an elephant: different parts are studied by different disciplines, with no coherent understanding of the whole across disciplines (Knaap, Song et al. 2005). In the following review we shall limit ourselves only to studies of the built environment, which suggest how urban form — the geometry of streets, blocks, parcels, and buildings — and land-use patterns — the spatial distribution of institutions and activities — are important from the point of view of retail location choices. Since the relationship between environmental geometry and retail location patterns seems to appeal to scholars across several disciplines, we aim to bridge some of the disciplinary divides in this review.

We begin our review by introducing high-level categories of spatial accessibility measures, which are most popular among planners, and subsequently turn to a more detailed inspection of one particular class of accessibility measures — graph theory measures — that have gained greater appeal among urban designers and architects. Spatial accessibility measures, such as cumulative opportunities-type indices, gravity-type indices, and utility-type indices, are typically used to estimate the qualities of a location's accessibility that are attributable to surrounding land-use attractions. Graph-theory type accessibility measures, in contrast, are typically used to estimate the qualities of a location's accessibility that are attributable to the geometric pattern of urban infrastructure.

Underlying the relationship between spatial accessibility and land use location choices are two broad propositions. The first proposition suggests that the layout of the city plays an important role in generating patterns of accessibility, encounter, density, and proximity between locations in a city, which may affect the suitability of a location for particular uses or activities (Kansky 1963; March and Steadman 1971; Anderson 1993; Porta, Strano et al. 2009). The principal criterion for describing a location's access to surrounding opportunities in this case is metric distance — places with better access economize aggregate transportation costs for patrons and therefore appeal to activities that value general ease of access. Since most disciplines of urban studies agree that metric distance is a fundamental indicator of spatial proximity, the reader might remember these measures as *objective* accessibility measures.

The second proposition suggests that there is also an important *subjective* dimension to accessibility. The notion of proximity in general and the perception of a location's accessibility in a network of city streets in particular are affected by the experience of physical travel through an urban environment, which involves much more than a simple distance or time cost of reaching a location. The more nuanced characteristics of spatial proximity arise when the faculties of perception and preference embedded in the mental 'image of the city', as Kevin Lynch has called it, are used to navigate the physical structure of the city (Trowbridge 1913; Lynch 1960; Hillier and Hanson 1984; Montello and Sas 2006). Unlike metric accessibility measures, which rely strictly on distance or travel time, cognitive research on access also accounts for the 'complexity' involved in navigating to a place. Which locations appear accessible or remote and which paths are chosen to access a place, the researchers argue, depend on people's wayfinding skills and mental conceptualizations of the environment. Systematic preferences and biases in navigation challenge the 'shortest' path postulates of transportation and accessibility models. Cognitive aspects of accessibility thus constitute another potentially important group of variables that a retail location choice model ought to incorporate. We turn to these cognitive aspects when we introduce the topological graph accessibility measures.

Having discussed how different accessibility measures describe a location with respect to surrounding locations, we move on to morphological measures, which illustrate the more immediate characteristics of buildings, parcels, and streets themselves. We end by describing some aggregate measures of city form, which have recently become widely popular in planning research, but suggest that the aggregate measures are not well suited to fine-grain spatial analysis and do not capture the viewpoint of a spatial decision maker as well as accessibility, graph theory, and morphology measures do.

2.3.1 Accessibility measures

Accessibility has emerged as a central concept in planning, transportation and economic literature for describing how different locations within a city are spatially linked to surrounding economic opportunities. There is generally a consensus among transportation researchers and economists that location choices of land uses are affected by the accessibility of a location. According to Hurd, "*Since value depends on economic rent, and rent on location, and location on convenience, and convenience on nearness, we may eliminate the intermediate steps and say that value depends on nearness*" (Hurd 1903). "*The more accessible an area is to the various activities in a community*", argues Hansen, "*the greater its growth potential*" (Hansen 1959). Von Thünen's agricultural location model, Webber's industrial location model, Alonso's residential location model, and Christaller's retail location model all implicitly rely on accessibility as a driver for location choices (Thünen 1826; Weber 1909; Alonso 1964; Christaller and Baskin 1966).

A large body of literature has been developed on accessibility since the 1950s. Though accessibility studies go back much longer (Weber 1909), it is often Hansen's classic paper of 1959, "How Accessibility Shapes Land Use" that is credited for paving the way for joint accessibility and land use studies (Hansen 1959). Since then, accessibility has emerged as a central concept that transcends transportation research, economic geography, city planning, and urban morphology. Though there is considerable variation in definitions (Wachs and Koenig 1979; Handy and Niemeier 1997; Bhat, Handy et al. 2000), accessibility is most commonly defined as the *ease of an individual to pursue an activity of a desired type, at a desired location, by a desired mode.*

The notion of accessibility is somewhat similar to the notion of density. However, unlike density, which summarizes features of the built environment per unit area of land, accessibility summarizes features of the built environment as seen from a specific location. For our purposes, accessibility can thus be thought of as density that is available within a given walking radius to a specific location in a city.

Researchers have divided the various existing accessibility indices into five groups (Bhat, Handy et al. 2000):

- Graph Theory and Spatial Separation Indices
- Cumulative Opportunities Indices
- Gravity Indices
- Utility Indices
- Time Space Indices.

A thorough comparison between these different types of measures is given in (Handy and Niemeier 1997; Bhat, Handy et al. 2000; Bhat, Handy et al. 2001). Out of the available indices, cumulative opportunities measures, gravity measures and utility measures appear to be most commonly used for analyzing retail accessibility (Wachs and Koenig 1979; Handy and Niemeier 1997; Bhat, Handy et al. 2000). Mike Batty has recently categorized these indices as 'Type One' indices (Batty 2009). Cumulative opportunities, gravity and utility type indices typically operate at relatively large geographic scales and do not account for the detailed geometry of physical infrastructure along which the opportunities are accessed. Access to activity centers is usually computed along straight-line distances.

Graph theory type indices, which Batty refers to as 'Type Two' indices (Batty 2009), are distinguishable for their explicit focus on spatial impedance between locations. Unlike type one indices, opportunities are considered to be equal everywhere, and the object of interest is the accurate description of spatial impedance that separates locations through the geometry of the environment. Graph theory indices are generally rarely used in transportation studies, because the measures do not consider attractions to any specific land uses and are based solely on the topology of the network. Graph theory measures are popular among urban form scholars.

Time-space measures, such as those proposed by Hagerstrand, are generally rare in studies of accessibility, because they require large amounts of temporal data (Hagerstrand 1970). We shall therefore only provide a short overview of the four most common accessibility approaches — graph theory measures, cumulative opportunities measures, utility measures, and gravity measures.

Graph theory indices of accessibility are effectively pure measures of spatial separation. The key focus of such measures is to describe the spatial impedance factors that separate locations, without considering the nature of the activities separated. Instead of distinguishing accessibility to a certain type of activity (e.g. work) from another (e.g. shopping), graph theory indices typically measure accessibility from a particular location to either all other locations in the study area or to all other locations that fall within a certain distance threshold from the location of interest. Since land uses are typically not considered, all destinations are accounted as equals. An explicit focus on the geometric and topological properties of a network has made graph theory measures particularly attractive to researchers of city form. We shall therefore focus on graph theory metrics in greater depth in section 2.3.2 dedicated exclusively to such metrics. Let us for now simply scratch the surface and examine a general version of the measure is in Equation 6.

$$A_i = \sum_{j=1}^{n} d_{ij}$$

Equation 6

where A_i is accessibility at location i, d_{ij} is an impedance measure (e.g. distance) between locations *i* and *j=(1,2,…n)*. Accessibility is defined as the total distance required to reach from one place to all others, measured as the sum of geodesic path distances from the location of interest to all other locations in the graph.

Using the inverse of distance yields a popular measure called 'Closeness', and dividing the outcome of Equation 6 by the number of accessible destinations (n) yields an 'average distance' between the location of interest and all other destinations around it.

Critics of graph theory type measures of accessibility have argued that the inclusion of land use and attraction factors is crucial for any sensible measure of accessibility. Access to residents differs from access to jobs. Furthermore, when evaluating access to residents, a large apartment block ought to be weighted differently from a small single family building. Most graph theory analyses to date have ignored the differences in destination attractions. The uniformity of graph indices is probably historically attributable to the lack of descriptive data at the fine-grain spatial resolution that graph indices operate in. Environmental data at the building level resolution is now becoming common in urban studies, and the graph theory type indices we introduce in the next chapter will take advantage of these features.

The cumulative Opportunities Index differs from the graph theory measures for its inclusion of a destination type parameter. The index defines a travel time or distance threshold around a location and counts the number of destinations located within a distance threshold as the accessibility measure for the location. In studying accessibility to residents, for instance, the index could count the amount of households within a given radius from a retailer. The generic form of the index is specified as follows:

$$A_{id} = \sum_{d} O_d$$

Equation 7

Where A_{id} is accessibility at location *i* within a distance threshold *d*, and O_d is an opportunity of a given type that can be reached within the distance threshold.

The index is attractive for its simplicity, but criticized for treating all opportunities within the distance threshold equally, regardless of their distance from the origin location. In the residential accessibility example above, this means that access to all residents within the boundary threshold is considered to be equal, regardless of whether they are immediately proximate or at the threshold border of the radius[27].

A utility type measure of accessibility is based on random utility theory (McFadden 1978; Ben Akiva and Lerman 1979). Random utility theory assumes that the probability that an individual will patronize a particular destination depends on the relative utility of that choice compared to the utilities of all other possible choices. An individual at location *i* is thought to attach a utility *V* to every destination *j*, which is positively related to the attraction of the activity *j* and negatively related to the travel costs involved with accessing *j* from *i:*

[27] In addressing this shortcoming, Handy has proposed a distance-decay function to weigh the opportunities, which makes the index similar to a gravity type measure with a radius (Handy 1992).

$$V_{ij}^{activity} = \alpha^{activity} Attraction_j - \beta^{activity} Travel_{ij}$$

Equation 8

The probability that a person in location *i* chooses to participate in an activity at location *j* is then given by the utility of the activity at *j*, divided by the utilities of an equivalent activity at all alternative locations *k*:

$$P_{ij} = \frac{e^{V_{ij}^{activity}}}{\sum_k e^{V_{ik}^{activity}}}$$

Equation 9

Assuming a multinomial logit form of destination choice, accessibility at *i* can therefore be defined as the denominator of Equation 9, which shows utilities of an activity at all possible locations *k* for a person located at *i*:

$$A_i^{activity} = \sum_k e^{V_{ik}^{activity}}$$

Equation 10

Where A_i^{activity} is the accessibility index for different instances of a certain type of activity from location *i, k* is the set of alternative locations where the activity is found and $V_{ik}^{activity}$ denotes the utility of each activity location k as seen from *i*.

A utility type measure of accessibility is more complicated to interpret, but its advantage lies in its behavioral basis. As opposed to the other indices outlined above, a utility based accessibility index can be explicitly formulated from the point of view of a decision maker who is maximizing his or her utility in a spatial location choice. Random utility type accessibility measures have become increasingly popular in empirical studies (Waddell and Ulfarsson 2003).

A gravity type measure also combines the attractiveness of the opportunities and the travel times required to reach them. The index assumes that travel between locations imposes friction, which is balanced by the attraction force of the destinations. The accessibility of a location can be quantified by calculating the time-distance relationships between the location and all possible destinations around that location. The first formulations of the index date back to the 1930s (Weber and Friedrich 1929), but Hansen is generally credited for applying the gravity model to land use location choices (Hansen 1959). His method has been widely adopted by professional land appraisers (RICS 1992) and recently included in automated GIS accessibility models (Wyatt 1997).

A common form of gravity type measure assumes that accessibility at location *i* is proportional to the attractiveness of all other locations *j* surrounding *i* and inversely proportional to the distance between *i* and *j*.

$$A_i = \sum_{j=1}^{n} \left(\frac{W_j}{d_{ij}^{\beta}} \right)$$

Equation 11

Where A_i is accessibility at point *i*, W_j is the attractiveness of location *j*, d_{ij} is the distance between location *i* and *j*, β is the exponent for distance decay, and *n* is the number of locations in the study area.

The gravity type index thus captures both the attraction of the destination (W_j) as well as the spatial impedance of travel to that location (d_{ij}) in a combined measure of accessibility. Consider two homes and two retailers. Each home lies a mile from a retailer. If one of the two retailers is larger than the other, then we consider the home corresponding to the larger store more retail accessible than the home corresponding to the smaller store. The gravity type measure remains the most popular form of accessibility measure in transportation literature.

In summary, accessibility is typically defined as a combined result of land use nodes and transportation links in the spatial network of a city. Accessibility indices generally consist of three key inputs: the number of destinations accessible to a location; the indicators of attraction for each of the destinations[28]; and a measure of spatial impedance required to reach each of the destinations. This composition suggests that accessibility of a location can change at minimum in three different ways. First, if the number of attractions around a location changes; second, if the mix or intensity of the attractions change; and third, if the physical linkages leading to the attractions change, leaving the attractions themselves unaltered. We refer to these scenarios as changes in 'attraction factors' in the former two cases, and changes in 'impedance factors' in the latter case (Bhat, Handy et al. 2000). Among architectural researchers, these effects have also been referred to as changes in the 'layout of activities' versus changes in 'spatial form' (Tabor 1970).

An example of each type of change is depicted in Figure 8 - Figure 10. In Figure 8, a number of attractions around a central location *i* gradually increases from left to right, whereas the previous attractions remain intact and the spatial form of the path network stays identical in all three cases. A gradual increase in accessibility at the central location *i* is thus attributable to the addition of surrounding attractions j (1,2, ...8). Such a scenario is typical to urban areas that experience growth or densification, adding new land uses sequentially over time.

Figure 9 illustrates a case where accessibility to a central location *i* is altered through changes in the mix of surrounding attractions j = (1,2, ...8). If locations j contain different activities, varying in nature, scale, and intensity, then their spatial reorganization around i, as shown in the three diagrams of Figure 9, can also alter the accessibility of i. This scenario can be observed, for instance, in the process of urban gentrification, where the nature of activities in an urban area is restructured.

Figure 10 below, on the other hand, illustrates how accessibility at *i* can change due to a geometric reconfiguration of the routes linking location *i* to locations j around it, keeping the number and nature of destinations unaltered. This scenario is commonly brought about by urban design or infrastructural interventions. A new road may be added, an old one closed down, or the carrying capacity of existing infrastructure improved through physical interventions or management strategies.

The joint effect of the three inputs is exemplified in the gravity type accessibility index in Equation 11. The summation notation of the index ($\sum$) captures the count of destinations. The numerator of the

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[28] Graph Theory indexes usually ignore this input.

index (W_j) captures the characteristics of the destination attractions, and the denominator (d_{ij}) captures the spatial impedance imposed by environmental geometry. Though the gravity type index combines all three characteristics of the environment in a single index, we argue that it is important to distinguish these inputs as they originate from different processes and constitute different aspects of accessibility. Affecting accessibility of a location via any of the three factors requires different means of intervention. Changes in the number of attractions can, for instance, result from urban growth or densifications, while changes in establishment mix could stem from policy and zoning interventions. Changes in spatial form can be directly affected by architects, planners, and urban designers, each of whom operates on the physical layout of the city. Analyzing different inputs of accessibility for the same location side by side, would allow one to estimate the importance of each input on an outcome of interest, such as retail location choices.

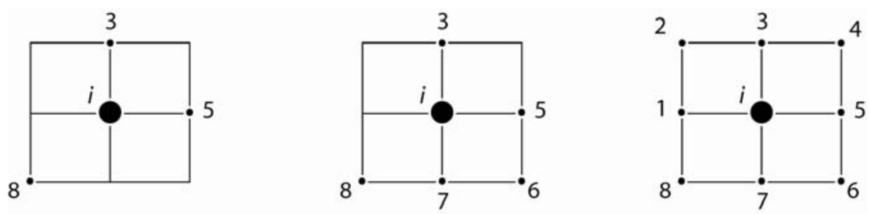

Figure 8 Changes in the number of attractions around a location i.

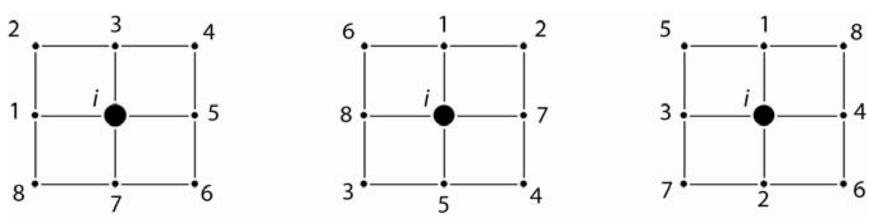

Figure 9 Changes in the layout of attraction factors around a location i.

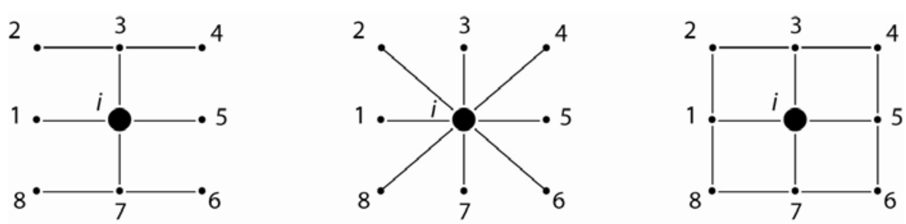

Figure 10 Changes in impedance factors or spatial form around a location i.

2.3.2 Graph theory type measures

A major historic difference between land use accessibility indices and graph theory indices has been the choice of destinations to which access is measured. At root, both land use and graph theory approaches to accessibility agree that the value of spatial proximity ultimately lies in the people and activities that are being accessed. The differences between the two approaches arise from the way that people and activities at the destinations are spatially described. Proponents of land use accessibility measures suggest that the use-characteristics of the destinations offer a more valuable approximation for the people in these spaces than the geometric descriptions of the spaces themselves. Land use accessibility indices, such as gravity and utility type measures, thus typically measure access to particular land uses and activities around a location of interest: employment locations, production plants, retail establishments, transit stations, and so on. The researchers argue that differentiating destinations according to their type of use is essential for a meaningful interpretation of an accessibility measure. Access to residents, for instance, ought to be distinguished from access to jobs, stores, or factories. Businesses that face a question of location choice might desire access to some land uses and not others. Describing a location as a function of its proximity to various land uses offers a useful way to decompose the pros and cons of a particular site for a particular business.

Proponents of graph theory type indices, on the other hand, describe a location's accessibility as a function of its proximity to surrounding elements of urban form. Instead of characterizing the activities accommodated by urban form, they characterize the urban form itself. The distribution of people in the network is approximated through the spatial distribution of urban form elements, such as street segments or street intersections. This difference — and, specifically, the lack of use-based destination characteristics — have led some researchers to avoid the use of graph indices all together (Bhat, Handy et al. 2000) and others to advocate for a unifying approach (Batty 2009).

An important strength of urban graph analysis has been the fact that it measures access from each element of urban form (i.e. street segment) to every other element of urban form in the graph. This allows the graph indices to essentially estimate a location's accessibility to all surrounding people and activities, regardless of their type. It is a fundamental feature that has historically generated more favor among architects and urban designers towards graph accessibility indices than land use accessibility indices. Evaluating a location's accessibility to *all* surrounding destinations, each of which is represented by an element of urban form (i.e. building), centers the analysis on *spatial configuration*, rather than *land use*. The outcome of the index is entirely determined by the spatial configuration of the environment and can only be altered if the buildings, streets, or intersections of the graph are altered. This makes graph analysis particularly useful for investigating the impact of urban form on establishment location choices.

2.3.2.1 Graph measures in building plans

Euler (1707-1783), with his famous puzzle of Königsberg's seven bridges, was probably the first to adopt graph representation into the study of transportation networks. The appearance of numerous applied graph theory publications after the second World War (Berge 1962; Harary 1969), catalyzed the spread of applied graph theory in the 20th-century. Spatial applications of graph theory were quickly adopted in transportation research, where the precedent for applying graph measures to large-scale road and rail networks was first established (Garrison 1960; Garrison and Marble 1962; Kansky 1963; Haggett and Chorley 1969). Architects soon also adopted the graph representation for the study of building plans (Levin 1964; Casalania and Rittel 1967; Rittel 1970; March and Steadman 1971).

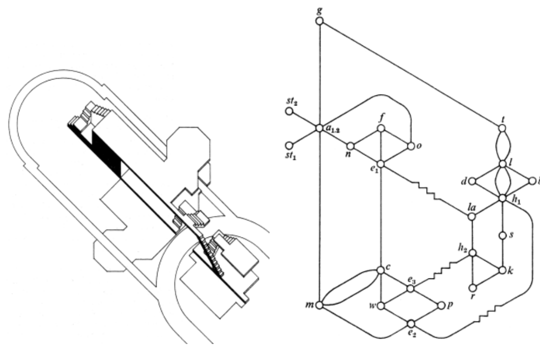

Figure 11 Adjacency graph for Frank Lloyd Wright's Aline Devin House . Source: (March and Steadman 1971: 259-261).

In representing buildings with graphs, each room is represented by a node and the availability of a direct circulation connection between rooms by a link (Figure 11). A graph representation of building plans opened up new opportunities for analyzing architectural plans using a variety of graph indices, including *degree* analysis, *diameter* analysis, *redundancy* index, *Alpha* index, *Beta* index, *Gamma* index, *Eta* index, *Theta* index , and so on (For a detailed description see March 1976: Ch 10; Rodrigue, Comtois et al. 2006: Ch 1). The adoption of graph representation made the otherwise highly labor-intensive combinatorial analysis of connectivity, adjacency and centrality feasible, allowing researchers to investigate the basic performance differences of alternative building plans.

Philip Tabor's work using graph representation, for instance, showed that different spatial arrangements of the same room program can fundamentally affect the circulation efficiency of a building (See Figure 12). Comparing three basic building types — the slab, the cross, and the court — and keeping the total floor area of rooms constant, Tabor showed how the geometric layout of buildings can either lengthen or shorten average commuting times within a building (Tabor 1970; Tabor 1976). He concluded that *"Although careful layout reduces circulation costs, it does so within the bounds set by the form of the building and the configuration of its routes, and these bounds differ from building to building"* (Tabor 1970).

In order to arrive at this conclusion, it was methodologically crucial to be able to distinguish the advantages in circulation that arise from a building's geometry from those that arise from a careful layout of the programmatic elements within the building. Tabor overcame this challenge by controlling the proclivity of interaction between neighboring rooms with a variable Q. A higher value of Q means that rooms with highest interaction needs are located adjacent to each other, leading to lower overall travel times. The effects of environmental geometry could be teased out when Q is kept constant in different building geometries. Figure 12 illustrates one of Tabor's central findings: at lower levels of Q: the cross typology produces lower commuting times than the slab and court typologies. As Q rises, the performance of different building geometries gradually evens out.

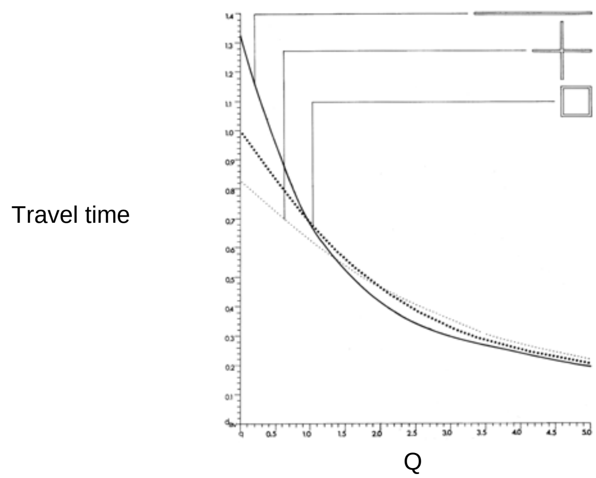

Figure 12 “Theoretical average distances for different values of q in a slab, cross, and court. The cross starts off best, the slab worst, and, though increases in Q reverse this order, the difference becomes negligible” (Tabor 1970). Note: Travel time is presented on the Y axis, Q on the X axis. Q represents the propensity of a traveler to choose neighboring destination. In effect, a higher Q represents a more efficient layout of functionally related rooms, while a lower Q represents the absence of order among functionally related rooms.

2.3.2.2 Graph measures in street networks

Hillier & Hanson applied the representation and analytic tools of graphs to street networks (Hillier and Hanson 1984), establishing the now well-known Space Syntax methodology. Over the last three decades, their work has argued that the spatial configuration of the street network is related to diverse social phenomena including the flow of pedestrians, the geography of crime rates, and the distribution of retailers (Hillier 1996). Through a configurational analysis of a street network, the Space Syntax methodology set out to reveal some of the social forces that shape urban form:

“… a society does more than simply exist in space. It also takes on a definite spatial form and it does so in two senses. First, it arranges people in space in that it locates them in relation to each other, either a greater or lesser degree of aggregation and separation, engendering patterns of movement and encounter that may be dense or sparse within or between different groupings. Second, it arranges space itself by means of buildings, boundaries, paths, markers, zones, and so on, so that the physical milieu of that society also takes on a definite pattern. In both senses a society acquires a definite and recognizable spatial order.” (Hillier and Hanson 1984: 27)

Several other approaches to graph analysis of street networks have appeared in the recent years. Among those, Porta and Xie have proposed a number of metric graph indices that differ from the topological graph analysis methods of Space Syntax (Porta, Crucitti et al. 2005; Xie and Levinson 2007).

2.3.2.3 Metric Graph Accessibility

Following the lineage of transportation research (Garrison 1960; Garrison and Marble 1962; Kansky 1963; Harggett and Chorley 1969), the most common approach to graph analysis of urban street networks assumes that the spatial separation between different locations in the graph is best captured with metric distance. Using metric distance as the measure of impedance, a graph index can illustrate how some location in the graph are closer, more 'between', or otherwise better accessible than others. A typical graph of street networks represents street segments as edges and street intersections as nodes, using the latter as spatial units of analysis. Though calculating the graph metrics in this form computes the results for nodes (street intersections), rather than edges (street segments), the results can easily be converted to street segments by computing the average value of two adjacent nodes and applying the outcome to the edge that lies between those nodes.

Sergio Porta and his colleagues have produced a toolbox of measures that use a number of different centrality measures from graph theory, calling them jointly the Multiple Centrality Assessment (MCA) method. Three common metrics employed in MCA are *betweenness*, *closeness*, and *straightness* centrality (Porta, Strano et al. 2009).

The *betweenness* centrality of a street segment i is defined as the fraction of shortest paths between pairs of vertices in a network that pass through *i* (Freeman 1977). In computing the *betweenness* index for a particular street, a shortest-path connection is first calculated between all nodes in the system[29]. Given a matrix of shortest paths between all node-pairs, a particular node's *betweenness* index is then calculated as the number of times that the node is traversed in this set of shortest paths. Formally, (Porta, Strano et al. 2009) express the betweenness of a node as:

$$Betweenness_i = \frac{1}{(N-1)(N-2)} \sum_{j=1;k=1;j\neq k\neq i}^{N} \frac{n_{jk}(i)}{n_{jk}}$$

Equation 12

where where N is the number of nodes in the system, n_{jk} is the number of shortest paths between nodes *j* and *k*, and $n_{jk}(i)$ is the number of these shortest paths that pass through the node i. When applied on street networks, the betweenness measure can be intuitively thought of as the potential amount of traffic on each street segment that results if one person were to travel from each intersection to each other intersection in the given road network along shortest paths[30]. The outcome of a betweenness measure is visualized on a tree leaf pattern in Figure 13 (left).

The *closeness* centrality of a node is defined as the inverse of distance required to reach from one node to all other nodes in the system along shortest paths (Sabidussi 1966). In order to make this measure comparable in different street networks, the resulting sum of distances at each node is usually normalized by the count of nodes in the system. Whereas the betweenness measure indicates the potential traffic passing a location, the closeness measure indicates how far each location is from all other locations. The closeness measure is mathematically defined as follows:

[29] With a hundred nodes for instance, this leads to a 100x100 origin-destination matrix, involving 10,000 paths. If the graph is assumed to be *undirected*, that is if traffic can flow on each street segment equally in both directions, then only a half of these paths (5,000) are unique.

[30] Some researchers have also argued that the 'shortest-path' assumption is not entirely realistic and proposed instead that all origin destination connections be calculated along all possible paths, giving shorter paths a higher likelihood than longer paths Newman, M. E. J. (2005). "A measure of betweenness centrality based on random walks." Social Networks **27 (2005)**: 39–54.

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$$Closeness_i = \frac{N-1}{\sum_{j=1;j\neq i}^{N} d_{ij}}$$

Equation 13

where N is again the number of nodes in the system, and d_{ij} is the geodesic shortest path distance between nodes i and j. Closeness centrality is illustrated in the center of Figure 13. One can notice the higher closeness values towards the centroid of the leaf and lower values towards the peripheral areas of the leaf. This geometric bias towards the centroid of the network is a well-known aspect of the closeness measure. If closeness is measured on an otherwise continuous network, then this boundary effect can be addressed by using a network that extends far beyond the area of analysis. As we shall demonstrate in the specification of analysis metrics in the next chapter, the closeness (as well as the betweenness and other) metrics can also be computed using a specific distance threshold. Given a threshold of 2000 feet, for instance, we would compute the sum of distances from a node to all other nodes that fall within the 2000-foot distance threshold from it.

The closeness centrality measure is similar in principle to the integration measure in Space Syntax analysis. Both metrics analyze how far each line segment is from all other line segments in the graph, but each uses a different impedance measure. Space Syntax uses the count of topological turns as the distance metric, and closeness centrality uses metric distance. If we used "turns" as the impedance measure in closeness centrality analysis, then we would obtain a result essentially equivalent to the Space Syntax integration measure[31]. We shall demonstrate this in Chapter 3.

The straightness metric illustrates the extent to which the shortest paths from a node of interest to all other nodes in the system resemble straight Euclidian paths. Put alternatively, the straightness metric captures the positive deviations in travel distances that result from the geometry of the road network in comparison to ideal straight-line distances in a featureless plane. The straightness measure is formally defined by (Porta, Strano et al. 2009) as:

$$straightness_i = \frac{1}{N-1} \sum_{j=1;j\neq i}^{N} \frac{d_{ij}^{Euclidian}}{d_{ij}},$$

Equation 14

where N is the number of nodes in the network, $d_{ij}^{Euclidian}$ is the straight-line Euclidian distance between nodes i and j, and d_{ij} is the geodesic network distance between the same nodes i and j. It is apparent from Figure 13 (right) that the *straightness* measure increases as distances become longer. Higher values (shown in red) indicate larger deviations from the shortest Euclidian paths. This is an expected outcome, suggesting that the longer the commute, the less likely the path is to resemble a Euclidian straight line.

Some supplemental centrality measures in MCA include *degree centrality* and *information centrality* (Crucitti, Latora et al. 2006). Xie and Levinson have recently proposed three additional measures called *entropy*, *connection patterns*, and *continuity* (Xie and Levinson 2007).

[31] Certain differences still remain, because the underlying graph itself is dual in the Space Syntax methodology and primal in the traditional graph theory representation, as mentioned above.

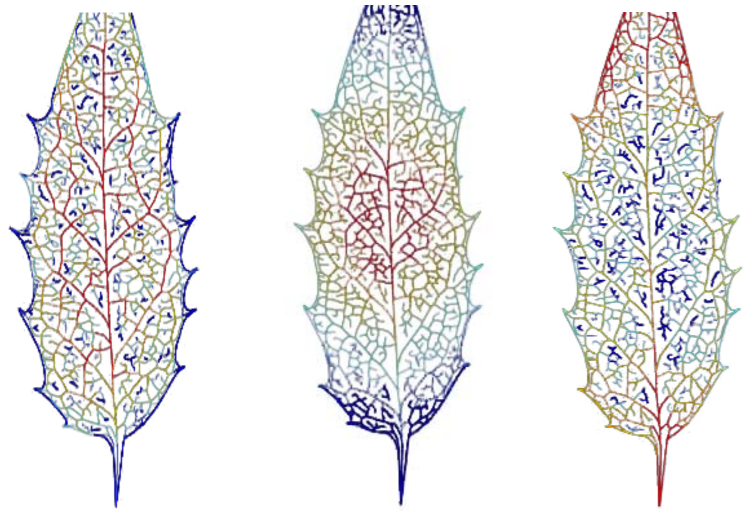

Figure 13Three graph theory centrality measures visualized on a leaf. Left: Betweenness centrality. Middle: Closeness centrality. Right: Straightness centrality. Red colors refer to higher values, blue colors to lower values. Source: http://www.humanspacelab.com/ (Accessed February 25, 2010).

2.3.2.4 Topological graph accessibility

The metric graph accessibility indices discussed thus far have relied on distance as the primary indicator of spatial separation. Most of these indices are in fact calculated exclusively along shortest travel paths in the graph. The 'betweenness' index discussed above, for instance, computes a metrically shortest travel path between each node pair in the system, and evaluates how many of these paths pass by a location of interest.

Numerous researchers argue, however, that metric distance is not the only important criterion for path choice in the network of city streets. Empirical studies of pedestrian path choices in urban settings have found that though distance or travel time are reported as dominant criteria for path choice, the actual paths taken are often longer than the shortest available path, typically remaining within a 20 per cent distance threshold of the shortest path (Takeuchi 1977; Li and Tsukaguchi 2005). In addition to minimizing distance, these researchers argue, urban travelers also tend to minimize route complexity and maximize opportunities along the way. Challenging the shortest-path axiom of metric graph accessibility measures, these scholars advocate the inclusion of alternative impedance measures, such as topological path characteristics, which capture cognitive aspects of path choice.

The Space Syntax methodology probably offers the most popular example of topological graph analysis that has been applied in numerous cities around the world. The original authors of Space Syntax, Hillier and Hanson, have chosen to represent streets not with centerlines, as in most transportation studies, but rather with *axial lines*. Axial lines are defined as the fewest and longest lines of sight that can be drawn through the open street spaces of a study area (Hillier and Hanson 1984). This approach has led to some criticism, since the specification of axial lines is subjective (there is more than one solution), and the concept of axial lines is theoretically controversial (Ratti 2004). Unlike typical transportation applications of graph theory, Hillier & Hanson also adopted a so-called *dual* graph representation, where streets are represented as nodes and intersections as edges[32]. Since most graph theory indices have been designed to focus on the properties of nodes (e.g. in social networks, nodes can represent people), this inverted form of graph representation allows the Space Syntax analysis to focus on streets (axial lines). For example, whereas 'degree centrality' in social networks indicates how many direct links (e.g. kinship ties or acquaintances) connect to a node of interest (e.g. a person), an analogous measure in Space Syntax describes the number of neighboring axial lines that intersect with a particular axial line of interest.

Though useful for centering the analysis on streets, the dual representation also introduces a well-known problem to the Space Syntax methodology. If streets are represented as nodes, then both long and short streets alike reduce to dimensionless points, thus effectively eliminating metric distance from the analysis. Space Syntax researchers address this problem by measuring travel from one line to another across the graph in topological terms, using the count of lines traversed (i.e. changes in direction on axial lines) as a metric of proximity. This metric, commonly referred to as *depth*, is central to most Space Syntax analysis. It is used as a kind of distance measure, which represents the minimum number of axial lines needed to go from an origin to any other segment in the network, thus replacing the more intuitive concept of metric distance. The depth measure leads to another central metric in Space Syntax literature: *integration* (See Hillier 1996). The integration measure is simply a relative description of each axial line's depth with respect to all other axial lines in the graph. It is obtained by repeating the depth measure from each line to all other lines in the system and normalizing the obtained sums for each line by the total number of lines in the graph. The integration measure thus outlines which axial lines require the least amount of connections to access from all other axial lines in the network. In traditional graph theory terms the *integration* analysis is analogous to the *closeness* metric outlined in the previous section (Crucitti, Latora et al. 2006), with the difference that distance is being calculated on the basis of topological turns instead of metric units. If *integration* is computed with a radius of only one turn (also referred to as one *step* in Space Syntax literature), then the result simply shows how many axial lines intersect with a given line of interest, analogous to the familiar *degree* centrality of nodes in graph theory.

Figure 14 Space Syntax Integration analysis visualized on axial-lines of the Old Market Square area in Nottingham. Red colors refer to higher values, green colors to lower values. Source: http://www.spacesyntax.com/en/downloads/gallery/spatial-accessibility.aspx (Accessed February 24, 2010)

[32] Some transportation models do use the dual graph representation (streets as nodes and junctions as edges), since this is useful for representing one-way streets and prohibited turns. See for example the TRANUS mode: de la Barra, T., B. Perez, et al. (1984). "TRANUS-J: putting large models into small computers." Environment and Planning B: Planning and Design 11(1): 87-101.

Embedded in Space Syntax analysis is an assumption that the most accessible locations are not necessarily those closest to all other locations in terms of metric distances, but rather those closest in terms of topological turns (Hillier, Turner et al. 2007). From a behavioral point of view, this assumption postulates that the cognitive complexity of the route, described as the number of directional changes on a route, is the primary consideration in pedestrian path choice, even more so than metric distance. Pedestrians are thus expected to prefer routes that involve less turns along the way, rather than shortest routes. This is a central postulate of the Space Syntax theory that has unfortunately received little empirical validation.

Dietrich Garbrecht has posited an alternative theory. In his view, and in the view of many other pedestrian researchers, paths are primarily chosen so as to minimize travel distance. When multiple routes of the same length are available, then pedestrian path choices follow an equal probability on each of the alternatives (Garbrecht 1969; Garbrecht 1971). This equal probability assumption can take two forms: a) all paths from *i* to j are equally likely, which is referred to as *equiprobable paths* or b) people assign an equal likelihood to all of the branching road segments on individual street intersections, subject to an equal distance constraint, which is referred to as *equiprobable choice*[33]. Figure 15 illustrates a hypothetical distribution of pedestrians that follows from the equiprobable choice model[34]. Garbrecht shows that the two options result in different distributions of pedestrian paths through a given network (Garbrecht 1970). Which option better describes the true behavior of pedestrians remains empirically unresolved (Garbrecht 1971; Hill 1982: 246).

Most applications of graph theory metrics outside of Space Syntax also assume that in the presence of multiple paths of identical distance, each alternative is equally likely, thus postulating that the *equiprobable path* choice prevails (Newman 2005). Given the active debate on its methodology (Hillier and Penn 2004; Ratti 2004b; Ratti 2004; Montello 2007), Space Syntax researchers have recently updated their methodology and now include metric and angular analysis in their system and operate on both street centerlines as well as axial lines. These developments bring the Space Syntax methodology closer to the traditional graph theory analysis in transportation research.

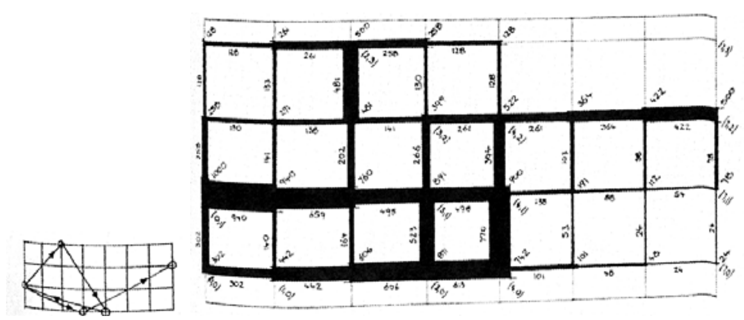

Figure 15 Distribution of pedestrians in a rectangular grid. The small diagram on the left illustrates the origins and destinations of walkers. 500 pedestrians are assumed to leave from each origin, distributing across the network using equiprobable choices at intersections, until reaching the destination marked with an arrow. No deliberate turns away from the destination are modeled. Source: (Garbrecht 1970)

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[33] Choices that would make the route longer than the shortest path are automatically given a zero probability.

[34] A careful reader will notice that Garbrecht's *equiprobable paths* result is in fact equivalent to a Betweenness measure, introduced below, where the set of destinations are limited to only a few nodes in the graph. Garbrecht published his studies eight years before the term 'betweenness' was coined and defined by Freeman in 1977.

The dominant theoretical explanation for *why* pedestrians might prefer 'simpler' routes is based on theories of environmental cognition (Trowbridge 1913; Golledge and Spector 1978; Montello 1992). Researchers in environmental psychology and related fields of behavioral geography or cognitive geography generally agree that people maintain a cognitive representation of spatial environments in the form of cognitive maps:

"*Cognitive maps thus are the conceptual manifestations of place-based experience and reasoning that allow one to determine where one is at any moment and what place-related objects occur in that vicinity or in surrounding space. As such, the cognitive map provides knowledge that allows one to solve problems of how to get from one place to another, or how to communicate knowledge about places to others without the need for supplementary guidance such as might be provided by sketches or cartographic maps*"(Golledge and Garling 2003).

Studies suggest that cognitive maps differ in important ways from physical maps. Instead of continuous Euclidean geometries and uniformly detailed representations, mental maps can be organized in multiple related but discontinuous zones (Istomin and Dwyer 2009), ordered around dominant environmental features (Lynch 1960; Lloyd and Heivly 1987), referenced with cardinal coordinates around the viewer (Gell 1985), biased towards orthogonal angles (Sadalla and Montello 1989), containing information with variable resolution that ranges from highly accurate to incomplete (Lloyd and Heivly 1987; Istomin and Dwyer 2009), representing routes from A to B and B to A asymmetrically (Sadalla, Burroughs et al. 1980; Golledge 1995), and having variable precision in distance measurements depending on remoteness of the destination (Cadwallader 1976). Accurate representation of route angularity has been shown to be particularly challenging for cognitive maps. Experimental research has found that non-orthogonal turns appear to be harder to remember (Sadalla and Montello 1989; Montello 1991; Montello and Frank 1996). Lynch's drawing experiments showed that routes with complex angular geometries, such as the pentagonal routes surrounding the Boston Commons, lead to considerable confusion in navigation (Lynch 1960).

The purpose of cognitive maps, the researchers argue, is not to accumulate environmental representations in accurate, true-life form, but rather to organize information in practically useful ways, so as to aid human navigation in a given environment while economizing storage space in memory. In order to successfully follow a previously experienced route, only limited information about the route itself is needed:

"*Learning a route involves identifying the origin and destinations, knowing the number of link segments and their appropriate sequencing, recognizing intersection nodes and identifying choice points where turning decisions have to be made; remembering the number and direction of turns embedded in a give route; being able to recognize on or off route landmarks that help interpret where one is along the route at any particular pint in space or time; and being able to retrace and/or reverse the route on an as-needed basis*" (Golledge and Garling 2003).

Routes involving a greater number of turns are more taxing on memory and therefore harder to integrate into cognitive maps. In unfamiliar urban settings, this could bias path choice towards simpler alternatives that require fewer changes in direction. A field experiment in children's route learning, conducted by Gale, Golledge, and their colleagues, showed that even though subjects tended to remember the number of turns they took, the experience of meandering routes led to considerable confusion in making global sense of the case study environment. Having traversed two partially overlapping routes with six to seven turns in an unfamiliar suburban setting, subjects found it difficult to integrate the two overlapping routes in cognitive map drawings (Gale, Golledge et al. 1990; Golledge, Gale et al. 1992).

Recent developments in computer navigation algorithms have come to a similar conclusion. Duckman and Kuliki have developed a computational path-choice algorithm that finds "simplest" routes instead of shortest routes (Duckham and Kulik 2003). Simplest, in their case, is defined as minimizing turns and choices at path intersections. Tests of the algorithm on the road network data set for the city of Bloomington, IN showed that simplest routes were, on average, only sixteen percent longer than shortest routes. The necessary memory load for representing the simplest routes was, however, substantially more efficient than shortest routes. "*In return for marginally longer routes, the simplest path algorithm seems to offer considerable advantages over shortest paths in terms of their ease of description and execution*" (Duckham and Kulik 2003). There is some evidence suggesting that a similar economy may affect the development of cognitive maps. The marginal addition of distance in Duckham and Kulik's simpler routes algorithm matches the observed distance threshold in pedestrian path choice. Empirical evidence on path length has shown that though distance is the primary factor in route choice, pedestrians do not necessarily choose *the* shortest available path, but do tend to remain within a twenty per cent distance threshold of the shortest path (Takeuchi 1977; Li and Tsukaguchi 2005).

In a typical urban street network, a twenty per cent distance threshold from the shortest path creates a surprisingly large set of route alternatives. An example is provided in Figure 16. Two parcels in Somerville, located at a fifteen minute walk from each other, have approximately eighty alternative route combinations within a twenty per cent travel distance threshold from the shortest path (left of Figure 16). In time difference, this means that eighty different routes become 'plausible' if the shortest walk is extended by only three minutes. Some of the 'plausible' walks can be less likely than others. For instance, making deliberate turns away from the destination could be considered unlikely. If such routes are eliminated, seventeen possible route combinations still remain (right of Figure 16). These seventeen routes vary considerably in the number of turns they contain. They range from a minimum of three turns to a maximum of seven turns. The quantity of route alternatives naturally depends on the length of the walk, as well as the characteristics of the street grid. Hill's study of Lincoln, NE showed that most pedestrian trips had, in fact, only a single plausible alternative route (Hill 1982). Longer walking trips and urban environments with smaller block sizes tend to increase route alternatives. Hierarchically organized street networks, on the other hand, such as the networks encountered in the medieval town centers of Europe, typically include fewer approximately equidistant path alternatives between two locations. However, variation in accessibility from the perspective of a store-owner could still be considerable even in the most hierarchical patterns, because stores do not optimize location with respect to a single approach path, but rather all available approach paths.

Unfortunately, little empirical evidence regarding the effects of route complexity on route choice can be found in geographic, transportation, and behavioral literature. Much of the empirical research on pedestrian path choice has focused on important route variables other than 'complexity' or 'turns', such as route pleasantness (Bovy and Stern 1990), visual stimuli (Zacharias 2002), pedestrian amenities (Guo 2009), or route familiarity, crowdedness, and weather (Senevirante and Morral 1985). The effects of turns and directional changes were explicitly addressed by Hill. In an empirical study of pedestrian route choice in a rectangular grid plan of Lincoln, NE, Hill found that when multiple walking routes of equal length are available, then people prefer routes that involve fewer turns along the way (Hill 1982). Hill's study is unique in that it not only quantified how many turns pedestrians took, but also compared this figure to environmental constraints, evaluating the observed turns with respect to possible turns. Hill's study also found that pedestrians tend to prefer routes that maximize street intersections along the way (Hill 1982). A larger number of intersections, keeping distance constant, Hill argued, allow a traveler to retain a larger choice of alternative routes during the walk. Each intersection can add one or more alternative route options to the path. Hill concluded that directness is the most common reason for selecting a particular route, but the concept of directness not only pertains to the length of the route, but also includes its simplicity in terms of directional changes and flexibility in terms of choice options. Most subjects were well familiar with the routes. Unfortunately, the small sample size of the study made the findings "*suggestive rather than definitive*" (Hill 1982: 240).

Figure 16 'Plausible' routes connecting two points in Somerville, MA. Shortest path shown in solid, longer routes in dashed line. Left: Two parcels, located at a 15 minute walk from each other, have approximately 80 alternative route combinations within a 20% travel distance threshold from the shortest path. Right: If routes that involve deliberate turns away from the destination are eliminated, 17 possible route combinations still remain.

Golledge, using a sample of 32 students, studied pedestrian route choice in a small-scale campus environment and similarly found that 'fewest turns' ranked high among criteria that characterize pedestrian path choice (Golledge 1995). However, statistical tests for the importance of turns remained lacking in the study. Conroy-Dalton studied pedestrian path-choice in a computer simulated environment and concluded that "*subjects are choosing the straightest possible routes as opposed to the more meandering routes*." (Conroy Dalton 2003: 47.10) The subjects were, however, explicitly instructed to walk "*by the most direct route possible*", and the test environment did not include a reasonable set of alternative equidistant routes with a variable number of turns. Hillier and Iida analyzed whether pedestrian and vehicular flow on particular road segments were better predicted by metric, angular, or topological accessibility measures (Hillier and Iida 2005).They concluded that "*It is then an unavoidable inference that people are reading the urban network in geometrical and topological rather than metric terms. Although it is perfectly plausible that people try to minimize distance, their concept of distance is, it seems, shaped more by the geometric and topological properties of the network more than by an ability to calculate metric distances*". Unfortunately, this study too suffers from a lack of methodological rigor. Conclusions are based on the spatial accessibility of the street segments where pedestrian and vehicular traffic were observed. The paths chosen by pedestrians were not explicitly observed. Simple Pearson's correlations were used in comparing the metric, topological, and angular measures of accessibility, with no control variables. More empirical evidence is required to demonstrate if and how route complexity, in terms of number of directional changes or other impedance characteristics beyond distance, affects pedestrian path-choice in the presence of alternative routes.

If topological attributes are important factors in path choices, then we should expect topological attributes of accessibility to also affect retail establishments' location choices. If locations that are most accessible according to metric distance are actually not perceived as accessible by patrons, then retailers might well need to adjust their location choices to these perception biases. Anecdotal evidence from popular retail clusters suggests that buildings that are physically close to the center of a cluster, yet topologically tucked away around a street corner, are often found as undesirable for retailing. We thus think that the research described above is sufficiently suggestive for including topological measures of access in our retail location choice analysis.

Overall, the substantive debates over the relevance and details of graph theory metrics indicate a growing interest in such measures. The content of the debates is focused mostly on the behavioral aspects of the measures: Which assumptions best describe pedestrian movement on the street network? Which definitions of streets and intersections describe human perception of urban space? Which environmental details should necessarily be incorporated into the indices to make them more realistic? Is closeness a more important indicator than betweenness — or vica versa? Answers to these questions can only come from empirical research, since the questions are behavioral in essence.

Though far from perfect as meaningful metrics of the built environment, graph theory type indices are well suited to fine-grain spatial analysis proposed in this dissertation. The disaggregate nature of the graph indices allows them to be computed individually for every element in the graph (i.e. street segment, or building), avoiding the smoothing error that comes along with aggregation. A theoretical reconciliation of Space Syntax, MCA, and other spatial graph theory applications could resolve some of the current debates between the proponents of metric and topological forms of representation. The addition of three-dimensional built-form indicators as well as land use characteristics would allow graph measures to capture a more realistic description of the built environment and address some of the criticisms from transportation and planning scholars. We intend to address this conundrum by proposing a novel application of spatial graph analysis in the next chapter.

2.3.3 Morphological measures

While accessibility and graph theory indices have been used to capture properties of the street network quantitatively, a number of scholars have also analyzed urban spatial configuration from a qualitative point of view. What we shall call *morphological measures* refers to a comparative analysis of urban form, where socially important features of built geometry are outlined through careful, qualitative analysis.

This sort of analysis of built configurations is best exemplified by the work of John Weeks, Team 10, Stanford Anderson, Michael Conzen, Anne Vernez Moudon, Allan Jacobs, Philip Panerai and others (Weeks 1963; Smithson and Team 10. 1966; Anderson 1978; Panerai 1980; Moudon 1986; Anderson 1993; Jacobs 1993; Conzen and Conzen 2004). Whereas graph theory analysis has focused on the spatial relationships between distributed elements of the built environment, morphological analysis has centered mainly on the attributes of individual elements themselves. We suggested at the outset that we shall not attempt to address the effects that layouts and aesthetics of individual structures might have on location choices. We therefore limit our discussion of morphological measures to only those attributes of built-form elements that contribute to their perception and access from the surrounding built environment.

Stanford Anderson's analysis of the plan of Savannah offers an elegant example (Figure 17). Referring to the planar composition of wards laid out by General James Oglethorpe in 1735, Anderson argues that the spatial configuration of the plan has become a source of information over time: it guides location choices of land uses and engendering patterns of diversity and adjacency that are rare in most American grid plans (Anderson 1993). He outlines seven typologically different kinds of parcels (1-7) and six typologically different kinds of streets (A-F) generated by the plan (Figure 17).The seven parcel types are distinguished on the basis of their immediate exposure to and relationship with the surrounding streets and parcels[35].

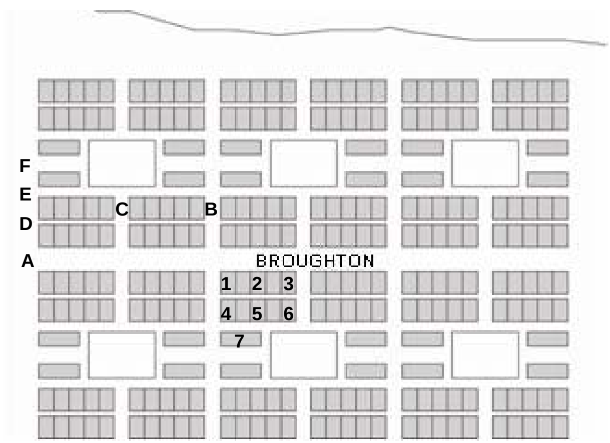

Figure 17 Plan of Savannah, GA, designed by General James Oglethorpe, showing six original wards around 1735.

Parcel type one is located on a corner of a continuous East-West street (street type A), and a continuous North-South street (street type B). Type A is the only street in the configuration with parcels opening onto the street on both sides[36]. Street type B is the only street that allows unobstructed North-South movement. The only parcels that open onto B are the back ends of the 'trustee lots' (parcels dedicated for public or communal uses in the Oglethorpe plan- type 7). Corner exposure to both of these streets gives parcel type one a topologically unique and distinctive setting, which could make type one and other analogous parcels in the grid more-or-less suited for certain activities. Anderson goes on to argue a

[35] The same typologies repeat in all four quadrants of a ward through transformations of reflection and rotation.
[36] Though street type D is also double-loaded with parcels on both sides, it differs from A in its very narrow width, which makes D a service alley rather than a street.

similar case for each parcel type (one through seven) and street types (A through F), suggesting that the particular situation of each of these elements has created an unusually rich topological diversity in the plan of Savannah, which through time, has acted as a source of information for locating different activities in each ward. Because vehicular traffic is hindered in the center of each ward by the presence of a landscaped pedestrian square, then parcels facing towards the interior of each square appear to be better-suited for pedestrian-oriented activities than vehicle-oriented activities. The unique double sided quality of street type A, Anderson argues, along with its proximity to the original port on the river, might have historically incentivized Broughton Street to become the city's primary commercial street.

"The decision to parcel the private development areas in a certain way (important features of which were the accessing of all such parcels on east-west streets; the establishment of no double-sided streets within a ward; the provision of as many private parcels at the edges as internal to the ward) established local use patterns that transformed the original arbitrary geometry into a structure filled with information. The small size of the wards and the importance of its periphery precluded the potential dominance of the central squares. Square, ward, and total structure, each had their character and strength in attracting appropriate uses. It was not as in most American grid cities composed of identical blocks, an arbitrary matter that one located a certain type of business or dwelling in one place or another. In Savannah, in growth, in decay, and in rebirth, energies knew where to flow first and from which to ebb last." (Anderson 1993: 275).

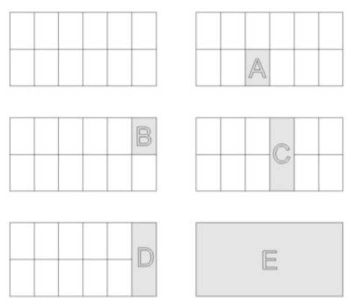

Figure 18 Classification of parcel geometry based on levels of direct access to surrounding streets . A: Middle parcel B: Corner parcel C: Through parcel D: End parcel E: Island parcel.

Different degrees of variations in access and exposure can be observed in all urban block structures. A simple classification of parcel geometries in a rectangular grid distinguishes at least five different types of parcels, shown in Figure 18. The most common type is the middle parcel (A), located in the middle of a block, between three adjacent parcels, with only one side exposed to a street. The corner parcel (B) has access to two perpendicular streets at an intersection. A through parcel (C) also accesses two streets, but these streets are parallel, separated by a block. An end parcel (D) combines the advantages of corner parcels and through parcels by having access to two parallel streets and one perpendicular street. Finally, the island parcel (E) is surrounded by streets on all sides, having no immediately adjacent neighboring parcels on either side. Exposure to multiple streets allows tenants to benefit from several traffic streams on the door steps of an establishment. If all of the streets in Figure 18 accommodated an identical amount of foot-traffic, then the geometric advantages of the island parcel would allow (E) to benefit from exposure to four times the foot traffic of a middle parcel (A). More pronounced traffic exposure, combined with advantageous access radii that result from the parcel's location, could well affect the location decision of a store owner.

The advantages of different parcel typologies are also apparent in their accessibility to surrounding parcels in a given walking radius, as we shall demonstrate in Chapter Three. We suspect that the widely encountered 'corner store' typology, for example, owes its popularity to an advantageous topological condition.

A substantively different, but methodologically similar analysis has been performed by Anne Vernez Moudon for a set of city blocks in San Francisco's Mission district (Moudon 1986). Moudon's detailed analysis of block sizes and subdivisions demonstrates how the geometric characteristics of these elements can also affect the types of buildings they end up accommodating. Moudon suggests that parcel dimensions can profoundly influence the typology and carrying capacity of buildings that come to occupy them. Geometric constraints on block and parcels can thus guide the process of growth and change that a city can accommodate through time. Mangin and Panerai have similarly shown how a careful dimensioning of parcels and city blocks can invite certain kinds of building types and lead to predictable patterns of densification and infill (Mangin and Panerai 1999). Allan B. Jacobs' analysis of streets around the world has led the author to suggest that particular configurational qualities of streets, such as the density of cross streets, are related to the qualities of streets as hosts to a diverse set of pedestrian friendly activities. "*Streets with one entry for every 300 feet (90 meters) are easy to find, and some of the best streets approach that figure, …., but there are more entries on the busiest streets*" (Jacobs 1993: 302).

Jane Jacobs has argued that the availability of sidewalks, as well as their width, could act as important public spaces and facilitate access to businesses that cater to pedestrians (Jacobs 1961). Other analysts suggest that continuous and well-defined building fronts can render streets more pleasant for pedestrians, while wider setbacks from sidewalks could degrade their access (Figure 19). Double-loaded streets open twice as many doors to a road as single-loaded streets, animating the street with a wider visual diversity of buildings and their inhabitants and doubling the potential influx of foot-traffic in and out of buildings on a street segment. We aim to test whether some of these propositions affect retail location choices in our study area.

Probably, none of the morphological qualities mentioned here could alone define a good store location, but a cumulative collection of favorable spatial conditions might well inform the appropriateness of a place for selling goods of whatever type. The work of morphological analysis suggests that a location model that aims to capture configurational differences between various locations ought also to integrate a series of detailed place measures that go beyond graph theory type accessibility metrics.

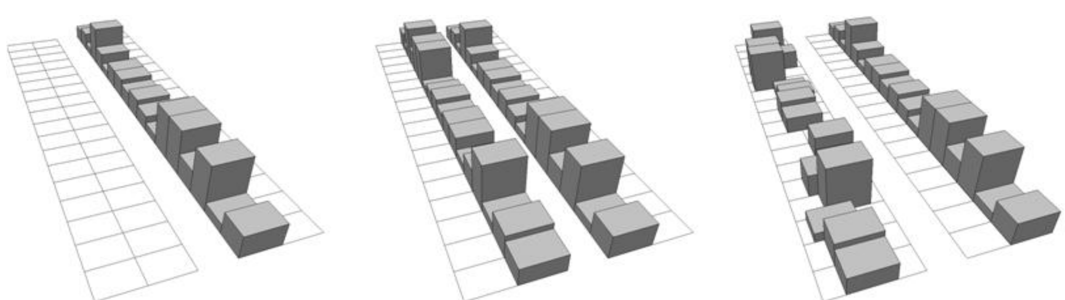

Figure 19 Relative effects of a street's building frontage on the suitability of a location for retailing. Left: single-sided streets tend to have half the doors on a street as double-sided streets (Middle). Right: Deep setbacks could be perceived less favorably than narrower setbacks by pedestrians who like animated and well-defined streets (Middle).

2.3.4 Aggregate measures of urban form

Active research on the configurational properties of the built environment has also re-emerged among urban planners in recent years. Researchers are studying the effects of the built environment on important social indicators, such as household travel behavior, energy expenditure, and public health. Several studies have found that all three outcomes are affected by urban form and land use mix around people's place of residence. A higher concentration of non-work land uses appears to reduce vehicle miles traveled (Frank and Pivo 1994; Krizek 2003; Zegras 2004), to decrease urban energy consumption (Newman and Kenworthy 1999), to produce better health indicators (Hoehner, Ramirez et al. 2005; Rundle, Roux et al. Forthcoming), and to foster social cohesion (Jacobs 1961; Pendola and Gen 2008). Though some of the metrics used to characterize the built environment in these studies overlap with the above mentioned graph and morphological measures, planners also tend to add *aggregate* urban form measures to the list.

Aggregate measures of urban form typically estimate densities of land uses or built elements per unit area of land. These could range from persons per square mile, street intersections per square kilometer, linear length of roads per acre, households per zip code, and so on. Aggregate measures can also provide summary statistics for given areal units, such as median income in a census block, mean distance to the city center, average perimeter of city blocks, total number of households, and minimum or maximum levels of connectivity, as well as different measures of variation, entropy, or distribution (i.e. the Gini coefficient). The key difference between the morphological and graph theory metrics on the one hand and aggregate metrics on the other, is that the latter summarize an outcome over a given unit area of space. Graph theory and morphological metrics typically describe individual elements of the built environment and therefore tend to operate at a finer spatial resolution. Aggregate measures of the built environment are useful when the outcome variables themselves are measured at an aggregated scale. For instance, a study of car ownership that uses the percentage of households owning private automobiles in a particular zip code as the outcome will also find it useful to measure independent variables, such as average building density or median income, at a similar zip code level of aggregation. An overview of different aggregate metrics that have been introduced to characterize urban form can be found in (Krizek 2003; Knaap, Song et al. 2005; Zegras 2005: Chapter V). Table 1 illustrates some aggregate metrics used in recent planning studies.

The effects of aggregate urban form measures are particularly sensitive to the choice of areal unit of analysis. Numerous studies have shown that the choice of aggregation scale itself can fundamentally affect analysis results (Holt, Steel et al. 1996; Openshaw and Alvanides 1999). This issue, which has become known as the Modifiable Areal Unit Problem or MAUP in literature (Openshaw 1984), is defined as "*a problem arising from the imposition of artificial units of spatial reporting on continuous geographical phenomenon resulting in the generation of artificial spatial patterns*" (Heywood 1998). MAUP typically leads to an upward bias in regression coefficients as the areal unit of analysis increases. A simple example for clusters of point data is given in Figure 20. If clusters are defined as co-locations of more than three points within a given distance threshold, then the number of clusters found can rely heavily on both the distance threshold chosen (scale problem) and the minimum number of points required in the definition of a cluster (unit problem).

Reference	Purpose	Aggregate built-environment metrics
(Forsyth, Hearst et al. 2008)	To study the built-environment factors that could affect residents' physical activity levels.	– Road length per unit area – Intersections per unit area – Ratio of three-way intersections to all intersections – Median perimeter of city blocks – Transit stop density – Percent of land area in retail uses – Retail employment per unit area – Entropy index – Herfindahl-Hirschman index (HHI) (Note: in total, over 200 environmental variables were measured)
(Frank and Pivo 1994)	To study the impact of density and mixed land uses on three modes of travel: car, transit, and walking.	Population density per unit area Employment density per unit area Entropy index of land use mix
(Song and Knaap 2003)	To study the effects of New Urbanist development on housing values	– Ratio of street segments to intersections – Linear length of streets per housing unit – Number of city blocks per housing unit – Median perimeter of city blocks – Number of households per unit area – Diversity index of land use mix – Percentage of single-family households within a given distance from a retailer – Percentage of single-family households within a given distance from a bus stop (Note: in total, 22 environmental variables were measured)
(Guo 2009)	To study the impact of subway stations and built environment on transit transfer choices.	– Pedestrian-friendly parcels per 100m – Average sidewalk width – Intersections per 100m

Table 1 Aggregate measures of urban form in recent planning and transportation studies.

Figure 20 illustrates how an overly short distance threshold can lead to the detection of no clusters including at least three points (left), whereas several clusters are found as the distance is increased (right).

MAUP in spatial aggregation decisions can also affect the study of location choices in important ways. Spatial clustering, as shown in Figure 20, can be used as an indicator of agglomeration effects among establishments' location choices. In this case the MAUP problem could in this case, critically affect the estimates of spatial agglomeration. MAUP could potentially pose an important hazard in the specification of our spatial weights matrix W, introduced in the next chapter, where we define retail adjacencies based on a 100-meter distance threshold. Due to MAUP, choosing a different distance threshold could affect our estimated coefficients and model results.

Several strategies have been recommended to address MAUP issues. First and foremost, it is important to use behaviorally-based scales and unit definitions to ad-hoc choices of aggregation (Zhang and Kukadia 2005). Yet choosing the behavioral basis for aggregation can itself pose a significant challenge. What is a sufficiently short distance to claim that stores are neighbors? How many neighboring stores make up a cluster?

Second, MAUP effects have also been shown to decrease as the scale of aggregation is reduced (Holt, Steel et al. 1996). In the analysis that follows, we make a conscious attempt to use both strategies, generating scale definitions on behavioral grounds and running our analysis at a fine spatial resolution.

Figure 20 The Modifiable Areal Unit Problem (MAUP)

2.3.5 Summary

Configurational studies of the built environment span across multiple disciplinary fields. The review we present has only touched upon different approaches of characterizing environmental geometry among architects, urban designers, planners, geographers, and transportation researchers. Each of these fields has developed valuable metrics to describe the inter-relationships between different elements of the built environment.

Accessibility analysis is popular among planners and transportation analysts and provides powerful metrics to describe a location with respect to activities located around it. Accessibility is generally viewed as a combined result of the number of attractions available around a location, the individual characteristics of each of the attractions, and the travel impedance required to overcome in accessing each of the attractions.

Though accessibility indices can readily be measured on actual street networks and building configurations, traditionally little attention has been paid to distinguishing the urban form components of index from the land use components of the index.

Graph theory indices, popular in architecture and transportation studies, typically characterize the planimetric properties of the street network. Graph theory application on spatial networks have suggested that the geometric layout of the street network plays an important role in generating patterns of accessibility, encounter, density, and proximity between locations, which could affect the suitability of a location for a particular land use. The disaggregate nature of graph analysis allows the indices to distinguish levels of accessibility for each individual element of the graph (i.e. street segement). Two currently popular approaches include the dual representation, exemplified in the Space Syntax Methodology (Hillier 1996) and the primal representation, exemplified in MCA and transportation applications of graph theory (Kansky 1963; Porta, Crucitti et al. 2005). The primary differences between these approaches lie both in the particular representation of the underlying graph environment and in the metrics that are used to measure the relationships between graph objects. Whereas MCA and most transportation applications of graph theory use metric distances to describe inter-relationships between graph elements, Space Syntax researchers have argued a case for topological distances (i.e. the number of connections, rather than the length of connections). At root, the two representations describe similar phenomena, and we believe that reconciliation is possible. We will attempt to demonstrate a joint approach in the next chapter.

Space Syntax researchers suggest that the notion of proximity in general and the perception of a location's accessibility in a network of city streets in particular could be affected by the experience of physical travel through an urban environment, which involves more than a simple distance or travel-time cost of reaching a location. The more nuanced characteristics of spatial proximity proposed by these researchers arise from the biases of perception and preference that result when a mental 'image of the city', as Kevin Lynch has called it, is used to navigate the physical structure of the city. These biases suggest that pedestrians might prefer routes that are cognitively simpler to navigate, involving fewer changes in direction. Some evidence also suggests that pedestrians might prefer routes with more cross streets, which offer more navigation alternatives along the way. Which locations appear accessible or remote could thus depend not only on physical distance, but also on the number of directional changes and street crossings required to reach them. Further empirical research is required to substantiate these debated biases. We suspect that ease of navigation to an urban location might also affect the location's suitability for retailing.

A well-known shortcoming in both Space Syntax and MCA methodologies is that neither method accounts for the three-dimensional geometry of the built environment, nor the land use characteristics of the network. A single path is computed between each node pair, and all paths are weighted equally in the analysis. In effect, this implies that a street that has no buildings on it is weighted equally with a street that has a number of tall buildings. Likewise, an area covered with industrial land uses, for instance, is weighted equally with an area full of commercial land uses. These graph theory applications are used strictly to measure the geometric and topological properties of the street network itself, ignoring all information about the buildings and activities located on the streets.

This methodological simplification has prompted some transportation researchers to discard graph theory type accessibility measures all together (Bhat, Handy et al. 2000). The critics argue that accessibility is generally defined as a combination of attraction and impedance attributes of a location. Since graph theory metrics only include the impedance part of the equation, they leave out an essential part of an accessibility measure[37]. Proponents of graph theory metrics, on the other hand, argue that the spatial properties of street networks can be analyzed independently from their contents, and that the latter can in fact be affected by the former and vice versa. Making reference to this debate, Batty has recently claimed that "*A unified theory is urgently required*" (Batty 2009: 194).

Whereas graph theory studies suggest that certain streets offer advantageous access by being either closer, more between, or otherwise favorably-located with respect to the distribution of potential customers, morphological analysis suggests that the geometric configuration of the destinations themselves can also play an important role in informing the suitability of a location for particular activities. Morphological analysis generally operates in finer spatial resolution than urban graph theory, describing the spatial characteristics of individual parcels, buildings, or blocks[38]. Analysts have generally used qualitative and comparative methods. It remains unclear, however, if and how the approach could be systematized in future research. Due to the lack of systematic methodological conventions, the quality of the analysis is subjective and heavily dependent on the quality of the analyst. However, since the state of knowledge on the social importance of environmental geometry is generally poor, this methodological flexibility can also be taken as a strength that could yield greater discoveries than standardized methods.

Aggregate measures, commonly employed in planning and geographic research, typically estimate densities of urban form elements or land uses per unit area of land. These could range from persons per square mile, street intersections per square kilometer, linear length of roads per acre, households per zip code, and so on. Aggregate measures can also provide summary statistics for given areal units, such as median income in a census block, mean distance to the city center, average perimeter of city blocks, minimum or maximum levels of connectivity, as well as different measures of variation, entropy, or spatial distribution.

Different approaches in configurational studies have typically analyzed different aspects of environmental geometry. None of the categories presented above described the two-dimensional planimetric characteristics of the street network, the three-dimensional volumetric characteristics of buildings, and the land use and activity characteristics inside the buildings, all together in a comprehensive framework. An attempt towards a more comprehensive approach, where several complementary metrics are combined to analyze the two-and three-dimensional geometry of urban form and land use effects side by side, is made in this dissertation.

A clear distinction between *land use* effects and *urban form* effects appears to be missing in numerous planning studies of the built environment. The term *built environment* is often used as an overarching definition to characterize both the formal and functional aspects of an urban area. Some studies that analyze

[37] This is not entirely accurate, because accessibility measures in fact comprise three parts: impedance measures, attraction measures, and the count of attractions. The count of attractions is implicitly included in graph theory measures. We shall further elaborate this detail in section 2.3.1 where we describe accessibility measures.
[38] Some excellent morphological analysis has also been done in much larger scale. See for instance Conzen, M. R. G. and M. P. Conzen (2004). Thinking about urban form : papers on urban morphology, 1932-1998. Oxford ; New York, Peter Lang.

the effects of built environment on social behavior (i.e. travel mode choice), only include land use accessibility indicators as predictors (Frank and Pivo 1994), while others focus purely on form-based indicators or include both types of variables almost interchangeably (Forsyth, Hearst et al. 2008). The lack of clear definitions and distinctions between *urban form* and *land use*, seems to result in considerable confusion over the importance of built environment on diverse social phenomena (Handy, Boarnet et al. 2002). For the purposes of the subsequent analysis we define urban form, land use, and the built environment in the following ways.

Urban form refers to the physical pattern of urban infrastructure — the two- and three-dimensional geometry of built form and its circulation routes, the shape of public space and paths that connect them. When we discuss the effects of urban form, we mean effects that are attributable to just these physical properties of the built environment. Some researchers further differentiate the different *elements* of urban form, studying one element at a time. Transportation scholars and some architectural researchers often focus on transportation infrastructure, analyzing only the planimetric properties of the street network (Porta, Crucitti et al. 2005; Hillier 2006; Xie and Levinson 2007). Others leave out the planimetric geometry of urban form and focus solely on the volumetric effects of buildings, using density- and floor-area ratio metrics. Studies analyzing planimetric and volumetric aspects of urban form simultaneously are more common in qualitative research (Anderson 1978; Conzen and Conzen 2004) and generally rare in quantitative studies.

Land Use refers to the activities accommodated within urban form, their distribution across buildings and open space, their intensity, or rate of change. Land uses are typically categorized into loose groupings, such as residential, commercial, industrial, and other activities. When we discuss the effects of land uses, we mean effects that are attributable just to the presence and characteristics of these activities. Researchers often analyze the effect of a particular land use (e.g. commercial) on residents' social behavior (e.g.vehicle miles travelled).

The term *built environment* encompasses both the urban form and the land use mix of an area. When we refer to the effects of the built environment, we generally point to the combined effects of land use and urban form simultaneously. However, two built environments can have the same urban form and a different land use mix, or vice versa. In comparing different built environments we therefore try to distinguish the differences in urban form, from the differences in the land use mix.

2.4 Hypotheses and expected findings

The review of economic literature on retail location choices and morphological literature on the effects of urban spatial configuration thereupon has outlined several important forces that shape the retail landscape of a city. Real-world location choices of retail establishments, however, include many more factors than have been characterized in this chapter, some of which have been explored elsewhere and others that remain yet to be confronted by empirical research. The diverse forces that we discussed, ranging from endogenous economies of multi-purpose shopping and demand externalities to exogenous location characteristics embedded in urban form and land use patterns, suggest that a comprehensive theoretical model that accounts for both endogenous and exogenous factors remains to be elaborated. But important fragments of a more comprehensive picture than offered by either discipline alone do indeed begin to emerge when an economic perspective is combined with a configurational study of the built environment.

Retail location theory has primarily addressed endogenous factors that affect the spatial distribution of retailers. The three dominant theories explaining retail location patterns are 1) Central Place Theory, which describes the aggregate pattern of stores; 2) multipurpose shopping and demand externalities, which explain the clustering of complementary stores; and 3) price comparison, Cournot competition, and minimum differentiation, which explain the clustering of competitive stores. Central Place Theory argues that retailers are expected to divide up a given market area in a regular pattern, with stores of the same type located at equal distances from each other, forming uniform hexagonal market areas (Lösch 1954; Christaller and Baskin 1966). Neo-classical theory, on the other hand, demonstrates that multipurpose shopping, can lead to savings in transportation costs and unplanned purchases, offering key insights into why stores of different types would locate close to each other — an aspect that Christaller left unexplained (e.g. Eaton and Lipsey 1982; Brueckner 1993). The agglomeration of competitive stores is explained by three additional factors: a) uncertainty and competition between competing stores (Hotelling 1929); b) the fact that people like to compare prices and products and thus prefer to shop at locations that allow them to do so (Eaton and Lipsey 1975); and c) that Cournot competition in clusters leads to lower prices, which attracts more customers (Dudey 1990).

An important limitation of each of these economic theories is that retail location choices are explained with other retailers' location choices. In Central Place Theory, for instance, location choices are determined by the spatial relationships to other competing stores, so that in equilibrium, all stores of a given type are equidistant from each other[39]. Complementary clustering literature explains location decisions with respect to nearby complementary stores. And competitive clustering literature explains location choices in the light of the locations of competing stores. Taken together, these theories tell us that in some situations we expect retailers to cluster and in others to repel one another. These theories do not instruct us, however, *where* clusters are expected to form in the first place. We suspect that including exogenous location factors in a retail location model could shed light on the basic question of why retail agglomerations emerge at particular locations.

Configurational studies of the built environment have suggested that retail location patterns are also influenced by environmental factors, such as urban form, land use patterns, and cognitive aspects of human navigation. Configurational studies have, however, rarely been developed from an economic perspective, which would merge insights from location theory with insights from formal analysis. Studies of urban form using different graph theory metrics have habitually been conducted in an ad-hoc manner, ranking different measures of urban form against an outcome of interest, without clear hypotheses, behavioral basis, or an economic foundation. Space Syntax researchers have even used stepwise regressions to investigate which accessibility measures best predict pedestrian volumes or a retail location pattern. Lacking a clear hypothesis about a given property of urban form and starting the analysis with ad-hoc data puts the cart before the

[39] Though the aggregate density of stores is indeed determined by exogenous factors, like range and threshold (see 2.1.2).

horse and leads to no fewer than an infinite number of possible explanations to the given measures of spatial configuration (Popper 1959). We think that a methodologically more rigorous approach for investigating the relationship between urban form and social processes that take place therein is urgently required.

Which factors, then, emerge from both bodies of literature as important for retail location choices? First, retail location theory suggests that an establishment's location decision can be strongly influenced by the location choices of other retailers. Data from shopping centers and anecdotal experiential evidence from urban settings suggest that spatial inter-relationships between retailers form an important factor to consider. We therefore specify our first hypothesis as follows:

1) *Retail establishments in urban settings are endogenously attracted to other retailers, controlling for exogenous location factors.*

Second, configurational studies of the built environment suggest that exogenous location factors could also influence retail location choices in important ways. We expect the influence of exogenous factors to be especially pronounced in urban contexts, since retailers in a city are embedded amidst other land uses and an omnipresent influence of urban form. Rather than collaboratively optimizing the store mix to attract the largest possible demand to the cluster as a whole, we expect un-coordinated urban retailers to exhibit a stronger preference towards locations with advantageous exogenous conditions. This leads us to the second and third hypotheses addressing the impacts of urban form and land use pattern:

2) *Advantages in accessibility that result from favorable proximity to all surrounding built form are positively related to retail location choices, controlling for land use distribution and clustering.*

3) *Advantages in accessibility that result from favorable proximity to residents, jobs, and transit stations are positively related to retail location choices, controlling for urban form and clustering.*

Behavioral studies of pedestrian route choice and route learning have suggested that not only does the geometric layout of a city generate objectively favorable accessibility at certain locations, but the notion of proximity in general and the perception of a location's accessibility in a network of city streets in particular, are also affected by people's navigational biases in cognitive maps. These studies propose that topological attributes of access, such as the number of turns taken or the number of intersections crossed can also affect the perceived accessibility of a location. Our fourth hypothesis thus suggests that:

4) *Urban retail establishments are not only attracted to locations with favorable access in terms of metric proximity to surrounding opportunities, but also topological proximity in terms of the number of turns and street crossings required to reach a location. We expect retailers to prefer locations that require fewer turns but more intersections crossings to access from all surrounding opportunities, controlling for distance and other covariates.*

Finally, economic theory suggests that retail location preferences also depend on the type of goods sold. Much of shopping center literature distinguishes the location factors of 'anchor' stores from 'non-anchor' stores. Since demand externalities are seen as flowing from anchors to non-anchors, then rents per square foot paid by small stores tend to be significantly higher for small stores (Bencjamin, Boyle et al. 1990; Benjamin, Boyle et al. 1992). Store size is not the sole factor behind anchor store; the frequency of patronage that the store attracts also plays a role. Grocery stores, for example, offer goods that are demanded frequently by their customers, but furniture stores, in contrast, are visited rarely. Stores that attract patrons more frequently tend to produce more positive externalities for other nearby stores and we therefore expect them to be less attracted to unpopular stores. On the other hand, typical urban retail clusters have no legal mechanisms in place to keep unwanted stores away from anchors. Observed clusters can therefore be asymmetrically beneficial for stores that receive, rather than produce, positive demand externalities.

At the same time a large agglomeration of small stores with relatively low patronage frequencies can collectively also start producing demand externalities that benefit anchor stores. Unlike a mall, we expect an urban cluster can be composed of stores who value the presence of other stores in the cluster and stores who do not[40]. Due to these opposing forces we do not have clear expectations on how location choices might differ between types of stores. We simply expect the location choices of different types of retailers to differ. This leads to our fifth and final hypothesis:

5) *Location choices of retail establishments differ significantly from each other depending on the type of goods sold.*

The five research hypothesis, presented above, broadly address three important areas of influence on retail location choices depicted in Figure 21. Land use distribution is addressed in hypotheses one and three. Hypothesis one conjectures that retail location choices are related to the locations of other retailers. Hypothesis three adds that location choices are also related to the spatial distribution of residents, jobs, and transit stations. The effects of urban form are addressed in the second hypothesis, which proposes that retail location choices are positively attracted to advantageous locations that have better access to *all* urban form around a location, regardless of land use. Our fourth hypothesis postulates that location choices of retail establishments are also affected by biases in travel behavior, with a systematic preference towards locations that are cognitively easier to find, as captured in the number of turns and number of intersection crossings required reaching a location. Finally, our fifth hypothesis suggests that the way these factors affect retail location choices should vary based on the type of retailers. The next chapter proposes a framework where all three fields of influence — land use distribution; urban form; and navigation biases — can be jointly represented and analyzed.

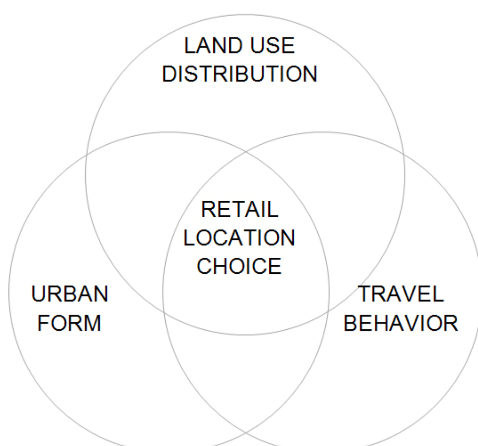

Figure 21 Three groups of factors affecting retail location choices, addressed in this study.

[40] In malls this asymmetry is compensated by differential rents.

3

Data and Methodology

This chapter focuses on our research design. We first propose a representational framework, where factors of urban form, land use, and travel behavior can be jointly represented. We then describe how we use the framework to measure meaningful characteristics of each factor individually and subsequently present the descriptive statistics. In section 3.4 the chapter turns to the estimation methodology. We introduce the strategic interaction framework that allows us to analyze how decisions of spatial economic agents depend on the decisions of other spatial economic agents. Since the strategic interaction framework has previously been used for other purposes, we propose a novel application where it is used for studying location choices. We conclude the chapter by describing the limitations of the proposed methodology.

3.1 Graph Representation

Spatial configuration of a built environment can be described through multiple forms of representation, including architectural drawings, images, mathematical, textual, graph and other forms of depiction. In order to distinguish detailed aspects of the built environment, we primarily focus on the graph representation in the scope of this study.

While they allow us to describe geometric relationships between various elements of the built environment in a quantitative manner, graphs also retain an intuitive spatial representation of the environment under investigation. An important advantage of the graph representation comes from the ease with which meaningful spatial measurements of urban form can be performed on a computer, which allows us to automate a large number of spatial calculations between different elements of the built environment. The graph formulation of urban form also allows us to apply and extend previously developed analytic tools from graph theory and accessibility research described in the previous chapter. We use ArcGIS Network Analyst extension to represent urban configurations in graph form in all of the following examples. However, a similar graph representation of urban form would work equally well in different computing environments including programming languages such as Java, Python, and others.

In section 2.3.2 we discussed spatial applications of graph theory in the context of built environment studies, where we showed that typical applications of urban graph analysis have to date focused primarily on the two-dimensional planimetric properties of street networks. In these studies, streets are usually represented as edges and street intersections as nodes of the graph (Garrison and Marble 1962; Kansky 1963; Harggett and Chorley 1969; Crucitti, Latora et al. 2006). Space Syntax researchers have chosen to represent street networks in a *dual* or inverted manner, "*translating a network into a graph in which lines are nodes and intersections are edges*" (Hillier and Iida 2005).The unit of analysis in these studies can be a node or an edge, and the outcome of the analysis illustrates the degree to which a street intersection or a street segment is spatially connected to the surrounding street network. The choice of focus on nodes or edges depends on the type of network analyzed and the objective of the study. In an urban context, nodes (street intersections) might be less obvious units of analysis than edges (street segments), because buildings, where the majority of human activities occur, are more commonly located around edges than nodes. Graph analysis on street networks has thus primarily used edges as units of analysis. Porta and his colleagues, using multiple centrality measures, initially compute the connectivity of each node, but then convert the results to edges by averaging the values of each edge's pair of end nodes (Porta, Strano et al. 2009). This conversion process is unnecessary in Space Syntax analysis, where the dual representation of the graph allows the values to be computed directly for edges (Hillier 1996). The focus of analysis, in both of these cases, falls on edges representing street segments. This approach economizes computation power and allows the analysis to be run on large networks. But the exclusive focus on streets also poses some difficulties for the theoretical interpretation and practical applicability of the results.

First, buildings, which accommodate activities where most urban trips begin and end, are missing from the picture. This makes the results of the analysis theoretically difficult to interpret. What does the connectivity of a street tell us if buildings are not accounted for? Whether the objective of the analysis is traffic flow, business location choice, spatial distribution of crime, or land values, buildings accommodate most urban activities and act as the crucial origins and destinations of urban movement. Edges and nodes of the street network are spaces that accommodate traffic, which flows between buildings.

Second, since a great deal of urban decision making happens at the building level, then the node or edge level results can also be difficult to use in practice. With edges as units of analysis, all activities or buildings located along a given street segment obtain identical values of connectivity. A building located at the corner of a major intersection is attributed the same level of connectivity as a building in the middle of a block. When axial lines are used instead of street segments, a building at one end of a long and straight street (e.g. Oxford Street in London, or Rue de Rivoli in Paris) is attributed the same level of connectivity as a building at the other end of the street.

In order to address these and other shortcomings described in section 2.3.1, this dissertation proposes two important modifications in the graph representation of the built environment. First, we add buildings to the representation, adopting a tripartite representation of the built environment that consists of three basic elements: *edges*, representing paths along which travelers can navigate; *nodes*, representing the intersections where two or more edges intersect; and *buildings*, representing the locations where traffic from streets enters into indoor environments or vice versa. Our unit of analysis thus becomes a building, allowing us to compute the different graph indexes separately for each building. This allows us to account for both uneven building densities and land use patterns throughout the network, neither of which are addressed in most urban graph analysis methods.

We represent buildings with points and assume each building connects to a street (edge) that lies closest to it along the shortest perpendicular connection. Conveniently, this representation is suited for GIS Network Analyst software, where origins and destinations of travel paths are represented with geographically positioned points. Some previous authors have chosen to merge the representation of nodes and buildings (or comparable elements of activity locations) into a single element (Kansky 1963; Okabe and Okunuki 2001). This makes sense in the analysis of rail networks, for instance, where the majority of rail intersections coincide with stations. A similar simplification has been made in graph representations of individual building plans, where each functional location (e.g. room in a building) simultaneously acts as a node in a network of paths that lead to neighboring rooms (March and Steadman 1971). We keep buildings and nodes apart as different elements because they serve a fundamentally different purpose: buildings are places where trips originate and end, whereas nodes are street intersections and public spaces through which trips pass. Though one might argue that good public spaces also contain amenities and often house non-transient activities, our approach postulates that particular control structures and use patterns make buildings clearly distinguishable from public spaces (Habraken and Teicher 1998).

The second modification we introduce for urban graph analysis is the weighted representation of graph elements. To date, most urban graph representations have been used in unweighted form, in which each element of the graph (i.e. edge or node) is treated as equal. This dissertation introduces a weighted representation, in which each element obtains attributes that are used in graph calculations. Each building, street segment, and intersection obtains a set of attributes that connect the abstract graph components with the true characteristics of the corresponding built elements in a city. Edges representing given street segments, for instance, obtain a table of attributes, indicating their length, width, traffic capacity, sidewalk characteristics, right of way, or any other qualities one can measure on actual streets. Likewise, the attributes of nodes can contain variables that represent street intersections: the presence of traffic lights, the number of edges intersecting at the node, whether or not the intersection forms a plaza, and so on. The attributes associated with buildings capture any measurable properties of the structures around them: their size, establishment mix, number of residents or jobs, height, etc. The simple graph of buildings, nodes, and edges thus offers virtually limitless options to add attributes to each of the three elements, producing a powerful representation of spatial relationships between the various elements of a city.

This type of representation is illustrated in Figure 1. The left side of the figure presents a fragment of Harvard Square in Cambridge MA in plan drawing. The same plan drawing is shown in graph form on the right.

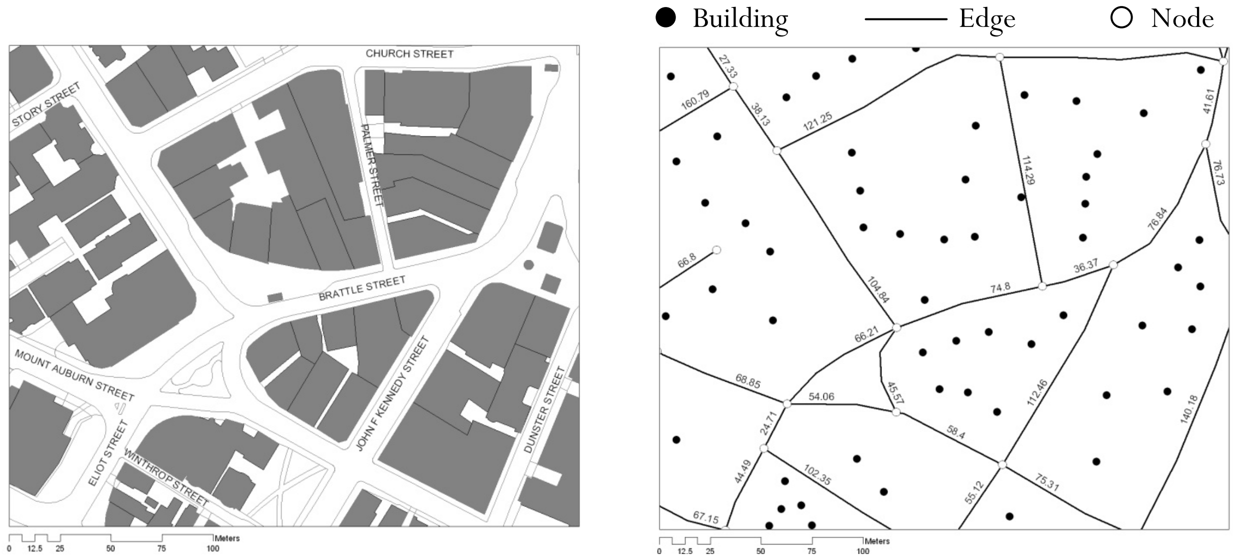

Figure 1 Left: Plan drawing of Harvard Square in Cambridge, MA. Right, a graph representation of the same plan drawing.

If the spatial configuration of the environment cannot be easily represented in a two-dimensional graph, then a similar graph can also be represented three dimensionally, as shown in Figure 2. Such a need can arise if the street network is three dimensional (e.g. containing bridges or overpasses), or if buildings are connected to each other above or below the street level (e.g. via skywalks or tunnels). The analysis of spatial relationships between the elements of the graph can, in this case, be computed on a three-dimensional or non-planar graph. However, most common urban form configurations do not involve such complexity and can be easily represented in two-dimensional graphs. In the analysis of our case study we use a two-dimensional graph.

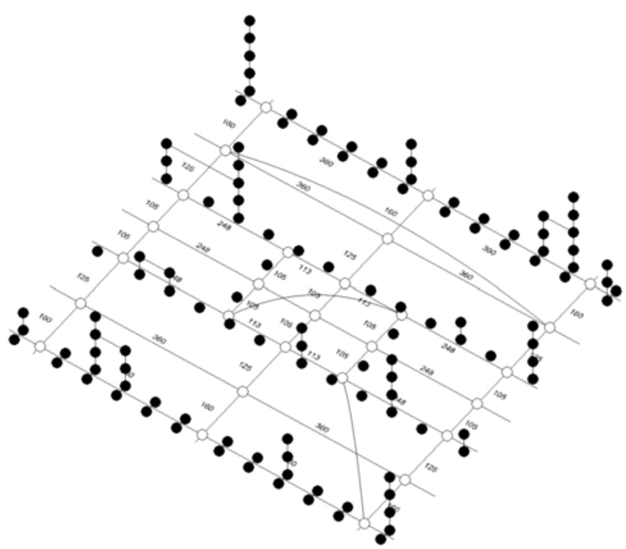

Figure 2 A three-dimensional graph of urban spatial configuration.

Using the proposed tripartite representation of urban configuration, an origin-destination (OD) matrix can be computed to describe the spatial separation between all building pairs in the graph. Although the most popular technique of linking any two locations across the graph is to use metrically shortest paths (also known as geodesic paths)[1], the graph representation also allows an OD matrix to be computed along other sensible metrics that describes the spatial separation of a pair of locations. Space Syntax researchers, for instance, have shown how an OD matrix can instead be computed according to the directional changes between destination pairs. Additionally, the OD matrix can be computed along routes that minimize or maximize certain types of edges or nodes along the way (e.g. minimizing street crossings), or a combination thereof. GIS Network Analyst, TransCAD, and other spatial network analysis platforms offer flexible algorithms to compute paths along different route characteristics.

Regardless of the criterions used for finding the OD routes, each computed path in the OD matrix can, additionally, store a series of variables describing impedance features encountered along the computed routes. If the OD matrix is computed along metrically shortest paths, for instance, then the attributes of the computed routes can also store information about the number of turns made along the way, the number of intersections crossed, the number of buildings (with this or that characteristic) passed, and so on. This list can be extended to capture any substantively important metrics of paths (Figure 3). We include the instructions and code to compute the number of turns and the number of intersections crossings in ArcGIS Network Analyst in Appendix One.

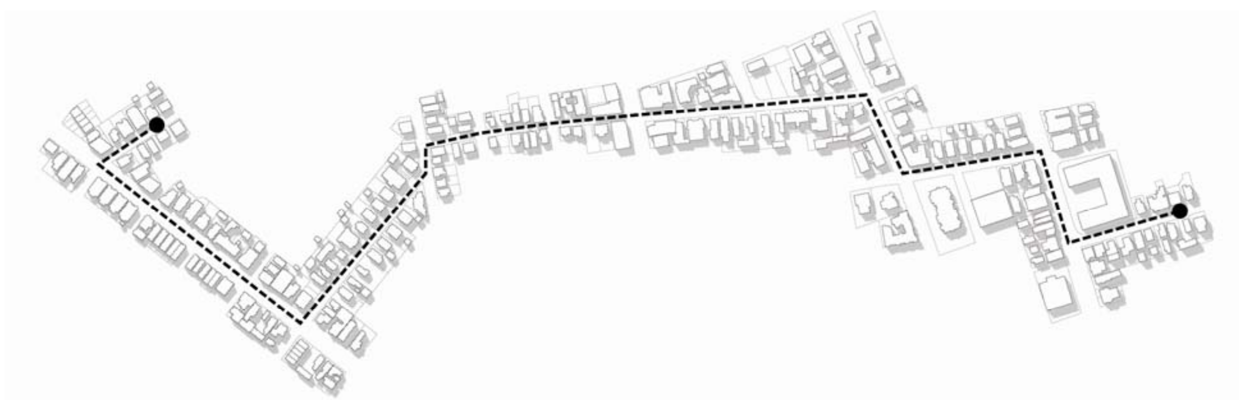

Figure 3 An impedance measure can be calibrated to capture any substantively justified attributes of spatial travel between two points on a network.

Describing the spatial separation between all location-pairs simultaneously with several impedance metrics (e.g. distance, turns, etc), consolidates the advantages of currently disparate primal and dual forms of graph representation and reconciliates the Space Syntax and MCA methodologies. Using the same underlying graph, but a different impedance measure, allows us to compute both a Space Syntax type integration analysis that focuses on topological connectivity and an MCA type metric analysis that focuses on metric connectivity at the same time. This is an important development, which could lead to future theoretical developments in urban spatial analysis.

We store an OD matrix in a database, using building IDs to distinguish the origins and destinations of each route. A common building ID field allows us to connect the OD matrix to a parallel database of building characteristics. A wide variety of spatial analytics thus become available when the OD matrix is connected to the list of building attributes, where OD paths originate and end. This allows us to query, for

[1] This is also the technique we employ in specifying our OD matrix.

instance, how many establishments, residents, or jobs of a certain type are reachable within a given distance threshold from each building along the actual network routes. It also offers a simple framework to measure how far each of those destinations are and what the route characteristics leading to them are like. A destination, in this case, can be anything from a building, transit station, or a workplace to a square foot of retail space. Linking the OD matrix with the attribute tables of buildings, edges, and nodes thus opens up a convenient analysis framework where urban form, land use distribution and route characteristics are jointly represented.

3.2 Case Study Location

Our case study analysis focuses on the cities of Cambridge and Somerville, MA. These two cities, located across the Charles River from downtown Boston, are spatially continuous and similar in size. The land area of Cambridge is 6.43 square miles; it housed 101,388 inhabitants in 2007. The land area of Somerville is 4.1 square miles; it housed 74,405 people in 2007. Cambridge and Somerville illustrate a characteristic urban environment of historic eastern U.S. cities. With average population densities of 25 inhabitants per acre, Cambridge and Somerville illustrate moderately dense urban environments that lie a few miles outside of the Boston city center. Their richness in pedestrian and transit commuters and the excellent availability of spatial and economic data made them particularly attractive for this study. Due to the relatively old age of both towns[2], the retail patterns encountered in Cambridge and Somerville predate modern zoning laws by a long margin — a quality we shall argue to support our methodology.

Cambridge and Somerville are also local towns, where the author has lived in the past six years and become familiar with their spatial structure firsthand. Acquaintance with the two cities enabled visits to almost all of the localities analyzed in the study, putting the hypotheses of the study under observational scrutiny. The local nature of the study also enabled conversations with multiple business owners, allowing the concepts of the study to be probed with real-world decision makers. The accumulative discoveries, encounters, and experiences in both towns facilitated the comprehension of their spatial structure, which, in turn, not only led to their appreciation, but also the desire to learn from these examples in future work as an urban designer.

3.3 Data

The unique location data for individual establishments in Cambridge and Somerville was obtained from the InfoUSA 2009 database[3], licensed for academic use at MIT through the Massachusetts Office of Geographic and Environmental Information (MassGIS). A business establishment is defined as a physical place where business is conducted, goods are made, stored, processed or sold, or where services are rendered (e.g. a factory, an assembly plant, a retail store, a warehouse, etc.). An establishment differs from a firm in an important way: a single firm can include several branch locations, but each establishment is

[2] Colonial settlements within the present-day boundaries of both cities were first established in the 1630s.
[3] http://www.infousa.com

defined as a unique location. Whereas a firm could own multiple establishments, all of which can be represented by the headquarters of the firm, establishment data shows locations of all individual establishments in the firm, making establishment data more attractive for studying location choices.

The individual business establishments in the data are given as geographically referenced points that include certain establishment attributes and a unique business category code. Geographic coordinates, as well as an address field associated with each establishment in the database, allowed us to match each business to a particular building in the two cities. A business category code associated each establishment with a six digit North American Industry Classification System (NAICS). NAICS is the standard used by federal statistical agencies for classifying business establishments for the purpose of collecting, analyzing, and publishing statistical data related to the U.S. business economy (Census 2009) . The number of NAICS category digits indicates the level of detail in the establishment description[4]. While the two-digit code "44" refers to the highest-level description, called "retail trade", a three-digit code can distinguish "441" — "Motor Vehicle and Parts Dealers"— from "442"— "Furniture and Home Furnishings Stores". We also obtained employment data from the InfoUSA database, which listed the estimated number of employees in every establishment.

Public transit data for Cambridge and Somerville were obtained from the Massachusetts Bay Transportation Authority (MBTA). The data show the routes and stops of subway and bus lines in both cities.

The spatial distribution of residents was obtained from the year 2,000 census records at the block level. Since census data was not originally obtained at the individual building level, it needed to be transformed to a building-level resolution in order to maintain buildings as common units of analysis. To match census counts from blocks to buildings, we first used the assessors databases of Cambridge and Somerville to determine which parcels contained residential buildings and then allocated the total population of each census block between the residential buildings in that block, weighing the allocations by building volume. Large apartment buildings thus obtained a proportionately larger share of residents than small single-family homes[5].

The urban form characteristics were obtained from the MassGIS, as well as the cities of Cambridge and Somerville. The roads data, which we used for all access calculations, are the official state-maintained street transportation dataset available from MassGIS (last updated in December 2007). The roads data represent the centerlines of all local and major streets and roads in the Boston metropolitan area. They also describe the attributes of each road segment in the area, including paved width, sidewalk width, and right-of-way. These road characteristics were spatially joined with individual buildings, so that each building obtained attributes describing the street segment in front of it.

Building footprints and heights were obtained from the 2002 LIDAR[6] scan database of MassGIS. Combining building footprints and heights allowed us to estimate each building's volume in cubic feet.

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[4] NAICS digits in the InfoUSA database are shown down to the six-digit level, though we only focus on the two- and three-digit categories.

[5] We acknowledge that this allocation procedure can introduce additional measurement error to the data. The procedure was necessary, however, for obtaining a common unit of analysis.

[6] LIDAR (Light Detection And Ranging) is an optical remote sensing technology that measures the topography of natural and man-made objects on the earth's surface from an airborne scanner.

Unfortunately the 2002 LIDAR scan cropped off an area of northern Somerville, leaving building heights unknown in that part of town (compare the northern tip of the city boundary in Figure 5 to the data map in Figure 11). We therefore eliminated the affected buildings from our dataset, which reduced the sample from n=29,829 to n=27,023.

Parcel data were obtained from the assessor's offices in Cambridge and Somerville and reflect the 2009 situation.

3.3.1 Dependent variable: the location of retail and food establishments

Our main question variables are the observed locations of retail and food establishments. The decision to couple retail and food establishments together originates from functional similarities in these types of establishments. In Webber's classification of economic activities as *production*, *exchange*, and *consumption*, both retail and food establishments belong to the exchange category, where the supplies of producers and the demands of consumers meet (Weber and Friedrich 1929). Unlike production activities, whose location choices maximize access to production inputs, or consumption activities, whose location choices maximize access to goods and services, exchange activities maximize access to customers. Location choices of retail and food establishments thus share an important commonality: both rely heavily on spatial access to patrons (See Figure 4). We therefore begin our analysis by treating retail and food establishments as a single group and later also look at the location preferences of each retail and food establishment *type* separately.

Figure 4 Davis Square in Somerville in 2009. The ground floor of a corner building is occupied by a number of retail and food establishments: a diner, a tobacco and convenience store, a café, a dollar store, and a pastry shop.

The InfoUSA 2009 data include a total of 8,163 individual establishments of all NAICS categories in Cambridge and Somerville. Of these, we selected establishments that are categorized as retail trade (NAICS 44-45) and food services (NAICS 722) as our dependent variables, which yielded a total of 1, 941 establishments in the two neighboring towns: 1,258 retail establishments, and 683 eating establishments. In accordance with retail location theory, the number of establishments reflects their frequency of visits (DiPasquale and Wheaton 1996). Food Services and Drinking Places, which are visited frequently, have the most establishments (683), followed by Food and Beverage Stores (231), Electronics and Appliance Stores (230), Miscellaneous Store Retailers (189), and so on. The three-digit NAICS categories observed in Cambridge and Somerville are listed in Table 1. Figure 5 illustrates how these establishments are geographically distributed across the two cities.

NAICS	Description	n
441	Motor Vehicle and Parts Dealers	86
442	Furniture and Home Furnishings Stores	11
443	Electronics and Appliance Stores	230
444	Building Material and Garden Equipment Dealers	66
445	Food and Beverage Stores	231
446	Health and Personal Care Stores	35
447	Gasoline Stations	45
448	Clothing and Clothing Accessories Stores	166
451	Sporting Goods, Hobby, Book, and Music Stores	142
452	General Merchandise Stores	41
453	Miscellaneous Store Retailers	189
454	Nonstore Retailers	16
722	Food Services and Drinking Places	683
	Total:	1941

Table 1 Categories and counts of retail or food establishments found in Cambridge and Somerville, MA.

We assigned each retail and food establishment to a corresponding building in both towns, as shown in Figure 6. Eighty-one per cent of the InfoUSA establishment points were matched to a building directly by address coding in GIS, the rest were spatially joined to the nearest building. Each building thus obtained a dichotomous variable (0 or 1) showing whether or not the building contains retail or food establishments and a continuous variable (0 – n) indicating the count of establishments in each of the three-digit NAICS categories. Since some buildings contain multiple retail establishments, the number of observations diminishes from 1,941 individual establishments to 961 buildings containing retail or food establishments. The dichotomous variable, representing the presence or lack of retail or food establishments in each building, defines our dependent variable in the following analysis.

Figure 5 Locations of retail and food establishments in Cambridge and Somerville, MA. (n=1, 941).

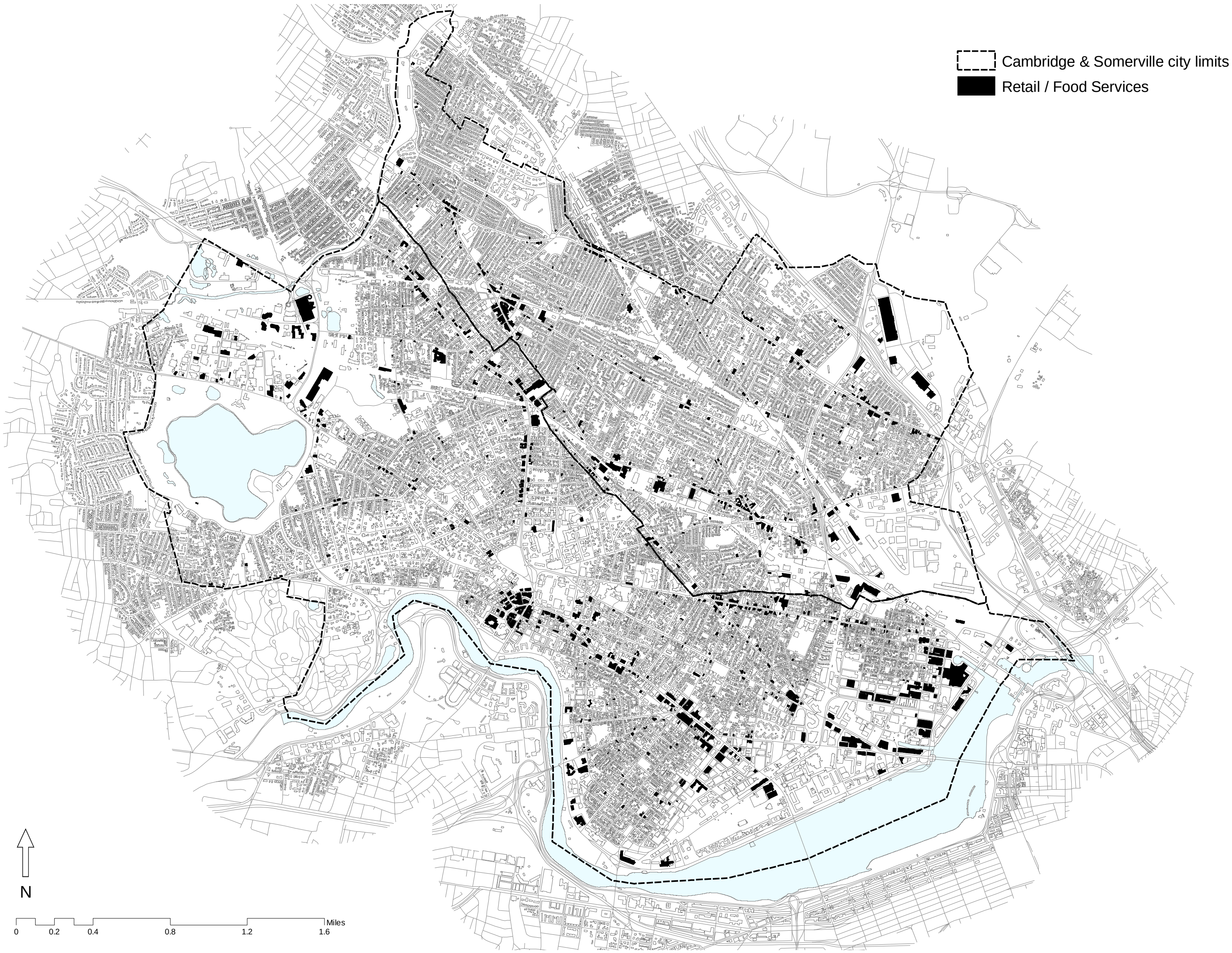

Figure 6 Map of 961 buildings containing retail or food establishments in Cambridge and Somerville, MA.

Figure 5 and Figure 6 suggest that retail and food service establishments in Cambridge and Somerville are spatially clustered in limited geographic locations, but often locate in the same places. Harvard Sq, Central Sq, Porter Sq, Davis Sq and other well-known business clusters accommodate a notably higher concentration of establishments than an average locality in the two towns. During a ten-minute walk around Harvard Sq, the busiest retail cluster in Cambridge, a visitor can find 131 retailers and 90 food service establishments. A similar pattern, with a smaller total count, is observed at other popular retail clusters of the area. Whether these spatial concentrations of retail and food establishments are statistically significant can be tested using spatial cluster analysis.

A commonly used index for describing the spatial clustering of geographic phenomena is the Moran's I index. The Moran's I, named after Patrick A. P. Moran, compares the observed distribution of retail and food establishments to a hypothetical random distribution of the same number of points (Anselin 1988). In order to describe adjacency relationships between observed events, a spatial weights matrix is first specified to describe binary neighbor relationships between buildings in a given radius. Using a 100-meter (328-foot) radius produces an adjacency matrix where a building is shown to be neighbors with all other buildings that are located within a 100-meter distance from it. Though this radius has traditionally been measured using straight-line Euclidean distances, we measured our weights matrix on the street network of Cambridge and Somerville. Our weights matrix thus lists binary (0 or 1) neighbor relationships between buildings that are up to a 100-meters apart from one another along actual street network paths. Using the dichotomous dependent variable of each building, indicating the presence or lack of retail and food establishments, allows the Moran's I to estimate the degree of clustering between businesses. If a greater number of neighboring retailers are observed within the 100-meter radius than in a random distribution, then establishments are considered clustered. If fewer retail neighbors are observed than expected in a hypothetical random distribution, then the establishments are considered dispersed. In order to achieve statistical confidence, the random point distribution is repeated numerous times in Monte Carlo simulations, 999 times in our case to achieve a 99.9% pseudo-significance level.

Our data show that Moran's I for retail and food establishments in Cambridge and Somerville is 0.1551 ($p < 0.001$), suggesting that the observed geographic concentration of businesses is statistically highly significant. However, since this global Moran's I is the mean of all local Moran's I statistics, then its reliability can be challenged if the distribution of local values is highly asymmetric, or dominated by a few outliers. Therefore in Figure 7 we illustrate how the significance levels of Moran's I are locally distributed among individual buildings. The map suggests that the 95 - 99.9% significance range distinguishes most of the anecdotally known retail clusters of both towns. Harvard Square, Central Square, Inman Square, and Union Square stand out with particularly significant clustering coefficients, but even very small business clusters that include only a couple of stores, also appear statistically different from a random distribution at the 95% significance level. Our data thus suggest that the pattern of intra-urban retail and food service establishments exhibit significant spatial clustering. Diverging from theoretical expectations of Central Place Theory, centers do not form a clearly hierarchical pattern of hexagonal market areas. Though indeed scattered throughout the two towns, centers appear concentrated around important intersections and thoroughfares of the street network.

Figure 7 Significance map of local spatial autocorrelation of retail and food service establishments in Cambridge and Somerville (n=961).

In order to gain further insight from the observed pattern, we also analyzed the degree of clustering using Nearest Neighbor Distance (NND) analysis (Okabe, Okunuki et al. 2001). The Nearest Neighbor Distance method measures the distance between each event and its nearest neighboring event. Similar to Moran's I, NND compares the observed neighbor relationships with the hypothetical random neighbor relationships, but additionally also outlines the differences in distance units. The index is expressed as the ratio of the observed distance between retailers divided by the randomly expected distance:

$$NND = \frac{\bar{D}_o}{\bar{D}_e}$$

where $\bar{D}_o$ is the observed average distance between neighbors and $\bar{D}_e$ is the expected average distance between neighbors. The observed average distance is determined as follows:

$$\bar{D}_o = \frac{\sum_{i=1}^{n} d_i}{n}$$

where d_i equals the distance between event i and its nearest neighbor event, and n is the total number of events. The expected distance is based on a hypothetical Poisson distribution with the same number of events covering the same total length of streets L:

$$\bar{D}_e = \frac{0.5}{\sqrt{n/L}}$$

Though NND, too, has traditionally been measured on a Euclidian plane (Diggle 1983; Boots and Getis 1988), the detailed intra-urban scale of our analysis required that the distances be computed on the actual street network. A GIS toolset for calculating event distributions on a network has recently been developed at the Center for Spatial Science in Tokyo University (Okabe, Okunuki et al. 2001). Professor Okabe, has generously shared their GIS-based SANET toolbox for the purposes of the present research. Figure 8 illustrates the results of NND analysis for retail and food establishments on the street network of Cambridge and Somerville.

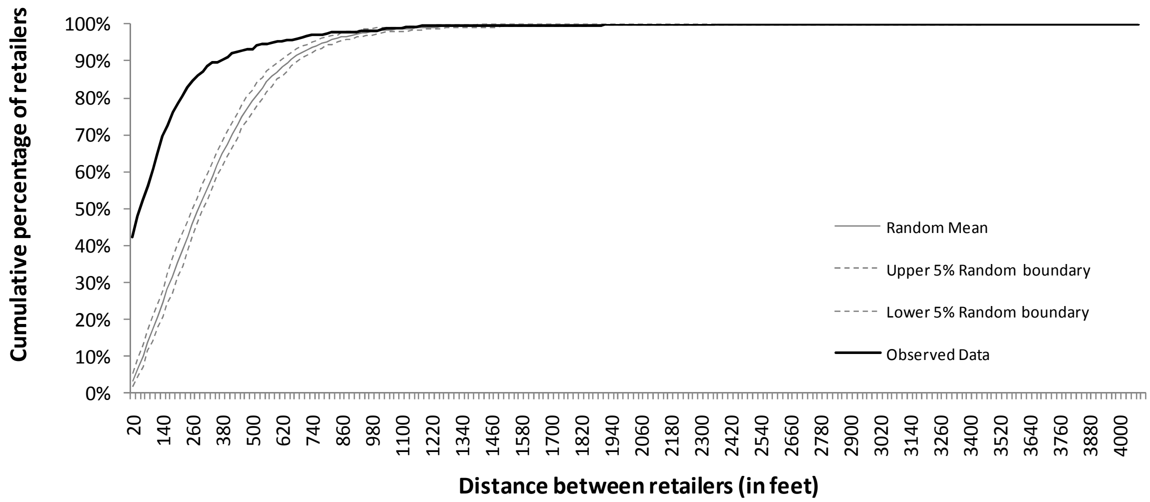

Figure 8 Observed and random nearest neighbor distances of Cambridge and Somerville retail and food establishments.

The graph shows that for approximately 95 % of retail establishments, the distance to nearest neighbors in the observed data is much shorter than it would be if the distribution were random. The solid black trajectory describes the observed nearest neighbor distances. The lighter gray trajectories describe the mean and ±95% significance boundaries of a hypothetical random distribution. At the bottom of the scale (lower left corner of the graph), we observe around 45% of retailers with nearest neighbors available at less than 25 feet from their location, suggesting that numerous retailers locate in the same or immediately adjacent buildings. Roughly half of the establishments have access to a neighboring establishment within 80ft from their location along the street network. In a random distribution, the average distance to the nearest neighbor among these 50% of retailers would be 320ft, which is four times as long. The exploratory analysis using network-based NND thus further confirms that retail and food establishments in our study area are significantly concentrated and suggests that our analysis of location choices should account for clustering as a possibly important location choice factor for retail and food establishments.

3.3.2 Mode of travel

Before proceeding to our independent variables and proposed measures of spatial accessibility, a clarification is also needed with regard to the mode of travel we assume our analysis to rely on. Accessibility between two locations in a city can be perceived very differently by travelers who walk and travelers who use automobiles or public transit. Given a 10-minute time budget, a particular location could seem isolated for pedestrians, but accessible for drivers. In contrast, locations of intense traffic and a high density of development could seem accessible to pedestrians, but poorly accessible to drivers. All modes of urban travel — walking, bicycling, driving and public transit — contribute to the notion of accessibility in ways that differ in speed, environmental perception, and travel range. Accessibility may also differ for various travel modes due to the spatial segregation of travel paths. Numerous city plans demonstrate how pedestrian, bicycle, and vehicular transportation networks can differ. Modernist town planning of the 20th century has notoriously advocated for this separation (Corbusier 1933).

We have chosen to focus our analysis on one mode of travel: walking. Walking has been the primary mode of travel in urban history, and its importance appears to be increasing again in the sustainable metropolis of the 21st century. Most notably for our analysis, walking is the primary mode of travel in neighborhood-scale shopping (Garbrecht 1980; Zacharias 2001). The analysis below models walking in a 2,000-foot network radius (ten-minute walking), allowing us to study the effects of spatial accessibility from a pedestrian point of view. There is no consensus in literature on which radius to use for capturing accessibility for walking. Our choice of 2,000 feet corresponds to Waddell's use of 600 meters, or roughly one third of a mile (Waddell and Ulfarsson 2003). People can, of course, cover much longer distances on foot, but a ten-minute walking radius appears to capture most pedestrian trips. Studies of walking have shown that average walking distances in central London (UK) were 800 meters, those in New York City (US) 524 meters, and those in downtown Edmonton (Canada) only 265 meters (Pushkarev and Zupan 1975; Zacharias 2001). Focusing specifically on shopping trips in Britain, Guy and Wrigley showed that half of all shopping trips were to locations under 500 meters away (Guy and Wrigley 1987). Handy and Niemeier estimated how pedestrian trips to convenience stores in Oakland, CA dropped off with increasing travel time, taking an inverse exponential form with a distance decay parameter of 0.1813 (Handy and Niemeier 1997). Figure 9 illustrates this decay rate. The shaded area on the graph shows that the majority of trips fall within a ten-minute walking distance. Though the shape of this function is likely to differ from city to city, empirical evidence from around the world suggests that a ten-minute walking distance captures most of the trips for neighborhood retail purposes, corroborating the use of a 2,000-foot network radius in our case study. Increasing the radius would potentially capture a somewhat larger share of actual walking trips, but at present, the gains do not seem to outweigh the computational costs[7].

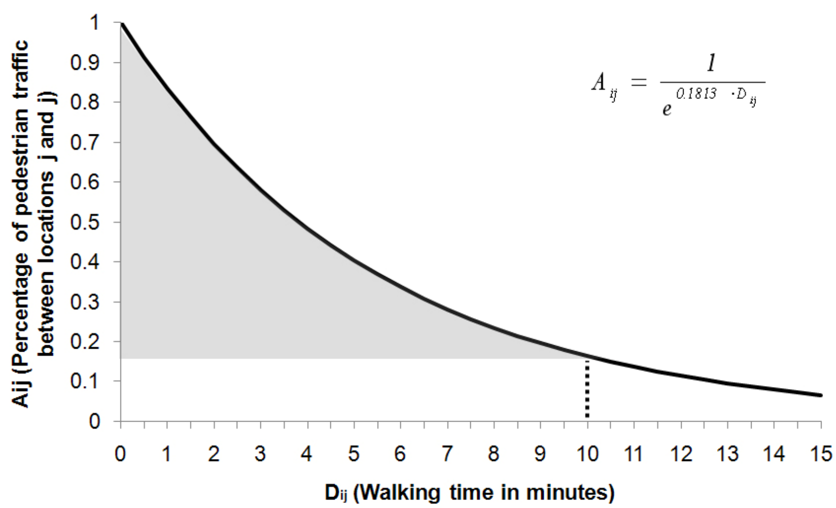

Figure 9 Estimated decay of pedestrian activity in visiting convenience stores according to the 1980 Metropolitan Transportation Commission of Oakland. Source: (Handy and Niemeier 1997).

[7] The number of computations needed for an OD matrix increase as the square of the access radius.

Due to our explicit focus on walking and neighborhood-scale retailing, our analysis will not adequately address mechanized modes of travel, nor competently discuss location-choice factors of establishments, which primarily rely on travel modes other than walking. Our focus on walking is also relevant for public transit users, who walk from transit stations to retail destinations, and car users, who drive relatively short distances. However, retail activities that rely heavily on distant vehicular travel, such as regional shopping malls and big-box retailers, are not addressed in our study. In order to address such establishments, the analysis can be repeated in future work with a focus on vehicular travel, using wider access radii and different accessibility measures that are more appropriate for car-based travel.

3.3.3 Independent variables: measures of spatial accessibility

We have suggested that, at the most basic level, an urban plan can be spatially characterized by edges, nodes, and buildings, and their attributes. Instead of using aggregate measures to describe the distribution of these elements per arbitrarily defined areal units, we are more interested in how the distribution of these elements appears as seen from different locations in the city. That is, in lieu of describing the densities of opportunities as seen from above, we aim to describe the density of opportunities as seen from each individual building. The ease with which individual buildings are accessed from surrounding destinations in a network of streets can be described using spatial accessibility measures.

Reviewing past literature, we found the land use accessibility approach, and the graph accessibility approach, to complement each other. Evaluating access to land uses allows us to test how proximity to particular types of destinations affects the distribution of retail and food establishments in Cambridge and Somerville. Evaluating access to elements of urban form, on the other hand, allows us to test whether and how qualities of access that are attributable to spatial configuration of the built environment, also affect the density and distribution of retailers in a city. Using the tripartite representation of buildings, nodes and edges, allows both land use, and graph accessibility indexes to be measured side by side.

In section 2.3.4, we showed that land use accessibility measures (i.e. gravity type measure) consist of three inputs: number of destinations available; the size of each of the destination; and the travel impedance required to reach each of the destinations. A gravity type index thus does not allow us to see how each of these inputs individually affects a building's accessibility, but instead summarizes the components into a single outcome. For instance, a building with a few small destinations nearby can obtain a gravity type accessibility index identical to that of a building with many large destinations farther away. In order to distinguish how each of the components of the index affects the accessibility of a location, we need to measure separately the number of destinations available; the size of each of the available destinations; and the travel impedance required to reach each of the destinations. Furthermore, impedance to each of the destinations can be measured along several metrics, including metric distance and topological distance.

Separating each of these accessibility characteristics allows us to analyze how each factor individually affects access to a building and ultimately the probability of observing retail activities in the building. Separating the components of the index also yields meaningful numeric values for each of the components. Whereas the values of a gravity type index have little absolute meaning without a comparison case, numeric values describing the number of destinations available, the size of each of the destination, and the travel impedance required to reach each of the destinations are easily and intuitively interpretable.

The previous chapter also described the underlying differences between topological units of measurement and metric units of measurement in popular urban graph analysis approaches, such as Space Syntax and MCA. Instead of taking one or the other as the basis of our analysis, we adopt a different approach, in which both metric and topological properties of access can be evaluated side by side. We propose a combined approach that allows us to estimate the degree to which retail location choices are affected by metric properties of access (i.e. physical distance to surrounding destinations) and topological properties of access (i.e. number of turns to surrounding opportunities) side by side.

Making reference to multi-purpose shopping, we argued that a store can benefit from demand externalities if it is conveniently located with respect to other stores that attracts higher levels of patronage (Brueckner 1993; Carter and Vandell 2005). We suggested that the "betweenness" measure from graph theory is well suited to capture the potential of a location for passing foot-traffic. In our selection of independent variables we not only aim to capture how close a location is to potential client sources, but also how conveniently it is located for unplanned trips "between" other destinations.

Last, previous morphological studies of urban form suggested that the spatial characteristics of buildings, parcels and their immediate surroundings could also influence the suitability of a location for particular activities. A comprehensive spatial location choice analysis should therefore also attempt to capture some of these destination characteristics.

This leads us to characterize each building's location in our case study area along three types of indicators. First, in section 3.3.3.1, we illustrate how we measure the ease with which a building can be accessed from surrounding locations in the street network. Second, in section 3.3.3.4, we illustrate how we estimate the probable frequencies of passersby at each building using the 'betweenness' measure. And, last, in section 3.3.3.5, we also describe some apparent characteristics of each building, parcel and street that a building is located on. In this case, our aim is not to quantify the ease with which a location is accessed by visitors or passersby from surrounding locations, but rather to capture the configurational typology of the destination itself.

3.3.3.1 Access to a building

We evaluate access to each building using two graph accessibility measures called "reach" and "remoteness". *Reach* is essentially a cumulative opportunities type accessibility measure (see section 2.3.4), which evaluates the number of destinations reachable from each building in a ten-minute walking radius along shortest paths in the street network. *Remoteness* measures the distance required to reach all available destinations in the same access radius. *Remoteness* can be measured along different impedance metrics, including both metric distance and topological distance. Based on previous research (see section 2.3.1), we have chosen to measure and test the effects of remoteness along three different impedance measures: metric distance, topological turns, and topological intersection crossings. This results in four different measures, each of which captures the ease of access to individual buildings in a different manner:

1. *Reach*: the number of destinations available in a given access radius along shortest paths.
2. *Distance Remoteness*: the cumulative distance required to reach each of the available destinations in a given network radius along shortest paths.
3. *Turns Remoteness*: the cumulative number of turns required to reach each of the available destinations in a given network radius along shortest paths.
4. *Intersections Remoteness*: the cumulative number of intersection crossings required to reach each of the available destinations in a given network radius along shortest paths.

Each of the four indexes can be estimated to different types of destinations. Based on past retail location studies and the hypothesis set out at the end of Chapter Two, we have chosen to measure each of these indexes to:

a) built volume
b) residents
c) jobs
d) transit stations
e) other types of retailers

in a ten-minute walking radius (2,000 feet, 600 meters) around each building in our case study area. The taxonomy of spatial accessibility measures that result are shown in Table 2.

In order to avoid endogeneity between our dependent variable and independent variables, the job access measures required an adjustment. We subtracted the retail and food jobs from the overall job counts for each building. Access to jobs should be interpreted as access to non-retail and food service jobs in a ten-minute walking radius.

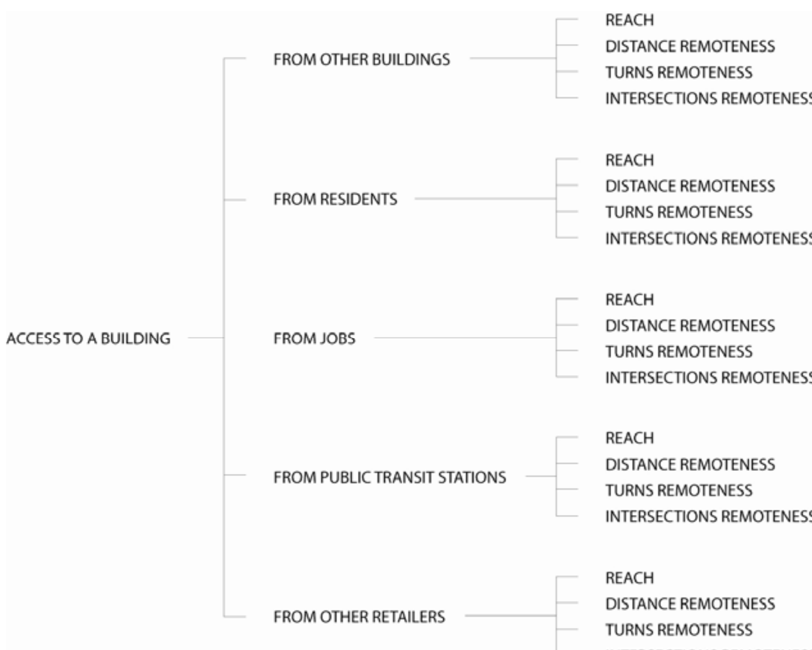

Table 2 Classification of access measures to each building in our analysis, shown by destination type.

3.3.3.2 Reach

The "Reach" measure captures how many destinations each building reaches within a given network radius[8]. The Reach measure we use is identical to a cumulative opportunities type accessibility index, described in the literature review, but applied on a network rather than Euclidian space. The mathematical specification of the 'Reach' measure is given as follows:

$$Reach_{i,r} = \sum_{j=1}^{n} O_r$$

Equation 1

where $Reach_{i,r}$ is the reach at location i within a distance threshold r, and O_r is an opportunity that can be reached within the distance threshold. Figure 10 illustrates how the Reach index works visually. An accessibility buffer is traced from the building of interest *i* in every direction on the street network until the limiting radius *r* is reached. The *Reach* index is then computed as the number of destinations *j* (represented as black points) that are found within the radius. In Figure 10, location *i* reaches twenty surrounding locations in network radius *r*.

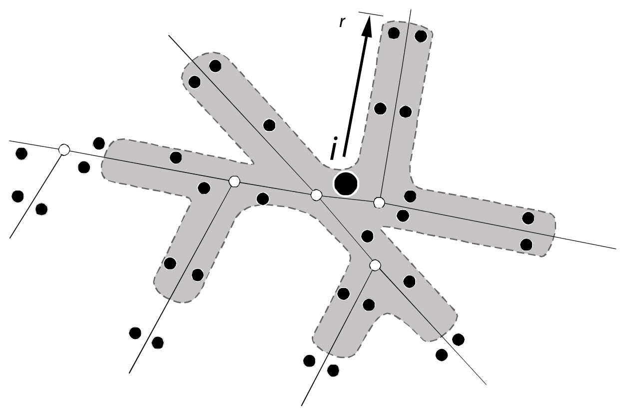

Figure 10 Visual illustration of the Reach index.

A *reach* indicator can be calibrated to measure access to any type of destination. In order to capture general accessibility to *built form*, we use all buildings as destinations, weighting them by volume. To capture accessibility to land use destinations, on the other hand, we use jobs, residents, other retail establishments, and transit stations as destinations.

Figure 11 – Figure 13 illustrate the Reach of each individual building in Cambridge and Somerville to three types of surrounding destinations: buildings weighted by total volume (in cubic feet), residents, and jobs.

[8] Due to computational difficulties, we do not here model buildings with multiple entrances, which can play an important role in a real-life context. *Corner* parcels, *through* parcels, *end* parcels, and *island* parcels, each facing an increasing number of streets, could considerably increase the 'reach' measure due to their direct access to multiple streets. Instead, we shall use a "parcel type" dummy variable in the analysis to capture this effect.

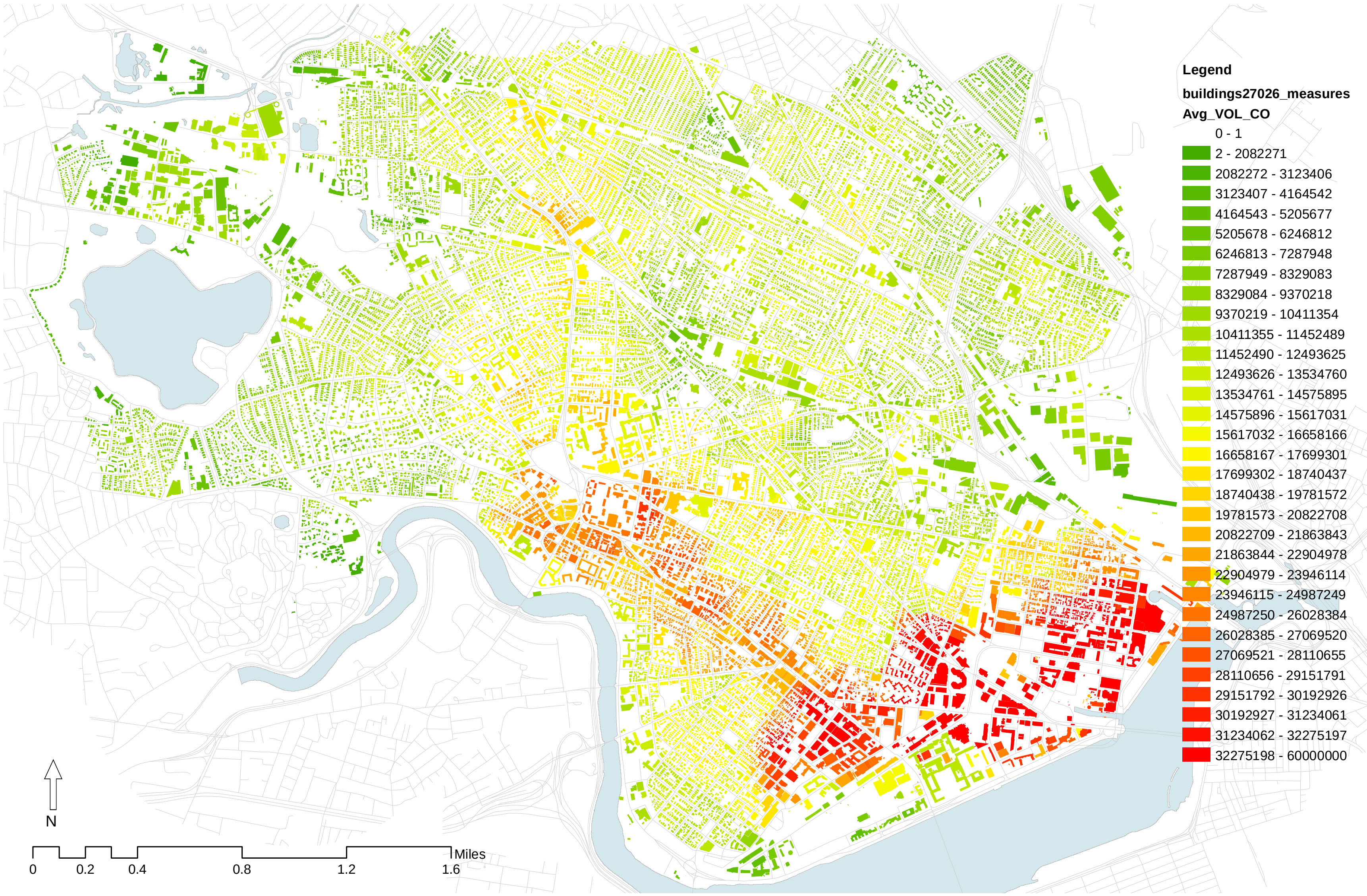

Figure 11 Reach to built volume within a 2,000ft network radius from each building in Cambridge & Somerville, MA (Source: MassGIS 2002).

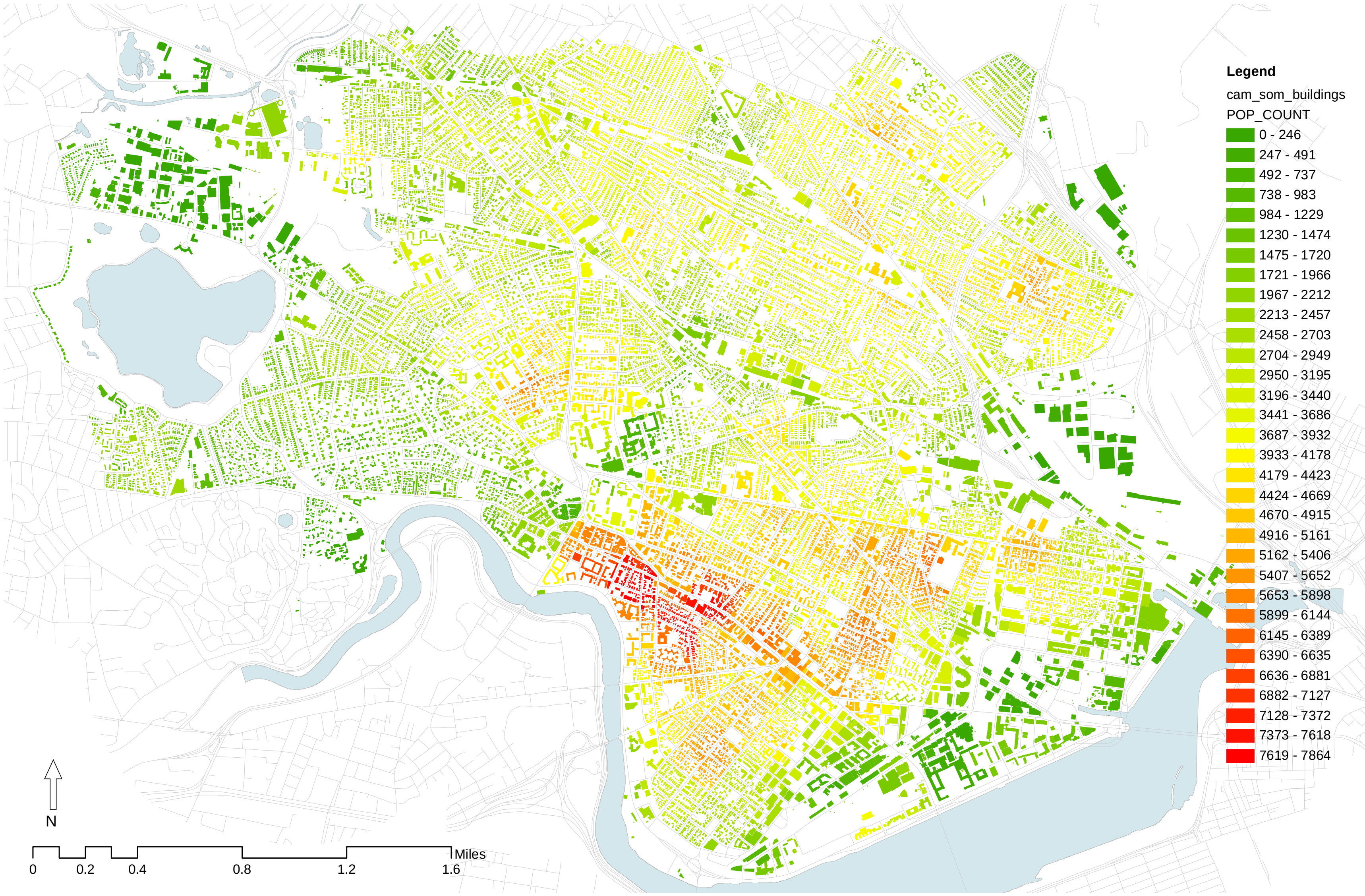

Figure 12 Reach-to-residents within a 2,000ft network radius from each building in Cambridge & Somerville, MA (Source: Census 2,000).

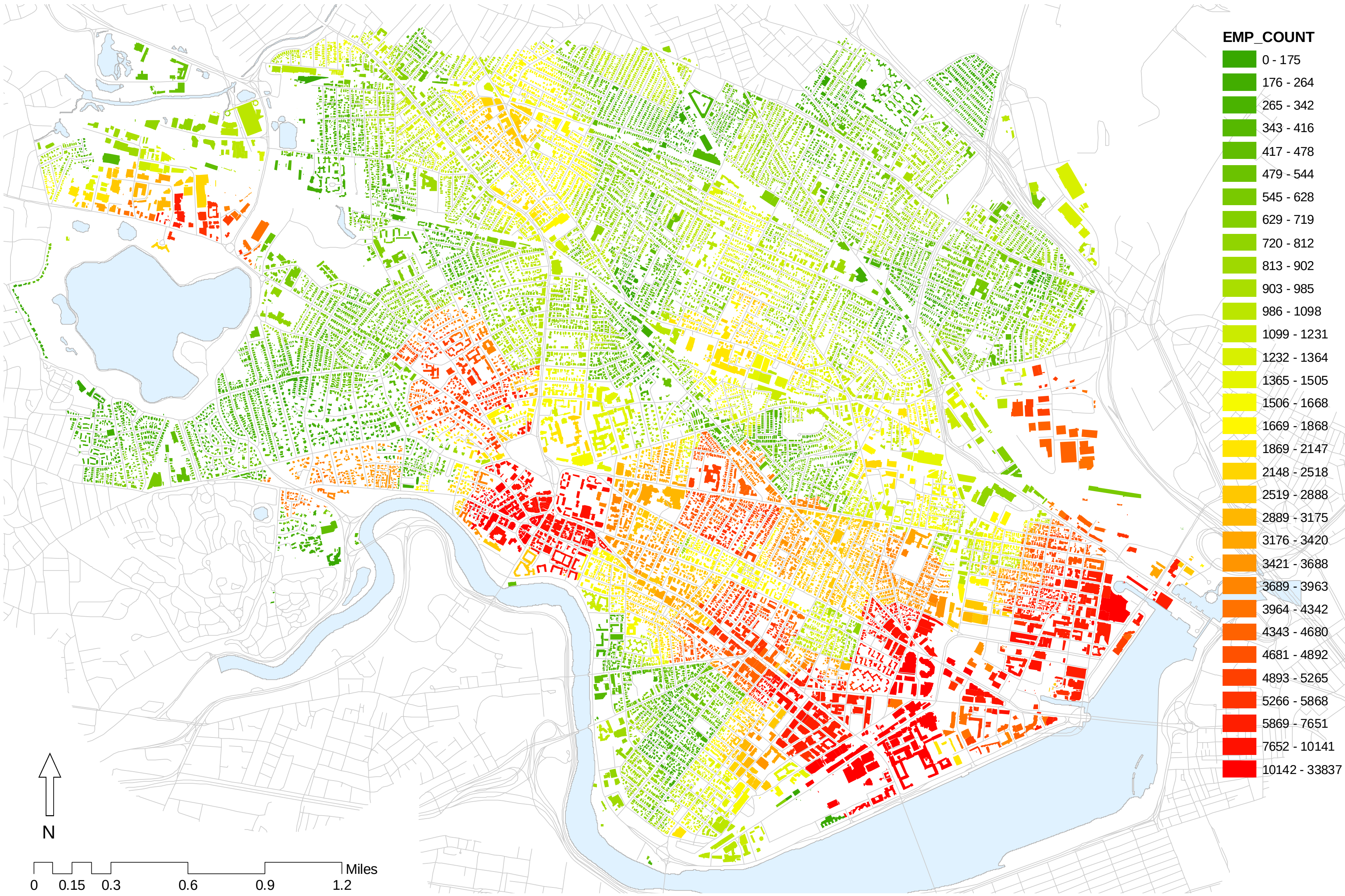

Figure 13 Reach to non-retail and food service jobs within a 2,000ft network radius from each building in Cambridge & Somerville , MA (Source: InfoUSA 2009).

Figure 11 suggests that Reach to built volume in Cambridge and Somerville ranges from roughly two million to sixty-million cubic feet in a 600-meter radius. Buildings located around Kendall Square, for instance, reach over fifty-million cubic feet of built space within a ten-minute walk, whereas buildings in a residential neighborhood around Fresh Pond reach less than five million cubic feet of built space during the same walk. The highest Reach-to-building-volume occurs around Kendall Square, Lechmere, Central Square, and the Massachusetts Avenue corridor between Harvard Square and MIT. At a typical neighborhood-scale business cluster, such as Davis Square in Somerville, an average building reaches up to twenty-million cubic feet of built space in a ten-minute walking radius.

Figure 14 illustrates the frequency distribution of building volume Reach in all Cambridge and Somerville buildings. The distribution shows that an average building accesses around 13 million cubic feet in a ten-minute network radius and only 0.1 % of all buildings more than 45 million cubic feet. The skew towards the lower part of the spectrum and a long upper tail indicate that Reach-to-building-volumes are not geographically uniformly distributed. The highest building volumes tend to cluster in limited geographic areas.

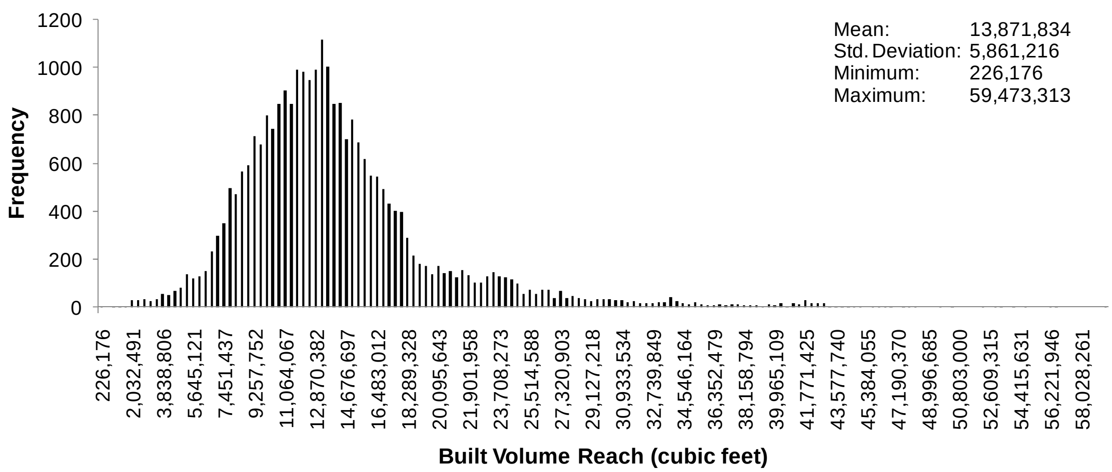

Figure 14 Frequency distribution of building volume Reach among buildings in Cambridge and Somerville in a 2,000 ft network radius (n=27,026)

Reach-to-built-volume is primarily affected by three distinct qualities of urban form. First, the measure can increase if the destination buildings that the index is computed to are larger in volume. If neighboring buildings in a ten-minute walking range around a location of interest have either larger footprints or are taller in height, keeping the spacing of buildings and the geometry of the street network constant, then the reach measure of the location rises. Second, if the number of neighboring buildings rises (that is, if we observe a higher number of buildings per linear length of street segments, keeping building sizes and the geometry of the street network constant), then the Reach-to-built-volume also rises. And third, if we keep the density of buildings per linear length of streets, and the sizes of destination buildings constant, then the Reach measure can also increase if a building has advantageous access to the street network. Corner parcels, for instance, have a higher Reach-to-built-volume than middle parcels, all else equal (See section 2.1.3 and Figure 5 in Chapter Two). Each of these three variables — destination sizes, linear density of buildings, and street network geometry — affect the outcome of a Reach measure.

Figure 12 illustrates the Reach of each building to surrounding residents. The map suggests that the highest number of residents is reached around the River Side neighborhood, east of Harvard Square, where a typical building reaches almost 8,000 inhabitants in a ten-minute walk. Population Reach is also relatively high in the central part of Cambridge, in an area roughly bounded by Harvard Square, Central Square and Inman Square, where an average house reaches approximately 4,000 residents within a ten-minute walk. According to the Census 2,000 data, population Reach is lowest around the MIT campus, in the North Point area, and north of Fresh Pond, where only a few hundred residents can be reached within the same walk. The frequency distribution of population Reach, shown in Figure 15, suggests that access to residents is almost normally distributed, with a mean of 3,725 people and a thicker tail in the lower half of the spectrum. Roughly 90% of buildings in both towns accommodate residential uses, which make almost any location in the two towns at least partially accessible to residents.

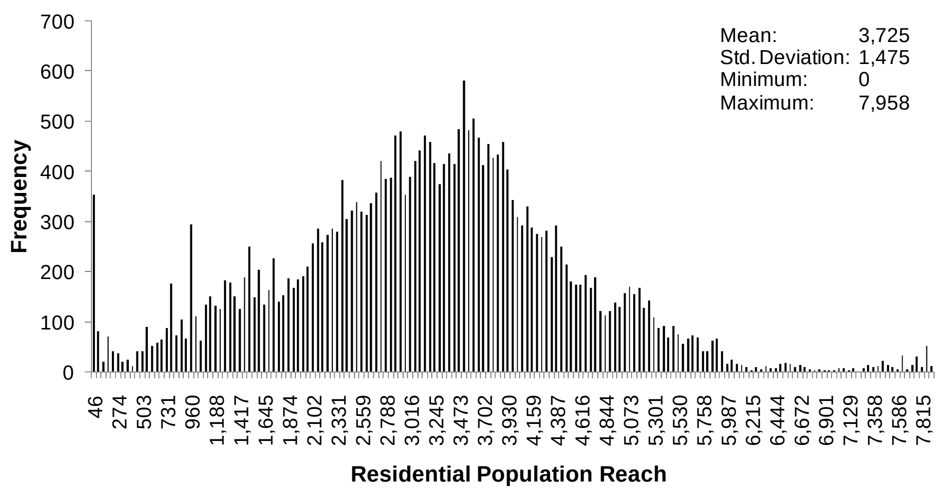

Figure 15 Frequency distribution of residential population Reach among buildings in Cambridge and Somerville in a 600-meter network radius (n=27,026).

The environmental factors that determine the Reach-to-residents are largely similar to those of built volume. Reach-to-residents rises if individual buildings around a location accommodate more residents. Unlike built volume, however, an additional parameter may affect the number of residents at the destination: the amount of space per inhabitant. A higher number of residents at a destination may therefore result from a greater building size or smaller unit areas per resident. Second, Reach-to-residents can also increase if building sizes are constant, but the number of residential addresses along a street segment is higher and space between buildings smaller. Finally, Reach-to-residents is also higher in buildings that have superior access to the surrounding street network, all else equal. While we typically encounter rather moderate variation in the former two variables within a neighborhood, access to streets varies considerably from parcel to parcel. Buildings that are closer to an intersection of multiple streets tend to have better Reach. Between neighborhoods, however, the former two variables — residents per building and buildings per linear length of street — can deviate substantially. The higher values of residential Reach around

Harvard Square are mostly explained by larger residential structures with higher inhabitation densities, as well as a denser spacing of buildings in the area. We suspect that a heavy concentration of student dormitories makes a particular impact on heightening the inhabitation density.

Figure 13 illustrates the Reach from each building to surrounding jobs. As mentioned above, these job estimates only include non-retail and food service jobs. The map indicates that the highest Reach-to-jobs is found north of Vassar Street, around MIT, Harvard, and the Galleria Mall at Lechmere, where up to 30,000 employees are reached within a ten-minute walk. Other locations with fairly high job access include the area around the Radcliffe Institute north-west of Harvard; Inman Square; the district north of Fresh Pond; and Davis Square. The frequency distribution of job Reach is heavily skewed towards lower values (Figure 16), indicating that most buildings in Cambridge and Somerville can reach less than five thousand jobs (a mean of 1,728), within a ten-minute walk. At the top of the scale, few buildings reach up to 30,000 jobs. Jobs appear to be heavily concentrated into select geographic areas of the two towns, an effect we surmise to weigh on retail location choices. While local variation in job Reach appears again to be tied to the relative position of a building in the street network, the main peaks and valleys of the distribution are attributable to the number of commercial buildings and the employment density in each building around a location.

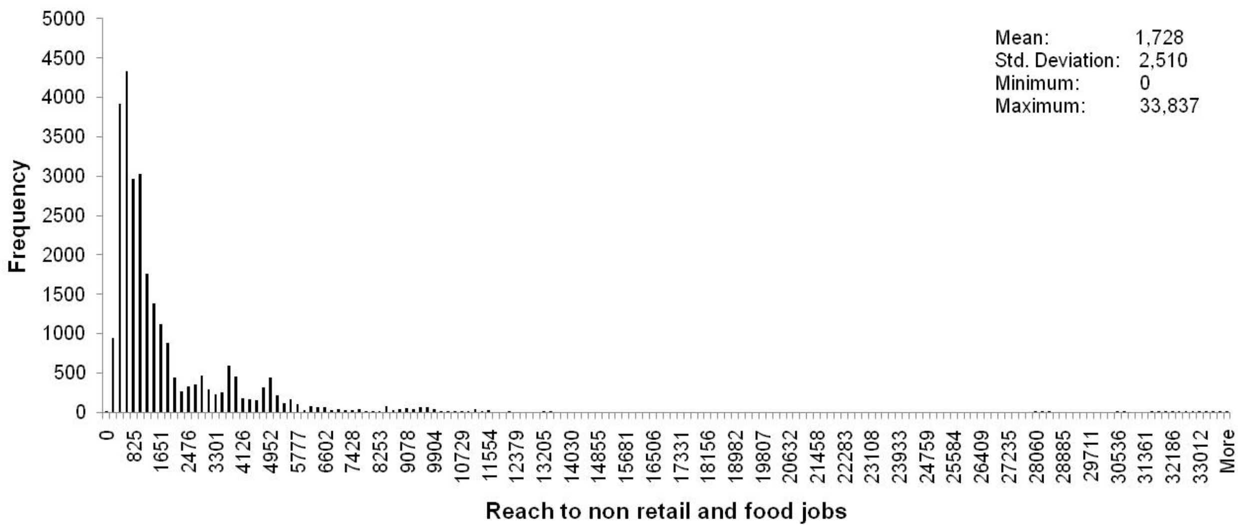

Figure 16 Frequency distribution of non-retail or food jobs Reach among buildings in Cambridge and Somerville in a 600-meter network radius (n=27,026).

3.3.3.3 Remoteness

The Reach measure summarizes the number of destinations that are reachable within a given radius, but it does not tell us how difficult it is to get to those destinations. Near or far, visible or hidden, the Reach measure counts all destinations that are located within a 2,000-foot distance along the street network from a location of interest. In order to describe the impedance required to reach each of the destinations, we use three different Remoteness measures.

The '*Remoteness*' measure differentiates nearer destinations from farther ones by measuring the network distance required to reach all available destinations. In order to maintain an intuitively meaningful numeric interpretation of the measure, we have opted to avoid the inversion of distance that is commonly defined as the Closeness measure in graph theory (Sabidussi 1966)[9]. Keeping the index not inverted also maintains a larger variation in its numeric scale, a quality that is valuable in regression models. The non-inverted measure tells us the real distance required to access a set of destinations along geodesic paths within a given network radius.

Using a 2,000-foot radius, our Remoteness indexes are measured only relative to the *available* destinations around each building. This means that if a particular building has only ten neighboring destinations in a 2,000-foot radius, then its Distance, Turns, and Intersections Remoteness indexes are estimated to these ten destinations. If another building, on the other hand, reaches a hundred neighboring destinations, then its Remoteness indexes are estimated to those hundred destinations. Despite the different number of destinations, the two buildings could thus have identical Remoteness measures. Such a relative specification is unavoidable when we use a fixed-access radius in the calculations[10]. However, since we eventually estimate the effects of remoteness while controlling for the number of destinations described in the Reach measure, then the differences in the number of destinations are controlled for. Measuring Reach, Distance Remoteness, Turns Remoteness, and Intersections Remoteness simultaneously on the same travel paths allows us to test how each indicator contributes to the likelihood of finding retail and food service establishments at the destinations.

We estimate all remoteness measures to the same destinations as the Reach measure described above: building volume; residents; jobs; different retail establishments; and transit stations. For the sake of brevity, the following graphic illustrations show only the three remoteness indexes as measured to surrounding built volume. We provide the descriptive statistics for job destinations, residential destinations, and transit destinations in table form at the end of this section.

Distance Remoteness

Distance Remoteness captures the cumulative distance required to reach a location from each of the available destinations in a given network radius along shortest paths. Buildings that require a higher cumulative distance to access the destinations around them will have a higher remoteness value, controlling for the number of destinations. We define *Distance Remoteness* mathematically as follows:

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[9] Whereas the inverted remoteness measure is difficult to interpret numerically, the remoteness measure tells us the real distance required to access a set of destinations. We can also easily obtain the average distance to all reachable buildings around *i*, if we divide the 'remoteness' at *i* by the 'reach' measure at *i*. A typical Closeness measure is the inverse of the sum of shortest path distances to neighboring nodes in a given network radius: $c_{i(2000ft)} = \left(\sum_{j=1}^{n} d_{ij} \right)^{-1}$

[10] One could alternatively measure Remoteness to a fixed number of nearest destinations, but behaviorally that would be poorly justified. Reaching the ten nearest buildings in some locations requires substantially longer walking trips than pedestrians are likely to undertake.

$$Remotness_{Dist\,|i,r} = \sum_{j=1}^{n} d_{ij}$$

Equation 2

where $\text{Remotness}_{\text{Dist } | \text{ i,r}}$ is the *Distance Remoteness* of location i in a network radius r, d_{ij} is the metric distance separating location i from a location j that falls within the threshold radius along a metrically shortest path. Figure 17 illustrates this calculation visually. Similar to the Reach measure, a threshold radius r is drawn from location i in all directions along the street network. Distance is measured from i to each destination that is found within the threshold radius around i along shortest paths, and the lengths of all paths are eventually summed.

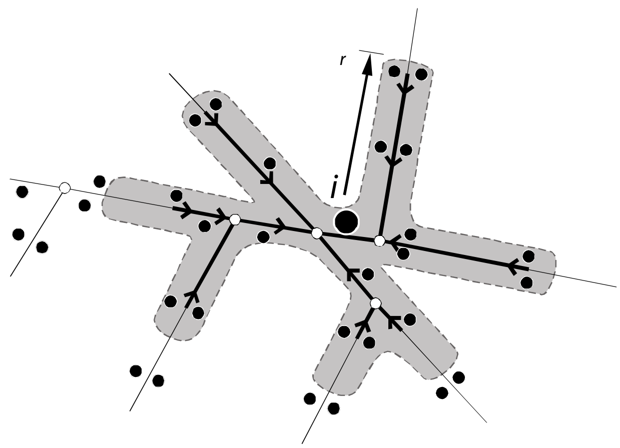

Figure 17 Visual illustration of the Remoteness index.

Figure 18 illustrates the Distance Remoteness indicators of individual buildings in Cambridge and Somerville, using buildings (weighted by volume) in a 2,000-foot radius as destinations. In order to make the data visually comprehensible and distinct from the Reach measures, we have normalized the values of Reach measures in Figure 18. The resulting Distance Remoteness measures in the figure illustrate the average distance to neighboring buildings, rather than the cumulative distance.

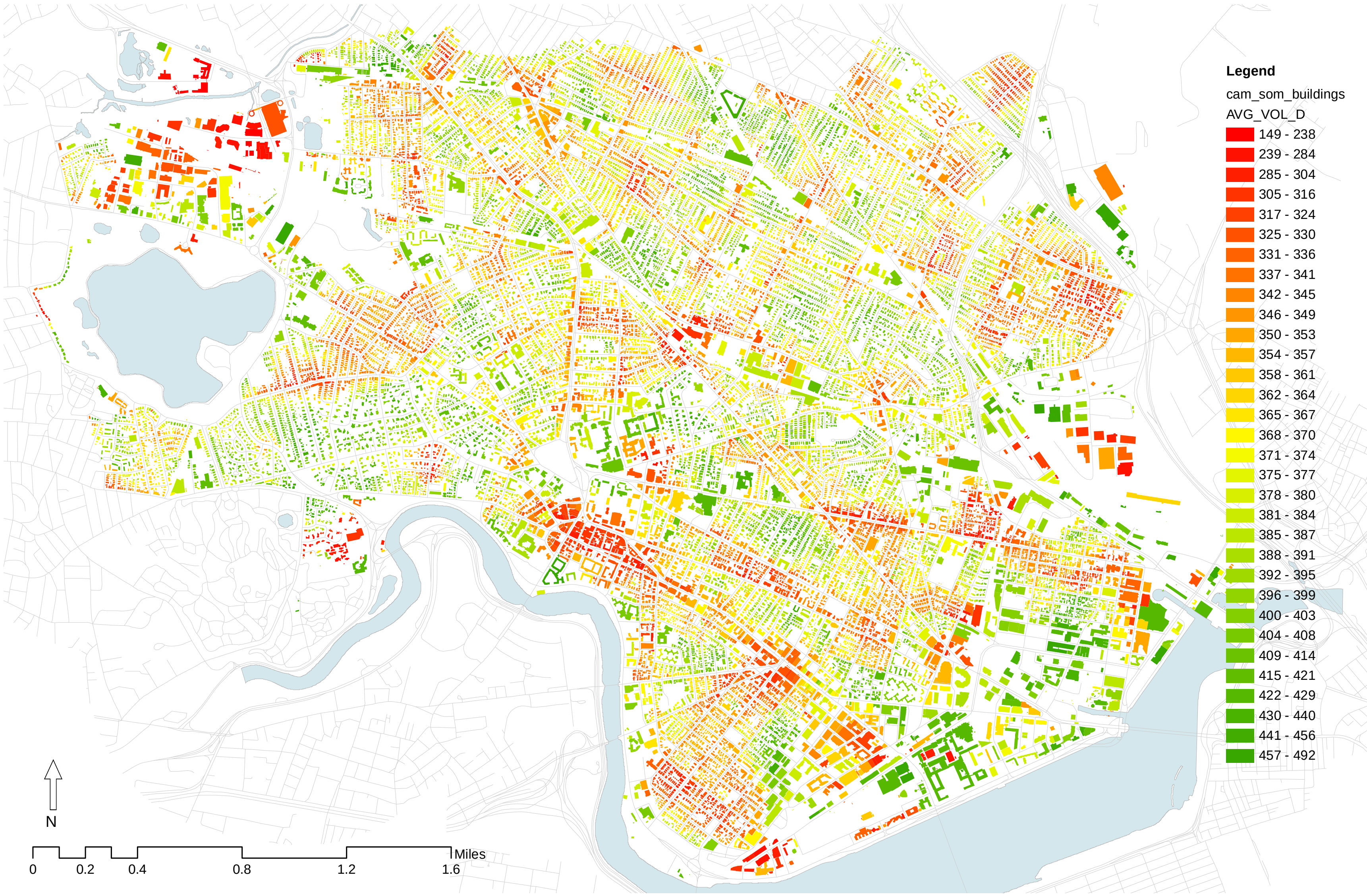

Figure 18 *Distance Remoteness* from built volume within a 2,000ft network radius of each building in Cambridge & Somerville, MA.

The map in Figure 18 suggests that the average distance to reachable buildings in a ten-minute walking range is remarkably lower on some of the major thoroughfares and dense building clusters of Cambridge/Somerville. As intuitively expected, analogous environmental qualities shape the Remoteness metrics as the Reach metrics, with one important difference: distance matters. By distance we describe not only metric distance, but also Turns and Intersections, depending on the measure in focus. The size and occupation density of the destination can either increase or decrease the Remoteness index, depending on how far the destinations are. A higher concentration of large and dense buildings nearby lowers Remoteness values, while a similar concentration further away (though still within the 600-meter range) increases Remoteness values. Second, if building size and density are kept constant, then the spacing of buildings also affects the index. A denser spacing of nearby buildings lowers the index, while a denser spacing of buildings by the 600-meter threshold radius elevates the index. And, finally, the remoteness measures are also affected by the relative position with respect to the street network. If the street network is denser around a location and sparser away from it, all else equal, then remoteness values are lower. Buildings located in smaller city blocks, surrounded by larger city blocks have lower remoteness values and vice versa. It is important to note, however, that what matters is not the block size per se, but rather how one is positioned relative to surrounding block sizes. If there is a high concentration of small city blocks near the outer periphery of the threshold radius, then Remoteness values increase rather than decrease. If block sizes are uniform in the entire 600-meter radius, all else equal, then the Remoteness measures are relatively little affected by street accessibility. In this case the effect will only distinguish a corner location from a middle location as we have already described.

Figure 18 shows that dense building clusters in Harvard Square, Central Square, and Inman Square and along many primary streets that accommodate continuous facades, have, on average, lower Distance Remoteness values to neighboring built volume in a 600-meter radius. The outcome also varies considerably within city blocks. While accessing corner locations and buildings facing densely built main streets from a 10-minute walking range takes, on average, a 300-meter (984 foot) walk, then accessing buildings in the middle of the same block can require, on average, an over 400-meter (1,312 foot) walk. This effect is mainly attributable to the fact that main streets and corner locations tend to have larger and more densely spaced buildings.[11]

Figure 19 illustrates the frequency distribution of *Distance Remoteness* measures in the two towns. The average distance from a building to its neighboring buildings, weighted by volume, is 369.3 meters in our case study area. The slight skew towards higher distances tells us that fewer buildings are as close to their neighboring building mass as a normal distribution would predict.

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[11] One might speculate that this in turn could be related to the advantageous Reach qualities of these locations as described above.

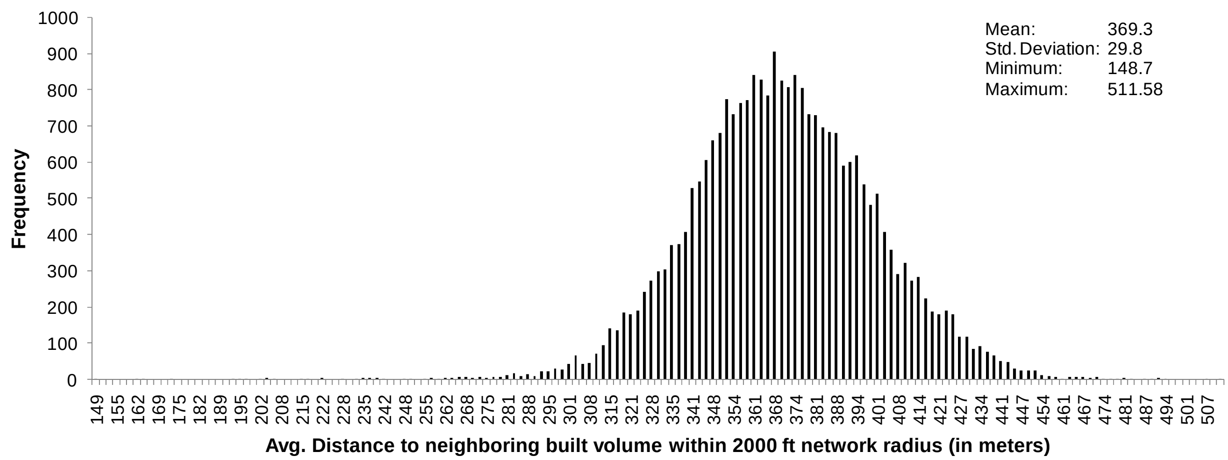

Figure 19 Frequency distribution of *Distance Remoteness* among buildings in Cambridge and Somerville in a 2,000 ft network radius (n=27,026).

Turns Remoteness

The *Turns Remoteness* measure is mathematically similar to the *Distance Remoteness* measure. Instead of describing the spatial separation between a location *i* and surrounding locations *j=(1,2,…n)* in terms of metric distance, however, the *Turns Remoteness* index counts the number of turns effectuated along the paths between i and all surrounding destinations j. *Turns Remoteness* is mathematically defined as follows:

$$Remotness_{Turns\ |i,r} = \sum_{j=1}^{n} t_{ij}$$

Equation 3

where $Remoteness_{Turns\ |\ i,r}$ is the *Turns Remoteness* of location *i* to reachable locations *j* in a network radius *r*, t_{ij} is the number of turns separating location *i* from a location *j* along a metrically shortest path. A *Turns Remoteness* index thus estimates the cumulative number of turns needed to travel to location i from all surrounding locations j that fall within the threshold radius r.

We define a "*Turn*" as a change in direction that is greater than twenty degrees, made at a street intersection (node). If a twenty-degree (or greater) change in direction is effectuated along a particularly curvy street segment, while not at a street intersection, then it is not counted as a turn, since no alternatives for the turn are available in that case. The choice of a twenty-degree threshold angle was determined based on numerous tests with smaller and larger angles. We concluded that a twenty-degree directional change was sufficiently important to distinguish a turn from a straight path (see Figure 20).

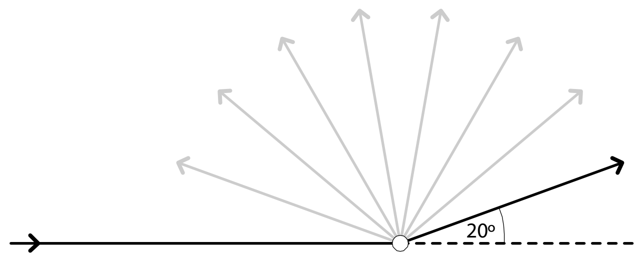

Figure 20 A “Turn” is defined as a change in direction, greater than 20 degrees, effectuated at a street intersection.

The *Turns Remoteness* measure aims to capture an important aspect of the cognitive complexity of routes that lead to a building: the number of turning decisions required to get to the building[12]. Previous research, discussed in Chapter Two, has suggested that routes that require a higher number of turns are cognitively more complex to navigate and require familiarity with the area (Lynch 1960; Montello 1991; Golledge, Gale et al. 1992; Golledge 1995; Golledge and Garling 2003). Since finding a destination requires a conscious decision at each intersection, it is probabilistically unlikely for unfamiliar travelers to ‘stumble upon’ a location that requires multiple turns to access. The *Turns Remoteness* measure also informs us about the visibility of a building: the fewer turns approaching a building from all surrounding origins requires, the more visible the building is expected to be. We thus expect commercial establishments to prefer locations that minimize the amount of turns required to access them. Anecdotal evidence from typical retail clusters also suggests that one often finds locations that are close to the center of the cluster, but tucked away behind corners, to be poorly preferred by retailers.

[12] Previous researchers have proposed different indexes to capture the turns of a route. Kansky used a detour index, and Porta and his colleagues used a straightness index (Kansky, 1963; Porta 2005). Straightness measures, however, are not only affected by turns, but also winding roads. An actual counting of turns on each calculated route was preferred in our case, in order to address turns explicitly.

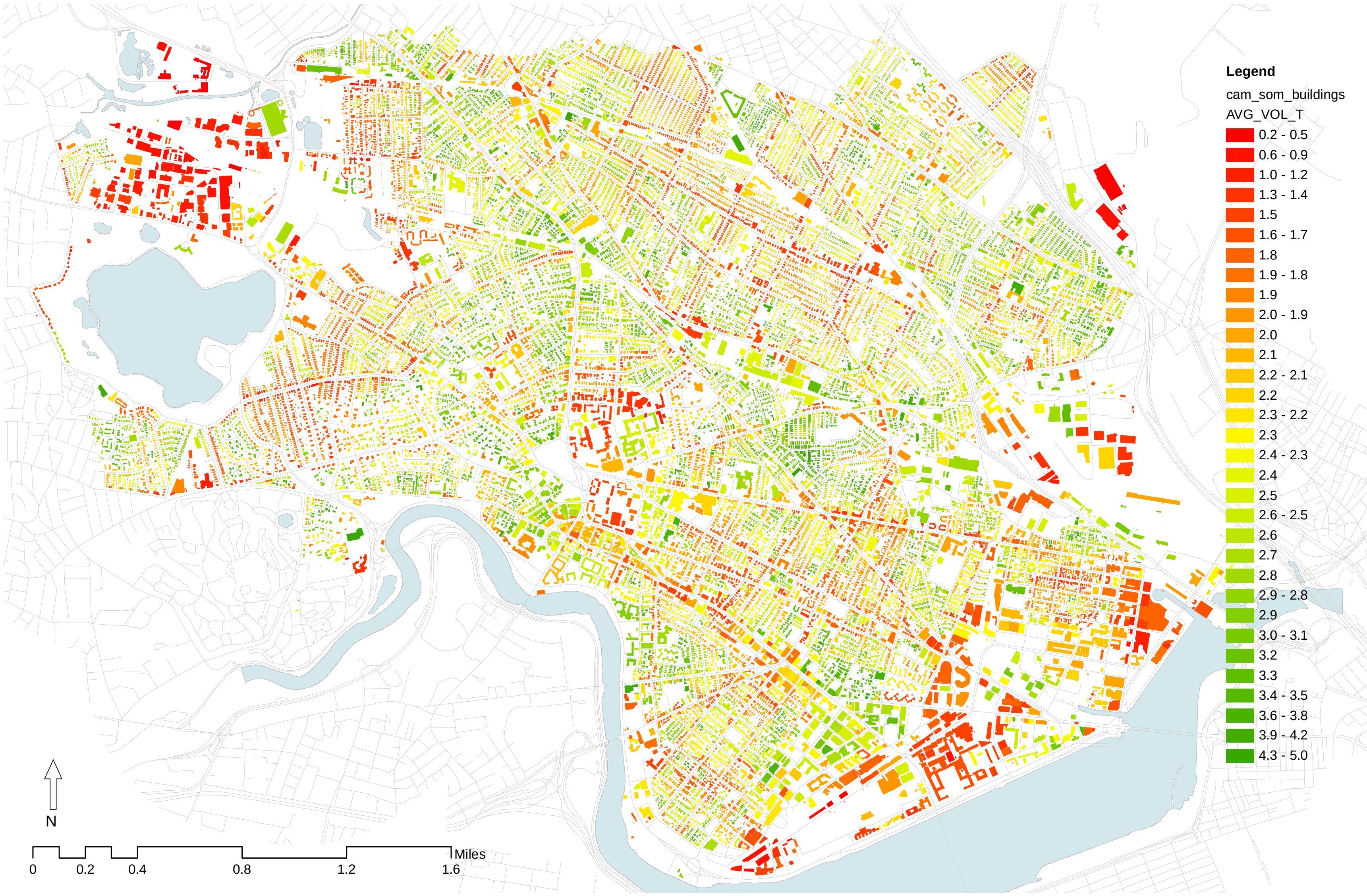

Figure 21 *Turns Remoteness* from built volume within a 2,000ft network radius of each building in Cambridge & Somerville, MA.

The spatial distribution of *Turns Remoteness* measure, depicted in Figure 21, suggests that spatial proximity to built volume in terms of metric distance differs notably from spatial proximity in terms of topological turns. The Turns Remoteness measure clearly contrasts more between buildings on main thoroughfares and off main thoroughfares. While the Distance Remoteness values fade gradually as distance increases from densely built areas, Turns Remoteness values can differ sharply, even between neighboring structures. Access to buildings located on corner lots and along straight thoroughfares tends to require, on average, fewer turns, with differences clearly notable even within the same city block. While buildings facing peripheral streets with double-loaded facades may require only 0.5 turns to access, on average, buildings in the same block, but facing less accessible streets, may require over 3 turns to access from a similar network radius (see Inman Square for example). Corner locations usually require less turns to access. We suspect that a substantial difference in the average number of turns required to reach a building might well influence the location decision of a store-owner. It is interesting to note that while Distance Remoteness is generally high at popular business clusters like Harvard, Central, and Inman Square in Cambridge, Turns Remoteness does not necessarily follow the same pattern. The small blocks around Harvard Square, for instance, increase the number of turns required to reach individual buildings, making the average number of turns relatively high in the area. The frequency distribution of Turns Remoteness, depicted in Figure 22, suggests that an average building in the two towns requires approximately 2.32 turns to access from neighboring structures in a ten-minute walking range.

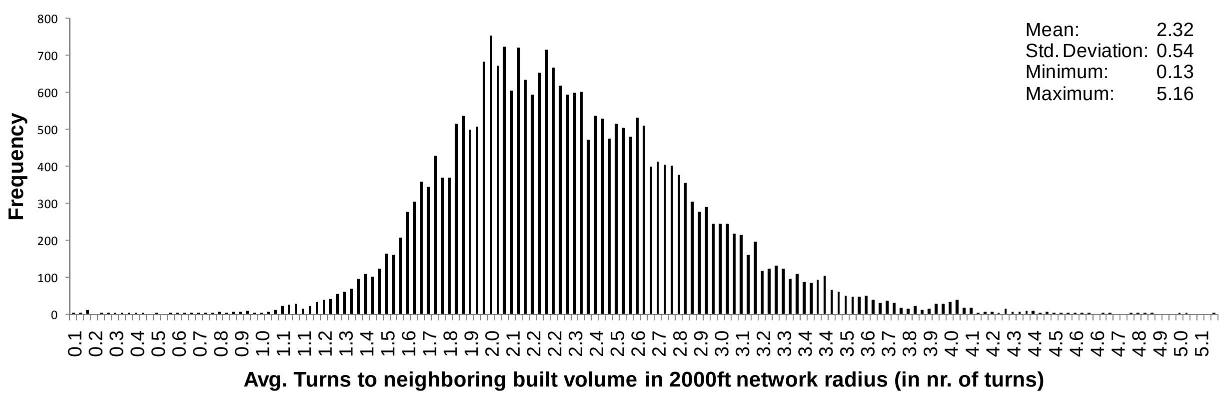

Figure 22 Frequency distribution of *Turns Remoteness* among buildings in Cambridge and Somerville in a 2,000 ft network radius (n=27,026).

Intersections Remoteness

The *Intersections Remoteness* measure describes the spatial separation between a location *i* and surrounding locations $j=(1,2,\ldots n)$ in terms of another topological separation metric: crossings of street intersections. The *Intersection Remoteness* index counts the number of street intersections (nodes) that are traversed when accessing a building from all other buildings within a given threshold radius along shortest paths. *Intersections Remoteness* is mathematically given as follows:

$$Remoteness_{Int\,|i,r} = \sum_{j=1}^{n} Int_{ij}$$

Equation 4

where $Remotness_{\mathrm{Int}\ |\ \mathrm{i,r}}$ is the *Intersections Remoteness* of location i to reachable locations j in a network radius r, and Int_{ij} is the number of intersection crossings separating location i from a location j along a metrically shortest path. An *Intersections Remoteness* index thus estimates the cumulative number of nodes that are traversed while travelling to building i from all surrounding buildings j that fall within a network radius r.

The Intersections Remoteness index aims to capture another important cognitive aspect of urban travel paths: the number of path-choice decisions required to reach a building. Unlike the Turns Remoteness measure, the Intersections Remoteness measure does not only count the nodes where a directional change is made, but all nodes that are traversed. A path can traverse several intersections in a straight line, involving no turns, but it can also involve a turn at every intersection that is encountered, in which case the *Turns Remoteness* and *Intersections Remoteness* measures of the route coincide. The two measures are thus expected to be fairly collinear. Due to this overlap, we anticipate that finding a significant effect for both measures in a controlled regression model could be challenging. One of the two indexes could turn out to be sufficient for capturing topological characteristics of paths that lead to a building.

The specification of the Intersections Remoteness, too, originates from prior literature in configurational studies of the built environment and environmental psychology, where researchers have argued that decision points of a route constitute important elements of a cognitive map (Lynch 1960; Jacobs 1993; Golledge and Garling 2003). By requiring extra caution, time, or simply a momentary mental consideration, each intersection crossing can impose a small cost or benefit on the journey. Studies of mental mapping have shown that intersection points often create memorable events along people's travel paths (Lynch 1960; Gale, Golledge et al. 1990). As points of decision-making, street intersection can be thought of as adding time cost to the journey. Hill has suggested, however, that maximizing intersection crossings increases the opportunities to change course along a journey (Hill 1982). Supporting the positive argument for intersections, Allan Jacobs has argued that streets with more numerous cross streets have advantageous access and higher occupancy patterns. "*Streets with one entry for every 300 feet (90 meters) are easy to find, and some of the best streets approach that figure … but there are more entries on the busiest streets*" (Jacobs 1993: 302). It is therefore possible that a pedestrian bias towards routes with a higher number of intersections could actually indicate a preference towards routes with more people and activities.

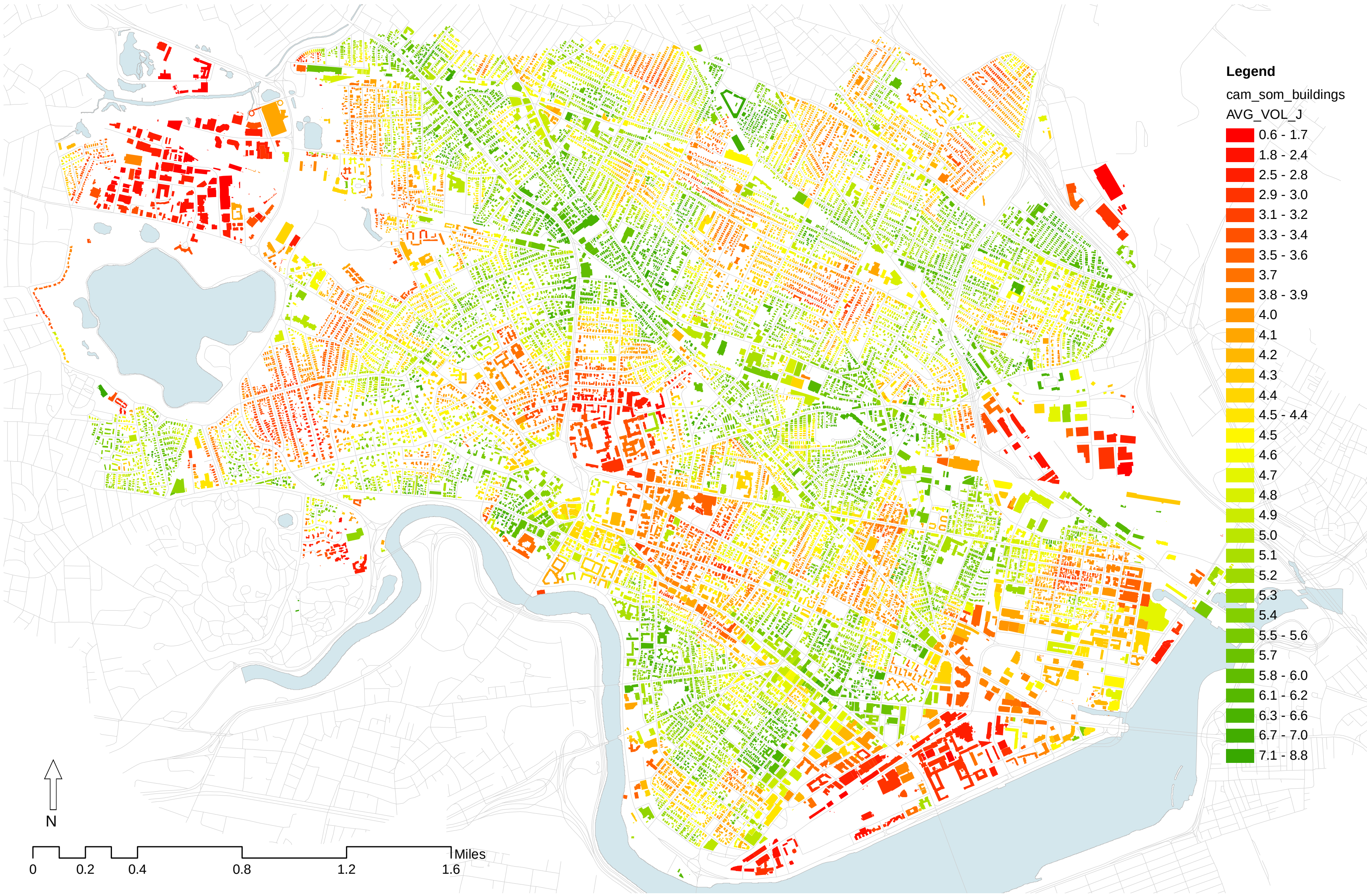

Figure 23 *Intersections Remoteness* from built volume within a 2,000ft network radius of each building in Cambridge & Somerville, MA.

Figure 23 illustrates the Intersections Remoteness values computed to the surrounding building volumes in a 2,000-foot network radius. As intuitively expected, the average number of intersection crossings required to reach a building is lower in areas where urban blocks are larger. Around parts of the MIT and Harvard University campuses, where blocks are relatively large, an average of only one intersection crossing is required to access a building[13]. Areas with small blocks, in contrast, can lead the average traveler to cross over eight street intersections before reaching a typical building in a ten-minute walking range. The frequency distribution of the values implies that accessing a typical building requires an average of 4.7 intersection crossings (Figure 24). It is not clear from the geographic distribution of Figure 23, however, whether maximizing or minimizing intersection crossings is an apparent location choice criterion for retail and food service establishments.

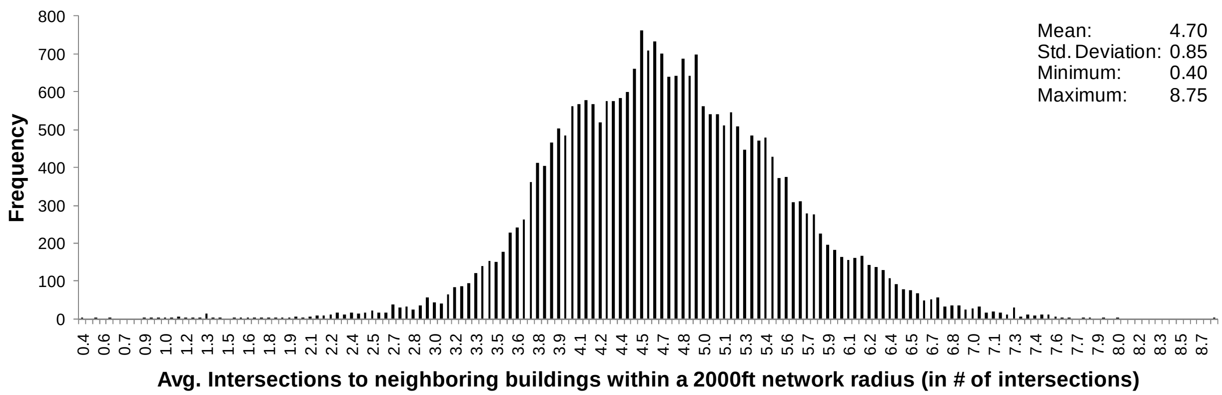

Figure 24 Frequency distribution of *Intersections Remoteness* among buildings in Cambridge and Somerville in a 2,000 ft network radius (n=27,026).

3.3.3.4 Betweenness

The discussion of Reach and Remoteness measures thus far has focused on access routes that lead to a building from neighboring buildings. The Reach measure counted the number of neighboring destinations available, and the Remoteness measures described the impedance characteristics of the routes leading from these destinations to the building of interest. In the review of literature in Chapter Two, we argued that spatial accessibility can also depend on the ease of accessing a location *en route* while travelling between other locations. A newspaper kiosk or an accessories store might find it less desirable to locate at places that are closest to people's homes or jobs and more desirable at places where people tend to pass by while travelling between other destinations. The potential of passersby at different locations of a spatial network can be estimated using a *Betweenness* measure from graph theory (see section 2.3.1).

The *betweenness* of an edge or node i is defined as the fraction of shortest paths between pairs of vertices in a network that pass through i (Freeman 1977). If more than one shortest path is found between

[13] Unfortunately our street network data does not include footpaths that are not officially categorized as streets. The intricate network of footpaths at Harvard Yard is therefore underestimated.

two vertices, as is frequently the case in rectangular grids, then each of the equidistant paths is given equal weight such that the weights sum to unity. The Betweenness measure is mathematically defined as follows:

$$b_i = \frac{\sum_{s<t} g_i^{(st)} / n_{st}}{(1/2)n(n-1)}$$

Equation 5

where $g_i^{(st)}$ is the number of geodesic paths from node s to node t that pass through i, and n_{st} is the total number of geodesic paths from s to t.

An important aspect of the betweenness index is the choice of location pairs that the index is estimated with. Most previous applications have included all available nodes of the graph in the analysis. It is easy to imagine, however, how location pairs could be restricted to particular types. For instance, betweenness could be estimated only for paths that lead from office buildings to subway stations, from homes to jobs and so on. Using all locations simultaneously is useful when a substantive theory for limiting the set is not available. Including all locations in the analysis implicitly assumes that all node pairs have an equal likelihood for generating trips. Alternatively, these likelihoods can be weighted by the size of the destinations. Larger buildings could thus contribute more trips than smaller buildings. Unfortunately, time restrictions did not allow us to experiment with such adjustments. The betweenness measure we settled for involves a simple and un-weighted street segment level estimation, where each node is used as an equal origin and destination. The outcome of the index is given at the street segment level resolution. The measures are not limited to the 600-meter threshold radius, but instead computed at radius n, reaching all other nodes in the system. Put alternatively, we simply use the traditional specification of a betweenness measure from graph theory (Freeman 1977), where all nodes in a graph are used as reciprocal origins and destinations to each other. A shortest path is thus computed from each node to every other node in the street network of Cambridge and Somerville, and the number of paths passing each building is summed. We include a 600-meter buffer around Cambridge and Somerville in the calculations in order to avoid the 'edge effect', which could otherwise produce lower values in the periphery of the graph due to an artificial cropping of external streets.

Figure 25 illustrates the outcome. It suggests that the index does indeed differentiate the main thoroughfares where most traffic is expected to flow. Massachusetts Avenue, Somerville Avenue, Western Avenue, Huron Avenue, Cambridge Street, Main Street and other important long and straight thoroughfares of the two towns clearly lie on a higher number of shortest paths between all other nodes in the graph. We know intuitively that these streets also contain a relatively high density of retailers, suggesting that 'betweenness' might be an important predictor for retail location choices in our study area.

Figure 25 Betweenness of street segments in Cambridge Somerville, radius n.

3.3.3.5 Destination Characteristics

In reviewing urban morphology literature in the previous chapter, we argued that the immediate characteristics of the spatial environment around each building can also play an important role in affecting the building's suitability for retail activities. In order to capture the configurational typology of each of the building destinations in our analysis, we measure each building's volumetric characteristics, such as the ground floor area, and height. We also describe the typology of the street in front of the building, measuring its paved width, right of way, and the average width of the sidewalks on the given street segment. Perhaps most important, we estimate how many streets each building has direct access to. We do so by counting the number of streets that immediately surround the parcel a building is located on, as we illustrated in Figure 15 in Chapter Two. A corner parcel, for instance, is sided by two streets, whereas a middle parcel by only a single street. The "parcel type" variable is continuous, ranging from one to five, depending on the number of street exposures. There are parcels in the data, which have direct access to more than five streets due to their complicated geometry, but in order to correct for outliers, we limited our "parcel type" variable to five at most, converting superior values down to five.

Last, we also estimate the family median income of the census tract that each house is located in. The spatial resolution of income information, which was obtained from the year 2,000 census records, was originally coarser than a building or block level. We thus simply attribute to each house within a given census tract the median values of the whole census tract. To the best of our knowledge, no resident income information at a finer spatial resolution was available.

3.3.4 Descriptive statistics of independent variables

Table 3 provides the descriptive statistics of each of the independent variables that we hypothesize to affect the probability of a building to contain retail or food service establishments. Reach, Distance Remoteness, Turns Remoteness, and Intersections Remoteness summaries are given for all destinations that we explored: built volume; jobs; residents; and public transit (distinguishing between bus stops and subway stations). Due to the more sporadic availability of transit stations, we measured access to the nearest subway station and the nearest bus stop, not just the stops that fell within a 2,000-foot range. The descriptive statistics thus indicate that the maximum observed distance to a subway stop is 3,870 meters (12,696 feet), well over 600 meters (2,000 feet).

	Mean	Min.	Max.	Std. Deviation
Reach:				
Built volume	13,871,834.00	226,176.00	59,473,313.00	5,861,216.00
Jobs (non-retail or food)	1,728.00	0.00	33,837.00	2,510.00
Residents	3,282.00	0.00	7,905.00	1,279.00
Distance Remoteness (Average):				
Built volume	369.30	148.70	511.58	29.80
Jobs (non-retail or food)	375.50	0.00	590.20	72.60
Residents	362.46	0.00	597.45	42.33
Nearest bus stop	190.27	0.17	995.76	126.87
Nearest subway station	1,272.48	2.13	3,870.11	658.84
Turns Remoteness (Average):				
Built volume	2.32	0.13	5.16	0.54
Jobs (non-retail or food)	2.28	0.00	6.24	0.78
Residents	2.31	0.00	6.00	0.56
Nearest bus stop	1.42	0.00	6.00	0.94
Nearest subway station	4.15	0.00	22.00	2.35
Intersections Remoteness (Average):				
Built volume	4.70	0.40	8.75	0.85
Jobs (non-retail or food)	4.91	0.00	11.69	1.33
Residents	4.63	0.00	9.05	0.90
Nearest bus stop	2.65	0.00	14.00	1.97
Nearest subway station	15.36	0.00	52.00	7.44
Betweenness	1,933,975.34	28,723.00	36,800,440.00	4,182,292.31
Destination Characteristics:				
Building footprint area (sq ft)	2,296.59	25.16	485,042.08	6,843.30
Building height (ft)	11.18	0.00	152.30	3.83
Road pavement width (ft)	26.29	0.00	80.00	7.94
Sidewalk width (ft)	5.84	0.00	14.00	2.29
Rigth of Way (ft set back of buildings from sidewalks	1.16	0.00	51.00	3.02
Parcel Type (# of streets the building directly facces: 1-5)	1.30	1.00	5.00	0.62
Median Income in census tracts ($)	66,803.19	12,750.00	191,541.00	29,869.56

Table 3 Descriptive statistics of independent variables.

3.3.5 Summary

The various metrics of spatial configuration presented in this chapter focus on the inter-relationships of only three elements of urban space: edges, nodes, and buildings. Despite the simplified form of representation, we have tried to demonstrate that joining these three elements in a spatial network of a graph allows us to produce a series of valuable accessibility measures that can help one understand the advantages and disadvantages of urban locations at a building-level resolution. The presented framework allows us to distinguish effects of accessibility that originate from urban form and land use distribution, as well as limited cognitive aspects of travel behavior.

Three categories of variables were presented to describe each building in Cambridge and Somerville. First, spatial accessibility measures including Reach, Distance Remoteness, Turns Remoteness, and Intersections Remoteness were proposed for capturing the number of available destinations around each location, as well as impedance characteristics required to reach each of the destinations. Impedance, in turn, was measured along three different scales: metric distance, turns, and intersection crossings. Second, the potential of passers-by at each building were described using the "betweenness" measure from graph theory. The betweenness measure describes the fraction of shortest paths between all other nodes of the graph that pass by the building of interest. Third, the characteristics of each of the building destinations were outlined using building volume characteristics and the adjoining street characteristics, as well as the number of exposures each building has to surrounding streets. Taken together, these data form the independent variables of the following analysis of retail and food establishment location choices in Cambridge and Somerville, MA.

The dependent variable of our analysis is dichotomous, indicating whether or not a building contains retail or food service establishments in NAICS categories "44", "45" or "722". The exploratory analysis of the dependent variable revealed that retail and food establishments are significantly clustered in our study area. The exploratory analysis could not inform us of the underlying reasons that might explain the observed clusters. Do retailers agglomerate around locations, such as Harvard Square because of exogenous location qualities, captured in the independent variables, or endogenous reasons, explained by neo-classical retail location theory? Or both?

The following section introduces a novel methodology that allows us to analyze the effects of both endogenous clustering and exogenous location factors on each building's probability of containing retail or food establishments.

3.4 Methodology

Numerous previous researchers of urban morphology have demonstrated a relationship between spatial accessibility and land use location patterns. However, in the urban design community, where graph measures have been most popular, estimation methods used to demonstrate these relationships have often remained overly simplistic, with evidence of the social effects of spatial configurations limited to mere Pearson's correlations (Hillier, Burdett et al. 1987; Hillier and Iida 2005; Crucitti, Latora et al. 2006) or linear multiple regression models with very limited control factors (Desyllas 2000). Since, according to retail location theory, establishment location choices depend on other establishments' location choices, we expect the dependent variable to be spatially autocorrelated and endogenous. Pearson's correlations and ordinary least squares (OLS) regression methods are unable to model such endogeneity: thus they ignore interdependent decision making, which could be a potentially important factor in actual location choice behavior. Ignoring this effect risks explaining observed location choices with exogenous spatial predictors, such as location characteristics, while the true explanation reasons might lie in strategic clustering between establishments, regardless of location. Indeed, exploring the dependent variable in the previous chapter revealed that retail and food establishments in our study area are significantly clustered in the limited geographic areas of Cambridge and Somerville. Proximity to complementary retailers can increase store revenues by allowing patrons to conduct multiple errands on a single trip, thereby economizing transportation costs (see section 2.2.1). But even proximity to almost identical competitive businesses can, in some cases, increase store revenues by providing the patrons an opportunity to compare products and prices in nearby stores (see section 2.2.2) and, in doing so, increase demand. In estimating the factors that relate to retail location choices, we therefore aim to separate exogenous location effects from endogenous agglomeration effects, estimating each while controlling for the other. The central methodological challenge we face is to untangle whether the observed spatial pattern of retailers is explained by strategic interaction in location decisions, exogenous location characteristics, or both.

An analysis of factors influencing establishments' location choices is also known to be sensitive to omitted spatial variables. Consider the following example of an omitted variables problem. Imagine a set of perfectly competitive restaurants clustered at a waterfront location on an urban riverbank, where the key attraction to the cluster for all restaurants is an exceptional view of the river. If an analyst who studies the location choices of these restaurants omits a 'waterfront' variable from the model, then the observed clustering behavior can erroneously be attributed to endogenous effects such as demand externalities or other exogenous variables, which could be collinear with the waterfront location, such as the socioeconomic status of surrounding residents. Omitting important variables can result in misleading parameter coefficients for variables present in a model. The hazard of omitted variables is especially important in spatial location studies, because actual business choices are commonly affected by a vast number of considerations, some of which are more pronounced than others, making it virtually impossible to include all of the important variables in a location choice model. The methodology introduced in this section aims to overcome these challenges by adopting the *strategic interaction* framework from urban and regional economics in our analysis of retail location choices.

3.4.1 The strategic interaction framework

The strategic interaction framework (Brueckner 2003) analyzes how decisions of spatial economic agents depend on the decisions of other, related spatial economic agents. The empirical methodology for estimating strategic decision-making using spatial econometric tools was first laid out by Case, Rosen et al. in their study of fiscal policy interdependence between states in the U.S. (Case, Rosen et al. 1993). The authors used the "spatial lag" and "spatial error" specifications from spatial econometrics to set up an empirical model (Anselin 1988). The spatial lag specification of an empirical strategic interaction model allows one to estimate whether and how the magnitude of a decision variable of one economic agent depends on the magnitudes of a similar variable set by neighboring economic agents in a system. The spatial error specification, on the other hand, estimates the spatial autocorrelation in the agents' error terms, explicitly addressing the hazard of omitted variables in a model. Since Case, Rosen et al.'s seminal paper, numerous studies have used their empirical framework to estimate how political decisions of one spatial jurisdiction depend on the decisions of other jurisdictions. Interdependencies of policy decisions have been studied in areas as diverse as urban growth controls (Brueckner 1998), tax policy (Bucovetsky and Wilson 1991; Hoyt 1991; Wilson 1991), provision of public goods (Scotchmer 1985; Scotchmer 1986; Helsley and Strange 1994; Hochman, Pines et al. 1995), and social policy (Saavedra 1999).

Though both the spatial lag and the spatial error specifications are individually quite common in urban economics literature, joint specifications of both spatial lag and error models have been relatively rare. A joint lag and error model, which both estimates the spatial interdependence in the decision variable and simultaneously controls for omitted variables, was used in Case and her colleagues' original paper. It has also been used by Saavedra, in his study of welfare competition between states (Saavedra 1999). The lack of joint lag and error specifications in literature is probably attributable to the technical difficulties involved in setting up a joint model. The specification has traditionally required custom modifications of standard statistical estimation routines. Recent developments in spatial econometrics have made a joint specification more accessible to non-econometricians (Kelejian and Prucha 2006; Anselin and Rey 2007). We propose that the joint spatial lag and error model is also theoretically appropriate for evaluating interdependent decisions in establishment location choices in our case study area.[14]

3.4.2 Strategic interaction in the context of location choices

The explicit focus on the interdependence of spatial decisions offered in the strategic interaction framework is ideally suited to study the spatial distribution of establishments who tend to choose localities based on the location decisions of other establishments. The interdependencies in location choices can be empirically estimated using the spatial lag specification. The fixed effects of location characteristics can be estimated with usual exogenous predictors. A spatial error specification, in addition, allows the location choice model to control for potentially important omitted spatial variables, thus increasing the reliability of the estimated coefficients.

[14] We shall further elaborate on how this appropriateness is empirically determined in the results section.

Instead of using political jurisdictions, such as states, towns, or counties, as the spatial units of analysis, we focus on the decisions made for individual buildings in our case study area. Instead of policy choices or public spending, our dependent variable becomes binary, indicating whether or not a building contains retail or food establishments. The zero-to-one range of the dependent variable turns the model into a linear probability model, where the estimated coefficients illustrate how our predictors relate to buildings' probability to contain retail and food service establishments. In lieu of interdependencies in policy choices, our strategic interaction framework thus captures the spatial interdependencies in retail location choices. To our best knowledge, this dissertation provides the first attempt to use the strategic interaction framework in the case of spatial location choices of business establishments.

3.4.3 Empirical Specification

We start by representing retailers as spatial economic agents whose profit maximizing behavior is captured in an objective function *U*. The *U* of each retailer is given as a function of 1) a retailer's decision to either run a shop in a particular building *i* or not, 2) other retailers decisions to run retail businesses in neighboring buildings or not, and 3) exogenous location characteristics around building *i*. We note *U* as follows:

$$U(y_i;\ y_{-i}; x_i)$$

Equation 6

where Y_i represents a retailer's choice to run a business in building *i*, Y_{-i} represents jointly the decisions of all other entrepreneurs to run retail businesses in neighboring buildings $-i$, and X_i represents a vector of exogenous location characteristics, such as population, job, and transit access, around building *i*. Y_{-i}, representing the magnitudes of other agent's dependent variables around each building i, which is technically referred to as the spatial lag of *Y*.

Using a binary dependent variable that indicates the presence or lack of retailers in a given building allows the objective function to model how the presence of neighboring retailers affects the utility of a retailer at building i, thereby capturing spatial clustering as a key variable in retail location choices. If we set the dependent variable Y_i to represent the presence or lack of a particular type of store (e.g. a clothing store), then the lagged variable Y_{-i} in the objective function *U* would represent how the utility of retailing at building i is affected by the presence or lack of not merely all other retailers, but the same type of stores (e.g. clothing stores) in neighboring buildings. In this case the objective function U would capture the effects of homogenous clustering between similar stores that we discussed in Chapter 2.2.

We shall use both forms of the dependent variable in the following analysis. First, we look at whether and how aggregated retail and food establishments, regardless of type, are attracted to other retail and food establishments, as well as to exogenous location characteristics. We shall then turn to disaggregated retail categories and investigate how stores of a particular kind are spatially attracted to stores of the same kind, as well as stores of a different kind and exogenous location characteristics. The latter specification allows us to separate competitive clustering effects from complementary clustering effects.

The objective function U at a particular building i can be maximized with respect to the choice to run a business in building i by setting the first order derivative of U equal to zero. Setting $\partial U/\partial y_i=0$ leads to a so-called reaction function R, which represents retailers' best response (y_i^*) to either run shop at building i or not, given the choices of other neighboring retailers, as well as exogenous location characteristics in the area:

$$y_i^* = R(y_{-i}; x_i)$$

Equation 7

The spatial lag model is an implementation of this reaction function, obtained by specifying a linear functional form of R and restricting the set of interacting retailers to the neighborhood structure expressed in an *a priori* specified spatial weights matrix W:

$$y = \rho Wy + X\beta + \varepsilon$$

Equation 8

where y is an n by 1 vector of observed dependent variables, W is a n x n spatial weights matrix that describes the adjacency relationships between n buildings in the spatial network, ρ is the spatial autoregressive parameter that illustrates the magnitude of strategic interaction in location choices, X is a vector of exogenous location variables with estimated parameters β, and ε is a vector of error terms (the error term is discussed further below).

The spatial weights matrix W has to be predetermined, since the lack in degrees of freedom does not allow W to be estimated from data[15] (Anselin 1988). As noted above (see section 3.3.1), we measured the spatial weights matrix along the network of streets in a 100-meter radius. We also tested two alternative specifications for the spatial weights matrix using 25-meter, and 50-meter network radii. W thus represents an adjacency matrix, which indicates buildings j that are reachable from a building i within the given network radius. Using the 100-meter network radius limits the estimation of strategic interaction to only those neighboring buildings, which can be reached within a 100-meter distance along shortest paths from a building of interest.

Retail location literature offers little insight on how to formally define retail clusters, and, consequently, what radii are theoretically appropriate for a spatial weights matrix capturing adjacency relationships between retailers. In an attempt to find substantively justified radii, we experimented with spatially clustering retailers in our case study area using different distances. Figure 26 illustrates retail clusters in Cambridge, MA using a 100-meter network distance as a limiting threshold to relate neighbors in a cluster. A cluster here is defined as a set of retailers, where every retailer in a cluster has a nearest neighboring retailer within a 100-meter shortest-path distance. The figure illustrates that a 100-meter network radius clearly distinguishes Central Square, Harvard Square, Inman Square, and other intuitively

[15] The number of neighbor relationships increases as the square of the number of observations. Consequently, the number of simultaneous equations is always smaller that the number of parameters in the spatial weights matrix, which makes it impossible to estimate the weights from data.

well-known retail clusters of Cambridge at a 99% significance level[16], suggesting that a 100-meter (328 feet) threshold distance between stores approximately corresponds to our intuitive understanding of retail clusters. We also tested the 25-meter and 50-meter radii, which did not result in such intuitive clusters. However, we generated three different spatial weights matrices based on the three radii (W_{25}; W_{50}; and W_{100}) in order to empirically test which specification of W produces the best fit with our data[17]. These experiments showed that using the W_{100} weights matrix, ceteris paribus, produced the highest fit statistics in the models, suggesting that the 100-meter-neighborhood radius was superior to the 50-meter and 25-meter radii from the model specification point of view[18]. The following results are therefore shown using only a W_{100} spatial weights matrix, where strategic interaction effects are constrained to a 100-meter distance band.

Due to technical reasons, we were unfortunately unable to weight the adjacency relationships by distance. This means that all neighboring stores around a particular building i that are reachable in a 100-meter walking radius are treated as equal, regardless of whether they are located immediately next door, or 100 meters away. As spatial econometric estimation techniques improve, it should be possible in future work to also differentiate the effects of neighboring stores by weighing the effects by distance.

Figure 26 Clustering of Cambridge retail and food establishments based on a 100-meter network radius. The different colors codes distinguish separate clusters at the 99.9% significance level, with white points representing insignificant clusters.

[16] This analysis was produced using Prof. Okabe's SANET toolbox for ArcGIS. In order to test the 99% significance level, the observed clusters are compared to randomly generated independent points in 999 Monte Carlo simulations.

[17] The appropriateness of different spatial weights matrices can be evaluated by comparing log likelihood statistics of otherwise identical models. See (Case, Rosen et al. 1993) for more details.

[18] Our general model M1, discussed in the results section, showed that the W25 log likelihood was 11035.6 (R^2: 0.138), the W50 log likelihood 11210.7 (R^2: 0.151), and the W100 log likelihood 11381.1 (R^2: 0.164).

It is important to note that even if the adjacency relationships in the W matrix are constrained to only *local* neighbors that fall within the given radius threshold, imposing a large number of zeros in the adjacency matrix, the corresponding spatial autoregressive parameter ρ of the spatial lag model in Equation 8 still captures the *global* range of interdependencies in location choices among all observed retail establishments in the data (Anselin 2002). The parameter ρ estimates whether and how the probability of retailers in buildings is affected by the presence of retailers in neighboring buildings that are reachable within a 100-meter threshold distance specified in the spatial weights matrix W_{100}. The autoregressive parameter rho (ρ) is constrained between negative one and positive one. If retailers are strategically attracted to each other, controlling for exogenous location factors, then we expect ρ to be positive and significant; if retailers are strategically repelled from each other, then we expect ρ to be negative and significant. If no interaction in the location choices of retailers is observed, then ρ is expected to be zero.

In the specification of our spatial lag model of Equation 8, we also allow the error term ε to be spatially correlated among observations. This "spatial error" specification allows us to address the hazard of omitted variables described above. The error term is thus composed of two parts: a spatially correlated part, which captures the effects of omitted variables within the same neighborhood structure W100 and a remaining random residual *u*:

$$\varepsilon = \lambda W \varepsilon + u$$

Equation 9

where λ is the spatial correlation parameter for error terms between neighboring buildings that can arise due to omitted spatial variables, W is the same n x n spatial weights matrix as in Equation 8, and u is the remaining error component, which is idiosyncratic and uncorrelated between neighbors.

The parameter estimate of lambda has at least two potential sources of influence. First, lambda can capture the effects of omitted spatial variables, thereby allowing the model to yield more reliable t-values for other substantive predictors. Second, lambda is also affected by the dichotomous nature of our dependent variable. In a 100-meter network radius around each building where the dependent variable equals one, we typically expect more buildings where the dependent variable equals zero: that is, buildings that contain no retail or food service establishments. This expectation simply reflects the reality of business distribution in our case study area, where only three per cent of all buildings contain retail or food service establishments. Due to the binary nature of our dependent variable, buildings with retailers are hence expected to produce a positive residual, while buildings with no retailers produce a negative residual. The correlation between each retailer's own error term and the weighted average of error terms in the 100-meter neighborhood is therefore expected to be negative. The error terms of the model are thus heteroskedastic by design. These two influences on lambda are difficult to untangle, but since we know that both affect lambda, it is essential to control for error correlations in the model.

Combining the spatial lag specification from Equation 8 with the spatial error specification from Equation 9 leads to a joint spatial lag and error specification:

$$y = \rho Wy + X\beta + \varepsilon \quad , \text{where} \quad \varepsilon = \lambda W\varepsilon + u$$

Equation 10

The joint spatial lag and error model in Equation 10 shows that the dependent variable y appears on both the left and right hand sides of the equation, indicating that y is endogenous. The dependent variable can be removed from the right-hand side by using matrix algebra and inverting the system. The reduced form of Equation 10 is shown in Equation 11, where the potential error correlation among neighbors is also incorporated. The solution to the reduced form equation yields the values of y_i that represent the Nash equilibrium probabilities of buildings to contain retail and food service establishments.

$$y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1}(I - \lambda W)^{-1}\varepsilon$$

Equation 11

The first part of Equation 11 illustrates how the dependent variable y_i is related to independent variables Xi at all locations in the system through the Leontief's inverse $(I\text{-}\rho W)^{-1}$. Even though the vector β of exogenous coefficients is the same for all buildings, the ultimate effects of the exogenous variables themselves differ for each building. When any of the exogenous location characteristics X changes in building i, producing a change in the probability y, then this change in y also alters the retail probabilities of i's neighboring buildings. The ripple change in i's neighbors ultimately feeds back to i itself via the spatial weights matrix and the autoregressive parameter rho (ρW), producing a tertiary effect on i's probability to contain retailers. Since the neighbor relationships in the W matrix are unique for each building, then the multiplier effect is also unique for each building.

The latter part of Equation 11 demonstrates that the dependent variable is also tied to the spatially correlated residual terms ε and the remaining random residual component *u* at all other locations in the system, not only at location i.[19] Building i's probability to contain retail and food service establishments is therefore not only related to the exogenous location characteristics and the error term at i's own location, but also at all the other locations in the system. Equation 10 can therefore not be consistently estimated using OLS, since the right-hand side dependent variables are correlated with error terms. This interdependence requires that all retailers' location choices be estimated together by solving a large number of simultaneous equations using matrix algebra, which requires the use of specialized estimation methods such as maximum likelihood (ML), generalized methods of moments (GMM), instrumental variables (IV), or a heteroskedasticity and autocorrelation consistent (HAC) estimation. The ability to solve a large number of simultaneous equations is contingent upon the capability to invert the W matrix, which becomes more difficult as the sample size or the number of adjacency relationships increases. In our analysis, we use the HAC estimator developed by Kleijian and Prucha (Kelejian and Prucha 2006). This recent HAC estimator is implemented in the GeoDaSpace spatial econometric software package, which uses an extremely efficient algorithm for inverting large sparse matrices (Anselin and Rey 2007).

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[19] Equation 11 illustrates that leaving out the correlation in errors part $(I\text{-}\lambda W)^{-1}$ would not bias the β estimates of exogenous location variables, but would instead affect the standard errors and therefore the significance levels of βs. Ignoring error correlation would also affect the spatial autoregressive parameter ρ, thus influencing our estimates of spatial interdependence in location choices.

Using the data presented in the previous chapter, our empirical model thus integrates three important factors that we hypothesized to affect retail location choices at the end of Chapter Two. First, the spatial autoregressive parameter ρ accounts for spatial autocorrelation in the dependent variable, estimating whether and how retail location choices are strategically attracted or repelled from other retailers. Second, the vector of β coefficients accounts for the effects of all the exogenous location characteristics illustrated in the first part of this chapter, including accessibility measures of urban form and land uses, as well as the spatial characteristics of the building destinations themselves. And third, our model also accounts for the spatial error correlation that can result from potentially important omitted variables.

3.4.4 Methodological limitations

The model presented above is far from perfect and could be improved in many ways. Some of the improvements require further developments in data collection and econometric estimation routines. Others simply necessitate more time and effort in our future research.

3.4.4.1 Using a binary dependent variable in a linear model

The joint spatial lag and error model that we have proposed assumes a linear functional form, ignoring the fact that our dependent variable is dichotomous. A linear estimation of a dichotomous outcome can lead to inconsistent predictions, such as predicted values that exceed the zero-one range of the actual dependent variable. In order to address the issue, a non-linear functional form, which constrains the outcome to a given range, is usually specified. The most common functions for estimating binary outcomes are known as probit or logit models. Both probit and logit functions enforce an upper and a lower boundary on the predicted outcome using an s-shaped function, as shown in Figure 27.

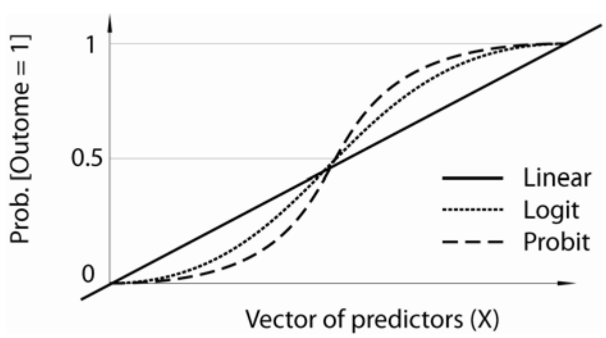

Figure 27 Functional forms of the probit and logit specifications.

Ideally, the estimation of binary retail probabilities in our case study should also be carried out using a probit or logit specification. Unfortunately, econometric theory on spatial probit and logit models has not yet advanced far enough to produce workable estimators of these types of models with a joint spatial lag and error specification. To our best knowledge, the only previous studies that have empirically applied a probit model with a spatially lagged dependent variable are given by LeSage, Pace, and their colleagues; Beron, Murdoch, and their colleagues; and Beron and Vijverberg (Beron, Murdoch et al. 2003; Beron and Vijverberg 2004; LeSage, Pace et al. 2010).[20] We are unaware of any probit models that have integrated both a spatial lag and error specification. While LeSage and Pace's study used the popular spatial econometrics toolbox for Matlab, built by James LeSage[21], the other studies used custom-built procedures to specify the models, which unfortunately remain inaccessible for general research purposes.

In their study of potential hazards involved in using a linear probability model with a binary dependent variable, Beron and Vijverberg compared the outcomes of a spatial linear probability model, analogous to the one we proposed, though without a spatial error term, to the theoretically more consistent spatial probit model (Beron and Vijverberg 2004). Their analysis is well-suited for outlining the potential hazards involved in our model specification. We summarize their findings below. The authors found that:

- The linear probability model with a spatial lag underestimated the spatial autoregressive coefficients ρ and λ. However, repeated simulations showed that the autoregressive parameter estimates of the linear model tended to fall within a standard deviation of the spatial probit model. This suggests that our estimates of autoregressive coefficients are likely to be conservative underestimates rather than overestimates.
- The β coefficients of exogenous variables were over-estimated in the spatial linear probability model compared to the spatial probit model, but the values also tended to remain within a single standard deviation of the spatial probit coefficients. This suggests that our estimates of the exogenous effects of location characteristics might be somewhat overestimated.
- Simulations showed that as the sample size increased, the parameter estimates of the probit and linear models tended to converge. The sample sizes tested by the authors were n=50, n=100, and n=200. Since our sample size is considerably larger (n=27,026), we expect our linear estimates to be correspondingly closer to the spatial probit estimates.
- The linear model also tended to converge better with the spatial probit model as the spatial dependence of the decision variable was more randomized (less organized). The probit model was advantageous in detecting more organized spatial dependence patterns than the linear model. Exploring the dependent variable in Chapter Three, we found that the clustering of retail and food establishments in Cambridge and Somerville was instead organized around the popular squares of both towns as well as around the main thoroughfare streets. Our linear autoregressive parameter estimates might therefore be less consistent than the corresponding probit model estimates, though, as noted above, the linear model estimates tend to be underestimates rather than overestimates.

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[20] Additional theoretical treatment of the issue have been outlined by Fleming, M. M. (2004). Techniques for Estimating Spatially Dependent Discrete Choice Models. Advances in Spatial Econometrics. L. Anselin, R. J. G. M. Florax and S. J. Rey. Berlin, Springer.

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[21] The spatial econometrics toolbox provides Baeysian estimates for a probit model with a spatial lag. However, under current computational constraints, we were not able to estimate models with a sample size of over roughly n=8,000. We have currently found no readily available tools for estimating a joint lag and error probit model.

- The researchers also found that as the 'true' underlying autoregressive parameters ρ and λ are higher, then the estimates of the probit model and the linear model tend to align better. This is an encouraging result, since our exploratory analysis shows a fairly strong spatial dependence between retail locations.

The authors concluded that "…*the linear spatial models will become obsolete as accessibility to spatial probit software becomes widespread*", but at present, "…*the linear model seems to provide a reasonably accurate upper and lower bound to what a spatial probit model would find* (Beron and Vijverberg 2004). We therefore think that the linear model proposed in this dissertation offers a reasonable tool for analyzing establishment location choices until robust and accessible spatial probit models become available. Additional research on spatial econometric methods for binary and categorical decision variables will probably improve the application of the strategic interaction framework to location studies in the near future.

3.4.4.2 Representing neighbor relationships with a spatial weights matrix

A second important issue of the proposed adaptation of the strategic interaction framework to the study of location choices stems from the reliability of the specified spatial weights matrix (W) and the related reaction function R (see Equation 7). The spatial weights matrix, which underlies our estimates of retail clustering, is determined from the 2009 conditions in Cambridge and Somerville, not necessarily the conditions that characterized the retail environment when the location choices of the observed retailers individually occurred. In order to accurately represent the true adjacency conditions when each of the location choices historically occurred, the weights matrix would need to be specified individually for each establishment according to the situation at the time of its choice. This would lead to an asymmetric weights matrix. For instance, when Legal Seafoods moved to Kendall Square, there might have been few other retail or food establishments in the area. When Cosi, a recent deli addition, moved into Kendall Sq, there were already a number of pre-existing establishments in the area. From Legal Seafoods' perspective, Cosi Cosi should thus not be considered as a 'neighbor' in the adjacency matrix, but from Cosi Cosi's perspective, Legal Seafood should indeed be specified as a neighbor. In order to accurately estimate if one retailer's location decision depends on another's, the weights matrix would need to be variable across time and take an asymmetric form, both of which substantially complicate an analyst's task.

Specifying a time-varying spatial weights matrix requires historic records that are unfortunately unobtainable at present. The available digital records of individual retail establishments do not go back longer than five years, while a considerable share of the retail buildings in Cambridge and Somerville goes back more than a century. Lack of longitudinal data thus prohibits us from specifying a historically consistent spatial weights matrix.[22]

Second, solving the reduced form of the spatial lag model relies on the capacity to invert the spatial weights matrix, which has traditionally been difficult to do with large asymmetric matrices. Maintaining the symmetry in the spatial weights matrix has therefore been important for technical reasons in previous strategic interaction studies. However, the latest HAC estimator proposed by Kelejian and Prucha and

[22] The recors could be laboriously assembled from historic Sanborn maps in future work.

implemented in GeoDaSpace and PySal software, offers an efficient algorithm that now allows asymmetric matrices to be inverted (Kelejian and Prucha 2006; Anselin and Rey 2007; and personal communication with Luc Anselin). Unfortunately, we were unable to take full advantage of this recent development due to lack of historic business location data in our case study area. We do intend to improve the methodology in future research, incorporating time-varying and asymmetric spatial weights matrices to the model.

3.4.4.3 Estimating inter-store externalities through strategic interaction in location choices

In the literature review of Chapter 2, we discussed several aspects of retail location theory, which explain how and why competitive retailers might want to cluster in order to benefit from positive externalities from neighboring retailers. The proposed strategic interaction model using empirical data from Cambridge and Somerville is unfortunately unable to explicitly quantify externalities between stores. Instead, the model analyzes whether location choices of retailers depend on the location choices of other similar retailers, controlling for exogenous factors, thereby illustrating strategic location choice behavior. Even though the most plausible explanation for interdependent location choices points towards economic externalities between stores, other possible explanations cannot be ruled out. For example, retail location choices can be strategically interdependent if inter-store externalities are negligible, but storeowners *think* that the externalities take place, and locate accordingly. Retailers may also simply mimic each others' location choices, preferring adjacency and clustering conditions that have been previously tested by other retailers. Relying on historic adjacency patterns could result in strategic interaction estimates that depict retailers' choice habits rather than actual externalities. It is impossible to determine from our model which one of these options is captured in our strategic interaction coefficient ρ. We think that inter-store externalities offer the most plausible explanation.

3.4.4.4 The inclusion of zoning in the study

Several people who have commented on this research have invoked zoning as a potentially important variable that is missing from our model. According to a widely accepted belief, commercial zoning regulations can limit the behavior of retail and food service establishments by prohibiting location choices from occurring in certain areas, such as reputable residential districts in historic Cambridge. By failing to restrict the location choices in our model to the current zoning regulations, one might argue, we do not represent the true spatial choice options available to retailers. There is thus a danger of interpreting model coefficients as "retailer preferences" whereas the model includes choices that would be considered illegal under current zoning conditions (e.g. locating in a residentially zoned area).

While acknowledging the critique, we deliberately chose not to restrict the location choices to buildings that are currently zoned for commercial land uses in Cambridge and Somerville. Our reasoning is based on the following considerations. First, a large share of retailing patterns in Cambridge and Somerville predate any official zoning attempts. The first comprehensive application of zoning in American planning practice was established with the 1916 Zoning Resolution of Manhattan. Cambridge first adopted zoning in 1924 and it has amended the Ordinance over 150 times since then (Cambridge 2004). Many of the retail clusters in Cambridge and Somerville active at present were established in mid-19th century with the appearance of street car suburbs (Warner 1962), and others long before (Nylander 1965). Figure 28 shows a Sanborn insurance map of Inman Square in 1900. Buildings that have stores on their ground floors are designated with a letter 'S' and buildings that have dwellings or flats with 'D' and 'Flats' respectively. Given the stores along both Hampshire St. and Cambridge St., it is clear from the map that Inman Square was a vibrant retail hub long before zoning came along. Commercial zoning has therefore largely been a retroactive practice, legitimizing retail uses where shops have already been established by market forces. Constraining business location choices in our spatial weights matrix strictly to buildings that are currently zoned as commercial, would fail to account for the grandfathered patterns of retailing in historic settings of Cambridge and Somerville.

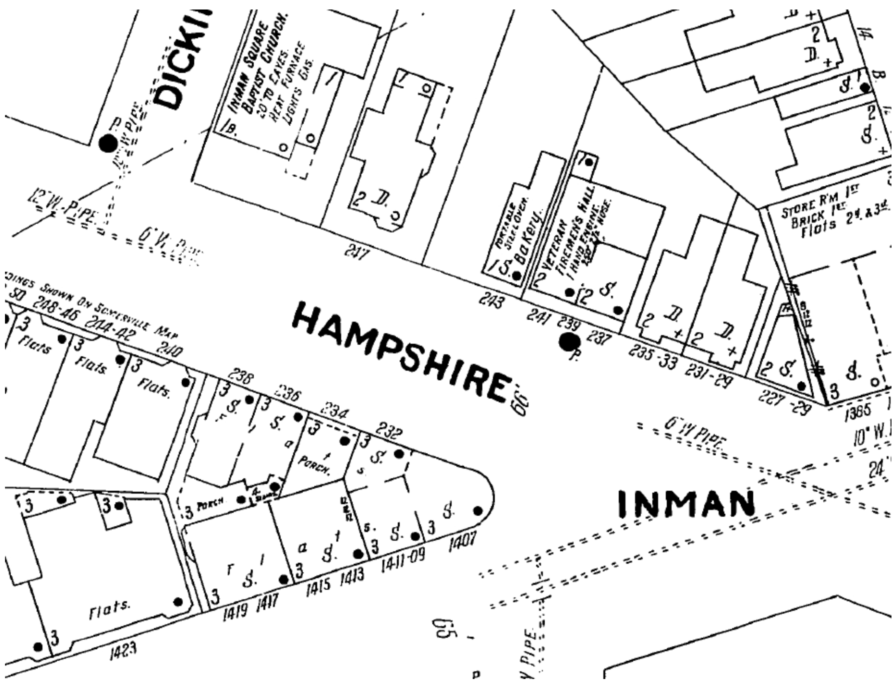

Figure 28 Sanborn Insurance map of Inman Square in 1900. Key: 'S' stands for 'Store'; 'D' stands for 'Dwelling'

Second, zoning regulations can be and are frequently altered based on market demands. A standard zoning petitioning processes, available in both Cambridge and Somerville, allows retail developers to gain approval to place retail and food service establishments in areas that are not currently zoned for these uses. The process, which takes up to six months to complete and currently costs $75, has taken effect twice a year, on average, since 1924 (Cambridge 2004).

Figure 29 illustrates a commercial beauty salon that has been added to a previously residential structure at Porter Square in Cambridge. The two neighboring residential buildings on the right side of the image have not developed an additional retail structure in the front of the building, but both also accommodate commercial establishments – a yarn store and an eyeglass store – on their ground floors. These and other businesses in Cambridge and Somerville illustrate that commercial zoning is an evolving process, where law often follows economic opportunities, rather than vice versa.

Figure 29 A commercial annex, containing a beauty salon, added to a historically residential building at Porter Square in Cambridge.

Last, it is not infrequently that we also find city governments using zoning regulations to incentivize new business development in areas that presently lack the land uses and establishments they are zoned for. The development of University Park in Cambridge which started in 1983, exemplifies an attempt on behalf of the city of Cambridge to incentivize retail land uses in the newly developed area between MIT and Central Square, which to this day falls short of the anticipated retail densities. Limiting our spatial weights matrix exclusively to buildings that are currently zoned for commercial uses thus also conceals the hazard of modeling planner preferences, rather than business preferences.

3.4.4.5 Rent as location choice factor

Several people introduced to this dissertation have also raised the question of rent as a potentially important criterion for retail location choices. Unaffordable rent can certainly prohibit retailers from moving to some otherwise desirable locations. Bargain rents, on the other hand, can also attract retailers to buildings that might otherwise fall short of ideal locations. Retail location literature in shopping centers, discussed in the previous chapter, has also demonstrated the importance of rent in attracting anchor stores to malls. Rent is therefore undoubtedly an important factor in retail location choices.

We are unable to include rent as a right-hand-side variable in our analysis because rent is not independent of our outcome — location choice. The list of independent variables in our model that capture access to residents, jobs, transit stations, and other retailers, provide, in fact, a disaggregate picture of individual components that jointly constitute economic rent. If all other independent variables in our model were kept constant, we could observe very little variation in rent. Rent can therefore not be used as an independent variable in our model. As already suggested in the previous chapter by Hurd, "*Since value depends on economic rent, and rent on location, and location on convenience, and convenience on nearness, we my eliminate the intermediary steps and say that value depends on nearness*" (Hurd 1903: 13).

Rent could instead be used as an alternative dependent variable in a future study. A similar methodology could in this case be used to predict rent in a hedonic model of exogenous location characteristics. Carter has illustrated the use of a spatially autoregressive model in predicting retail rents inside shopping centers (Carter and Haloupek 2000).

3.4.4.6 Historic inertia and moving costs

Finally, our methodology also falls short in representing retailers' moving costs and historic inertia in location patterns. Locations that have become suitable for retailing for various reasons in history might still remain active today, despite their disadvantages in accessibility compared to alternative locations. Several retail clusters in Cambridge and Somerville are located on historic street-car lines, which played an important role in the original genesis of these clusters, but stopped operating decades ago (Warner 1962). Over time, these locations have developed historic significance and self-sufficiency and become well-registered on people's mental maps, even as street-cars and other historic influences have disappeared. Historic inertia can also be embodied in the architecture of buildings, where structures with favorable typologies and sizes keep attracting successive retail tenants, despite disadvantages of location. One might argue that some of these businesses are 'locked' into their locations by the considerable moving costs involved in migrating to potentially better locations today. Prohibitively high moving costs, combined with uncertainties of doing business at new locations (Caplin and Leahy 1998, and see section 2.2.1), could thus lead to inconsistent conclusions regarding exogenous location factors.

We acknowledge the importance of historic inertia in our analysis and aim to capture the influence of some of these factors in the spatially correlated error terms of our model. The continuing influence of historic street-car stops, for instance, is modeled as an omitted spatial variable that jointly influences all businesses around a historic street-car station, captured in the spatial error correlation coefficient λ. We also argue that despite the fact that more advantageous business locations might be available today than indicated in the inert location patterns of the cities' businesses, the observed retail location patterns nevertheless reflect real economic value, since their continued existence offers testimony to their economic viability.

4

Results

We now turn to the empirical data and present the results of our analysis in Cambridge and Somerville. This chapter is organized as follows. We first present exploratory analysis and discuss how different predictors relate to the outcome individually, using simple Pearson's correlations. We then move to multiple regression models where the effects of all predictors are estimated while controlling for other predictors. These regression analyses fall into two broad subsections. First, we present the regression results in aggregated form for all retailers as a group. This allows us to discuss the built environment characteristics that relate to the location choices of all retailers, regardless of type. We subsequently turn to disaggregated results, where we look at the factors that are related to the location choices of various types of retailers, analyzing whether and how location choices differ between retail categories.

4.1 Exploratory analysis

Table 1 presents the Pearson's correlations between the individual predictors from Chapter 3 and the dichotomous outcome indicating whether buildings contain retail or food establishments. In order to put the outcome into a more intuitive spatial context, we also illustrate the distribution of the outcome, where the dependent variable equals one, in Figure 1.

The Reach measures to residents, jobs, and built volume in Table 1 are all positively and significantly related to retail and food establishments' location choices. The more residents, jobs, and built volume are within Reach in a ten-minute walking radius around buildings in Cambridge and Somerville, the higher the odds that the buildings contain retail establishments. The r-value for jobs (0.10225, $p<0.0001$) is considerably higher than the r-value for residents (0.00618, $p<0.0001$), suggesting that retail and food establishments' location choices are driven more strongly by workplaces than homes.

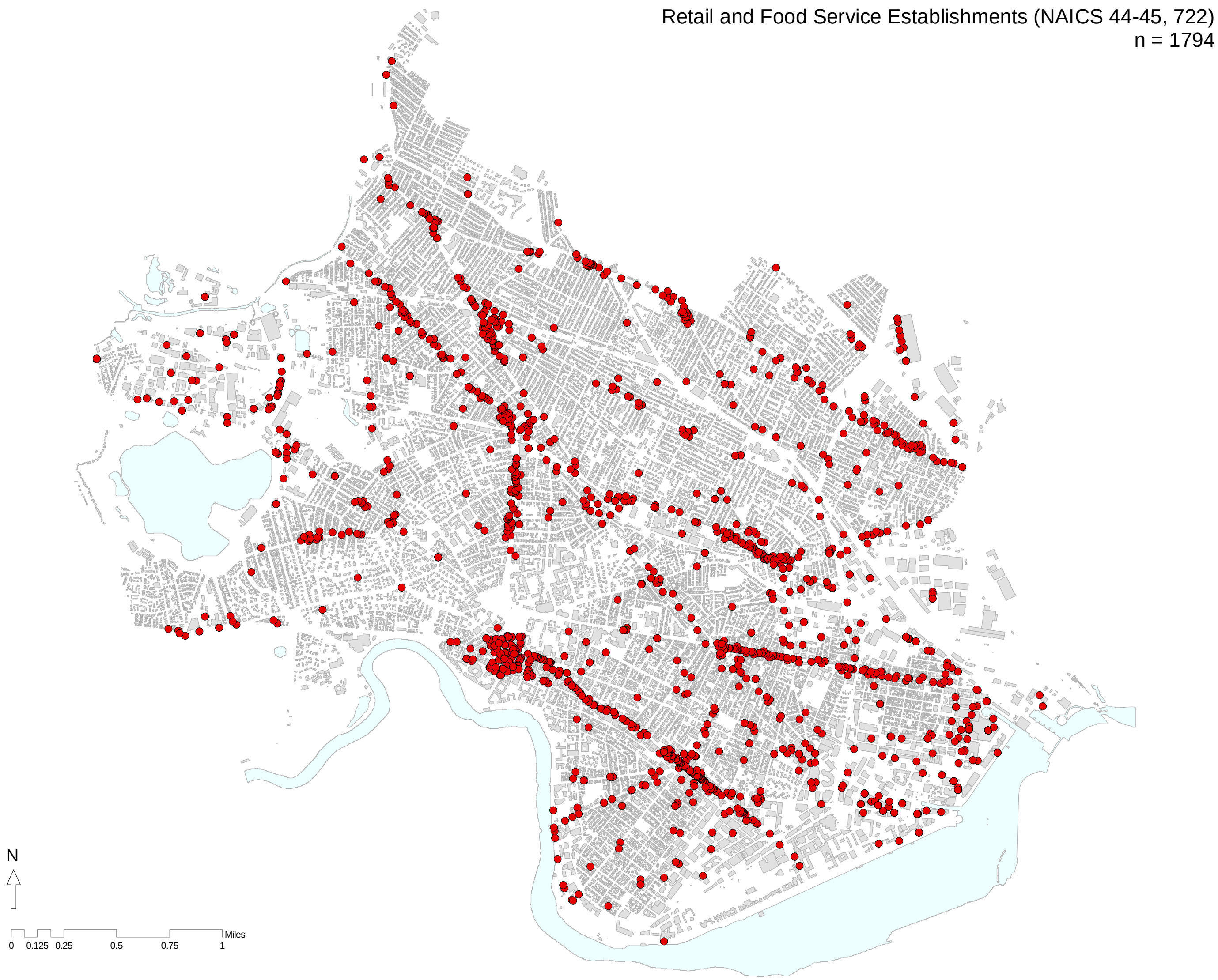

Figure 1 Observed locations of retail and food services establishments in Cambridge and Somerville, MA (n=1,794).

Distance measures to bus stops and subway stations are negative and significant, as expected, suggesting that retailers tend to choose locations that are closer to transit stations and workplaces, as well as the surrounding buildings. Distance to residents is also negative, but insignificant, which further suggests that retailers might not commonly locate at places that are most accessible to people's homes.

Distance to jobs and built volume are significantly negative, indicating that proximity to workplaces and surrounding built volume could be important factors in placing a store. Turns Remoteness effects are negative and significant for all destination types, suggesting that stores might prefer locations that are cognitively easier to find from homes, jobs and transit stations, as well as buildings in general, regardless of their particular function. Intersections Remoteness measures also appear significant in uncontrolled correlations, but the direction of the effect differs between destination types. For bus stops, subway stations, and jobs, Intersections Remoteness is negative, suggesting that the more street crossings separate buildings from these destinations, the lower the chances of their accommodating retailers. For residents and built volume, on the other hand, the effect occurs in the opposite direction. Betweenness, as well as destination characteristics, Shown in Table 1, are highly significant and positive, suggesting that these are desirable location qualities for retailers.

Predictor	r-value	Significance
Reach		
Residents	0.00618	***
Jobs	0.10225	***
Built volume	0.10179	***
Distance Remoteness		
Bus stop	-0.098	***
Subway stop	-0.0736	***
Residents	-0.00507	
Jobs	-0.134	***
Built volume	-0.0774	***
Turns Remoteness		
Bus stop	-0.06805	***
Subway stop	-0.09447	***
Residents	-0.0406	***
Jobs	-0.0932	***
Built volume	-0.0627	***
Intersections Remoteness		
Bus stop	-0.06805	***
Subway stop	-0.06908	***
Residents	0.0470	***
Jobs	-0.0628	***
Built volume	0.0112	*
Betweenness	0.17607	***
Destination characteristics		
Building footprint area	0.16245	***
Building height	0.03542	***
Road width	0.09245	***
Sidewalk width	0.0905	***
Right of way	0.10154	***
Parcel type	0.26658	***
Family median income	-0.02987	***

Significance level *** p<0.0001, ** p<0.01, * p<0.05

Table 1 Bivariate Pearson's correlations between the predictors and the dichotomous outcome indicating whether buildings contain retail or food service establishments (n= 27,023)

The urban form characteristics in the immediate vicinity of buildings also exhibit significant effects in expected directions. Building footprint area, height, road width, sidewalk width, and right of way, are all positively related to retail location choices, suggesting that retailers tend to choose buildings with larger footprints, taller heights, wider streets, wider sidewalks, and wider right of ways[1]. Parcel type and street Betweenness have the strongest positive effects, indicating that the more streets a building can directly access (see section 2.3.2 and 3.4.3 for the details of this measure), the higher the likelihood of retail or food establishments in the building. Likewise, the higher the Betweenness value of the street segment the building is located on, the more likely the building is to host retail businesses. Using betweenness values as proxies for passing traffic[2], the Pearson's correlation suggests that retailers are indeed attracted to locations with higher pedestrian and vehicular traffic at their doorsteps. Family median income in the census tract is negatively correlated with retail probabilities. Wealthier neighborhoods in Cambridge and Somerville thus appear to contain fewer retail and food establishments.

These exploratory findings are encouraging, since they corroborate the methodological pertinence of the spatial accessibility measures we proposed in Chapter 3. They confirm most of our expectations and suggest that both access characteristics to neighboring land uses and urban form, as well as the morphological characteristics of retail destinations themselves, could play an important role in retail and eating establishments' location choices. More important, the relevance of the different types of urban form measures also suggests that the geometric properties of the built environment can play a significant role in establishments' location choices. However, we caution the reader not to use these uncontrolled correlations as conclusive for the analysis, because, when analyzed in isolation the distance, turns and intersections Remoteness measures are highly collinear with each other. A transit station that is remote in distance is often also remote in terms of the number of turns and intersection crossings. Likewise, the destination characteristics, betweenness and Reach effects are measured in isolation from control variables. Whether these factors remain significant in the presence of other predictors needs to be further investigated in controlled multiple-regression models.

4.2 Aggregate location choices of all retail and eating establishments

In order to estimate controlled effects in the presence of covariates, we start by specifying an OLS multiple-regression model that includes all of the above predictors from Table 1, and additional diagnostics for spatial dependence. The OLS model allows us to address two important questions. First, whether the individual predictors explored above remain significantly related to retail location choices in the presence of covariates, and, second, whether our data is suitable for the further spatial lag and error specification described above.

[1] Again, we remind the reader that these are uncontrolled effects. As we shall see, some of these predictors obtain opposite signs in controlled models.

[2] See section 2.3.1 for the limitations and details of the Betweenness measure.

The OLS results, shown in Table 2, demonstrate that most of the variables remain significant at the 99% level in a controlled multiple-regression model. The Distance, Turns, and Intersections measures are not all significant, however. Among the Turns measures, for instance, only the total number of turns to subway stops appears highly significant, suggesting that, controlling for distance from the nearest subway station, as well as other covariates, retailers tend to locate in buildings that require fewer turns to access from subway stops. Turns Remoteness is also significant at the 95% -level for built volume, signifying that retail location choices also appear to minimize topological turns to surrounding buildings, regardless of their use.

The Distance Remoteness measures are mostly significant (except for bus stops) and generally have expected negative signs, confirming that, as distances to destinations increase, controlling for the number of destinations, the likelihood of encountering retailers decreases. Two of the distance Remoteness indicators — distance to residents and distance to the nearest bus stop — have positive signs, though the latter also loses its significance in the presence of covariates. The fact that distance to residents is highly significant and positive suggests that an average retailer does not tend to locate at places that have most advantageous access to residents. A similar result appears from the negative residential Reach measure in Table 2, which suggests that retail location choices are also negatively correlated with the number of residents in a ten-minute walking radius around a building.

Most important, the diagnostics for spatial dependence signal that the OLS model in Table 2 exhibits significant spatial dependence, making the estimated coefficients unreliable. The null hypothesis for both the spatial lag as well as the spatial error specifications are rejected, indicating that the OLS results may not be consistent and that a joint spatial lag and error model would provide a better fit for the data[3]. These spatial dependence diagnostics are interpreted as follows (Anselin 1988; Anselin 2005). We first observe the two Lagrange Multiplier tests for the spatial lag (LM Lag) and the spatial error dependence (LM Error). If neither of these tests rejected the null, then we would have to conclude that the data exhibit no significant spatial correlation in the dependent variable or error term and confirm that OLS provides consistent parameter estimates. If only one of the LM tests rejects the null, then the appropriate model would be either a spatial lag or a spatial error model, depending on which of the tests rejects. The LM(Lag) and LM(Error) tests in Table 2 tell us that the null hypothesis is rejected for both lag+errors at a 99 % confidence level. Because both of the LM tests reject the null, we need to examine the robust LM tests proposed by Anselin (Anselin 1988).

The robust LM tests are interpreted as follows. If only one of the robust tests rejects the Null, then the appropriate model should be either the lag or the error model, favoring the one that rejects the robust test. If both of the robust tests reject the Null, then the data suggest a joint lag and error specification to be most appropriate. We find in Table 2 that both of the Robust LM tests for spatial lag and spatial error reject the Null in our sample data. The OLS diagnostics thus indicate that that our data exhibit significant spatial dependence in both the dependent variable, which captures strategic interaction in retail location choices, as well as in the error term, pointing to the presence of omitted variables.

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[3] All of the diagnostics for spatial dependence, except for LM (SARMA), in Table 2 are distributed as X^2 with one degree of freedom. LM SARMA is distributed as X^2 with two degrees of freedom.

Model M1

Variable	**Wd = 100m**		
Constant	-5.45E-02	***	(0.0086925)
Reach			
Residents	-3.33E-05	***	(-8.173984)
Jobs	1.37E-05	***	(8.879168)
Built Volume	1.43E-08	***	(11.29135)
Distance Remoteness			
Nearest Bus Stop	2.91E-06		(0.1958859)
Nearest Subway Stop	-6.04E-06	*	(-1.901687)
Residents	5.66E-08	***	(4.247246)
Jobs	-4.03E-08	***	(-9.790852)
Built Volume	-3.46E-11	***	(-9.000228)
Turns Remoteness			
Nearest Bus Stop	9.92E-04		(0.6643935)
Nearest Subway Stop	-1.74E-03	***	(-3.452019)
Residents	1.67E-06	~	(1.355139)
Jobs	5.74E-07		(0.9846293)
Built Volume	-4.83E-10	*	(-1.553514)
Intersections Remoteness			
Nearest Bus Stop	-2.21E-03	**	(-2.210086)
Nearest Subway Stop	4.20E-04	*	(1.673434)
Residents	-1.80E-07		(-0.196611)
Jobs	3.42E-07	~	(1.165971)
Built Volume	5.47E-10	**	(2.325174)
Betweenness	4.99E-09	***	(17.84458)
Destination Characteristics			
Building Height	-1.54E-03	***	(-5.704991)
Building footprint area	2.41E-06	***	(15.47415)
Sidewalk Width	2.70E-03	***	(4.139618)
Road Width	-1.50E-04		(-0.647936)
Right of Way (set back of buildings from street)	2.38E-04	*	(1.750566)
rcel Type (# of streets the building directly facces: 1-5)	6.04E-02	***	(35.00411)
Family Median Income in Census Tract	-1.65E-07	***	(-4.202933)
Fit Statistics			
R^2 (adjusted)	0.127		
F	152.21		
Log Likelihood	10923.80		
Diagnostics for Spatial Dependence			
LM (Lag)	1709.85	***	
Robust LM (Lag)	145.11	***	
LM (Error)	1585.63	***	
Robust LM (Error)	20.89	***	
LM (SARMA)	1730.73	***	

Significance level ~<p<0.25, *p<0.10, **p<0.05, ***p<0.01

Cell etries are coefficients, t-values in parenthesis

Table 2 OLS parameter estimates for location choice variables of retail and food establishments in Cambridge and Somerville (n= 27,023). Spatial dependence diagnostics based on a 100-meter distance band spatial weights matrix.

An additional LM (SARMA) diagnostic provided in the output of Table 2 tests the joint null hypothesis that both spatial lag and error together are insignificant in the data. Since LM(SARMA) test too rejects the null hypothesis by a large margin, we further ratify that a joint lag and error model is appropriate for our data. We therefore need to consider the estimated coefficients of the OLS model with great caution and reserve the interpretation of the model parameters to a more accurate spatial lag and error model.

Table 3 presents a taxonomy of spatial lag and error models. The first model we fit, Model 2, contains the same set of predictors as the previous OLS model, but also includes two additional parameters rho (ρ) and lambda (λ), which estimate the spatial lag and spatial error effects respectively. The following Models 3 and 4 gradually reduce the number of predictors, eliminating variables that exhibit no statistical effects at the 75% significance level, do not improve the model fit, and do not seem to be substantively essential in the model as control factors. Model 3 first drops the insignificant Intersections Remoteness predictors from Model 2. We suspected that this might improve the t-values of the Reach, Distance, and Turns Remoteness estimates, because the latter are highly collinear with the Intersections Remoteness measures. As a result of these eliminations, we do observe higher t-values in the remaining predictors of Model 3. However, most of the predictors that were not significant at the 75% level in Model 2 remain insignificant in Model 3. After experimenting with their inclusion in the model one by one, we subsequently dropped the remaining insignificant predictors that neither contributed to the model fit nor embodied substantive reasons to be kept, and so we arrived at our final aggregate location choice Model 4, which provided the best fit to our data in Cambridge and Somerville. We shall therefore primarily focus our interpretation of parameter estimates on Model 4.

Let us first examine the autoregressive parameter rho in Model 4. As the OLS diagnostics already suggested, rho is highly significant with a t-value of 13.014. Rho is positive, indicating that even when we control for exogenous location characteristics and spatial error correlation, retail and food service establishments are strategically attracted to similar neighboring establishments. Put alternatively, the rho coefficient suggests that retailers are endogenously attracted to each other, controlling for exogenous location characteristics.

The parameter coefficient for rho, 0.491, is far from zero, implying that spatial clustering with other retailers is a strong factor in explaining retail location choices. Controlling for covariates, buildings, whose neighboring buildings in a 100-meter network radius all contain retailers, are 49.1% more likely to also contain retailers than buildings that have no retailers around them in the same radius. Since the mean number of neighboring buildings in a 100-meter radius in our study area is 26, then we conclude that the presence of a single store in a 100-meter walking range increases an average building's probability to also accommodate retailers by approximately 2% (49.1/26). As the model includes a series of location-specific control factors for land use destinations, urban form, and destination characteristics around each building, as well as spatially correlated error terms that can arise from omitted variables, we conclude that our data suggest endogenous factors, such as demand externalities and inter-store dependencies that were hypothesized in the literature review of Chapter 2, play a central role in retail and food establishments' location choices in Cambridge and Somerville.

	Model 2		Model 3		Model 4	
Variable	**W_d = 100m**		**W_d = 100m**		**W_d = 100m**	
rho (ρ)	0.501 ***	(13.246)	0.496 ***	(13.156)	0.491 ***	(13.014)
lambda (λ)	-0.219 ***		-0.211 ***		-0.205 ***	
Constant	-5.76E-02 ***	(-6.779)	-5.68E-02 ***	(-6.731)	-5.80E-02 ***	(-6.998)
Reach						
Residents	-1.37E-05 ***	(-3.225)	-1.39E-05 ***	(-3.290)	-1.38E-05 ***	(4.752)
Jobs	6.90E-06 ***	(4.333)	7.10E-06 ***	(4.491)	7.40E-06 ***	(4.550)
Built Volume (in millions of cubic feet)	5.99E-03 ***	(4.303)	5.93E-03 ***	(4.292)	5.99E-03 ***	(4.366)
Distance remoteness						
Nearest Bus Stop	1.50E-05	(1.033)	6.80E-07	(0.068)	-2.07E-06	(-0.236)
Nearest Subway Stop	-5.61E-06 *	(-1.808)	-5.36E-06 *	(-1.735)	-5.16E-06 *	(-1.686)
Residents	3.00E-08 **	(2.075)	3.00E-08 **	(2.337)	3.00E-08 ***	(2.521)
Jobs	-2.00E-08 ***	(-5.146)	-2.00E-08 ***	(-5.229)	-2.00E-08 ***	(-5.332)
Built Volume (in millions of cubic feet)	-1.42E-05 ***	(-3.473)	-1.38E-05 ***	(-3.821)	-1.43E-05 ***	(-4.080)
Turns remoteness						
Nearest Bus Stop	7.21E-05	(0.049)	-7.76E-04	(-0.584)		
Nearest Subway Stop	-7.35E-04 *	(-1.477)	-7.53E-04 *	(-1.513)	-8.20E-04 *	(-1.657)
Residents	1.80E-07	(0.149)	8.00E-08	(0.070)		
Jobs	9.00E-08	(0.149)	4.40E-07	(0.861)		
Built Volume (in millions of cubic feet)	-1.77E-04	(-0.579)	-1.62E-04	(-0.559)		
Intersections remoteness						
Nearest Bus Stop	-1.29E-03 ~	(-1.320)				
Nearest Subway Stop	4.31E-04 *	(1.758)	4.23E-04 *	(1.730)	4.13E-04 *	(1.693)
Residents	-2.10E-07	(-0.232)				
Jobs	2.80E-07	(0.989)				
Built Volume (in millions of cubic feet)	2.10E-04	(0.906)	1.76E-04 *	(1.626)	1.50E-04 *	(1.579)
Betweenness	3.27E-04 ***	(10.815)	3.29E-04 ***	(10.882)	3.36E-04 ***	(11.325)
Destination Characteristics						
Building Height	-1.69E-03 ***	(-6.380)	-1.68E-03 ***	(-6.353)	-1.69E-03 ***	(-6.425)
Building footprint area	2.05E-06 ***	(13.213)	2.05E-06 ***	(13.247)	2.07E-06 ***	(13.359)
Sidewalk Width	2.98E-03 ***	(4.649)	2.95E-03 ***	(4.856)	3.02E-03 ***	(5.085)
Road Width	-3.46E-05	(-0.153)	-8.30E-05	(-0.467)	-7.33E-05	(-0.416)
Right of Way (set back of buildings from street)	-3.08E-05	(-0.229)				
Parcel Type (# of streets the building directly facces: 1-5)	5.28E-02 ***	(29.872)	5.27E-02 ***	(29.959)	5.27E-02 ***	(29.990)
Family Median Income in Census Tract (in tens of thousands)	-5.04E-04 ~	(-1.280)	-4.96E-04 ~	(-1.271)	-4.86E-04 ~	(-1.250)
Fit Statistics						
R^2 (adjusted)	0.166		0.166		0.166	

Significance level ~<p<0.25, *p<0.10, **p<0.05, ***p<0.01
Cell etries are coefficients, t-values in parenthesis

Table 3 Spatial lag and error model parameter estimates for location choice variables of retail and food service establishments in Cambridge and Somerville, MA (n= 27,023).

The spatial error correlation coefficient lambda is significant and negative (-0.205, p<0.001)[4]. As we explained in the methodology section, lambda has two key sources of influence. It can on the one hand

[4] The significance of lambda is determined in Robust (LM) error and LM (SARMA) diagnostics of the OLS model in Table 2. The lack of t- and p-values for lambda in Model 4 occurs because the estimation method is generalized moments (Kelejian-Prucha 1999), in which lambda is treated as a nuisance parameter. The only thing needed is a consistent estimate for lambda, which is the reported value. This is then used in a spatially weighted least squares procedure to get the betas. The test reported on rho is the asymptotic t-test. Source: personal communication with prof. Luc Anselin.

be affected by omitted spatial variables and on the other by the limited distribution of the binary dependent variable.

Lambda illustrates the correlation between an average building's own residual and the weighted average of its neighboring buildings' residuals. A negative spatial error correlation caused by omitted spatial variables in our model would tell us that the correlation between an average building's own residual and the weighted average of its neighboring buildings' residuals[5] is negative due to some missing spatial predictors that cause this rift. This is a rather unlikely scenario because omitted spatial variables are expected to cause a positive, rather than negative spatial error correlation. For example, an omitted spatial variable that is desirable to retailers, such as a waterfront view, would have the model equally under-predict retail probabilities in all neighboring buildings around that variable, resulting in a positive error correlation. An omitted spatial variable that is undesirable for retailers, on the other hand, such as a high rate of burglaries around a particular location, would have the model equally over-predict retail probabilities in all neighboring buildings around that variable, also producing a positive error correlation between these buildings' own residual and their neighbors' weighted average residual.

A negative spatial error correlation in our model appears to be instead explained by sample differences between buildings with and without retail and food service establishments. Because there are many more buildings without stores than with stores, the weighted average of neighbors' residuals is usually negative. Since buildings that contain stores (where the dependent variable equals one) always produce a positive residual, the correlation between their residuals and their neighbors' residuals is mostly negative. A negative lambda in Model 4 can therefore be explained by the limited sample of buildings that accommodate stores.

The constant term (-5.80 E-02, $p<0.0001$) tells us the average probability of buildings to contain retailers when all other predictors are at their mean. This parameter cannot be interpreted in a useful manner, since in reality we do not find any buildings where all model parameters are centered on the sample-wide mean.

The three Reach predictors, however, are clearly interpretable and tell an interesting story. Figure 2 illustrates a simple diagram to provide intuition for interpreting the positive and negative effects of Reach variables, when controlling for distance, turns, and intersections. Keeping the access radius constant, a hypothetical building i, shown in black, reaches less neighboring built volume on the left and more neighboring built volume on the right. Though Figure 2 suggests that a Reach measure increases as more destinations become available within a given walking radius, we should note that a Reach measure can also increase as the density of uses within each of the destination buildings grows. According to Model 4, Reach to residents is significant and negative (-1.38E-05, $p<0.0001$), while Reach-to-jobs (7.40E-06, $p<0.0001$) and Reach-to-built-volume (5.99E-03, $p<0.0001$) are significant and positive. Retail and food establishments tend to locate in buildings with advantageous access to both jobs and built volume, but at the same time away from locations that reach the highest number of residents in a ten-minute walking radius. The positive effects of jobs and built volume suggest that the likelihood of retail or food establishments increases by 0.0007% as one job is added, or by 0.599% as a million cubic feet (roughly equivalent to

[5] In a 100-meter network radius as shown in the spatial weights matrix W_{100}

100,000 square feet, or 10,000 square meters) of built volume is added in a ten-minute walking radius. Through simple arithmetic we find that that the effect of one job is roughly equivalent to the effect of 1,169 cubic feet of built volume or 116 square feet[6] (11 square meters) of built space, which corresponds intuitively to the average floor area occupied by a single employee. The negative effect of Reach-to-residents and the positive effects of Reach-to-jobs and volume jointly suggest that all retailers as a group tend to follow employment locations rather than homes. Retailers appear to locate in places where the highest number of people can visit them either on the way to, during, or after work, rather than from their homes.

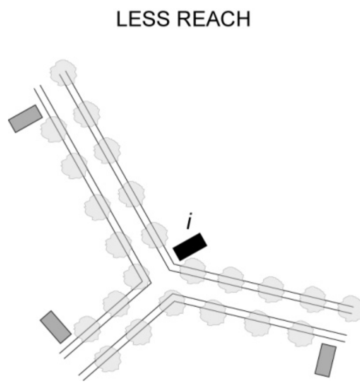


Figure 2 Positive and negative illustrations of a Reach effect, controlling for Distance, Turns, and Intersections Remoteness.

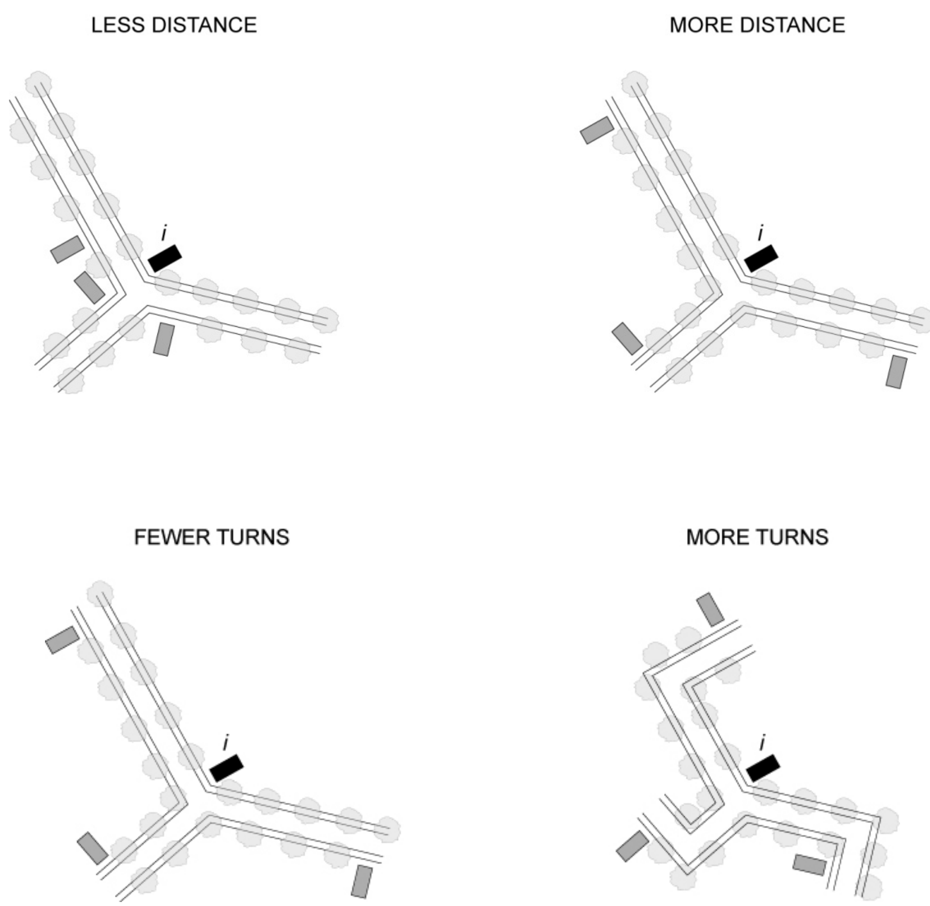
A similar conclusion emerges from the Distance Remoteness coefficients in Model 4. In order to facilitate the interpretation of these controlled coefficients, we also provide a simple illustration of their positive and negative effects in Figure 3. We again show a hypothetical building i in black at the center of the branching roads in the diagram, and illustrate different environmental configurations on the left and right producing lower and higher Remoteness measures for i accordingly. Model 4 suggests that Distance Remoteness to jobs, built volume, and subway stations is negative and highly significant, indicating that as the cumulative distance to these types of destinations in a ten-minute walking radius increases, the likelihood of observing retailers decreases. Each kilometer of distance away from the nearest subway station, for example, decreases retail probabilities by 0.0516% on average ($p<0.1$). Distance Remoteness to residents, however, is positive (3.00E-08, $p<0.0001$), telling that retailing activities increase as we move further from locations that are closest to residents, controlling for the number of residents and other covariates.

Attraction towards subway stations stands out as the only destination type that also exhibits significant effects for Turns Remoteness. The negative coefficient of Turns suggests that retailers tend to locate in buildings that require fewer changes in direction when approaching from subway stations, controlling for distance and other covariates. Each turn away from the nearest subway station along the shortest path decreases retail probabilities by 0.082% ($p<0.1$) on average. Put alternatively, our data

[6] We are assuming an average floor height of ten feet.

indicate that shops and eating establishments generally locate in places that provide good visual connections and cognitively facilitate navigation to/from subway stations.

The Intersections Remoteness measure is significant and positive for subway stations and built volume, indicating that when distance and turns to these destinations are kept constant, then typical retailers choose buildings that require more intersection crossings when arriving from subway stations and neighboring buildings. Each additional intersection crossing to the nearest subway stop increases an average building's retail probability by 0.041%. Each additional intersection crossing to a million cubic feet of built spaces that is reachable in a 10-minute walking range increases a typical building's retail probability by 0.015%, controlling for covariates. In the literature review of Chapter Two (see section 2.3.2) we postulated that intersections crossings might exhibit either negative or positive effects. A negative effect would theoretically suggest that a higher number of street crossings could impose both a time and cognitive cost on access, requiring retail patrons to face a higher number of waiting points and navigational decisions along the way. A positive effect, on the other hand, would corroborate Hill's argument, suggesting that paths with a higher number of intersection crossings offer their users a wider palette of choices to change course. A positive effect also supports Allen Jacobs' proposition that streets with a higher number of intersecting paths signify better accessibility and possibly more pedestrians and pedestrian oriented land uses. Our evidence in Model 4 favors the latter explanations.



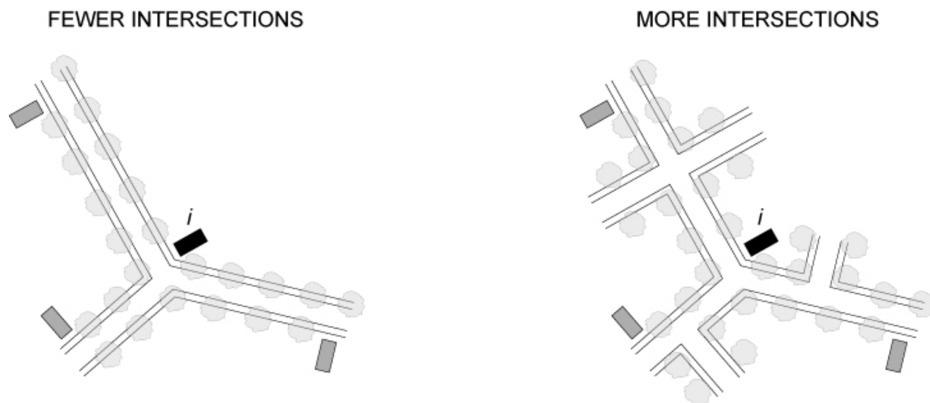


Figure 3 Positive and negative illustrations of the Distance Remoteness, Turns Remoteness, and Intersections Remoteness effects, controlling for covariates in each case.

Taken together, the built volume, residential, jobs, and transit access variables suggest that retailers tend to aggregate at locations that are surrounded by jobs, large amounts of floor area, and transit stations, yet located away from peak residential densities. The negative effects of residents do not suggest a causal relationship, but simply a geographical correlation in our study area. Dense clusters of jobs attract retailers away from residential areas, which in turn seem to reinforce the attractiveness of these locations for jobs. Such circular influence seems to generate distinct zones in Cambridge and Somerville, with building mass, jobs, transit stations and stores agglomerating in bundles, surrounded by large tracts of residential development.

Betweenness values in Model 4 are highly significant and positive, with a high t-value of 11.325 (see sections 2.3.1 and 3.4.2 for a description of Betweenness measures). Let us recall that we have specified the 'betweenness' measure to indicate the fraction of shortest paths between pairs of nodes (street intersections) in the network that pass by building i. Buildings that lie on a higher number of paths obtain higher betweenness values and those that are less frequently passed, lower betweenness values. The strong positive effect in Model 4 indicates that the probability of retailers tends to be significantly higher on streets that lie on a higher number of shortest-path connections between all other streets in Cambridge and Somerville. Figure 4 provides some intuition to interpreting this effect. When building i lies on the shortest path between other destinations in the area (right), then it faces more traffic and higher betweenness values. If it lies off the shortest path connection between other destinations (left), then its betweenness values are lower. Our data show that retail probabilities are significantly higher on streets that have a higher likelihood for passing traffic flow that occurs between other node pairs in the network. The effect is significant even in the presence of control factors for land use destinations, transit stations, and built volume in a ten-minute walking radius, as well as the morphological characteristics of destinations. We thus conclude that the geometry of the street network plays an important role in affecting retail location choices in urban settings.

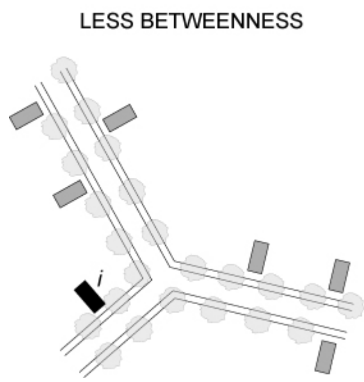


Figure 4 Positive and negative illustrations of the Betweenness measure.

The bottom of Table 4 also presents the estimated effects of morphological destination characteristics. We find that most variables, with the exception of right of way[7], which describe building, parcel, or street characteristics, are significantly related to retail location choices. Retailers in Cambridge and Somerville typically locate in buildings that are lower in height and have a larger ground floor area. The direction of the building height coefficient, which we found to be positive in uncontrolled correlations, has obtained a negative sign in the controlled model. Intuitively, larger footprints and lower heights are also features that seem to characterize common shop buildings in our case study area, illustrated in Figures 6 and 7 of Chapter 2. Table 4 tells us that a 1,000-square-foot increase in the building footprint area increases a typical building's retail probability by 0.207 %. Sidewalk width produces a positive effect (3.02E-03, $p<0.0001$), suggesting that retailers tend to locate in buildings with wider sidewalks at their doorsteps, controlling for covariates. A 10-ft increase in sidewalk width increases an avg. building's retail probability by 3.02%. Road width, which we found to be positive in Pearson's correlations, has a negative (-7.33E-05) but insignificant effect in Model 4. The effect cannot be confirmed at a 95% confidence level. Nevertheless, the direction of the effect is not entirely surprising, since real-estate literature on retailing has long advocated that doubling store fronts on both sides of a street requires that patrons be able to cross the dividing road with ease (Urban Land Institute 2008). Proponents of traditional urban design have also suggested that narrower streets provide a better sense of place and enclosure (Krier and Porphyrios 1984; Jacobs 1993).

The parcel type variable, which captures the number of streets that a parcel can directly access (e.g. while middle parcels typically access a single street, corner parcels access at least two streets) has a highly significant and strong positive effect. Retailers are much more likely to locate in corner parcels, end parcels, through parcels, and island parcels (see section 2.3.2) than the most common middle parcels. This effect has a very high t-value (29.99), suggesting that the relative location of parcels in a city block is truly important for establishment location choices, as previously suggested in Anderson's research on Savannah (Anderson Savannah, 1978). Our data suggest that direct access to an additional street increases a building's likelihood of accommodating retail or food service establishments by 5.27%, controlling for

[7] Street right of way is highly collinear with street width ($r=0.815$, $p<0.0001$). Including both right of way and street width in the model appears to cancel out both effects in Model 2.

covariates. Direct access to more streets means more footfall around the perimeter of a retail establishment, as well as better visibility from different streets.

Finally, Model 4 also exhibits a weak negative effect for family median income, suggesting that wealthier census tracts are less likely to accommodate retail business than census tracts with lower median family incomes. The coefficient suggests that as tract-level family median incomes rise by $10,000, retail probabilities decrease by 4.86%. The coefficient is significant only at a 75% confidence level and should therefore not be taken as conclusive. We can certainly find neighborhoods in Cambridge and Somerville, where both incomes and retail densities are relatively high (e.g. Harvard Square). At the same time, a high percentage of student population in both cities could also explain unusually low family median incomes around some of the most vibrant retail clusters of the towns.

Even though least square statistics are difficult to interpret in a model with binary dependent variable, we should also mention that our R^2 of 16.6% is very high for such data in Model 4.

4.2.1 Summary of findings in aggregate retail location choices

What can we conclude from these findings in the light of the hypotheses set forth at the end of Chapter Two? Our first hypothesis stated that *retail and food establishments in urban settings are spatially attracted to other retail and food establishments, controlling for exogenous location factors*. Since we found the spatial lag parameter rho to be positive and highly significant, we fail to reject the first hypothesis and conclude that retailers in our case study area are indeed spatially attracted to each other, controlling for exogenous location factors. This finding is important in the light of previous retail location studies that have analyzed the effects of spatial accessibility and urban form without controlling for the mutual interdependencies between retailers' location choices. Our results suggest that retailers choose establishment locations strategically with respect to other retailers' location choices. Failing to control for this effect could result in inconsistent parameter estimates for exogenous location factors.

Our second hypothesis in Chapter Two postulated that *Advantages in accessibility that result from favorable proximity to surrounding built volume are positively related to retail location choices, controlling for land use attractions and spatial clustering*. We also fail to reject this hypothesis. The highly significant coefficients for Reach and Distance Remoteness to built volume in Model 4 confirm that the density of built fabric around store locations is positively and significantly related to retail location choices, controlling for land use accessibility, spatial clustering effects, and other covariates. A higher density of built volume, regardless of the particular use mix accommodated in this volume is related to higher densities of retail and food service establishments. We should add, however, that since vacant buildings are a relatively rare sight in Cambridge and Somerville, we should not take this finding *ab absurdo*, and argue that even empty or abandoned buildings attract retailers. Rather, we interpret the effect captured in the Reach and Distance Remoteness measures to built volume as signifying that all occupied buildings, regardless of whether they contain homes, workplaces, or other activities, tend to generate customers for retailers in their neighborhoods.

From an urban design and planning perspective, this finding suggests that manipulating density controls and floor area ratios (FAR) in urban neighborhoods could provide a powerful spatial planning tool for achieving desired retail densities. Gary Hack and his colleagues have suggested a similar idea in their 1996 plan for metropolitan Bangkok, where the researchers argued that "controls over intensity of development are potentially the most powerful way of carrying out the intentions of the new development plan" (BMA Department of City Planning 1996, p.48). Our findings corroborate this view. We would like to emphasize, however, that the way we have measured access to built volume using the Reach and Distance Remoteness metrics, suggests that urban density is influenced by not only the vertical height of a given built fabric, but also the spacing of buildings, as well as the planimetric density of access path that lead to them. The Reach and Remoteness measures illustrate how the density of an area can appear different when seen from each individual building. The plan layout of a neighborhood plays as critical of a role as verticality in affecting how density is perceived from building to building.

The significant effects of Reach and Distance to built volume in the presence of covariates have important implications on the central question of this dissertation — does the geometry of the built environment affect retail location choices? In the diagram of Figure 5 of Chapter 2, we demonstrated how advantageous access near an intersection of multiple street segments can lead to a higher density of retailers at such locations. We proposed that retail densities could rise, in such locations, as a result of exogenous agglomeration, where multiple stores are drawn towards a similar location not because of mutually positive externalities, but rather geometric advantages of a location that can reach a higher number of customers in a given distance range. Both the Reach and Distance Remoteness coefficients to built volume, as well as the Parcel Type coefficient in Model 4 support this proposition. The significance of these measures suggests that the geometry of the built environment is indeed related to retail location choices.

Can we be more specific and untangle which particular characteristics of urban form are responsible for this effect? Let us focus on two different areas of the city of Cambridge in order to provide a practical example. In Figure 5 we have chosen a typical area of western Cambridge, where building footprints and heights and the linear density of building spacing along street segments are relatively uniform. The dominant source of variation, which causes variation in the Reach-to-built volume measure between adjacent buildings, is the relative location of the buildings with respect to the street layout[8]. The observed range in the Reach measure is remarkable: buildings closer to street intersections, particularly intersections where more than four segments meet in close proximity, reach considerably more built volume in the same walking radius than buildings near the midpoints of lengthy street segments. The Reach values in Figure 5 range from 8.3 to 13.6 million cubic feet of built volume, indicating a 40 per cent increase in the most accessible locations. A difference is not unique to only the most accessible intersections, but also notable in smaller scale around other street corners of the area. The horizontally elongated building at the lower right corner along Huron Avenue also happens to accommodate two popular specialty markets in Cambridge: the Formaggio Kitchen and the Fishmonger.

[8] Since Reach is measured in a 600-meter radius, then a series of buildings outside the bounds of Figure 5 also affects the outcome. Small variations in building sizes and spacing are present within and outside of Figure 5, also affecting the outcome, but in magnitudes that are less pronounced.

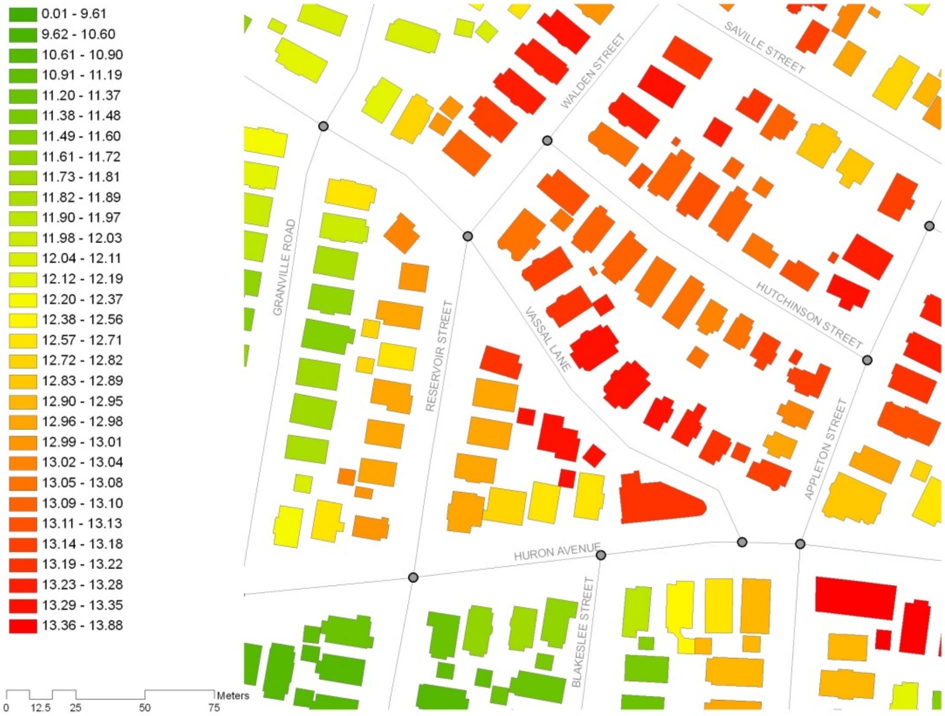


Figure 5 Reach-to-built volume shown in a part of Western Cambridge. The color coding and building titles reflect the number of cubic feet of built space reachable within a 600-meter network radius (in millions), with green shades indicating lower, and red higher values. Values range from 8.3 to 13.6 million cubic feet.

Figure 6 Reach-to-built volume in the Riverside neighborhood of Cambridge. The color coding and building titles reflect the number of cubic feet of built space reachable within a 600-meter network radius (in millions), with green shades indicating lower, and red higher values. Values range from 12.68 to 38.19 million cubic feet.

Figure 6 illustrates a more complex situation, depicting a much larger and diverse urban environment in the Riverside area of Cambridge, an area roughly bounded by Central Square to the east, Harvard Square to the northwest, and the Charles River to the west. Buildings in this popular area of Cambridge vary in footprint sizes, heights, as well as spacing. Variation in the Reach-to-built-volume thus originates from not only the relative location of each building with respect to the street network, but also from the relative differences in footprints, heights, and spacing around each building. We can detect noticeably higher Reach values along Massachusetts Avenue, where typical buildings reach over 30 million cubic feet of neighboring built volume in a 10-minute walking radius. Massachusetts Avenue is not only advantageously positioned in the street network, but it also has a densely spaced building frontage, distinctly larger building footprints and dramatically taller building heights. In concert, these features result in high Reach values to built volume. In the residential neighborhoods along River street and Memorial Drive, on the other hand, some of those advantages are lacking, and we observe a 60 per cent drop in the Reach-to-built-volume values, down to approximately 13 million cubic feet. Even if individual buildings are voluminous on Memorial Drive along the Charles River, they do not reach as many equally voluminous neighboring buildings as their counterparts on Massachusetts Avenue. The overall spatial distribution of the Reach measure in Figure 6 suggests that all three variables — building volumes, building spacing and access to the street network — are jointly advantageous at locations with highest Reach-to-built-volume.

The difference between Figure 6 and Figure 7 leads to an important observation. The plan layout of the street network is the key factor explaining variations in accessibility to built volume in neighborhood scale, where building types are fairly uniform. But building spacing and height are the primary factors explaining variations in the district scale. In Figure 6, variation in the outcome is mainly attributable to the relative position of buildings with respect to the street network, while variation in Figure 7 stems more from differences in the sizes and spacing of buildings. The highest Reach-to-built-volume values in Cambridge and Somerville are found around MIT, University Park, Lechmere, and along Massachusetts Avenue — all areas with distinctively larger building footprints, heights, and denser spacing. Variation continues, however, within each of these areas where the relative position of the building *vis a vis* the street network becomes the primary source of variation.

The reported Reach-to-built-volume coefficient in Model 4 illustrates the average effect across all buildings in our study area. We do not expect the relative position in the street network to have an equal effect on retail location choices in dense and sparse areas of the city. Rather, we expect the effect to be more important in sparser areas and less important in denser areas. Even though the accessibility advantage of a location remains the same in a dense or sparse built fabric, there is usually a tipping point in terms of patronage where a business becomes feasible — a "threshold" as Christaller called it (Christaller and Baskin 1966). We expect this tipping point to be felt more in sparser neighborhoods, where the most advantageous locations might be the only ones to pass the accessibility "threshold" to make a business feasible. In dense areas, on the other hand, the relative location of a building might matter less, as the majority of buildings face enough foot-traffic to pass the "threshold".

The third hypothesis in Chapter Two stated that *Advantages in accessibility that result from favorable proximity to residents, jobs, and transit stations, are also positively related to retail location choices, controlling for urban form and agglomeration effects*. We again fail to reject the hypothesis, affirming that retail location patterns in Cambridge and Somerville are indeed significantly related to the spatial distribution of jobs, residents, and transit stations. Controlling for covariates, we find retailers locating closer to jobs and subway stations, but farther from the centers of gravity of residential density. Access to subway stations stands out in particular, since not only are retail probabilities higher at locations that are closer to a subway stop in terms of distance, but also in terms of the number of turns required along the way. These effects lead us to conclude that a high concentration of jobs is an important attractor of stores and eating establishments.[9] This finding might be partially explained by savings in transportation and time costs that result from linking shopping and eating errands to work trips. We suspect that much of retail demand in our study area might be coming from employment locations either during lunch hours, or on the way home from work.

However, we think that the key to understanding this effect emerges when we look back to the spatial distribution of jobs and residents in our study area in Chapter Three. Figures 15 and 16 in Chapter Three illustrate cumulative distribution of both variables. Whereas residents are almost normally distributed throughout both cities, the job distribution is highly skewed into limited geographic areas. This suggests that most location in the area have relatively decent access to residents. Moving from the mean residential accessibility, where 3,725 people are reached within a ten-minute walk, to the maximum residential accessibility of 7,958, allows retailers to increase residential access by 113%. For jobs, however, the contrast is much bigger. Moving from an average building, which accesses 1,728 jobs, to an area where buildings reach the maximum of 33,837 jobs in the same walking range, increases job access by 1,958 %. Our data thus suggests that by sacrificing some residential access, retailers have a lot to gain by moving closer to jobs in Cambridge and Somerville.

A clear gravitation to jobs and not residents in our study area might also be explained by zoning restrictions in Cambridge and Somerville. As explained in the methodology section of Chapter Three, we do not restrict the location-choice options of our model to currently commercially zoned buildings. The results of our analysis might therefore suggest that zoning could indeed provide an explanation to why retailers are observed commonly around employment locations, and less commonly at location of excellent residential access. We suspect, however, that it is rather unlikely that business interests and zoning regulations are systematically misaligned. Though zoning could certainly play a role in keeping commercial land uses away from residents, we think that an inherent attraction between jobs and retailers is also at stake.

A strong attraction to jobs, transit and built volume, could be unique to shops and eating places in Cambridge and Somerville, where jobs are highly concentrated into limited areas of the two cities. However, in most cities of the world, roughly 80% of all building stock is residential, suggesting that homes are usually much more dispersed than jobs. In cities, where jobs are relatively concentrated, as in our study area, and homes relatively evenly dispersed, we would expect retailers to also gravitate towards the employment agglomerations. In cities where the jobs are evenly scattered throughout, a case that is rather

[9] This finding characterizes an average store across all retail and food service categories. As we shall see in the disaggregated analysis, the results can differ for particular types of retailers.

unlikely given the positive benefits that jobs typically gain from agglomerating, retailers' attraction towards jobs and residents might even out.

The fourth hypothesis proposed that accessibility to surrounding opportunities is important not only in terms of distance, but also in terms of the number of turns and street crossings required to reach the destinations. The results of our analysis suggested that only one type of destination — subway stations — manifests a significant effect for the Turns and Intersections Remoteness variables. Other destinations, including residents, jobs, and built volume, showed no significant effects for impedance metrics other than distance in a controlled regression model. We are therefore left to conclude that Turns and Intersections impedance metrics do not appear as important for retail location choices as distance. We can only partially reject the null hypothesis given that the Turns and Intersections Remoteness effects were uniquely significant for access paths that lead to subway stations. The hypothesis does not hold for employment, residential, and built volume destinations. From a retailer's viewpoint, optimizing an establishment's location choice with respect to a large number of employment destinations, residential destinations, or built volume is a considerably more complex task than optimizing one's location choice with respect to a single nearest subway station. The center of gravity to surrounding land use destinations and built volume can change over time, while subway stations tend to provide more permanent destinations of access.

The estimated effects of several of our predictors (e.g. road width, building height, Distance Remoteness to residents) changed direction when moving from simple Pearson's correlations to controlled spatial lag and error models. Others, such as Turns and Intersections effects, lost their significance in the presence of covariates. Yet other variables, whose coefficients remained significant in the controlled model, changed in magnitude when fitted in a spatial lag and error model. These findings challenge the reliability of location effects that are estimated in simple Pearson's correlations and OLS models used in numerous past location choices studies. They also suggest that the newly available spatial econometric methods used in this dissertation can provide more reliable estimates of environmental, social and economic factors affecting business location choices.

4.3 Disaggregate location choices of different retail and eating establishment categories

The location choice variables analyzed in the previous section have so far addressed all retail and food service establishments in Cambridge and Somerville that fall into NAICS categories 44,45 and 722 as a single group. The unifying feature for grouping these establishments was that they all belong to Weber's exchange category of business activities, where goods of suppliers and the demands of consumers meet in a designated facility (Weber and Friedrich 1929). Retail trade in Cambridge and Somerville is wide and varied, however, with available merchandise ranging from automobiles to liquor, building materials to musical instruments, or Brazilian specialty foods to German books. Capturing the location choice factors of sellers of such different goods as a single group can take us only part way to understanding the specific factors that matter for particular types of retailers. Book stores can serve a very different clientele than food stores. Buying books might be more common, for instance, on weekends, when residents have ample time to walk out of their homes and browse the shelves at different dealers. Food stores, on the other hand, might care to locate conveniently on paths that lead to peoples' homes from work locations. We consequently also expect the preferences for location and access to vary accordingly. Confirming this variation formed the basis for our fifth hypothesis, set forth at the end of Chapter Two.

In order to verify this hypothesis, we shall specify an individual spatial lag +error model for each type of retailer category of interest. We separate the analyzed categories at the three-digit NAICS classification levels. The previously combined group of retail and eating establishments (NAICS 44, 45, 722) thus splits into thirteen individual categories, shown in Table 1 of Chapter Three. Of these thirteen categories only some offer a sample, where the number of buildings containing the corresponding types of stores is large enough for statistical analysis. Our exploratory analysis showed that in categories where less than 50 buildings with appropriate stores were observed, statistically significant findings were not achievable.[10] We therefore retained only the categories where the sample of buildings with corresponding establishments was greater than 50. These eight remaining categories are listed in Table 4.

NAICS	Description	n (buildings)	Moran's I
442	Furniture and Home Furnishings Stores	58	0.027
443	Electronics and Appliance Stores	120	0.0468
445	Food and Beverage Stores	157	0.0338
446	Health and Personal Care Stores	53	0.0407
448	Clothing and Clothing Accessories Stores	90	0.0623
451	Sporting Goods, Hobby, Book, and Music Stores	94	0.0303
453	Miscellaneous Store Retailers	134	0.0357
722	Food Services and Drinking Places	399	0.1353

Table 4 Three-digit NAICS categories used for disaggregate analysis of location choices.

[10] The list of 26 variables we have tried to fit to the models considerably reduces that number of degrees of freedom.

Considerable variation in the number of establishments can be observed even in the selected eight groups. While 399 buildings contain food services and drinking places, health and personal care stores and furniture and home furnishing stores are found in fewer than 60 buildings across the two towns.

As a reference to interpreting the disaggregated results, we also provide a set of maps corresponding to each store category[11], which show the spatial distribution of each type of retailer in red dots, as well as the distribution of all other types of retailers in dark grey dots. These maps, featured on the left side of the page for each retail category, should allow the reader to see where the given types of retailers are located (see red dots), how their location choices relate to competitive retailers (other red dots), and how their location choices relate to complementary retailers of different NAICS categories (gray dots). In the captions of these maps we note the univariate Moran's I index for each retail category. Moran's I, described in section 3.3.1, illustrates the degree of spatial clustering among the dependent variables of each retail category using a 100-meter spatial weights matrix. These Moran's I values are uncontrolled, ignoring the potential effects of other exogenous factors that might explain part of the variation in the observed location patterns. Nevertheless, these indices provide valuable descriptive analyses of each retail category's overall tendency to cluster. Moran's I coefficients for the eight retail categories are also shown in the last column of Table 4.

Food services and drinking places have the highest Moran's I, exhibiting the strongest tendency to cluster with other like establishments (0.1353, $p<0.01$), followed by clothing and clothing accessory stores (0.0623, $p<0.01$), electronics and appliance stores (0.0468, $p<0.01$), and health and personal care stores (0.0407, $p<0.01$). The lowest Moran's I statistics of all thirteen three digit NAICS categories were estimated for general merchandise stores (0.0010, $p<0.01$) and building material and garden equipment dealers (0.0022, $p<0.01$), suggesting that these kinds of stores tend to locate relatively far from similar stores (See Appendix 2). These findings are suggestive, distinguishing categories of stores that seem to value endogenous clustering and others that do not, but we caution such conclusions at this point due to the uncontrolled nature of the indexes. Based on the exploratory analysis, we cannot rule out the possibility that the observed clusters might be attributable to some shared exogenous spatial attractions instead.

Changing the dependent variable from all retailers to one of the selected categories of retailers changes the interpretation of the lag and error coefficients in the model. The rho (ρ) coefficient no longer estimates how the likelihood of establishments in a building is affected by the presence of all retailers in neighboring buildings. Since the dependent variable now only describes whether a building contains a particular type of store, then the spatial lag of the dependent variable simply estimates how the outcome is affected by the spatial distribution of the same dependent variable in neighboring buildings. In a model for food and beverage stores, for instance, rho describes how the presence of other food and beverage stores in neighboring buildings, as specified in the weights matrix, affects the outcome. Rho can thus be interpreted as a coefficient for homogenous clustering, which estimates how stores that operate in the same retail sector locate with respect to each other.

The altered nature of the spatial lag coefficient rho also allows us to introduce a few new accessibility variables into the model. Since rho describes how proximity to other similar types of retailers

[11] The distribution maps for the five remaining categories, which were not selected among the eight, can be found in Appendix 2.

affects the likelihood of a particular store category in a building, then an additional variable, describing how proximity to different types of retailers in a ten-minute walking range, can be used to capture the effects of heterogeneous retail clustering. In the following disaggregated models we thus introduce three new variables describing the Reach, Distance Remoteness, and Turns Remoteness to other types of retailers. [12] The additional Reach measure describes how many retail and food service establishments, other than the NAICS category specified in the dependent variable, lie within a 600-meter radius from each building. The Distance measure to other types of retailers captures the cumulative distance required to reach each of the complementary retail destinations along the shortest paths in the street network. Similarly, the Turns measure estimates the cumulative number of turns required to reach the destinations along the same shortest paths. These three new accessibility metrics to other types of retailers are included in the disaggregate location choice models alongside the previously familiar set of predictors from the aggregate analysis.

Before specifying spatial regression models, we first verified the existence of spatial dependence in both the dependent variable and error term by examining the OLS diagnostics in each individual retail category. The Lagrange Multiplier and the robust LM (Lag) and LM (Error) tests in the OLS models, included in Appendix 3, showed that spatial dependence was significant in both the dependent variable as well as the error terms in each of the selected eight retail categories. The OLS estimates for exogenous location factors in the model are therefore inconsistent. More reliable estimates for the exogenous predictors can instead be obtained from the spatial lag and error models presented in Appendix 4.

Spatial lag and error models for each NAICS three-digit retail category using a full set of predictors are shown in Appendix 4. Several variables, included in these full models exhibit no significant relationships to the outcome, however. Our tests examining each of the predictors individually in Pearson's correlations revealed that some were not related to the outcome even when taken alone, while some lost their significance due to high collinearities with other variables in a controlled model. In order to obtain more reliable estimates for the variables that are significantly related to the outcome in each of the eight retail categories, we reduced the set of predictors in each model, eliminating variables that showed no statistically significant effects at the 75% level, did not improve the model fit, did not appear otherwise substantively necessary as controls[13]. This process of led us to the taxonomy of final fitted reduced models and the results presented in Table 5 and Table 6. Each of these final models contains a unique set of variables that correspond to the specific variations in the data of different retail categories. We shall therefore briefly describe the results of each category individually.

[12] We leave out Intersections Remoteness variables since our exploratory analysis showed that the small sample size of the models made the inclusion of both Turns and Intersections, which are highly collinear, difficult.

[13] As shown in Table 5and Table 6, some insignificant variables were kept as important controls for other effects.

Dependent Variable:	NAICS 442 (n= 58) Furniture & Home Furnishing Stores	NAICS 443 (n= 120) Electronics & Appliance Stores	NAICS 445 (n= 157) Food & Beverage Stores	NAICS 446 (n= 53) Health & Personal Care Stores
Independent Variables:				
rho (ρ)	0.663 *** (4.93)	0.505 *** (8.90)	0.246 *** (2.49)	0.186 * (1.75)
lambda (λ)	-1.38E-06 ***	-6.73E-06 ***	-1.47E-06 ***	-1.35E-07 ***
Constant	-1.10E-04 (-0.07)	-1.94E-02 *** (-8.26)	-9.89E-03 *** (-3.07)	-6.75E-03 (-4.06)
Reach				
Other types of retailers	-1.58E-05 ~ (-1.34)	3.34E-04 *** (4.64)	2.64E-04 *** (2.79)	6.21E-05 *** 3.78
Residents		-6.09E-06 *** (-5.55)	-6.60E-07 (-0.84)	-1.66E-06 *** (-3.30)
Jobs		7.90E-07 ~ (1.29)	2.18E-06 *** (3.15)	1.76E-06 *** (3.70)
Built Volume (in millions of cubic feet)		4.68E-04 (0.95)		-1.12E-04 ~ (-1.40)
Distance Remoteness				
Other types of retailers		-7.90E-07 *** (-4.33)	-6.60E-07 *** (-2.83)	
Nearest Bus Stop			-8.11E-06 ** (-1.96)	
Nearest Subway Stop	-4.60E-07 (-0.95)	1.20E-07 (0.16)		-9.50E-07 ** (-1.90)
Residents				
Jobs		-3.80E-09 *** (-2.55)	-4.19E-09 ** (-2.36)	-4.29E-09 *** (-3.88)
Built Volume (in millions of cubic feet)		3.36E-06 *** (2.94)		
Turns Remoteness				
Other types of retailers				
Nearest Bus Stop				
Nearest Subway Stop			-3.08E-04 ~ (-1.42)	
Residents		2.14E-06 *** (5.05)	4.70E-07 ~ (1.58)	
Jobs			-3.80E-07 * (-1.77)	
Built Volume (in millions of cubic feet)		-5.79E-04 *** (-5.66)		
Betweenness	4.27E-05 *** (4.32)		7.61E-05 *** (5.47)	2.37E-05 *** (3.05)
Destination Characteristics				
Building Height	-1.80E-04 ** (-2.33)	6.95E-04 *** (6.18)	-6.89E-04 *** (-5.61)	
Building footprint area	3.80E-07 *** (8.48)	1.14E-06 *** (17.47)	5.90E-07 *** (8.30)	6.10E-07 *** (14.05)
Sidewalk Width	5.57E-04 *** (3.17)		1.13E-03 *** (3.95)	3.84E-04 ** (2.31)
Road Width	-1.83E-04 *** (-3.50)	1.32E-04 *** (2.36)	-1.35E-04 * (-1.62)	1.11E-04 ** (2.29)
Parcel Type (# of streets the building directly faces: 1-5)	2.95E-03 *** (5.85)	4.71E-03 *** (6.89)	1.33E-02 *** (15.69)	3.20E-03 *** (6.96)
Family Median Income in Census Tract (in tens of thousands)				
Fit Statistics				
R^2	**0.069**	**0.102**	**0.038**	**0.029**

Significance level ~<p<0.25, *p<0.10, **p<0.05, ***p<0.01
Cell etries are coefficients, t-values in parenthesis

Table 5 Spatial Lag and error model parameter estimates for location choice variables of individual three-digit NAICS retail and food establishment categories in Cambridge/Somerville (n 27,023).

Dependent Variable: / Independent Variables:	NAICS 448 (*n*= 90) Clothing & Clothing Accessory Stores		NAICS 451 (*n*= 94) Sporting Goods, Hobby, Book & Music Stores		NAICS 453 (*n*= 134) Miscellaneous Store Retailers		NAICS 722 (*n*= 399) Food Services & Drinking Places	
rho (ρ)	0.680 ***	(6.81)	0.874 ***	(7.88)	0.423 ***	(3.99)	0.512 ***	(9.72)
lambda (λ)	-1.98E-06 ***		-4.74E-06 ***		-3.14E-06		-2.00E-05 ***	
Constant	-7.08E-03	(-3.17)	-6.19E-03 ***	(-3.05)	-9.29E-03 ***	(-3.34)	-3.75E-02 ***	(-7.70)
Reach								
Other types of retailers	4.93E-05 *	(1.77)			4.69E-04 ***	(3.66)	1.38E-03 ***	(5.73)
Residents							-2.09E-06 ***	(-2.92)
Jobs	3.48E-06 ***	(3.91)	1.72E-06 **	(2.15)	1.58E-06 **	(2.30)	3.04E-06 ***	(2.84)
Built Volume (in millions of cubic feet)	-1.81E-04 *	(-1.85)			-9.08E-04 **	-1.98	4.25E-04 **	(2.13)
Distance Remoteness								
Other types of retailers					-1.03E-06 ***	(-3.51)	-3.16E-06 ***	(-5.62)
Nearest Bus Stop	4.99E-06 *	(1.69)					1.03E-05 *	(1.69)
Nearest Subway Stop					-6.60E-07	(-0.84)		
Residents								
Jobs	-1.00E-08 ***	(-3.87)	-3.30E-09 *	(-1.69)	-1.98E-09 ~	(-1.17)	-1.00E-08 ***	(-3.78)
Built Volume (in millions of cubic feet)								
Turns Remoteness								
Other types of retailers								
Nearest Bus Stop								
Nearest Subway Stop							-4.18E-04 ~	(-1.30)
Residents								
Jobs			-2.40E-07 ~	(-1.46)	-5.20E-07 ***	(-2.70)	4.60E-07 ~	(1.44)
Built Volume (in millions of cubic feet)					2.06E-06 *	(1.85)		
Betweenness	5.01E-05 ***	(4.82)	2.06E-05 *	(1.87)	2.75E-05 ***	(2.50)	2.02E-04 ***	(9.55)
Destination Characteristics								
Building Height	-2.06E-04 **	(-2.20)			-2.42E-04 **	(-2.09)	-8.74E-04 ***	(-4.68)
Building footprint area	3.10E-07 ***	(5.83)	4.20E-07 ***	(7.09)	6.60E-07 ***	(9.86)	1.02E-06 ***	(9.41)
Sidewalk Width	8.21E-04 ***	(3.95)	5.04E-04 **	(2.30)			2.32E-03 ***	(5.51)
Road Width	-1.70E-04 ***	(-2.74)	-1.10E-04 *	(-1.65)			-2.27E-04 *	(-1.83)
Parcel Type (# of streets the building directly facces: 1-5)	5.36E-03 ***	(8.73)	3.29E-03 ***	(4.79)	9.02E-03 ***	(12.19)	2.85E-02 ***	(22.97)
Family Median Income in Census Tract (in tens of thousands)	1.35E-04 ~	(1.14)	1.72E-04 ~	(1.35)	2.92E-04 *	(1.99)		
Fit Statistics								
R^2	**0.087**		**0.126**		**0.052**		**0.141**	

Significance level ~<p<0.25, *p<0.10, **p<0.05, ***p<0.01
Cell etries are coefficients, t-values in parenthesis

Table 6 Spatial Lag and error model parameter estimates for location choice variables of individual three-digit NAICS retail and food establishment categories in Cambridge/Somerville (n 27,023).

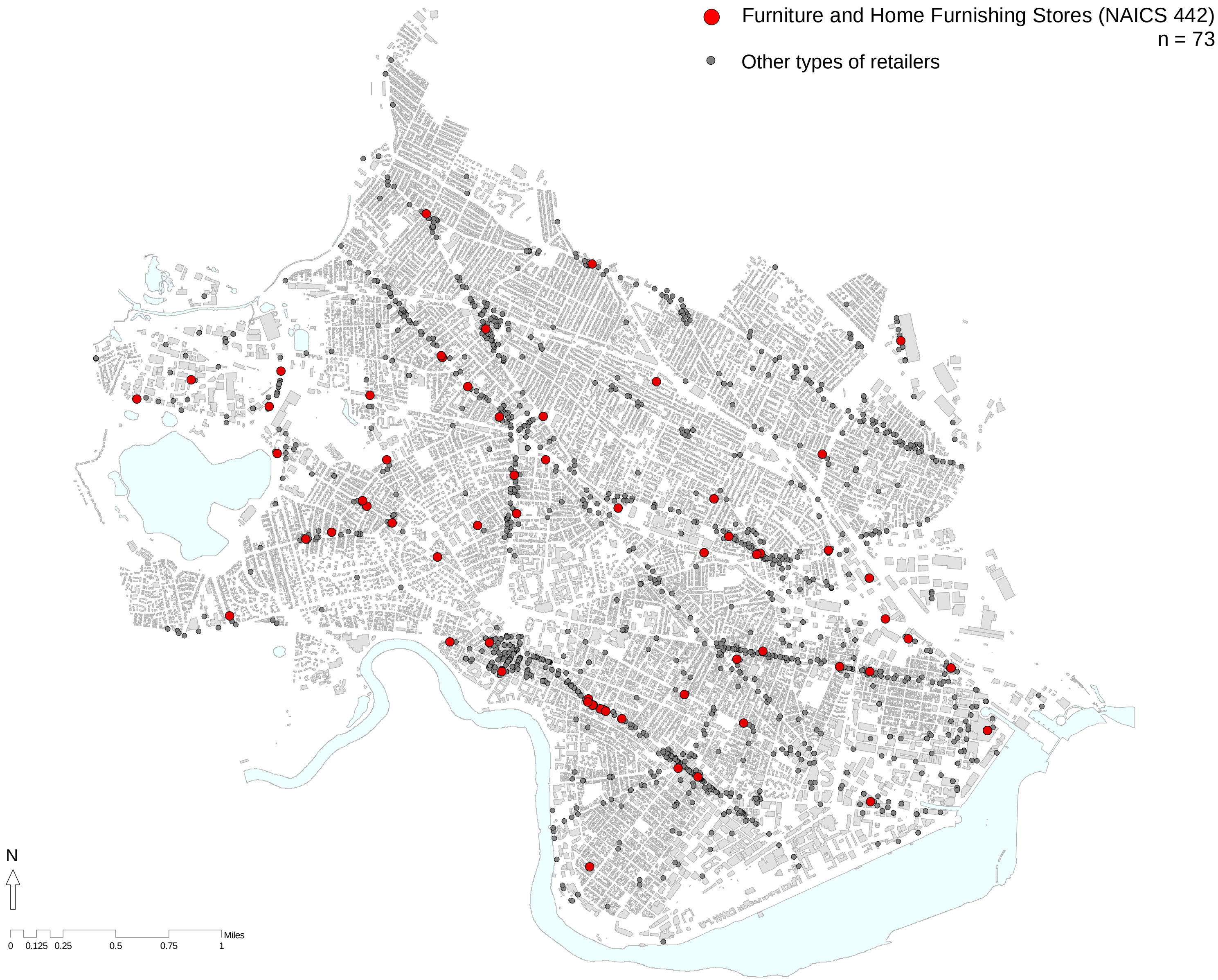


Figure 7 The spatial distribution of furniture and home furnishing stores (NAICS 442) in Cambridge and Somerville, MA. Moran's I = 0.027

4.3.1 Furniture & Home Furnishing Stores (NAICS 442)

Let us start by examining the first model, in which the dependent variable indicates the presence or lack of furniture and home furnishing stores (NAICS 442). The spatial lag coefficient rho is positive and significant (0.663, $p<0.0001$), suggesting that the likelihood of encountering furniture and home furnishing stores is higher in buildings that have more similar stores around them in a 100-meter walking radius, controlling for covariates. Despite the relatively low Moran's I in Table 4, we find that furniture and home furnishing stores do indeed tend to cluster with each other.

The only significant Reach destinations are other types of retailers, which exhibit a negative relationship with the outcome. Controlling for spatial autocorrelation and error correlation, subway access, betweenness, and morphological destination characteristics, furniture stores in Cambridge and Somerville appear to locate farther from other types of retailers.

Distance Remoteness to subway stations is negative, suggesting that, as distance to subway stations increases, the likelihood of encountering furniture stores decreases. The coefficient is not significant at a 75% level, but we include it in the model as a potentially important control factor.

The highly significant betweenness coefficient suggests that furniture and home furnishing stores locate on streets with higher transient traffic potential.

The destination characteristics' coefficients indicate that furniture and home furnishing stores tend to locate in buildings that are lower in height and larger in ground floor area and face streets with wider sidewalks, but narrower roads. The parcel type variable suggests that the stores locate significantly more often in parcels that provide direct access to more than a single street, such as corner parcels, through parcels and so on.

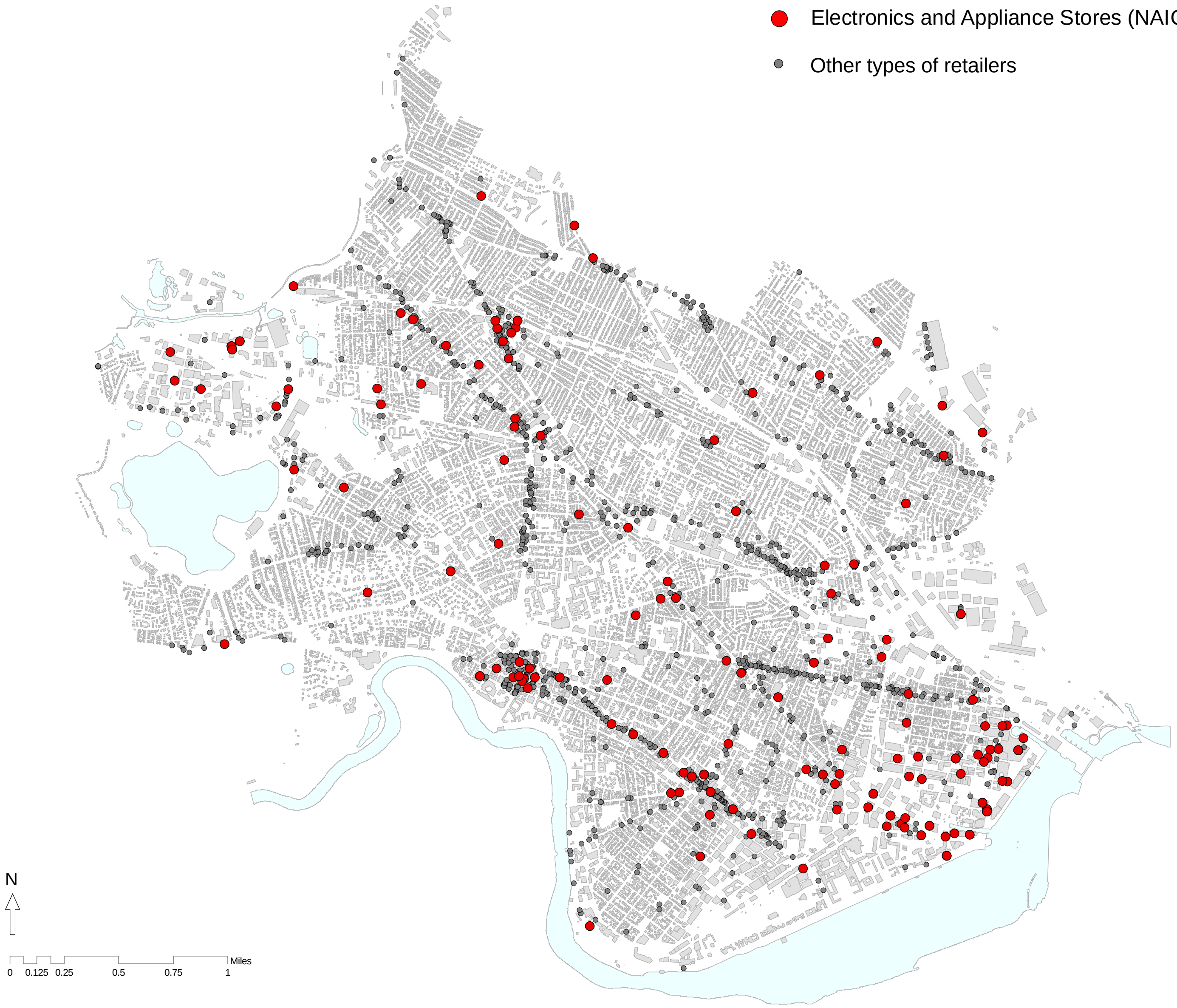


Figure 8 The spatial distribution of electronics and appliance stores (NAICS 443) in Cambridge and Somerville, MA. Moran's I = 0.046.

4.3.2 Electronics & Appliance Stores (NAICS 443)

Results of Table 4 suggest a relatively long list of significant factors for electronics and appliance stores. The spatial clustering coefficient rho is again positive and significant (0.505, t=8.90), with a highly significant t-value, suggesting that electronics and appliance stores too tend to locate near other similar stores, controlling for exogenous location factors.

The Reach measure is highly significant to two types of destinations — other retailers and residents — and also significant at a 75% level to jobs. Electronics and appliance stores tend to locate in buildings that are surrounded by other retailers, yet further away from residential addresses. The Reach-to-jobs coefficient suggests that establishments of this type are also more likely to locate in buildings that are surrounded by more jobs.

The Distance and Turns Remoteness indicators largely corroborate these conclusions. Distance Remoteness is significantly negative to other types of retailers and jobs. Keeping the respective number of destinations constant, electronics and appliance stores are more likely to locate in buildings that are positioned closer to these destinations. Distance Remoteness to built volume is positive, however, suggesting that these stores tend to locate farther away from locations that are closest to all surrounding built volume in a 600-meter walking radius, controlling for covariates. The Turns coefficient to built volume, on the other hand, indicates that electronics and appliance stores do indeed pick locations that require significantly less turns to access from all surrounding buildings, weighted by volume. Turns Remoteness is also significantly positive to residents, making retail probabilities higher in buildings that require more turns to access from surrounding homes.

The betweenness measure has no effect on electronics and appliance stores in the presence of covariates. Passing traffic flow might therefore not be a crucial location choice factor for these types of stores. We suspect that most patrons visit these types of stores on designated trips rather than "drop in" when the stores are conveniently located on the way to other destinations.

The coefficients for destination characteristics suggest that, unlike most other retailers, electronics and appliance stores are more often found on taller buildings and wider streets, controlling for covariates. Sidewalk dimensions appear to have no consequential effect on the location choices of electronics and appliance stores. As for most other categories, parcel type is positive and significant, confirming that better exposure to abutting streets increases that likelihood of encountering electronics stores, controlling for other covariates.

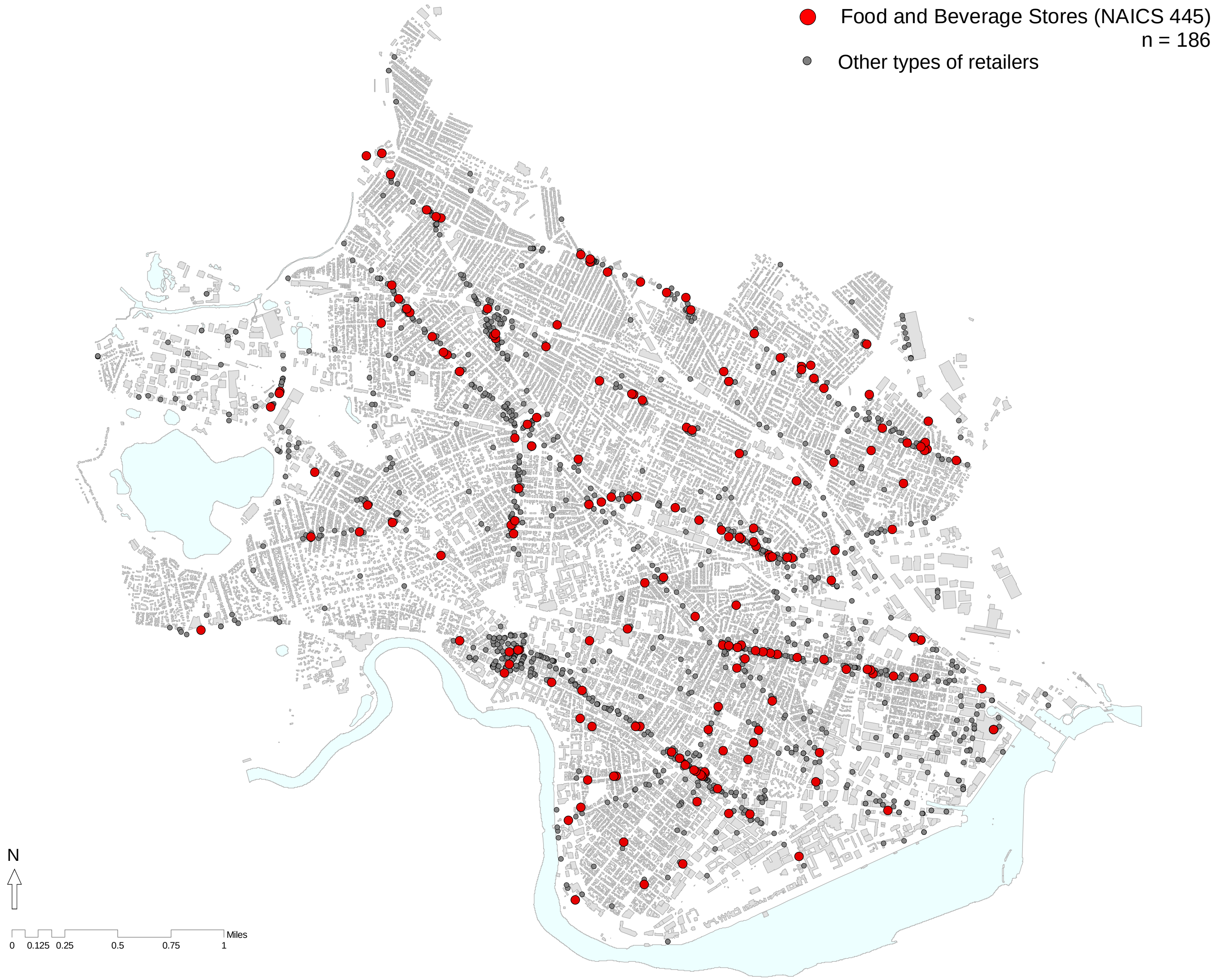


Figure 9 The spatial distribution of food and beverage stores (NAICS 445) in Cambridge and Somerville, MA. Moran's I = 0.033.

4.3.3 Food & beverage stores (NAICS 445)

Food and beverage stores also exhibit a positive and significant rho coefficient, suggesting that the presence of similar neighboring stores in a 100-meter radius has a positive effect on buildings' probabilities to host these types of retailers. The Reach coefficients to other types of retailers and jobs suggest that food and beverage stores also locate in places that are surrounded by larger numbers of complementary stores and more workplaces[14].

Distance Remoteness indicators show that when we keep the number of other types of surrounding retailers and jobs constant, then stores are more likely to locate closer to, rather than farther from, these destinations. Distance Remoteness is also significantly negative for bus stops, suggesting that food and beverage stores value access from buses.

Access from surrounding buildings, regardless of use, and access from subway stations did not produce significant coefficients, even though we do find stores in high density areas and near subway stations (See Figure 9). Since food and beverage stores are numerous and widely distributed across both towns, we suspect that the spatial concentration of subway stations and built volume in limited areas of the towns, renders the overall effect of access to these destinations insignificant, even if they might be locally significant.

Turns Remoteness to subways is significant at a 75% confidence level, suggesting that food and beverage stores do indeed choose to locate in buildings that require fewer turns to access, when coming from subway stations. Visibility and ease of navigation from subway stations therefore seem to be more important criteria for food stores than immediate proximity. The results also suggest that store locations tend to minimize turns to jobs and maximize turns to residents, controlling for the respective numbers of these destinations and other covariates.

The betweenness coefficient is highly significant, suggesting that streets positioned on a higher number of shortest path connections between other surrounding streets in the two cities make higher odds for food and beverage stores.

Destination characteristics suggest that food and beverage stores tend to locate in lower structures, but larger ground floors; on wider sidewalks, but narrower roads; and on parcels that have frontages on more than a single street.

[14] Since we initially expected food and beverage stores to gravitate towards residential locations, we kept the Reach to residents variable in the model as a potentially important control, even though its coefficient is insignificant.

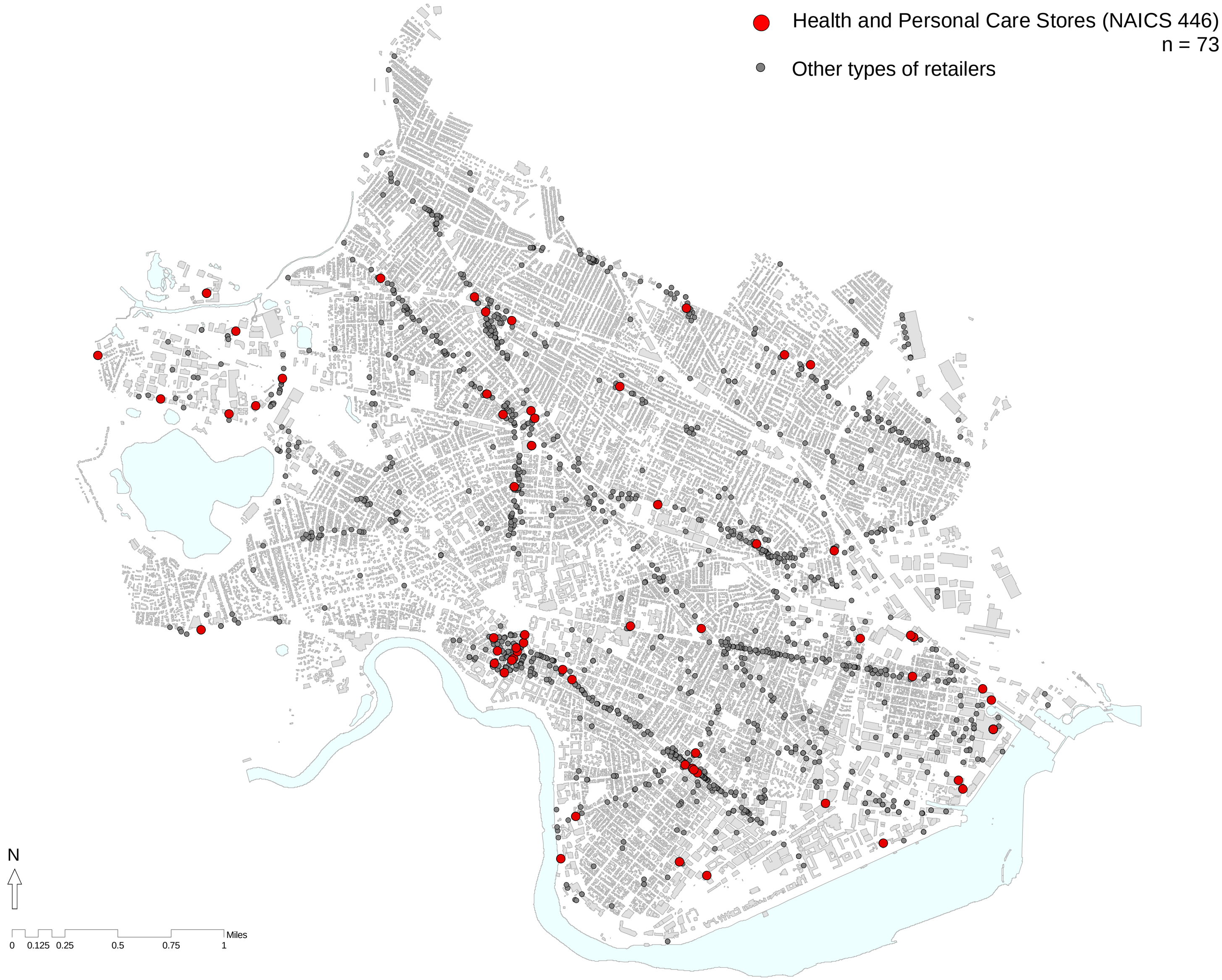


Figure 10 The spatial distribution of health and personal care stores (NAICS 446) in Cambridge and Somerville, MA. Moran's I = 0.0407.

4.3.4 Health & Personal Care Stores (NAICS 446)

Health and personal care stores make an interesting case. While their overall spatial distribution and Moran's I in the map of Figure 10 suggest that they have a relatively strong tendency to cluster, we find that this effect diminishes considerably in a controlled model. The spatial clustering coefficient rho is small and statistically significant only at the 90% confidence level. At the same time, distance to subway stations and jobs has a significantly negative effect. A close examination of the distribution map in Figure 10 suggests that the observed clusters of health and personal care stores occur only around the Central, Harvard, Porter, and Davis subway stations. In other parts of the city, the stores tend to locate at greater distances from each other. This makes intuitive sense, as health care stores commonly offer substitutable products and act as competitors to each other. After controlling for distance to subway and other covariates, much of the clustering effect around subway stations diminishes in rho. The Moran's I index here seems to pick up agglomeration, which is in fact attributable to exogenous location characteristics, like accessibility to subway.

The Reach coefficients indicate that these stores too tend to located in buildings that are surrounded by fewer residents, but more jobs and other types of retailers. The highly significant effect of Reach from other retailers suggests that health and personal care stores value proximity to complementary businesses that provide positive demand externalities.

Street betweenness has a positive effect, as do all the destination characteristics, except for building height, which does not appear to play an important role for health and personal care store location choices.

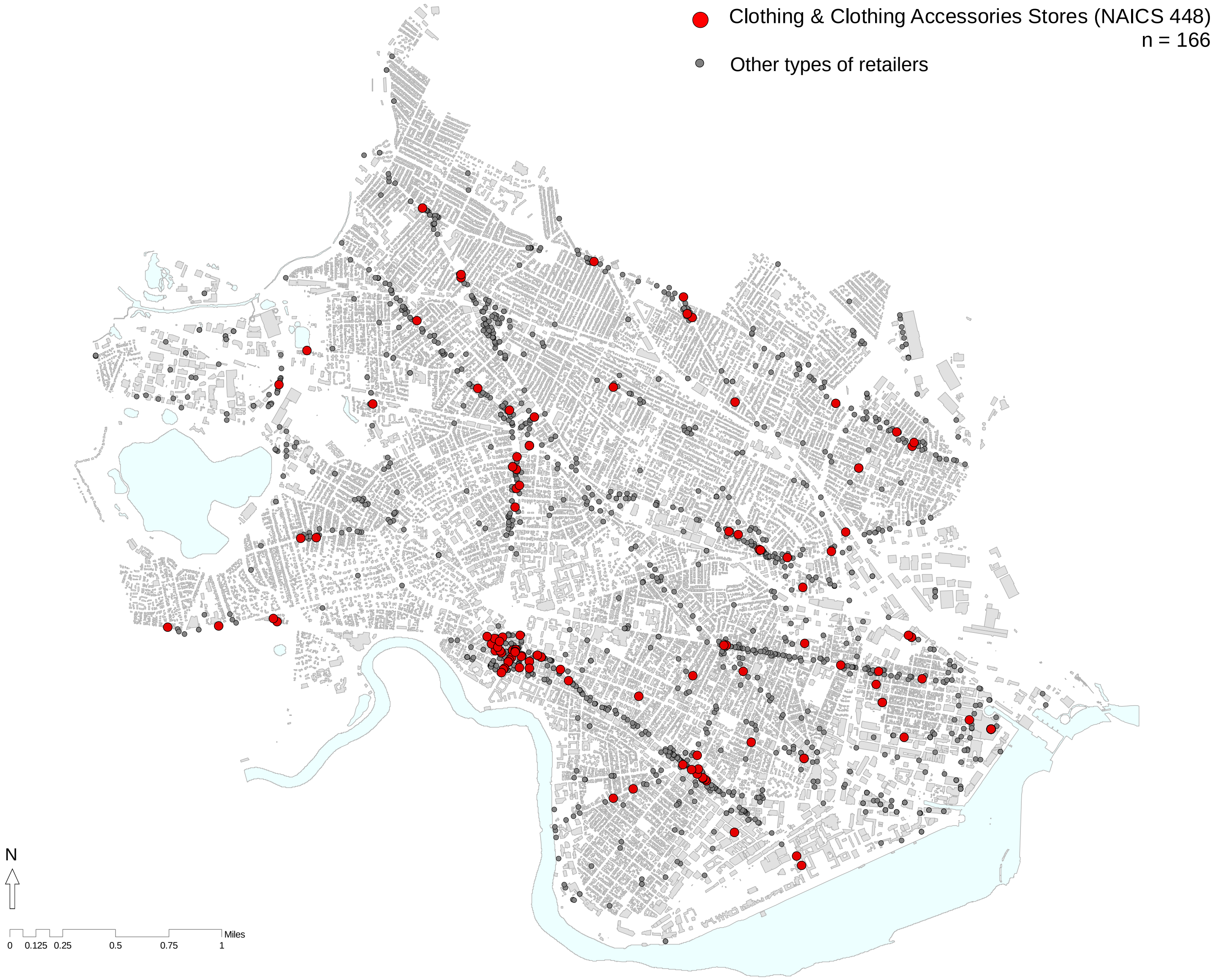


Figure 11 The spatial distribution of clothing and clothing accessory stores (NAICS 448) in Cambridge and Somerville, MA. Moran's I = 0.0623.

4.3.5 Clothing & Clothing Accessory Stores (NAICS 448)[15]

Clothing and clothing accessory stores have a relatively high and significant clustering coefficient rho, even after controlling for covariates. Unlike health and personal care stores, clothing stores do not only appear to cluster around subway stations (though considerable clusters are present around Harvard and Central stations on the map of Figure 11), but also on Massachusetts Avenue between Harvard and Porter subway stations, Union and Ball Square, and other accessible locations in the area.

The Reach metrics suggest that clothing and clothing accessory stores have higher odds to locate in proximity to other types of retailers, as well as jobs, but not necessarily around most building-volume.

After controlling for these Reach effects as well as other covariates, Distance Remoteness yields a significant coefficient only for bus stops, but the direction of the relationship is positive, instead of negative as we expected. Buildings located farther from bus stops have a higher likelihood of accommodating clothing stores, controlling for covariates. Despite the two important clothing store agglomerations at Central and Harvard, Distance Remoteness to subway stations remains insignificant. This might be explained by the general lack of clothing store clusters in the immediate vicinity of other subway stations at Porter, Davis, and Alewife. Distance Remoteness to jobs is highly significant and negative, indicating that clothing and clothing accessory stores tend to locate in buildings that have good access to workplaces.

The betweenness coefficient confirms that clothing stores are also attracted to streets with a high potential for passing traffic. Controlling for betweenness, however, clothing and clothing accessory stores are more commonly found on narrower, rather than wider streets, facing wider sidewalks, and on parcels with exposure to more than a single street.

Family median income, in Table 6, is also significant at a 75% level, suggesting that clothing stores are more common in census tracts with wealthier families.

[15] Different types of stores included in this category are shown in Table 7.

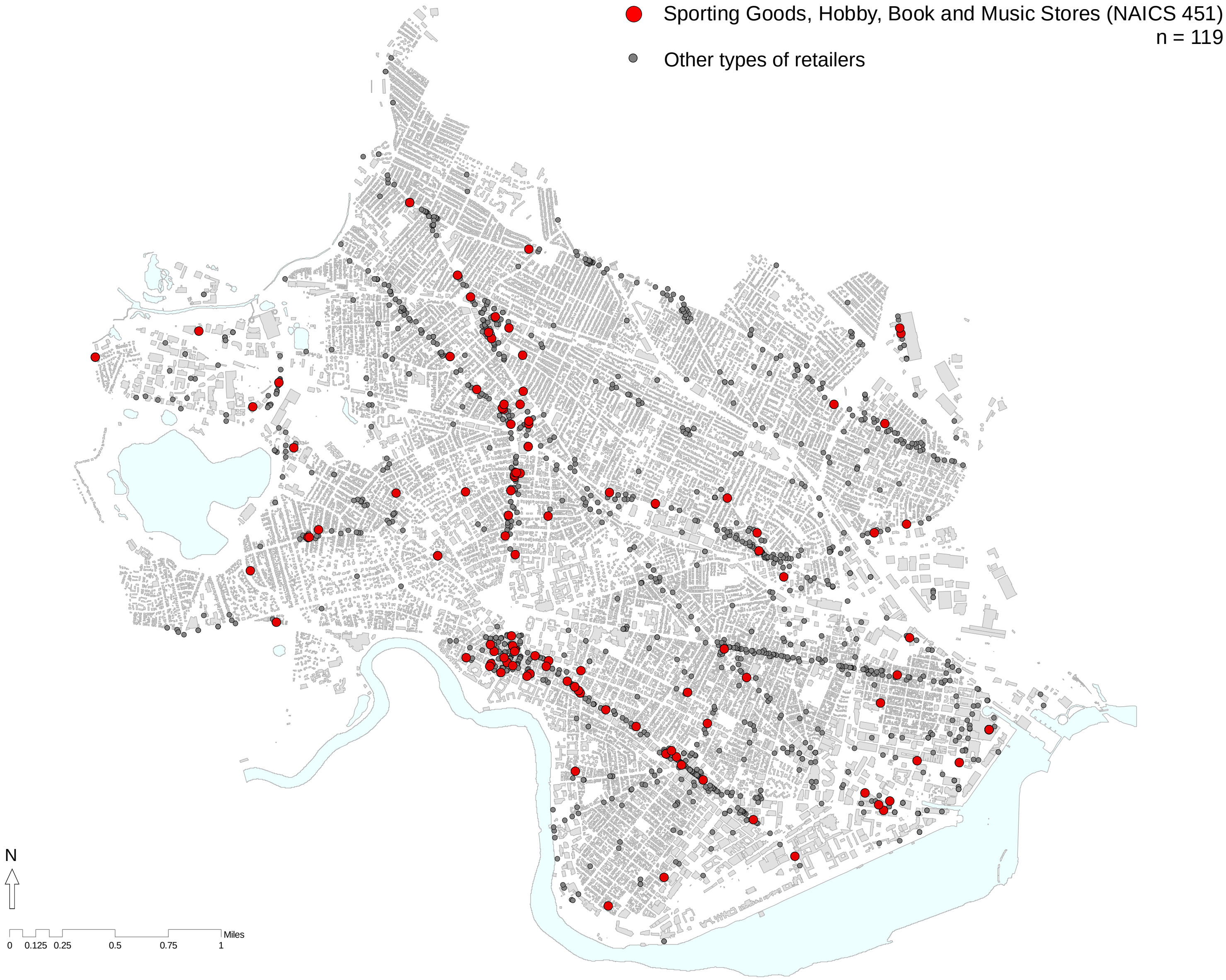


Figure 12 The spatial distribution of sporting goods, hobby, music and book stores (NAICS 451) in Cambridge and Somerville, MA. Moran's I = 0.0303.

4.3.6 Sporting Goods, Hobby, Book, and Music Stores (NAICS 451)

NAICS category 451 stores also have a positive and significant rho coefficient with a rather high t-value (7.88). Sporting goods, hobby, book, and music stores are significantly attracted to other similar stores, controlling for covariates.

The lack of significant Reach and Remoteness coefficients to other types of retailers suggests that NIACS 451 stores exhibit no important attraction towards other types of retailers[16] in the presence of covariates. Though the map in Figure 12 indicates that sporting goods, hobby, book, and music stores do often collocate near other types of retailers, the lag and error model suggests that this might be explained by a common attraction towards other exogenous factors, such as jobs, passing traffic, etc. Indeed the Reach, Distance Remoteness, and Turns Remoteness measures all show significant effects to jobs in expected directions[17].

Building height appears to play no role in these location choices, but building footprint, sidewalk width, and parcel type are all positive and significant as expected. Road width is negative, suggesting that sporting goods, hobby, book, and music stores tend to locate on narrower roads, controlling for covariates.

Median family income is also positive and mildly significant at the 75% level in this category, telling us that sporting goods, hobby, book, and music stores are more frequently found in wealthier areas, ceteris paribus.

[16] The model would not converge when the Reach to other types of retailers was present. We thus leave open the possibility that this could also signal an estimation issue rather than the lack of effect.

[17] Turns Remoteness to jobs is only significant at a 75% level.

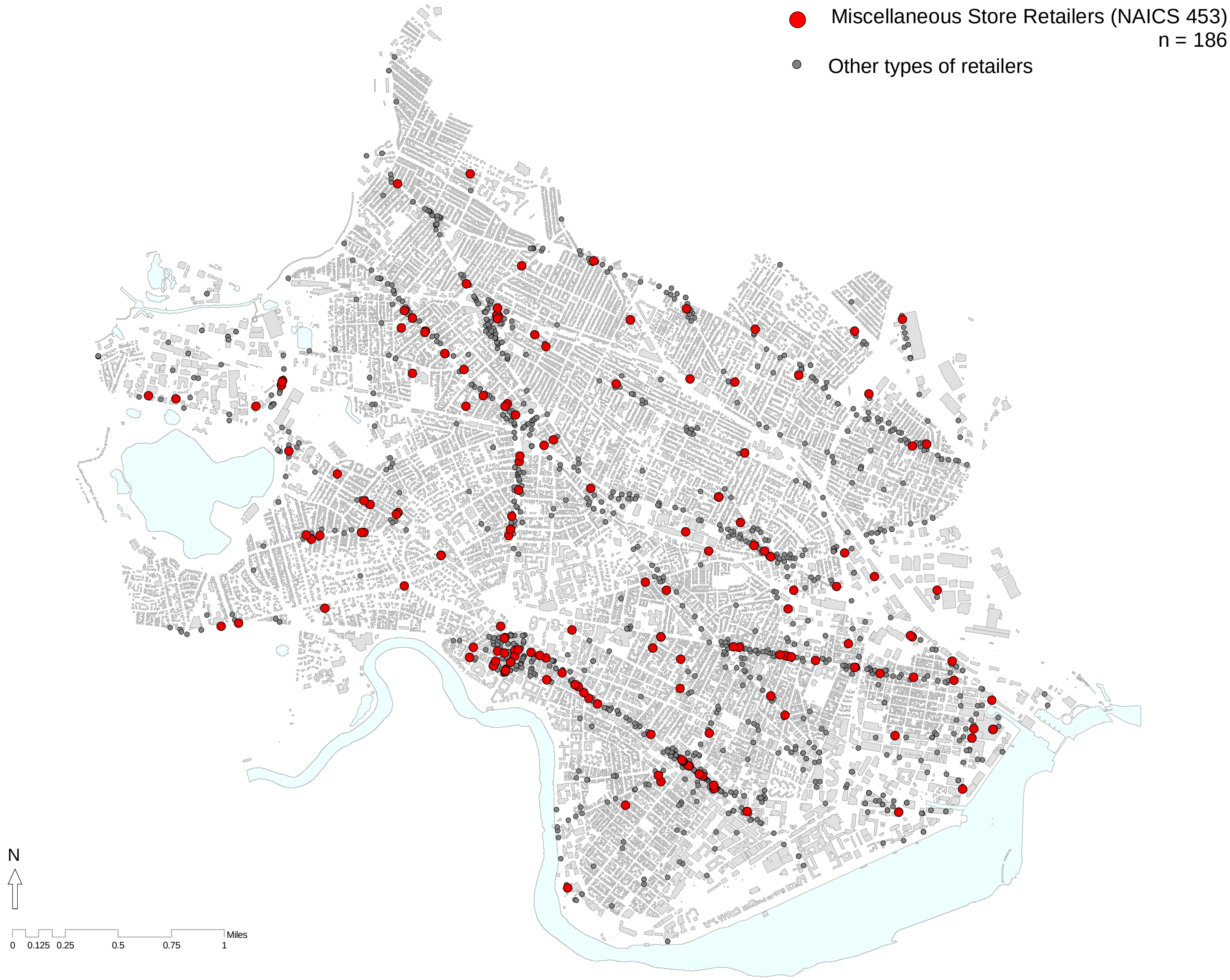


Figure 13 The spatial distribution of miscellaneous store retailers (NAICS 453) in Cambridge and Somerville, MA. Moran's I = 0.0357.

4.3.7 Miscellaneous Store Retailers (NAICS 453)

The results of Table 6 suggest that miscellaneous store retailers[18] are primarily drawn to three types of land use destinations: neighboring miscellaneous store retailers, other types of retailers, and jobs. This conclusion follows both from the rho and Reach parameters, as well as the Distance and Turns Remoteness coefficients. The highly significant and negative Turns Remoteness measure to jobs suggests that the stores tend to locate in buildings that are more visible and easier to navigate to from the surrounding job destinations. Controlling for these effects, however, miscellaneous store retailers tend to locate farther from, rather than closer to, buildings that reach the highest amount of built volume around them.

The effect of Distance Remoteness is also negative for the nearest subway station, suggesting that the odds of encountering miscellaneous store retailers are higher in buildings that are closer to a subway station. The effect is not significant at the 75% confidence level in the presence of covariates, but we include it in the model as a control factor for other variables.

Like most other stores, miscellaneous store retailers are significantly more likely to run a business on streets with higher betweenness values, parcels that are advantageously exposed to surrounding streets, and lower buildings with larger footprints. Their location choices exhibit no significant relationship with road width or sidewalk width.

Miscellaneous store retailers in Cambridge and Somerville are more often found in census tracts with higher median household incomes ($p < 0.1$).

[18] The list of stores that belong to this group with an ambiguous name are given in Table 7.

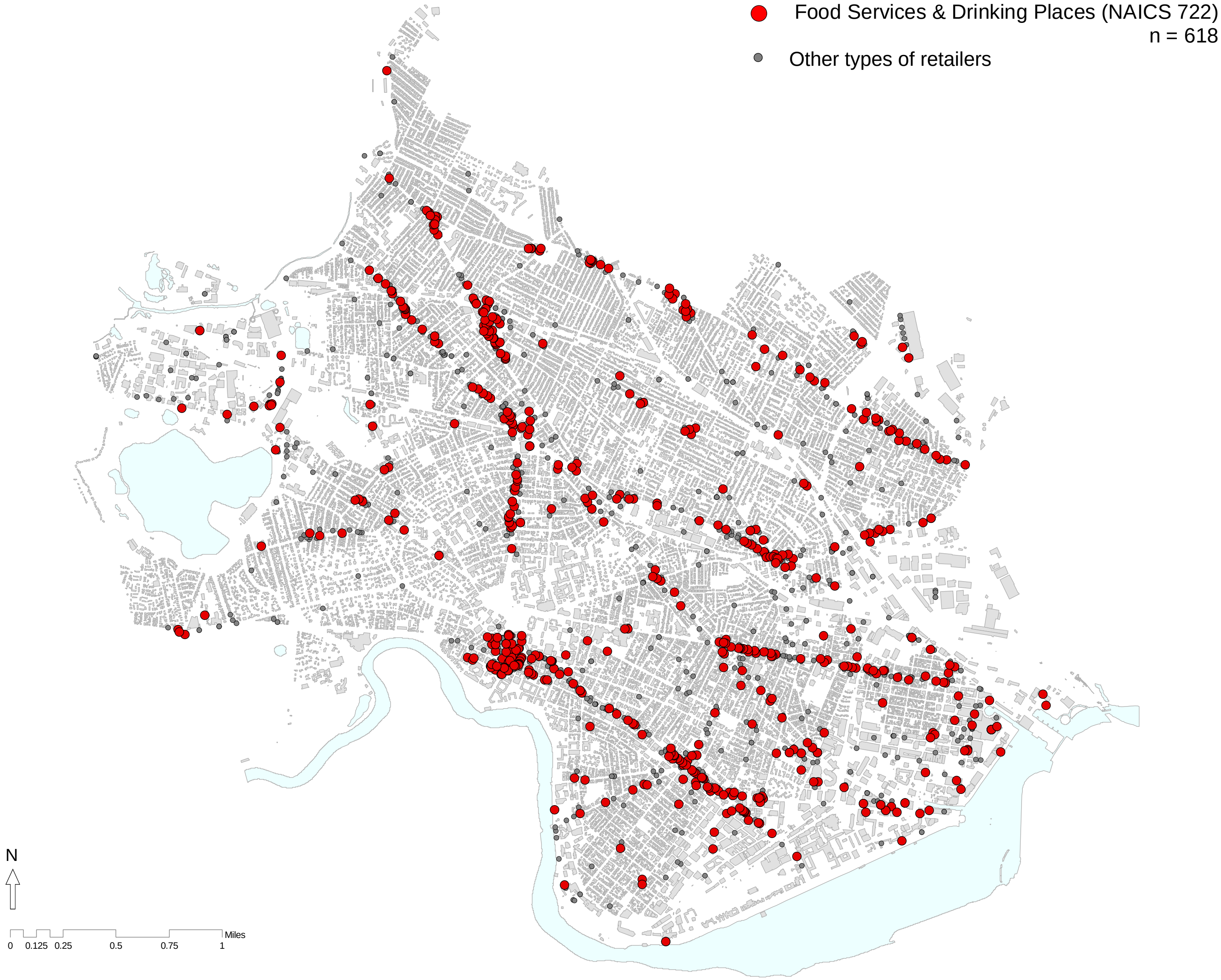


Figure 14 The spatial distribution of food services and drinking places (NAICS 722) in Cambridge and Somerville, MA. Moran's I = 0.1353.

4.3.8 Food services and drinking places (NAICS 722)

Food services and drinking places have the highest number of establishments of all categories (618 establishments in 399 individual buildings). The larger sample size allows the spatial lag and error model to achieve higher t-values and consequently more significant parameter estimates.

The spatial clustering coefficient rho tells us that food services and drinking places are positively attracted to other establishments of the same category (rho=0.512, t=9.72). Restaurants and bars tend to cluster with other restaurants and bars, controlling for exogenous location characteristics. Since various eating and drinking establishments may be considered almost perfect substitutes (i.e. the chances of patronizing more than a single restaurant in a succession are slim), our evidence points to a strong comparison shopping effect, discussed in section 2.2.2. We suspect that a larger choice of adjacent eating establishments gives patrons an opportunity to settle on the choice of establishment last minute, reducing search and costs for customers and thereby attracting a larger clientele.

Eating and drinking establishments are also significantly more likely to locate in buildings that can reach a higher number of other retailers, jobs, and built volume around them, but a lower number of residents. These Reach coefficients suggest that stores tend to agglomerate simultaneously with competitive and complementary establishments. Controlling for these effects, Remoteness to subway stations is insignificant, but distance to bus stops is significant and positive ($p<0.10$), suggesting that restaurants and bars tend to distance themselves from bus stops when all other variables are kept constant. Turns to the nearest subway station are negative and significant at a 75% level, indicating that food services and drinking places tend to retain visible ties with and facilitate navigation from subway stations.

A highly significant betweenness coefficient suggests that they are strongly attracted to streets that are advantageously positioned on shortest-path connections between other streets. The highest t-value among all categories signals that eating and drinking establishments are more sensitive to the potential of passing traffic than most other retailers. Since these establishments are also most numerous, we reckon that a strong attraction towards buildings that are most conveniently passed during other trips is indicative of a vigorous competition for patrons.

The destination characteristics indicators have largely expected effects. Eating and drinking places are more likely to locate in lower buildings with larger footprints, on larger sidewalks, but narrower streets, controlling for covariates. Parcel type has a very high t-value (t=22.97), indicating that immediate exposure to multiple streets is also a strong criterion for location choices in this category.

4.3.9 Summary of disaggregated location choice findings

Each of the eight retail categories we analyzed produced positive and significant spatial clustering coefficients rho. Our findings thus suggest that most three-digit NAICS store categories exhibit a tendency to cluster with other similar stores in uncoordinated urban settings. Health and personal care stores were the only category where the spatial lag coefficient was not significant at the 95% confidence level.

Finding ubiquitously positive spatial lag effects was somewhat unexpected to us, since the review of retail location theory in Chapter Two suggested that similar stores selling competitive products often compete over market area and consequently distance themselves from each other. In contrast, our findings suggest that different degrees of attraction towards similar stores can be found across all eight retail categories we analyzed[19]. What might explain this inconsistency?

We think that one plausible explanation to the largely positive clustering of similar stores in urban settings stems from regulatory differences between shopping malls and an uncoordinated urban retail environment. The majority of previous retail clustering literature, reviewed in Chapter Two, is based on data from shopping malls. The central management model of shopping malls allows mall-owners to restrict entry to the center, keeping out competing stores that would sell substitutable products. This restriction benefits those retailers who are chosen by the mall, allowing them to exercise a certain degree of monopoly power over a given product type inside the mall. This, in turn, increases revenues, giving individual store owners a strong incentive to locate in malls and consequently generates higher percentage rents for mall-owners.

In uncoordinated urban settings no legal regulations restrict competitive stores from entering a cluster. Urban retail agglomerations are thus more open to competition, producing a vigorous contest over quality. Our findings suggest that multiple stores of a similar kind are often found in close proximity, competing over clients by differentiating products, prices, or service. When asked about why apparently competitive stores tend to cluster in a part of our case study area in Somerville, one business owner commented that "the best strategy for gaining market area is to open a shop next to smaller competitors and to provide a better service than others". Though evidence of competitive clustering has also been found in shopping malls (Nevin and Houston 1980; Hise and Kelly 1983; Ingene 1984; Bloch, Ridgeway et al. 1991), our findings suggest that unrestricted store entry in urban settings results in notably higher levels of competitive clustering than previous literature has found.

Another factor explaining the largely positive autoregressive parameters in our models stems from the underlying composition of the analyzed retail categories. Each of the three-digit NAICS categories consists of multiple further subcategories of retail types. Table 7 illustrates how the eight three-digit categories we analyzed consist of 55 six-digit subcategories. Food and beverage stores (NAICS 445), for instance, consist of nine subcategories, including supermarkets, convenience stores, meat markets, seafood

[19] We should note that in one of the categories that we left out from the analysis — General Merchandise Stores (NAICS 452) — we obtained a negative rho coefficient (see Appendix 4).Since general merchandise stores appear to be perfect competitors, then a negative clustering coefficient makes intuitive sense. However, the small sample of such stores did not allow us to confirm the significance of this effect. See the map in Appendix 2 for the spatial distribution of General Merchandise stores.

markets, fruit and vegetable markets, bakeries, and so on. The diversity of these subgroups suggests that the spatial autoregressive coefficient rho in our disaggregated location choice models does not uniquely capture agglomerative effects between perfectly competitive stores. Rather, what appear to be identical stores at the NAICS three-digit level also include some complementary subcategories at the six-digit level. The rho coefficients of meat markets, for instance, capture how location choices are affected not only by other neighboring meat markets, but also by fish markets, liquor stores, bakeries, and so on. The spatial lag in our disaggregated models is therefore not a perfect measure for competitive clustering, since it can also capture some complementary relationships.

Across all models, we also found that individual retail categories are more likely to locate near workplaces than homes. As already suggested in the aggregate analysis in the preceding section, this might reflect both the significant gains in patronage that stores achieve by moving closer to jobs, and nature of shopping trips, where patrons are more likely to visit stores near their jobs than homes.

The Reach-to-built-volume coefficients told us that some categories of stores tend to locate within higher levels of surrounding built volume (e.g. Electronics and Appliance Stores; Food Services and Drinking Places), while others in lower levels of surrounding built volume (e.g. Health and Personal Care Stores; Miscellaneous Store Retailers).

The disaggregated relationships with transit stations were varied. While most Remoteness coefficients that were significant at the 95% confidence level were negative, as expected, we also found some positive effects. Clothing and accessory stores and food services and drinking places, for example, exhibited a positive Distance effect with respect to bus stops, suggesting that these types of stores tend to locate farther away from bus stops in our case study area. At the same time, food services and drinking places also produced a negative Turns coefficient for subways, indicating that they tend to minimize turns from T-stations. Health and personal care stores stood out with the only significant and negative Distance coefficient to subway stations. Encountering these stores is therefore more likely nearer to subway stations.

Betweenness coefficients were also generally positive and significant, except for Electronics and Appliance Stores. Most individual store categories are thus significantly more likely to locate on street segments that have a higher potential for passing traffic. Destination characteristics exhibited similar and expected effects in most for most of the store categories. Direct access to multiple streets, as captured in the Parcel Type variable, is valued positively by all stores. Sidewalk width was also ubiquitously positively related to store probabilities. Road width, however, was negatively related to most stores' probabilities, suggesting that most retail and food service categories locate on narrower rather than wider streets, keeping everything else equal. But furniture and Food and Beverage Stores provided exceptions — these stores are more likely to be found on wider streets. The morphological features of buildings and parcels, as well as streets, are therefore important predictors of retail location choices.

With regard to the fifth hypothesis set at the end of Chapter Two, we can therefore partially reject the Null, and confirm that location choices of retail establishments differ significantly from each other depending on the type of goods sold. The aspects of location choices that did not differ much, include an attraction to jobs and to streets with higher betweenness values, parcels that have direct access to more than a single street segment, larger-than-average building footprints, and generally lower structures.

442	FURNITURE AND HOME FURNISHING STORES	442110	FURNITURE STORES (n= 39)
		442210	FLOOR COVERING STORES (n= 13)
		442291	WINDOW TREATMENT STORES (n= 1)
		442299	ALL OTHER HOME FURNISHING STORES (n= 20)
443	ELECTRONICS AND APPLIANCE STORES	443111	HOUSEHOLD APPLIANCE STORES (n= 11)
		443112	RADIO, TELEVISION, AND OTHER ELECTRONICS STORES (n= 33)
		443120	COMPUTER AND SOFTWARE STORES (n= 142)
		443130	CAMERA AND PHOTOGRAPHIC SUPPLIES STORES (n= 6)
445	FOOD AND BEVERAGE STORES	445110	SUPERMARKETS AND OTHER GROCERY (EXCEPT CONVENIENCE) STORES (n= 64)
		445120	CONVENIENCE STORES (n= 58)
		445210	MEAT MARKETS (n= 2)
		445220	FISH AND SEAFOOD MARKETS (n= 10)
		445230	FRUIT AND VEGETABLE MARKETS (n= 2)
		445291	BAKED GOODS STORES (n= 0)
		445292	CONFECTIONERY AND NUT STORES (n= 3)
		445299	ALL OTHER SPECIALTY FOOD STORES (n= 13)
		445310	BEER, WINE, AND LIQUOR STORES (n= 34)
446	HEALTH AND PERSONAL CARE STORES	446110	PHARMACIES AND DRUG STORES (n= 31)
		446120	COSMETICS, BEAUTY SUPPLIES, AND PERFUME STORES (n= 14)
		446130	OPTICAL GOODS STORES (n= 17)
		446191	FOOD (HEALTH) SUPPLEMENT STORES (n= 7)
		446199	ALL OTHER HEALTH AND PERSONAL CARE STORES (n= 4)
448	CLOTHING AND CLOTHING ACCESSORIES STORES	448110	MEN'S CLOTHING STORES (n= 6)
		448120	WOMEN'S CLOTHING STORES (n= 20)
		448130	CHILDREN'S AND INFANTS' CLOTHING STORES (n= 5)
		448140	FAMILY CLOTHING STORES (n= 57)
		448150	CLOTHING ACCESSORIES STORES (n= 4)
		448190	OTHER CLOTHING STORES (n= 22)
		448210	SHOE STORES (n= 20)
		448310	JEWELRY STORES (n= 30)
		448320	LUGGAGE AND LEATHER GOODS STORES (n= 2)
451	SPORTING GOODS, HOBBY, BOOK, AND MUSIC STORES	451110	SPORTING GOODS STORES (n= 30)
		451120	HOBBY, TOY, AND GAME STORES (n= 15)
		451130	SEWING, NEEDLEWORK, AND PIECE GOODS STORES (n= 6)
		451140	MUSICAL INSTRUMENT AND SUPPLIES STORES (n= 12)
		451211	BOOK STORES (n= 37)
		451212	NEWS DEALERS AND NEWSSTANDS (n= 6)
		451220	PRERECORDED TAPE, COMPACT DISC, AND RECORD STORES (n= 13)
453	MISCELLANEOUS STORE RETAILERS	453110	FLORISTS (n= 30)
		453210	OFFICE SUPPLIES AND STATIONERY STORES (n= 15)
		453220	GIFT, NOVELTY, AND SOUVENIR STORES (n= 38)
		453310	USED MERCHANDISE STORES (n= 37)
		453910	PET AND PET SUPPLIES STORES (n= 8)
		453920	ART DEALERS (n= 19)
		453930	MANUFACTURED (MOBILE) HOME DEALERS (n= 0)
		453991	TOBACCO STORES (n= 4)
		453998	ALL OTHER MISCELLANEOUS STORE RETAILERS (EXCEPT TOBACCO STORES) (n= 35)
722	FOOD SERVICES AND DRINKING PLACES	722110	FULL-SERVICE RESTAURANTS (n= 44)
		722211	LIMITED-SERVICE RESTAURANTS (n= 19)
		722212	CAFETERIAS (n= 15)
		722213	SNACK AND NONALCOHOLIC BEVERAGE BARS (n= 71)
		722310	FOOD SERVICE CONTRACTORS (n= 19)
		722320	CATERERS (n= 27)
		722330	MOBILE FOOD SERVICES (n= 0)
		722410	DRINKING PLACES (ALCOHOLIC BEVERAGES) (n= 23)

Table 7 Subcategories (n=55) of the right three-digit NAICS types used for disaggregate analysis of location choices.

5

Discussion and Conclusions

When urbanist Peter Smithson proposed the term "*the charged void*" he said he was referring to "*architecture's capacity to charge the space around it with energy, which can join up with other energies, define the nature of things that might come, anticipate happenings… a capacity we can feel and act on, but cannot necessarily describe or record*" (Smithson and Smithson 2005). Recognizing this 'charge' that occupies the space between buildings and acts as a source of information for both social and spatial interventions in cities remains one of the central challenges of urban design. Throughout this dissertation we have tried to argue that the '*charged void*' can indeed be described and understood. To move towards this understanding, we collected large amounts of fine-grain data, and ventured into urban economics, configurational studies of the built environment and spatial statistics, probing each of these fields together to produce a whole that is greater than the sum of its parts.

The specific topic we have explored concerns the spatial location choices of retail and eating establishments. Retail location studies in urban settings have been rare in the last decades. Most studies have focused on retail patterns in malls, where data is readily accessible and research welcomed by mall owners. But important differences in the regulatory structure of malls and urban settings shed doubt on the applicability of findings from one setting to the other. Restricted store entry, discriminatory rent contracts, and coordinated management make retail location patterns encountered in malls distinctly different from urban centers. The relatively isolated spatial context of malls also makes tenants less sensitive to numerous exogenous location influences that are omnipresent in urban settings. These differences, coupled with a growing social and political support for dense urban environments, call for new investigations of retail operations in urban settings. This dissertation has taken a step towards that goal.

We have particularly focused on whether and how these establishments' location choices are related to the spatial configuration of the built environment in urban settings. Though the work we have presented is limited in scope, we have argued that a better understanding of retail and food establishments' location choices is essential for designing sustainable urban environments. Controlling for endogenous strategic interaction between retailers and the spatial distribution of land uses, we have demonstrated that the geometry of the built environment exerts a distinct influence on these establishments' location choices, one that has been largely ignored in most previous retail location studies. By setting constraints on accessibility, visibility, and adjacency, the geometry of the built environment produces a rich landscape of information that helps guide opportunities for business from building to building. Understanding this landscape is not only important for producing a better explanation of urban retail patterns, but also essential for informing the practice of urban design.

Our results are specific to Cambridge and Somerville, MA. Studies of other cities could yield different findings, appropriate for different contexts. We have proposed a systematic and replicable methodology that allows a similar analysis to be conducted in different urban settings. This methodology relies on spatial data that can be harvested from many cities' databases as well as free online mapping sources. Though retailing has been our object of analysis, a similar location choice model using detailed spatial accessibility measures and a spatial lag and error model with a binary dependent variable could also be specified for other types of establishments, such as financial institutions, biotechnology companies, design firms, and so on. Our research framework is flexible, and ease of replicability has indeed been an important criterion in our choice of methods.

We have proposed two new types of graph measures — *Reach* and *Remoteness* — to capture qualities of spatial accessibility in urban context at the individual building scale. Two important modifications were proposed to traditional urban graph theory methods. First, instead of limiting ourselves to two elements of representation — links and nodes, representing street segments and street intersections respectively — the graphs we proposed introduced a third element to the picture — buildings. The resulting tripartite graph environment consisting of buildings, nodes, and links allowed us to study not only the planimetric geometry of the urban street network, but also the variable density of buildings and land uses accommodated throughout the network, which has been lacking from most popular urban graph analysis applications to date. The second modification we introduced for urban graph analysis was the addition of a list of attributes to each graph element. These attributes were used to weight the elements according to their properties in accessibility calculations. The attributes of each building, link, and node thus connected the abstract graph elements with the true characteristics of the corresponding buildings, streets, and intersections in a city. The two modifications opened up a series of new and powerful urban accessibility metrics. Diverging from currently popular urban graph measures, they allowed our indices to account for the variable densities and compositions of buildings and land uses throughout a city. A street segment with small single family homes could thus be appropriately differentiated from a street segment with tall apartment buildings. Similarly, access to jobs could be distinguished from access to residents and other types of destinations. These capabilities unite the advantages of the detailed representation of spatial impedance, offered by graph measures, with the detailed representation of destination attributes, offered by land use accessibility measures, producing a more powerful joint platform for urban analysis.

The proposed graph framework also allowed us to compute accessibility indices using multiple impedance measures simultaneously. Calculating access to a location along metrically shortest paths allowed us to collect information about the number of turns, intersections-crossings, or other topological impedance factors along the way. We produced a list of attributes for each computed path, the significance of which could be tested in a statistical model. We addressed the ongoing debate over the primacy of topological accessibility measures (Hillier, Turner et al. 2007) versus the metric accessibility measures (Porta, Crucitti et al. 2005) by comparing the two types of impedance characteristics side by side against a common outcome of retail location choices, in a controlled statistical model. Incorporating both types of impedance measures in our case study of retailers in Cambridge and Somerville, MA allowed us to test whether cognitive aspects of navigation, such as the number of turns on a path, play a significant role in retail location choices, while controlling for distance and other covariates.

Alongside the urban form and land use variables, which we considered exogenous, we also addressed endogenous agglomeration effects, which through externalities between stores, can attract or repel stores to or from other stores, regardless of location. Most previous studies addressing the role of urban form on retail location choices have ignored this strategic co-dependence of retail location choices due to significant methodological complications that appear when location choices are treated as endogenous. The methodology developed in this dissertation overcame this challenge by introducing the strategic interaction framework from regional economics to the context of spatial location choices. Using matrix algebra, the strategic interaction framework takes advantage of recent empirical methods in spatial econometrics to estimate the simultaneous effects of endogenous spatial variables. The framework has been previously applied to estimate strategic interdependency of policy choices between political jurisdictions, such as states, cities, or counties. Using a binary dependent variable to represent the presence or lack of particular establishments in individual buildings, we have demonstrated how the strategic interaction framework can be used in spatial location choice problems. We developed a linear probability model that estimated how retail and food service establishments' location decisions related endogenously to other similar establishments' location decisions and exogenously to the accessibility characteristics around their location. By including a spatial error specification, our methodology also explicitly addressed the commonly ignored hazard of omitted spatial variables in a location choice model. The joint spatial lag and error model was estimated for a large number of buildings (n=27,023) in Cambridge and Somerville, MA, producing significant results for all retail and food service establishments as a group, as well as different NAICS three-digit categories of stores individually.

5.1 Overview of findings

Our findings demonstrated that the number of parameters that storeowners appear to optimize in selecting business locations is remarkable. We have found significant effects in approximately twenty different predictors, but suspect there are many more that we have not tested, which were captured in the error terms of our model.

The findings across all stores as a group showed that retail and food service establishments' location choices are positively related to other retailers' presence in a neighborhood, controlling for covariates. Strategic attraction to other stores is a decisive factor in the location decision of an average retailer. If all neighboring buildings in a 100-meter walking radius contain retail establishments, then the probability of a given building to also accommodate a retailer is 49.1% higher, on average, than in the case where no retailers are found in the same walking radius. The availability of a single store in a 100-meter walking range from a building increases the building's probability to accommodate retailers also by 2% on average[1]. Retail clusters, observed in Cambridge and Somerville, MA, are therefore partially attributable to a mutual attraction between retailers, regardless of location. Failing to account for inter-dependencies in retail location choices could produce unreliable coefficients for exogenous location parameters.

We also found that exogenous land use factors matter. Retailers have a significantly higher likelihood to locate in buildings that are closer to transit stations and reach more jobs in a ten-minute walking range around them. An increase of a thousand jobs in a ten-minute walking range around an average building increases its likelihood of retailing by 7 %. A notable positive attraction towards jobs suggested that much of retail patronage might come from work locations, wither during lunch hours, or on the way home from work. Each kilometer of distance away from the nearest subway station, however, decreases the likelihood of retailing by 0.00516 %,[2] and each turn away from the nearest subway station decreases the likelihood of retailing by 0.082% on average, controlling for covariates.

We found access to residents to be negatively related to retail location choices. An increase of a 1,000 residents around a typical building decreases its likelihood for retailing by 1.36%. Retailers in our study area were therefore not located in places that reach the most residents. We explained this finding by differences in the distribution of workers and residents. While residents were normally distributed throughout our study area, making most buildings relatively well accessible to surrounding residents, jobs were highly concentrated in limited parts of the towns. By gravitating towards jobs, retailers could gain access to a high concentration of patrons at employment locations, while compromising rather little on residents. The negative Reach-to-residents coefficient does not suggest a causal relationship, but rather a geographic correlation in our study area. An agglomeration of jobs attracts retailers away from residential areas, which in turn could reinforce the attractiveness of these locations for jobs. Such circular influence appears to generate distinct zones in our study area, with jobs, transit stations and stores agglomerating in bundles, and surrounded by large areas of residential development.

The negative effect of residential accessibility is also likely to be specific to the fine-grain resolution of our analysis. We suspect that at a coarser resolution of analysis, such as at the census-tract or zip code area level, retailers would indeed appear positively attracted to areas with large aggregate numbers of residents. However an intuitive positive relationship to residents appears to give way to an interesting counter-intuitive dynamic at smaller scale, where retailers tend to cluster near jobs instead of residents.

Controlling for both spatial autocorrelation with other retailers and accessibility to jobs, residents, and transit stations, however, the spatial configuration of urban form around the location of stores also exhibited statistically significant effects. The geometry of the built environment thus plays an important role in affecting retail location patterns. The urban form effects can be broadly categorized into four groups: built volume effects; topological access effects; betweenness effects; and morphological destination effects.

The built volume effect told us that buildings that reach more built floor area in a ten-minute walking range, regardless of the type of occupation of this floor area, were more likely to accommodate

[1] Since an average building has 26 neighbors within a 100-meter reach, then 49.1% divided by 26 ≈ 2%

[2] The relatively low magnitude of the subway coefficient was explained by the fact that there are only six subway stations in our area of study, but many more retail clusters.

stores. Increasing access in a ten-minute radius by 10,000 square meters increased the probability of retailing in an average building by roughly half a percentage point (0.599 %) [3]. We demonstrated that access to built floor area depends on three key variables of urban design. These variables are: the sizes of individual buildings, the spacing of individual buildings, and the geometry of the street network around the location of interest. Manipulating any one of these variables might allow urban designers to influence store density. We concluded that at the neighborhood scale, where building sizes and spacing are often uniform, the relative location of a building with respect to the surrounding street network was the key urban form variable affecting Reach-to-built-volume. Buildings located at places with advantageous access to the surrounding street network, such as corner locations, access significantly more built volume in a 100-meter walking range. The most advantageous locations in a typical Cambridge neighborhood reached approximately 40 per cent more built volume in a ten-minute walking range than the least accessible locations in the same neighborhood. We suggested that in low density environments this variation between the more accessible and less accessible locations in a street network could make or break the minimum threshold of patronage required to operate a business. But we expect this location effect is expected to be less pronounced in high density neighborhoods, where each parcel reaches sufficiently high levels of surrounding floor area to make a business survive.

In district scale, however, the relative differences in building sizes and spacing were key to explaining large differences in the reach-to-built-volume between neighborhoods. While a typical building in a quiet residential area around Fresh Pond in Cambridge reaches roughly five million cubic feet of built volume in a ten-minute walking range, an average building around Kendall Square reaches roughly fifty million cubic feet during the same walk. The tenfold difference in this case is attributable not so much to the relative differences in the street network[4], but rather to the different sizes and spacing of buildings in the two areas — Kendall Square hosts very large structures, spaced close together.

Our evidence suggested that topological characteristics of access paths also affect retail location choices in significant ways. For all retailers as a group, topological access characteristics played a substantial role in accessing subway stations. Controlling for distance and other covariates, we found that buildings are more likely to accommodate retailers if the shortest paths between them and the nearest subway station involve fewer turns, but more intersection crossings. We suggested two possible explanations for these effects. One, originating from cognitive navigation studies suggested that minimizing turns makes paths easier to remember and find and maximizing intersections increases alternative route options along the way, keeping distance constant. The other suggested that locations that require more intersection crossings to access from subways might be preferable, because a higher intersection count might signify better accessibility and therefore more people as well as more pedestrian-friendly activities that retail patrons are attracted to on such paths (Guo 2009). Which explanation prevails will have to remain the subject of future research.

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[3] 10,000 square meters corresponds roughly to a ten-story building with a footprint of 30 x 30 meters (100 x 100 feet).

[4] Note that the relative position in the street network still plays a role, but a less important one. For instance, if we kept building footprints and spacing constant, an average building in the grid of Savannah GA, would consistently reach more neighboring buildings in a given walking radius than a typical building in the grid of Manhattan. This is mainly due to the high density of streets in Savannah's layout.

We also found a strong and positive 'betweenness' effect, suggesting that locations that lie on a higher number of shortest path connections between other locations in the area have significantly higher chances for accommodating stores. The high significance of this effect suggests that retailers are strongly attracted to places that have a higher potential for passing traffic. Such locations tend to be located on Massachusetts Avenue, Somerville Avenue and other centrally located main thoroughfares — streets that Granovetter might call 'strong ties' in the network (Granovetter 1973). A similar effect has been documented in previous research (Porta, Strano et al. 2009), but our results are the first to use a fully controlled model that accounts for other important covariates as well as spatial autocorrelation in the dependent variable, thereby yielding more reliable coefficients.

Last, we found that certain morphological characteristics of buildings, parcels, and streets also significantly affected retail location choices in our study area. Retailers were more likely to locate in buildings that had direct exposure to multiple streets, rather than a single street. Corner parcels, through parcels, end parcels, and island parcels, a classification that we proposed in Chapter Two, were more likely to accommodate retailers than middle parcels. Direct access to an additional street increased a building's likelihood for retailing by roughly five per cent on average, controlling for covariates. A typical 'island' parcel therefore had a 21% higher probability for retailing than a middle parcel. Stores were also more likely to choose buildings with larger ground floor areas and buildings that faced wider sidewalks, controlling for covariates. A 10-foot increase in sidewalk width increased an average building's probability to accommodate retail or food service establishments by 3%. A 1,000-square foot increase in a building's footprint increased its retail or food service probability by 0.2% on average. These findings broadly corroborate earlier morphological propositions, which have suggested that the parceling of private development areas in a certain way can "*…transform an original arbitrary geometry into a structure filled with information*" for retailers (Anderson 1993) .

The analysis of disaggregated retail categories revealed that the effects of spatial accessibility factors varied by type of retailer. We analyzed eight different three-digit NAICS categories of stores, where the sample was greater than 50 in our study area. The attraction towards complementary stores, as well as exogenous land use and transit attractions and built volume, varied significantly between different categories of stores. While most stores tended to locate near other complementary stores, furniture and home furnishing stores provided an exception. Controlling for covariates, these types of stores located farther from, rather than nearer to other stores in our study area[5]. All other stores were significantly more likely to locate near complementary retailers. The Reach coefficients to neighboring complementary stores ranged from 6.21E-05 in the case of Health and Personal Care Stores, to 1.38E-03 in the case of Food Services and Drinking Places, suggesting that the presence of a single complementary store in a ten-minute walking range typically increases a building's probability of containing a health care store by 0.00621% and an eating or drinking establishment by 0.138%. Across all the three-digit NAICS categories that were investigated, however, we found a positive attraction towards jobs.[6]

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[5] The coefficient was significant only at the 75% level.

[6] Furniture and home furnishing stores again offered an exception, where the job coefficient was insignificant.

Contrary to our initial expectations, stores of the same category were also significantly more likely to locate near competing stores of the same category. Though competitive clustering of homogenous stores has been previously found in the context of malls (Nevin and Houston 1980; Hise and Kelly 1983; Ingene 1984; Bloch, Ridgeway et al. 1991), our data suggested that even frequently visited stores, such as food and beverage stores, which rarely cluster in shopping malls, are often found agglomerating with other food and beverage stores in urban settings. The coefficients for spatial autocorrelation ranged from 0.186 in Health and Personal Care Stores[7] to 0.874 in Sporting Goods, Hobby, Music, and Book Stores[8]. The only negative clustering coefficient was found in the category of General Merchandise Stores (NAICS 452), suggesting that these types of stores tend to locate away from one another (see Appendix 4). The coefficient was not statistically significant however, possibly due to the small sample of such stores in our case study area (n=41).

These findings suggested two post-hypotheses for future research. On the one hand we hypothesized that unrestricted store entry in urban retail agglomerations might lead to a more vigorous competition over quality and prices than agglomerations in shopping centers. New entrants can always attempt to challenge existing competitors by opening shop nearby. The retail potential of each location could thus become fully exploited until competition lowers profits to the same level as the next best alternative location. Unlike malls, the agglomerations encountered in urban settings therefore seem to benefit customers by offering price comparison and a wider choice of each type of good in close proximity. From a retailers' perspective, however, the vigorous competition between similar stores, combined with the lack of differential rent contracts between anchor stores and non-anchor stores, disadvantages the more popular stores in urban clusters compared to malls.

On the other hand we also suspected a considerable degree of complementarity among the subcategories of stores that we investigated. The three-digit category of 'Food and Beverage Stores', for instance, contains several complementary subcategories, such as, 'Meat Markets', 'Fish and Seafood Markets', and so on. We leave it for future research to confirm what explains unexpectedly strong clustering of like stores in urban settings.

5.1.1 From correlations to causality

Throughout our analysis of retail location choices we consciously refrained from commenting on causality in the relationships found. Averting causal inference has been largely conditioned by the limitations of the data and methods used in our analysis. A single cross-sectional dataset of retail location patterns in Cambridge and Somerville, MA includes no time dimension, which would be vital for observing causal reactions over time. We cannot tell from the analysis whether retailers follow built density, jobs, and

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[7] Health and Personal Care Stores' rho coefficient was significant only at a 75% level.

[8] Note that the interpretation of these coefficients requires accounting for the number of observed establishments in the respective categories. There are 53 Health and Personal Care Stores and 94 Sporting, Hobby, Music, and Book stores in our study area.

transit stations or the other way around. Addressing causality with rigor will have to remain the subject of future research. However, some speculation might be warranted.

We suspect that the effects of location factors we have addressed — jobs, residents, transit stations, other retailers, and urban form — might involve a considerable degree of circular causality. Exceptions aside, we think it is unlikely that a subway station is clearly an egg and a cluster of stores around it the chicken. Rather, some historic advantage, possibly related to pre-existing retail patterns, probably also led to the selection of the particular location for the subway station. Stores are more likely to locate in places with advantageous exogenous conditions, but the latter are also more likely to develop at a higher rate around the former. Retailers at Harvard Square in Cambridge, for instance, might have been attracted to the land uses, excellent transit access, and advantageous urban form in the area, but the historic patterns of retailing most probably also gave weight to the development of land uses, the construction of the subway, and urban form at Harvard Square. Where might this chain of circular causality begin? What are the basic conditions that lead to clustering at particular locations?

There is a certain hierarchy and order in the traditional process of urban growth. Buildings are rarely erected before circulation paths leading to them are in place. Land use patterns do not take shape before buildings are in place. Transit stations are usually planned in areas that already have a need for them. One is therefore tempted to argue that the network of circulation paths tends to precede all other factors, establishing a landscape of opportunities and information that will influence the subsequent development of built volume and land uses in an area. This is the familiar argument that centers form at the crossing of roads. Our findings provided some backing to this argument, suggesting that locations that are more "between" other locations and those that reach a wider street network in the same walking radius are more likely to accommodate stores. The spatial configuration of urban form thus appears to be an important variable in guiding where centers form and businesses locate.

But one must inevitably confront the fact that circulation paths tend to develop in response to some pre-existing locations of human activity. A path becomes beaten due to routine travel between locations that have already been fixed. The network of circulation routes cannot therefore be a clear 'egg' either. Each environmental intervention is likely to be influenced by pre-existing environmental conditions, but once implemented, the intervention becomes part of the environmental conditions for the subsequent interventions.

Though the causal chain of factors that lead to retail location choices poses a fascinating theoretical paradox, its full resolution might not be so important from a practical point of view. What matters more in the practice of urban design is that we have some understanding of the implications of our own interventions in the built environment. Given that a developer is planning to add ten million square meters of new floor area around a particular location, for instance, a practitioner might desire to know how that intervention would affect the existing retail pattern of the area. Or given that a new store is planned to open, one might like to assess its potential impact on the existing stores. Given a physical plan for an entire new town, one might want to know which locations in the plan are best suited for businesses. In situations where interventions are planned in a pre-existing urban context, the chain of causality thus shrinks to a manageable set of variables, which the research presented in this dissertation, can begin to inform.

Causal inference about specific reactions, such as the ones described above, can be addressed in future research by using longitudinal data and natural experiments. A longitudinal dataset describing the distribution of retailers over time can be used to test whether a distinct change in one of the question predictors is followed by a change in the outcome. A possible experiment of this kind could, for instance, test whether increasing the Reach-to-built-volume in an urban area increases the density of retailers, controlling for covariates. The Reach-to-built-volume could increase when smaller buildings are replaced by larger ones or when new buildings are added to an existing context. Alternatively, an addition of segments in a street network could also lead to an increase of Reach-to-surrounding-built-volume. Since street networks tend to evolve very slowly, the test could rely on a natural experiment using historic data.[9] Closing of old railway lines, for example, often leads to the opening up of cross streets that introduce significant changes to the connectivity of surrounding locations. Similarly, the addition of a bridge or tunnel could change the accessibility of a location rather abruptly. Observing sudden changes in any of these factors, while simultaneously controlling for covariates, could allow an analyst to test for causal reactions in retail density over time. From an agglomeration point of view, a natural experiment could test whether an addition of new stores to a previously underused part of town would lead to a natural gravitation of other stores to the cluster. Similarly, a relatively sudden increase in jobs or transit access can be used as natural experiments for detecting causal reaction in retail location choices over time.

5.1.2 Methodological Improvements

Working on our case study of Cambridge and Somerville, MA revealed several directions for future methodological improvements. Some of these directions were already mentioned in Chapter Three, but we shall briefly summarize and expand them below.

One methodologically important question that emerged from our results concerns the classification of competitive retailers. Our use of disaggregated three-digit NAICS categories revealed a considerable degree of complementarity between subcategories of stores. The six-digit NAICS categories offer a finer classification of competitors than a three-digit classification. However, a six-digit category, such as a baked goods store, might include a cupcake store, a candy store, a pie shop, or a cookie store, which are also somewhat complementary to each other, though probably to a lesser degree. Hotelling's principle of minimum differentiation (see section 2.2.2) has suggested that even minor differences between otherwise identical sellers can lead to significant perceived differences in customer's minds. Developing a more precise definition of competitive retailers could thus be an important theoretical task in future retail location studies.

The spatial weights matrix used in our strategic interaction model reflected the spatial adjacency conditions in 2009, not necessarily the conditions that characterized the retail environment at the time when location choices of the observed retailers individually occurred. In order to accurately represent the

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[9] Desyllas has, for instance, analyze the street network of Berlin during and after the dividing wall (Desyllas, J. (2000). The relationship between urban street configuration and office rent patterns in Berlin. Architecture. London, University College London. **PhD:** 345.

true adjacency conditions when each of the location choices historically occurred, the weights would need to be specified individually for every establishment according to the situation at the time of each location choice. Two adjacent retailers, which appear as reciprocal neighbors today, probably chose their locations at different times. Since the first arrived before the second, the second should not be considered a neighbor to the first, but the first should indeed be considered a neighbor to the second. We remain hopeful that future extensions of this study will be able to assemble records that illustrate historic conditions of the retail location pattern over time. Time-specific adjacency relationships will also lead to an asymmetric spatial weights matrix, posing significant technical issues for solving the model. However, the latest HAC estimator used in GeoDa and PySal software offers an efficient algorithm that can handle asymmetric weights (Anselin and Rey 2007). Future specifications of a location choice model could take advantage of the opportunity to depict true adjacency conditions at the time of each location choice, leading to more reliable estimated model parameters.

The spatial lag specification that was used in this dissertation also did not weight the neighbor relationships in the spatial weights matrix by distance. Instead, all buildings that were reachable in a 100-meter distance band were weighted equally as neighbors. Econometric methods allowing neighbors to be weighted by distance, so that nearer neighbors obtain greater significance than further neighbors, are now becoming available in Luc Anselin's and Sergio Rey's work on PySal (Anselin and Rey 2007). Future estimation of analogous location choice models should take advantage of this development.

We have already talked at length about the potential shortcomings of using a linear model with a binary dependent variable in section 3.4.4.1. Unfortunately, no probit or logit type models are readily available to estimate spatial lag and error models at the present time. We remain hopeful that future location-choice research will be able to utilize a more appropriate logit or probit model. This will depend on the development of spatial econometric methods in the coming years.

From a more substantive perspective, there is also ample room for improvement in the spatial accessibility measures used in this dissertation. Following currently popular conventions, all our accessibility indices were measured along a single metrically shortest path between two locations in the graph. In order to better reflect the true pedestrian path choice options, accessibility could instead be measured along all "plausible" paths (See Figure 15 in section 2.3.2). The "plausible" paths could contain all paths between two locations that remain within a twenty per cent distance threshold from the shortest path. Previous research on pedestrian travel behavior has shown that choosing paths that are roughly twenty per cent longer than the shortest path is common among urban walkers. The inclusion of all "plausible" paths in the accessibility calculations would lead to a more reliable description of a location from a pedestrian point of view.

The description of a location's accessibility can also improve by including additional cognitive measures of access in a model. The impedance measures we used to describe access to a location included metric distance, turns, and intersection crossings of paths. These measures can be collected from maps with relatively little effort. Future research could complement these metrics by additionally accounting for the establishments passed along the way, for instance (Guo 2009). This would enable one to verify whether a positive attraction towards routes with a higher density of intersections, found in our results, is explained by an attraction towards pedestrian-friendly land uses on these routes, by greater navigational options, or both. An addition of a 'visibility' metric could also benefit a future analysis. Though destination visibility was implicitly embedded in some of the accessibility measures used in this dissertation (e.g. Turns Remoteness, Parcel Type), a more explicit measure could be proposed in future research. Such a measure could for example quantify the percentage of path length at which a destination becomes visible when approaching from all surrounding origins.

Future specifications of the betweenness measure could experiment with measuring betweenness more accurately between buildings, rather than street intersections. Choosing buildings as origins and destinations of the measure would allow the calculated shortest paths to be weighted by building volume, producing a more reliable representation of the spatial distribution of potential trips in the network. Though this specification is currently quite taxing on computation power even in moderate-size networks[10], such as the one used in our study area, we are confident that it will soon become feasible as computation power grows.

Finally, future extensions of this research would also benefit from adding other means of transportation than walking to the analysis. Despite the current technical barriers of computer power and memory, we think that spatial accessibility measures in future work will be able to account for all available transportation modes around each location of interest, not just walking. Adding private automobile, public transit, bicycle, and taxicab accessibility measures to the analysis could eventually produce a more holistic and realistic description of transportation opportunities in urban settings. Instead of specifying a distance radius for accessibility, the radius could instead be defined in terms of time (e.g. a ten minute access radius on all transportation modes). We hope to move towards this goal in the near future.

5.1.3 Technical improvements

The increasing availability of spatial data describing both the transient activity patterns of citizens and the more permanent physical pattern of cities, coupled with continuously improving computational tools, suggests that urban spatial analysis can grow in breadth and depth in the years ahead. Historic deficiencies in fine-grain urban data collection are already being reversed by electronic databases and digital communication technology. Computer applications capable of analyzing large amounts of spatial data are growing exponentially as the scholars of the city learn about programming and programmers learn about the city. Spatial econometric methods are evolving fast as open-source software allows thousands of users to test and improve new estimation routines. Though these developments do not always overlap in the same labs or research projects, they collectively suggest that urban spatial analysis offers unprecedented opportunities to better understand the relationships between the social and spatial processes of a city.

The key data requirements we have relied on consist of a) a description of activities accommodated in buildings, b) a description of building sizes, c) locations of transit stations, and d) a description of the street network. Though we have used buildings as our spatial units of analysis, it would also be possible to

[10] The author used a Mac Pro desktop computer with eight 2GH Intel processors, 2GB of RAM, and the OS Windows XP.

use other units, such as city blocks or street segments. Each of the variables describing establishments, land uses, building volume etc. could, in this case, be aggregated to the block or street level accordingly.

In cities where official establishment distribution and land use data are not available, user generated data from online sources could be used instead. Online mapping sources, such as Google Earth, Yellow Pages, Bing, and Yahoo among others, can be used to automatically compile a list of various businesses in a city, including their accurate location coordinates. We have already started an effort towards automating the process of online business location information harvesting for such a purpose in the MIT-Portugal program. Should the available online maps prove to be too unreliable or inaccurate for analysis, then data could also be gathered by surveying a moderate sample of local residents. An analyst could ask respondents to mark establishment locations, building heights, transit stations, and other useful information on a digital map whose attributes can be readily converted into tables or GIS or CAD layers. Tapping into user-generated and online geographic information sources allows fine-grain urban location choice studies, analogous to the one presented in this dissertation, to be replicated in cities in different parts of the world.

5.1.4 Conclusion

Cities are the arenas where the future of human development will unfold in this century and probably beyond. The United Nations projects that between 1.6 and 2.1 billion people will be added to cities around the world by 2030 (UN-HABITAT 2006; UNFPA 2007).[11] China alone is projected to accommodate an additional 318 million inhabitants in cities by 2030 (UNFPA 2007). This translates roughly to building all the current cities of the U.S. within twenty years. So great is this global rate of urbanization that, taken together, it will add a million people to cities around the world every five days between now and 2030.

These developments place high expectations on urban designers and planners around the world. The breadth of issues involved with cities demands that planners' expertise span across disciplinary boundaries, involving economics and sociology, environmental studies and transportation, sanitation and public health, education and culture, finance and management among others. These important areas of planning usually deploy social and economic development instruments and other policy delivery mechanisms to improve life in cities. However, the success of policies depends in part on where they are implemented, and whether the built environment that accommodates them facilitates or thwarts their effectiveness. The application of economic, environmental and social policies in the physical structure of the city thus links each of these fields intricately to urban design. Understanding how the physical environment affects, and desirably benefits these and other diverse facets of urban life, constitutes an interesting agenda for further research, as well as an important goal for creating more functional, beautiful, prosperous, equitable, sustainable, and healthy cities.

[11] UNFPA projects an addition of 1.6 billion urbanites between 2008 - 2030. UN-Habitat projects an additional 2.1 billion urbanites between 2000 - 2030.

Throughout this dissertation we have argued that physical configuration of a city offers ample data for improving our understanding of the processes that unfold therein. Rather than trying to exert increasing control over urban form and land use development in cities, we think it is more important that planners understand the mechanics that underlie urban growth and change, and learn to intervene strategically. The urban population is inventive and clever. There is little doubt that it will produce solutions that best satisfy its needs under given circumstances, and developing neighborhoods with vibrant retail activities is no exception. As urban designers, we therefore need not worry so much about planning new retail and service establishments, as we do about understanding which conditions allow these land uses to emerge and thrive on their own. There are tremendous energies in cities to generate desirable urban environments. The designers' challenge will be to recognize and harness these energies. This dissertation has provided a methodology that can help planners and urban designers address this challenge.

Perhaps most important is that the different professionals engaged in the process of urban development share a common language in talking about the built environment. For urban designers it is essential to be able to demonstrate and communicate the value of spatial planning to representatives of different professions. For economists it is important to describe the effects of spatial configuration with clarity and precision. For city governments it is imperative to articulate the advantages of different development options with lucidity. Discussion of the spatial configuration of the built environment creeps into every one of these domains and the ability to describe the subject clearly across disciplines is vital for advancing common goals. The descriptive framework used for depicting the urban spatial configuration in this dissertation has taken a step towards establishing a common language on urban form and land use distribution. The critical elements of this language consist of a) a simple spatial framework of representation, b) intuitive and clearly interpretable measures that can be applied on this framework, and c) a flexible numeric representation of outcomes that can be incorporated into different analysis methods. A conceptually important particularity of this language is its simultaneous focus on both paths and places. The built environment of a city consists of a network of paths — streets, which constrain and guide all urban movement and shape our understanding of urban structure. Each path, at the same time, is more than simply a transient space — a path is made up of individual places. The joint representation of path and place has allowed our description of the built environment to focus simultaneously on its physical structure and its patterns of use. Though far from sufficient, this language has allowed us to bridge an economic analysis of location choices with a configurational study of the built environment.

Beyond the scope of this dissertation, we think that the methods of study that were developed suggest that the relationship between the physical form of a city and its quality as a host to human activities is pregnant with opportunities for further investigations. Not only did we find plentiful room for improving the analysis of retail location choices, but we also became convinced that addressing other important relationships between urban form and social processes with methodological rigor could lead to numerous exciting paths for understanding and designing vibrant urban environments. It is time for urban designers to take advantage of these opportunities and carry the field into a constant cross-disciplinary dialogue with other fields of urban studies, allowing the design of cities around the world to benefit from the best available knowledge in each context.

Appendix 1

1. Open (or create a new) network dataset (ND) in ArcCatalog
2. Riht-Click / Properties / Attributes / Add (when creating a new ND, the default settings will automatically generate a length attribute)
3. Make it a Cost Attribute / Unknown Units / Integer
4. Go to Evaluators / Default Values
5. Element "Turn" / Type "VB Script" / Default --Click Evaluator Properties
5. Enter the following VB script:

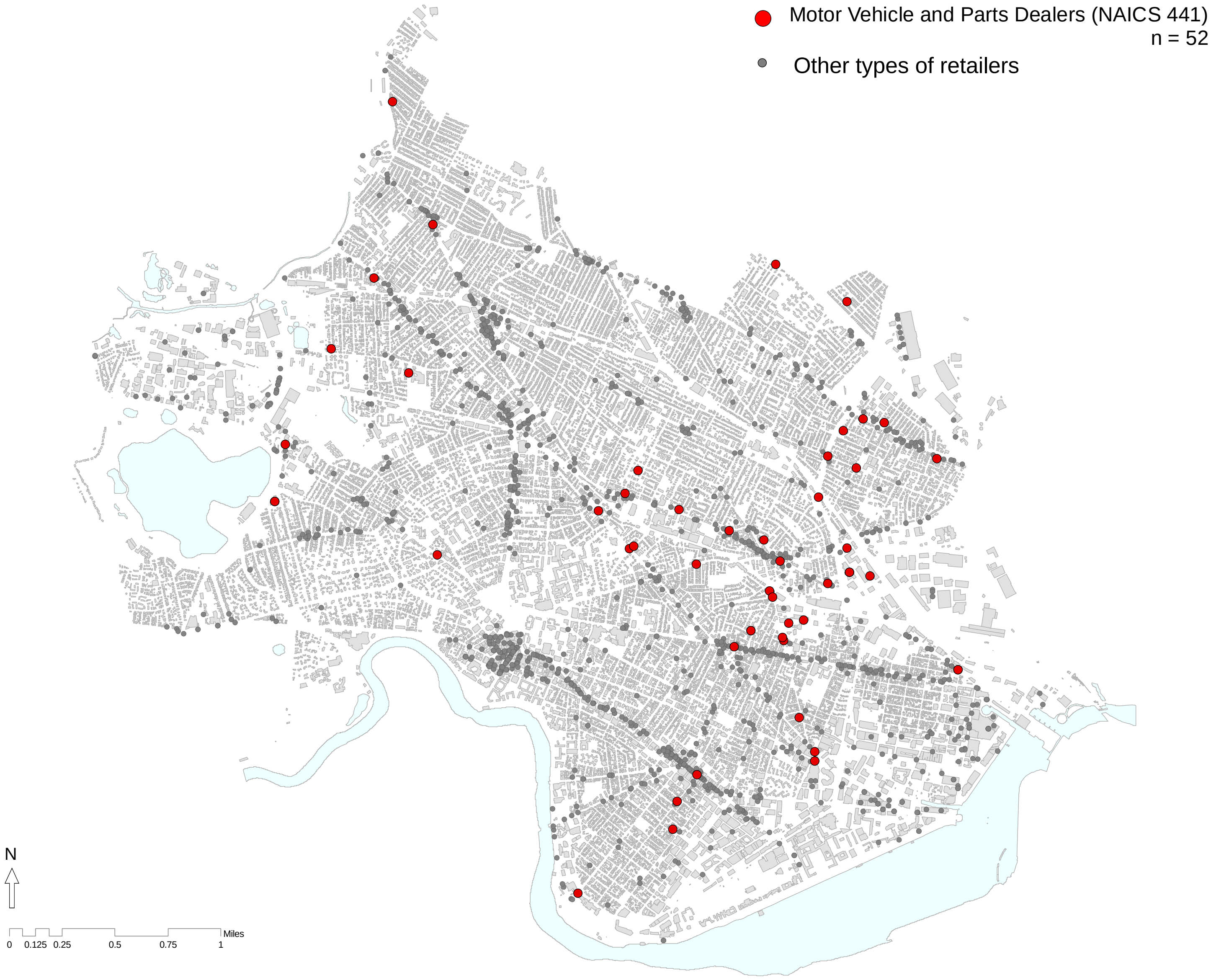
```
 turnscount = 0
a = Turn.Angle
If a >= 20 And a<= 340 Then
  turnscount = 1
Else
  turnscount = 0
End If


Value= turnscount
```

Notes:

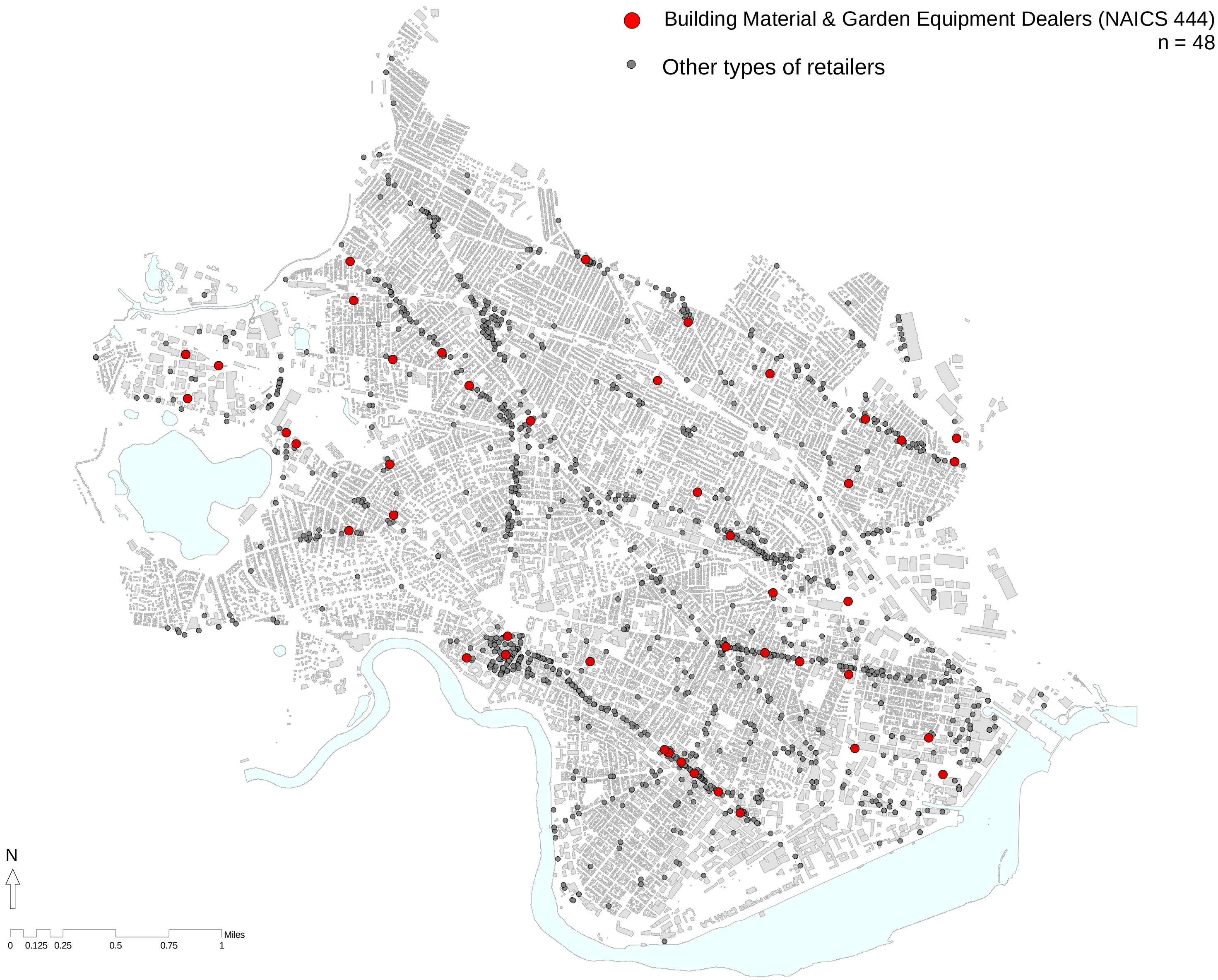
This script will count every turn that is more than 20deg sharp as a turn.

For counting junctions, do another attribute, and in Default Values, click "Junction", Default=1
This will count every junction as 1

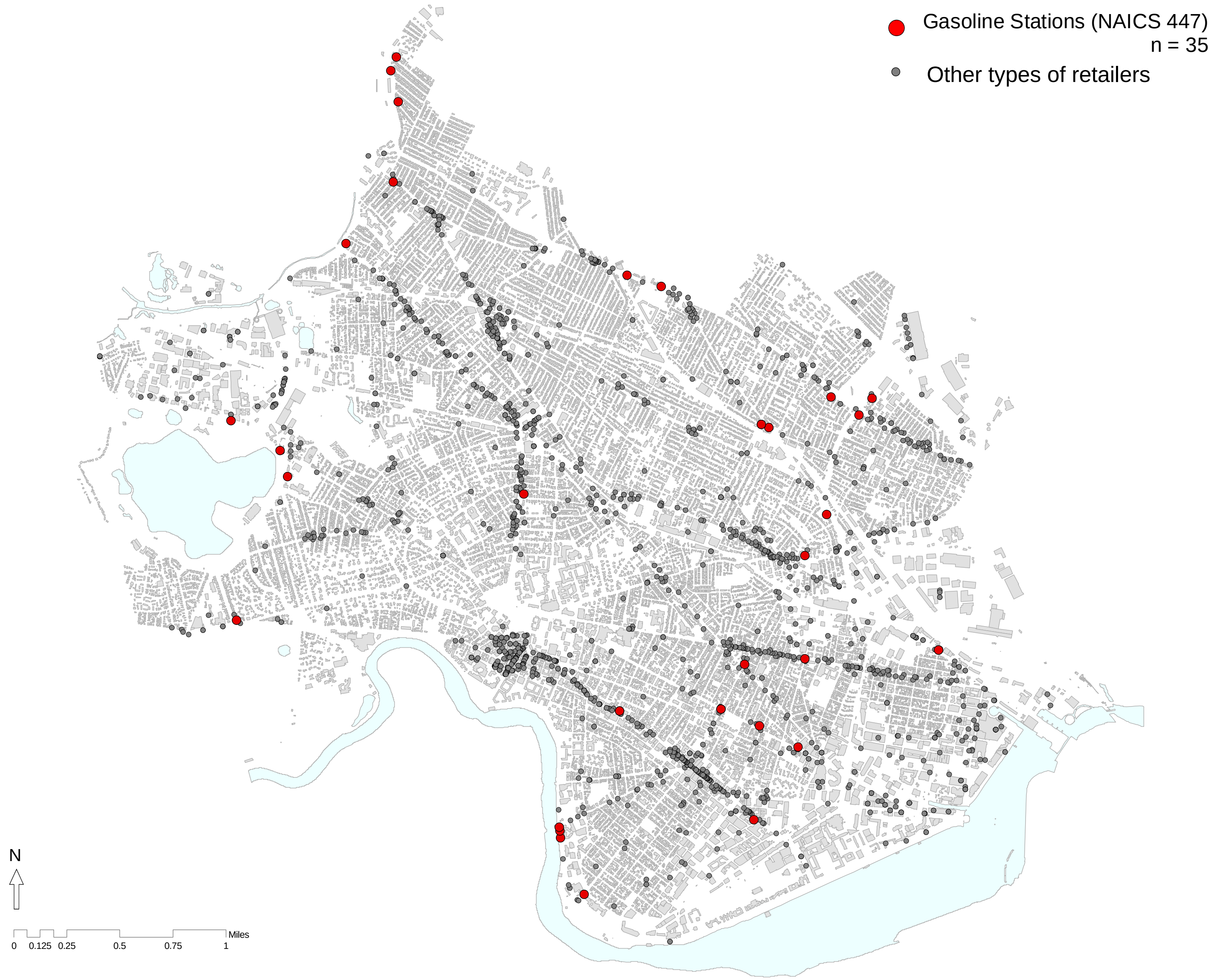
Appendix 2



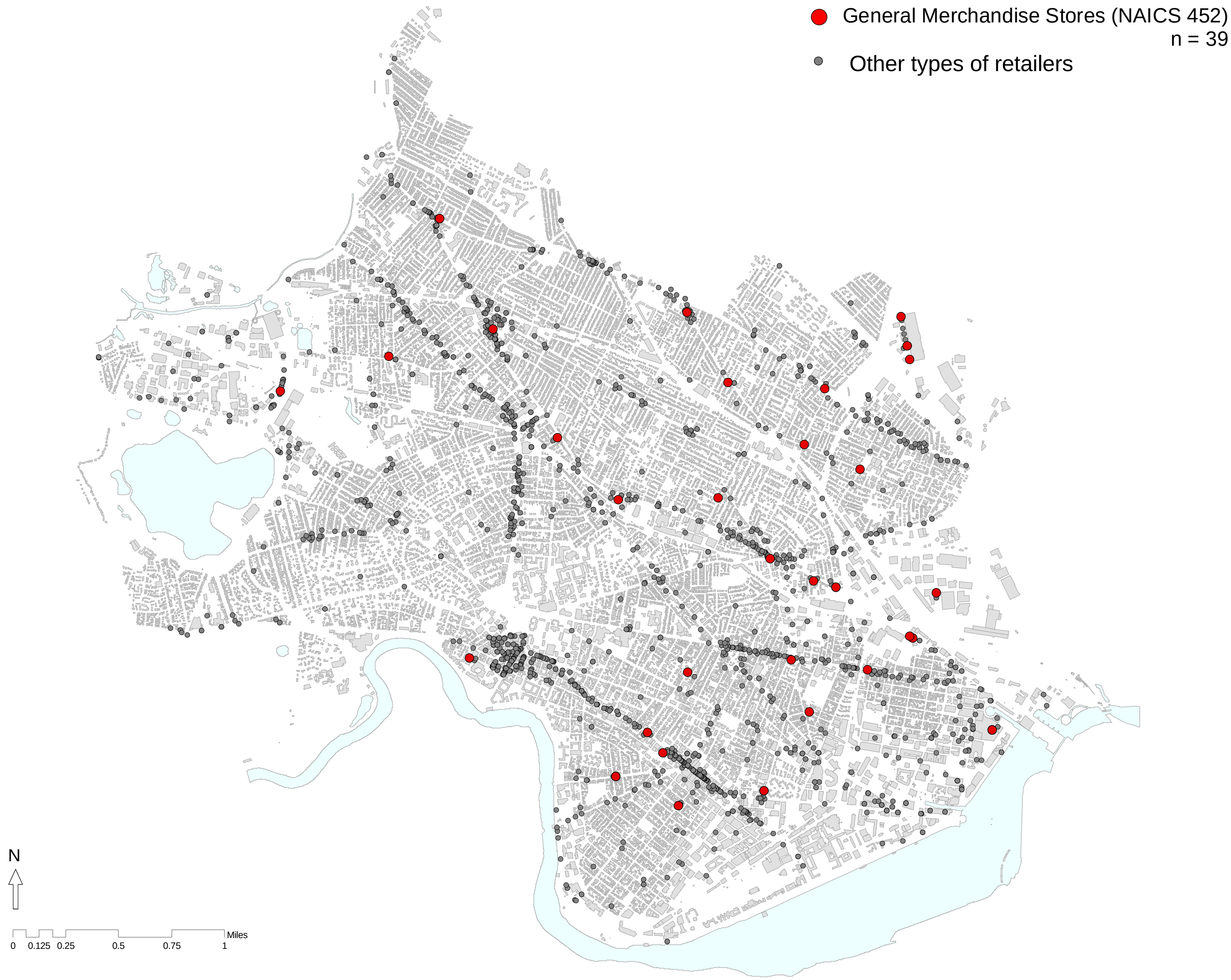
The spatial distribution of motor vehicle and parts dealers (NAICS 441) in Cambridge and Somerville, MA. Moran's I = 0.0117



The spatial distribution of building material and garden equipment dealers (NAICS 444) in Cambridge and Somerville, MA. Moran's I = 0.0022



The spatial distribution of gasoline stations (NAICS 447) in Cambridge and Somerville, MA. Moran's I = 0.0272



The spatial distribution of general merchandise stores (NAICS 452) in Cambridge and Somerville, MA. Moran's I = 0.0010

Appendix 3

OLS estimates (n=27,023)

Variable:	NAICS 441 (n= 43) Motor Vehicle and Parts Dealers		NAICS 442 (n= 58) Furniture & Home Furnishing Stores		NAICS 443 (n= 120) Electronics & Appliance Stores		NAICS 444 (n= 42) Building Material & Garden Equipment Dealers	
Constant	2.65E-03 ~	(1.344)	8.72E-04	(0.381)	-2.99E-02 ***	(-9.313)	-9.15E-04	(-0.469)
Reach								
Other types of retailers	-3.29E-05	(-0.867)	1.35E-04 ***	(3.016)	7.14E-04 ***	(10.903)	2.29E-04 ***	(6.011)
Residents	-3.61E+00 ***	(-3.589)	-4.36E-01	(-0.375)	-1.26E+01 ***	(-7.734)	-1.91E+00 **	(-1.919)
Jobs	2.73E-01	(0.696)	-4.72E-01	(-1.038)	6.36E-01	(0.998)	3.11E-02	(0.080)
Built Volume	4.19E-04 ~	(1.264)	-3.51E-05	(-0.092)	2.46E-03 ***	(4.599)	-1.32E-04	(-0.404)
Distance Closeness								
Other types of retailers	1.63E-07 ~	(1.213)	-7.18E-07 ***	(-4.512)	-1.36E-06 ***	(-5.855)	-4.30E-07 ***	(-3.199)
Nearest Bus Stop	-5.43E-06 *	(-1.481)	-1.25E-06	(-0.295)	1.46E-05 ***	(2.451)	5.67E-06 *	(1.564)
Nearest Subway Stop	7.72E-07	(1.058)	-1.88E-06 **	(-2.224)	1.97E-06 *	(1.657)	3.41E-07	(0.473)
Residents	4.62E-03 ~	(1.395)	-9.56E-04	(-0.249)	1.49E-02 ***	(2.776)	-7.74E-04	(-0.236)
Jobs	-1.23E-03 ~	(-1.185)	3.83E-05	(0.032)	-6.51E-03 ***	(-3.870)	-1.02E-03	(-0.999)
Built Volume	-7.06E-07	(-0.663)	1.82E-06 *	(1.476)	-1.40E-06	(-0.820)	1.01E-06	(0.963)
Turns Closeness								
Other types of retailers	-1.02E-05	(-0.796)	1.07E-05	(0.712)	1.23E-05	(0.560)	-2.92E-05 **	(-2.281)
Nearest Bus Stop	-2.58E-04	(-0.701)	-6.00E-04 ~	(-1.406)	1.22E-03 **	(2.045)	-5.34E-04 *	(-1.467)
Nearest Subway Stop	-9.38E-05	(-0.763)	9.40E-05	(0.660)	-2.40E-04 ~	(-1.200)	-2.64E-05	(-0.217)
Residents	2.02E-02	(0.065)	8.50E-01 **	(2.376)	3.64E+00 ***	(7.276)	2.07E-02	(0.068)
Jobs	-6.15E-02	(-0.421)	3.86E-02	(0.228)	7.19E-02	(0.303)	-3.42E-02	(-0.236)
Built Volume	6.85E-05	(0.806)	-2.18E-04 **	(-2.211)	-1.10E-03 ***	(-8.078)	1.83E-05	(0.218)
Intersections Closeness								
Other types of retailers	-2.88E-06	(-0.349)	2.23E-05 **	(2.293)	-3.70E-05 ***	(-2.586)	5.85E-06	(0.709)
Nearest Bus Stop	5.24E-05	(0.213)	-1.63E-05	(-0.057)	-4.56E-04	(-1.136)	-2.16E-04	(-0.885)
Nearest Subway Stop	-8.33E-05 ~	(-1.412)	7.41E-05	(1.082)	-8.15E-05	(-0.849)	1.84E-05	(0.314)
Residents	3.55E-01 *	(1.561)	-3.04E-01 ~	(-1.154)	-9.56E-01 ***	(-2.590)	2.91E-01 ~	(1.295)
Jobs	5.69E-02	(0.725)	2.19E-02	(0.241)	2.55E-01 **	(2.013)	7.31E-02	(0.943)
Built Volume	-6.90E-05	(-1.121)	-2.53E-05	(-0.354)	3.61E-04 ***	(3.638)	-3.87E-05	(-0.636)
Betweenness	2.59E-05 ***	(3.718)	6.45E-05 ***	(8.012)	-2.46E-06	(-0.217)	1.62E-05 **	(2.351)
Destination Characteristics								
Building Height	-3.52E-04 ***	(-5.315)	-1.23E-04 *	(-1.606)	9.64E-04 ***	(8.953)	-2.18E-04 ***	(-3.328)
Building footprint area	2.03E-07 ***	(5.308)	4.21E-07 ***	(9.509)	1.31E-06 ***	(21.023)	1.31E-07 ***	(3.462)
Sidewalk Width	2.39E-04 *	(1.488)	1.30E-04	(0.700)	-8.32E-05	(-0.318)	4.30E-04 ***	(2.706)
Road Width	-5.87E-05	(-1.029)	-2.60E-04 ***	(-3.932)	2.51E-04 ***	(2.705)	-8.89E-05 *	(-1.576)
Rigth of Way (set back of buildings from street)	1.04E-05	(0.311)	1.15E-04 ***	(2.989)	-2.60E-05	(-0.479)	1.15E-05	(0.348)
rcel Type (# of streets the building directly facces: 1-5)	3.76E-03 ***	(8.872)	3.57E-03 ***	(7.269)	5.27E-03 ***	(7.647)	2.71E-03 ***	(6.457)
Fit Statistics								
R^2 (adjusted)	0.008		0.013		0.057		0.007	
F	8.11		13.43		57.37		7.49	
Log Likelihood	48852.60		44893.30		35715.40		49161.10	
Diagnostics for Spatial Dependence								
LM (Lag)	15.09 ***		104.71 ***		43.80 ***		1.91 ~	
Robust LM (Lag)	9.77 ***		26.25 ***		111.42 ***		5.41 **	
LM (Error)	12.61 ***		91.40 ***		14.59 ***		2.59 *	
Robust LM (Error)	7.29 ***		12.94 ***		82.21 ***		6.10 ***	
LM (SARMA)	22.38 ***		117.65 ***		126.01 ***		8.01 **	

Significance level ~$p<0.25$, *$p<0.10$, **$p<0.05$, ***$p<0.01$

Cell etries are coefficients, t-values in parenthesis

OLS estimates (n=27,023)

Variable:	NAICS 445 (n= 157) Food & Beverage Stores		NAICS 446 (n= 53) Health & Personal Care Stores		NAICS 447 (n= 25) Gasoline Stations		NAICS 448 (n= 90) Clothing & Clothing Accessory Stores	
Constant	-9.93E-03 ***	(-2.670)	-8.34E-03 ***	(-3.849)	-2.05E-03 ~	(-1.362)	-1.01E-02 ***	(-3.590)
Reach								
Other types of retailers	5.03E-04 ***	(6.587)	4.78E-04 ***	(10.952)	-3.79E-05 ~	(-1.319)	9.55E-04 ***	(15.371)
Residents	-2.75E+00 *	(-1.452)	-2.88E+00 ***	(-2.606)	-2.36E+00 ***	(-3.077)	2.90E+00 **	(2.033)
Jobs	2.20E+00 ***	(2.978)	1.26E+00 ***	(2.925)	7.45E-02	(0.249)	6.65E+00 ***	(11.944)
Built Volume	2.86E-04	(0.457)	-8.14E-04 **	(-2.236)	4.03E-04 *	(1.592)	-1.81E-03 ***	(-3.865)
Distance Closeness								
Other types of retailers	-1.30E-06 ***	(-4.808)	-1.05E-06 ***	(-6.686)	5.82E-08	(0.568)	-2.14E-06 ***	(-9.108)
Nearest Bus Stop	-1.10E-05 *	(-1.590)	7.00E-06 ***	(1.737)	-1.64E-06	(-0.585)	2.07E-05 ***	(3.971)
Nearest Subway Stop	-2.61E-06 *	(-1.901)	-1.01E-06 ~	(-1.260)	2.94E-07	(0.529)	-4.32E-07	(-0.417)
Residents	-3.64E-03	(-0.581)	-8.94E-04	(-0.246)	7.70E-03 ***	(3.049)	-7.58E-03 *	(-1.615)
Jobs	-5.96E-03 ***	(-3.045)	-1.88E-03 *	(-1.646)	-2.90E-04	(-0.367)	-1.36E-02 ***	(-9.270)
Built Volume	1.41E-06	(0.696)	2.58E-06 **	(2.207)	-1.12E-06 ~	(-1.378)	3.18E-06 **	(2.118)
Turns Closeness								
Other types of retailers	-7.03E-05 ***	(-2.723)	-1.33E-05	(-0.900)	1.42E-05 *	(1.466)	3.15E-05 *	(1.483)
Nearest Bus Stop	-1.33E-03 *	(-1.917)	1.58E-04	(0.391)	1.10E-04	(0.393)	-7.94E-04 *	(-1.517)
Nearest Subway Stop	-4.43E-04 *	(-1.917)	-6.56E-05	(-0.486)	-1.72E-04 *	(-1.837)	1.71E-05	(0.098)
Residents	1.62E-01	(0.278)	2.92E-01	(0.862)	2.07E-01	(0.880)	-5.32E-01 ~	(-1.224)
Jobs	-3.33E-01 ~	(-1.207)	-8.93E-02	(-0.555)	5.18E-02	(0.464)	2.39E-01 ~	(1.151)
Built Volume	2.46E-04 *	(1.528)	-1.41E-05	(-0.151)	-1.04E-04 *	(-1.612)	-3.01E-05	(-0.253)
Intersections Closeness								
Other types of retailers	3.74E-05 **	(2.273)	5.60E-06	(0.583)	-4.56E-06	(-0.725)	-6.98E-06	(-0.497)
Nearest Bus Stop	5.06E-04	(1.090)	-1.28E-05	(-0.047)	-1.00E-04	(-0.532)	-3.14E-04	(-0.895)
Nearest Subway Stop	2.66E-04 **	(2.393)	3.76E-06	(0.058)	9.36E-06	(0.208)	1.46E-04 *	(1.735)
Residents	1.01E+00 **	(2.367)	3.95E-01 *	(1.582)	-1.89E-01	(-1.092)	2.09E-01	(0.647)
Jobs	1.39E-01	(0.937)	-7.63E-02	(-0.888)	-1.90E-02	(-0.318)	-2.36E-01 **	(-2.147)
Built Volume	-3.35E-04 ***	(-2.890)	-5.21E-05	(-0.771)	7.12E-05 *	(1.517)	6.00E-05	(0.680)
Betweenness	7.88E-05 ***	(6.013)	1.74E-05 **	(2.276)	1.92E-05 ***	(3.610)	6.10E-05 ***	(6.159)
Destination Characteristics								
Building Height	-7.17E-04 ***	(-5.753)	-1.80E-05	(-0.248)	-2.52E-04 ***	(-4.990)	-1.33E-04 ~	(-1.418)
Building footprint area	6.12E-07 ***	(8.497)	6.17E-07 ***	(14.681)	6.64E-08 **	(2.276)	3.25E-07 ***	(5.991)
Sidewalk Width	1.28E-03 ***	(4.223)	2.64E-04 *	(1.493)	-7.94E-04 ***	(-6.475)	7.99E-04 ***	(3.499)
Road Width	-7.43E-05	(-0.691)	1.44E-05	(0.229)	-1.34E-05	(-0.307)	-1.72E-04 **	(-2.120)
Rigth of Way (set back of buildings from street)	-3.16E-05	(-0.503)	1.04E-04 ***	(2.828)	2.03E-04 ***	(7.971)	-3.10E-06	(-0.066)
rcel Type (# of streets the building directly facces: 1-5)	1.41E-02 ***	(17.698)	3.10E-03 ***	(6.645)	1.39E-03 ***	(4.290)	6.06E-03 ***	(10.054)
Fit Statistics								
R^2 (adjusted)	0.033		0.028		0.008		0.042	
F	32.44		27.61		8.21		42.13	
Log Likelihood	31757.40		46310.30		56172.70		39377.40	
Diagnostics for Spatial Dependence								
LM (Lag)	72.53 ***		120.21 ***		110.61 ***		221.64 ***	
Robust LM (Lag)	16.65 ***		42.69 ***		27.04 ***		90.00 ***	
LM (Error)	61.37 ***		97.98 ***		98.81 ***		180.51 ***	
Robust LM (Error)	5.50 **		20.46 ***		15.25 ***		48.87 ***	
LM (SARMA)	78.02 ***		140.67 ***		125.86 ***		270.51 ***	

Significance level ~<p<0.25, *p<0.10, **p<0.05, ***p<0.01

Cell etries are coefficients, t-values in parenthesis

OLS estimates (n=27,023)

Variable:	NAICS 451 (n= 94) Sporting Goods, Hobby, Book & Music Stores		NAICS 452 (n= 27) General Merchandise Stores		NAICS 453 (n= 134) Miscellaneous Store Retailers		NAICS 722 (n= 399) Food Services & Drinking Places	
Constant	-1.09E-02 ***	(-3.768)	1.37E-03	(0.877)	-7.92E-03 ***	(-2.308)	-4.74E-02 ***	(-8.332)
Reach								
Other types of retailers	7.53E-04 ***	(12.695)	7.12E-06	(0.237)	9.97E-04 ***	(13.675)	3.39E-03 ***	(19.826)
Residents	1.69E+00 ~	(1.153)	1.18E+00 *	(1.476)	-6.65E-01	(-0.380)	-5.81E+00 **	(-2.005)
Jobs	3.78E+00 ***	(6.609)	7.91E-02	(0.254)	2.38E+00 ***	(3.496)	5.25E+00 ***	(4.683)
Built Volume	-1.09E-03 **	(-2.258)	-4.94E-04 *	(-1.878)	-1.13E-03 **	(-1.947)	2.00E-03 **	(2.087)
Distance Closeness								
Other types of retailers	-2.08E-06 ***	(-9.796)	-9.86E-08	(-0.912)	-1.82E-06 ***	(-7.023)	-6.37E-06 ***	(-11.277)
Nearest Bus Stop	7.62E-06 ~	(1.423)	-4.18E-06 ~	(-1.438)	-5.13E-06	(-0.804)	2.76E-05 ***	(2.619)
Nearest Subway Stop	-4.80E-07	(-0.450)	-4.15E-09	(-0.007)	-3.00E-06 **	(-2.368)	-4.82E-07	(-0.230)
Residents	-7.49E-03 *	(-1.549)	-4.28E-03 *	(-1.629)	1.23E-02 **	(2.127)	1.61E-02 *	(1.686)
Jobs	-8.44E-03 ***	(-5.571)	-5.51E-04	(-0.671)	-3.86E-03 ***	(-2.143)	-1.49E-02 ***	(-4.994)
Built Volume	3.86E-06 ***	(2.481)	1.55E-06 *	(1.828)	-1.19E-06	(-0.642)	-1.07E-05 ***	(-3.494)
Turns Closeness								
Other types of retailers	5.40E-06	(0.275)	-1.58E-06	(-0.155)	-8.37E-05 ***	(-3.432)	-2.19E-04 ***	(-4.095)
Nearest Bus Stop	4.57E-04	(0.849)	-7.68E-05	(-0.263)	-4.88E-04	(-0.762)	1.26E-03 ~	(1.192)
Nearest Subway Stop	-1.19E-05	(-0.066)	-1.41E-04 *	(-1.445)	5.81E-05	(0.271)	-1.12E-03 ***	(-3.168)
Residents	2.55E-01	(0.566)	3.71E-01 *	(1.516)	7.28E-01 ~	(1.355)	-6.59E-01	(-0.740)
Jobs	-3.34E-01 *	(-1.567)	1.17E-01	(1.007)	-6.04E-01 **	(-2.378)	7.06E-01 *	(1.683)
Built Volume	-1.97E-04 *	(-1.587)	-1.64E-04 ***	(-2.437)	6.66E-05	(0.450)	5.28E-04 **	(2.155)
Intersections Closeness								
Other types of retailers	2.28E-05 *	(1.743)	6.16E-06	(0.934)	2.33E-06	(0.146)	-1.27E-05	(-0.347)
Nearest Bus Stop	-2.80E-04	(-0.777)	1.08E-04	(0.553)	2.51E-04	(0.584)	-1.38E-03 **	(-1.947)
Nearest Subway Stop	-6.00E-05	(-0.695)	-1.42E-05	(-0.304)	1.49E-04 *	(1.450)	6.99E-05	(0.412)
Residents	-1.08E-01	(-0.326)	-3.94E-02	(-0.219)	-1.39E+00 ***	(-3.516)	-8.15E-01 ~	(-1.250)
Jobs	-2.01E-03	(-0.018)	-3.12E-03	(-0.050)	1.04E-01	(0.765)	-1.43E-01	(-0.636)
Built Volume	4.85E-05	(0.539)	3.71E-05	(0.760)	2.62E-04 ***	(2.439)	3.81E-04 **	(2.176)
Betweenness	3.31E-05 ***	(3.257)	6.97E-06 ~	(1.264)	2.11E-05 *	(1.743)	2.83E-04 ***	(14.127)
Destination Characteristics								
Building Height	3.98E-04 ***	(4.120)	-6.16E-05 ~	(-1.175)	-1.50E-04 ~	(-1.305)	-6.61E-04 ***	(-3.473)
Building footprint area	4.98E-07 ***	(8.907)	3.42E-07 ***	(11.273)	7.23E-07 ***	(10.855)	1.19E-06 ***	(10.836)
Sidewalk Width	-1.95E-05	(-0.083)	2.24E-05	(0.176)	-1.08E-04	(-0.386)	2.80E-03 ***	(6.068)
Road Width	-1.43E-04 *	(-1.712)	-1.57E-04 ***	(-3.470)	1.30E-04 ~	(1.305)	-2.55E-05	(-0.155)
Rigth of Way (set back of buildings from street)	1.18E-04 **	(2.425)	7.15E-05 ***	(2.705)	2.20E-05	(0.380)	-8.29E-05	(-0.864)
rcel Type (# of streets the building directly facces: 1-5)	4.47E-03 ***	(7.221)	1.94E-03 ***	(5.773)	9.69E-03 ***	(13.130)	3.23E-02 ***	(26.475)
Fit Statistics								
R^2 (adjusted)	0.030		0.009		0.032		0.103	
F	29.96		9.34		32.03		107.97	
Log Likelihood	38621.80		55150.10		33880.50		20297.30	
Diagnostics for Spatial Dependence								
LM (Lag)	8.30 ***		2.64 *		49.07 ***		1231.93 ***	
Robust LM (Lag)	220.11 ***		0.00		45.09 ***		124.12 ***	
LM (Error)	0.11		2.71 *		33.85 ***		1107.94 ***	
Robust LM (Error)	211.92 ***		0.07		29.88 ***		0.13	
LM (SARMA)	220.22 ***		2.71		78.94 ***		1232.06 ***	

Significance level ~<p<0.25, *p<0.10, **p<0.05, ***p<0.01

Cell etries are coefficients, t-values in parenthesis

Note: Though the NAICS 451 and 722 category models here indicate that the LM(Error) in the former and Robust LM(Error) in the latter case are insignificant, they do turn significant in the reduced models, and therefore justify the use of lag + error models in both of these categories.

Appendix 4

Spatial lag+error model parameter estimates for location choice variables of individual three digit NAICS retail and food establishment categories in Cambridge/Somerville (n 27,023)

Dependent Variable:	NAICS 441 (n= 52) Motor Vehicle and Parts Dealers		NAICS 442 (n= 73) Furniture & Home Furnishing Stores		NAICS 443 (n= 192) Electronics & Appliance Stores		NAICS 444 (n= 48) Garden Equipment Dealers	
Independent Variables:								
ρ (rho)	0.388 ***	(0.113)	0.591 ***	(0.140)	0.506 ***	(0.055)	0.597 ***	(0.168)
λ (lambda)	-3.91E-07 ***		-1.21E-06 ***		-6.76E-06 ***		-4.19E-07 ***	
Nr of other types of retailers in 10 min walking radius	-4.34E-05	(3.83E-05)	-3.06E-06	(5.57E-05)	3.40E-04 ***	(7.81E-05)	6.26E-05	(6.07E-05)
Total distance to other types of retailers in 10 min walking radius	1.50E-07	(1.40E-07)	-3.10E-07 *	(1.90E-07)	-6.50E-07 ***	(2.50E-07)	-1.80E-07	(1.50E-07)
Total nr of turns to other types of retailers in 10 min walking radius	-4.95E-06	(1.29E-05)	1.67E-05	(1.53E-05)	8.13E-06	(2.24E-05)	-1.03E-05	(1.40E-05)
Total nr of intersections to other types of retailers in 10 min walking ra	-1.68E-06	(8.31E-06)	1.30E-05 ~	(1.01E-05)	-1.94E-05 ~	(1.47E-05)	6.22E-06	(8.38E-06)
Constant	7.36E-04	(2.06E-03)	-9.00E-06	(2.32E-03)	-2.35E-02 ***	(3.34E-03)	-1.25E-03	(1.98E-03)
Distance to nearest bus stop	-2.69E-06	(3.78E-06)	8.50E-07	(4.32E-06)	5.57E-06	(6.15E-06)	3.95E-06	(3.71E-06)
Turns to nearest bus stop	-1.39E-04	(3.72E-04)	-3.30E-04	(4.35E-04)	9.97E-04 *	(6.10E-04)	-2.03E-04	(3.82E-04)
Intersections to nearest bus stop	4.22E-06	(2.49E-04)	-1.67E-05	(2.88E-04)	-1.49E-04	(4.09E-04)	-1.83E-04	(2.48E-04)
Distance to nearest subway stop	1.80E-07	(7.50E-07)	-1.37E-06 *	(8.60E-07)	2.50E-07	(1.22E-06)	-1.00E-07	(7.40E-07)
Turns to nearest subway stop	2.38E-06	(1.27E-04)	1.11E-04	(1.44E-04)	-4.86E-05	(2.04E-04)	-3.44E-06	(1.24E-04)
Intersections to nearest subway stop	-3.73E-05	(6.09E-05)	5.77E-05	(6.93E-05)	2.08E-05	(9.83E-05)	3.47E-05	(5.95E-05)
Nr of residents in 10 min walking radius	-2.255 **	(1.086)	0.060	(1.181)	-5.772 ***	(1.817)	-0.107	(1.130)
Total distance to residents in 10 min walking radius	3.65E-03	(3.35E-03)	-4.59E-04	(3.88E-03)	7.78E-03 ~	(5.51E-03)	-2.76E-03	(3.37E-03)
Total nr of turns to residents in 10 min walking radius	4.10E-02	(3.11E-01)	3.80E-01	(3.78E-01)	2.71E+00 ***	(5.18E-01)	1.72E-02	(3.10E-01)
Total nr of intersections to residents in 10 min walking radius	1.55E-01	(2.36E-01)	-1.83E-01	(2.67E-01)	-9.86E-01 ***	(3.75E-01)	1.42E-01	(2.32E-01)
Nr of jobs in 10 min walking radius	2.36E-01	(3.95E-01)	-2.06E-01	(4.64E-01)	7.55E-01 ~	(6.49E-01)	7.92E-02	(3.95E-01)
Total distance to jobs in 10 min walking radius	-8.85E-04	(1.05E-03)	-4.75E-04	(1.22E-03)	-4.47E-03 ***	(1.72E-03)	-6.92E-04	(1.05E-03)
Total nr of turns to jobs in 10 min walking radius	-2.51E-02	(1.48E-01)	3.07E-02	(1.71E-01)	-2.10E-02	(2.42E-01)	-1.13E-01	(1.49E-01)
Total nr of intersections to jobs in 10 min walking radius	2.03E-02	(7.96E-02)	5.96E-02	(9.23E-02)	1.38E-01	(1.30E-01)	7.48E-02	(7.88E-02)
Built volume in 10 min walking radius	2.47E-04	(3.38E-04)	-2.20E-04	(3.90E-04)	6.44E-04	(5.79E-04)	-3.42E-04	(3.38E-04)
Total distance to built volume in 10 min walking radius	-5.30E-07	(1.07E-06)	1.47E-06 ~	(1.25E-06)	5.50E-07	(1.75E-06)	1.40E-06 ~	(1.08E-06)
Total nr of turns to built volume in 10 min walking radius	3.22E-05	(8.62E-05)	-1.31E-04 ~	(1.02E-04)	-7.98E-04 ***	(1.42E-04)	6.66E-06	(8.54E-05)
Total nr of intersections to built volume in 10 min walking radius	-2.79E-05	(6.31E-05)	-5.99E-06	(7.22E-05)	3.09E-04 ***	(1.01E-04)	-2.56E-05	(6.19E-05)
Betweenness (radius n)	2.13E-05 ***	(7.13E-06)	4.41E-05 ***	(9.48E-06)	-4.26E-06	(1.15E-05)	1.56E-05 **	(6.99E-06)
Building Height	-2.96E-04 ***	(6.86E-05)	-1.74E-04 **	(7.84E-05)	7.09E-04 ***	(1.13E-04)	-1.67E-04 ***	(6.80E-05)
Building footprint area	1.90E-07 ***	(4.00E-08)	3.80E-07 ***	(5.00E-08)	1.16E-06 ***	(7.00E-08)	1.20E-07 ***	(4.00E-08)
Sidewalk Width	2.77E-04 *	(1.62E-04)	5.08E-04 ***	(2.09E-04)	-3.50E-06	(2.66E-04)	5.33E-04 ***	(1.64E-04)
Road Width	-3.78E-05	(5.78E-05)	-2.15E-04 ***	(6.76E-05)	2.00E-04 **	(9.45E-05)	-1.23E-04 **	(5.81E-05)
Rigth of Way (set back of buildings from street)	-1.01E-05	(3.41E-05)	3.54E-05	(4.34E-05)	-1.90E-05	(5.52E-05)	3.77E-06	(3.36E-05)
Parcel Type (# of streets the building directly facces: 1-5)	3.35E-03 ***	(4.44E-04)	3.10E-03 ***	(5.08E-04)	4.75E-03 ***	(7.04E-04)	2.35E-03 ***	(4.37E-04)
R^2	**0.028**		**0.058**		**0.103**		**0.036**	

Significance level ~p<0.75, *p<0.10, **p<0.05, ***p<0.01

Cell etries are coefficients, standard errors in parenthesis

Spatial lag+error model parameter estimates for location choice variables of individual three digit NAICS retail and food establishment categories in Cambridge/Somerville (n 27,023)

Dependent Variable:	NAICS 445 (n= 186)		NAICS 446 (n= 73)		NAICS 447 (n= 35)		NAICS 448 (n= 166)	
Independent Variables:	Food & Beverage Stores		Health & Personal Care Stores		Gasoline Stations		Clothing & Clothing Accessory Stores	
ρ (rho)	0.316 ***	(0.098)	0.967 ***	(0.116)	0.653 ***	(0.104)	0.992 ***	(0.125)
λ (lambda)	-2.21E-06 ***		-1.47E-06 ***		-2.36E-07 ***		-2.95E-06 ***	
Nr of other types of retailers in 10 min walking radius	2.50E-04 **	(1.09E-04)	-1.48E-04 *	(8.82E-05)	-2.99E-05	(2.93E-05)	-1.11E-04	(1.48E-04)
Total distance to other types of retailers in 10 min walking radius	-7.40E-07 **	(3.20E-07)	2.80E-07 ~	(2.30E-07)	4.00E-08	(1.00E-07)	1.20E-07	(3.70E-07)
Total nr of turns to other types of retailers in 10 min walking radius	-3.94E-05 ~	(2.75E-05)	9.69E-06	(1.56E-05)	1.17E-05 ~	(9.83E-06)	3.04E-05 ~	(2.17E-05)
Total nr of intersections to other types of retailers in 10 min walking ra	2.68E-05 *	(1.68E-05)	-3.00E-07	(1.01E-05)	-2.07E-06	(6.41E-06)	-2.69E-06	(1.44E-05)
Constant	-8.51E-03 **	(3.74E-03)	-9.73E-03 ***	(2.27E-03)	-1.93E-04	(1.56E-03)	-5.70E-03 **	(2.92E-03)
Distance to nearest bus stop	-7.73E-06	(6.97E-06)	1.10E-06	(4.27E-06)	-2.40E-07	(2.85E-06)	7.03E-06 ~	(5.60E-06)
Turns to nearest bus stop	-1.16E-03 *	(6.95E-04)	-1.34E-04	(4.24E-04)	-1.49E-04	(2.88E-04)	-3.82E-04	(5.37E-04)
Intersections to nearest bus stop	4.11E-04	(4.65E-04)	1.50E-04	(2.84E-04)	-3.45E-06	(1.92E-04)	-1.32E-04	(3.59E-04)
Distance to nearest subway stop	-2.75E-06 **	(1.37E-06)	-5.90E-07	(8.40E-07)	8.00E-08	(5.70E-07)	-1.02E-06	(1.06E-06)
Turns to nearest subway stop	-2.34E-04	(2.40E-04)	9.38E-05	(1.42E-04)	-8.13E-05	(9.64E-05)	-4.04E-05	(1.79E-04)
Intersections to nearest subway stop	2.35E-04 **	(1.11E-04)	6.90E-05	(6.82E-05)	1.94E-05	(4.58E-05)	1.39E-04 *	(8.58E-05)
Nr of residents in 10 min walking radius	-1.912	(1.914)	1.214	(1.253)	-1.196 *	(0.801)	0.551	(1.488)
Total distance to residents in 10 min walking radius	-2.83E-03	(6.28E-03)	1.52E-03	(3.81E-03)	4.05E-03 *	(2.63E-03)	6.65E-04	(4.91E-03)
Total nr of turns to residents in 10 min walking radius	1.65E-01	(5.83E-01)	4.29E-01 ~	(3.54E-01)	-2.15E-02	(2.42E-01)	-8.01E-02	(4.48E-01)
Total nr of intersections to residents in 10 min walking radius	7.17E-01 *	(4.38E-01)	-5.63E-01 **	(2.85E-01)	-4.18E-02	(1.78E-01)	-1.39E-01	(3.33E-01)
Nr of jobs in 10 min walking radius	2.12E+00 ***	(7.41E-01)	3.18E-01	(4.64E-01)	6.84E-02	(3.04E-01)	1.64E+00 **	(8.49E-01)
Total distance to jobs in 10 min walking radius	-5.43E-03 ***	(1.96E-03)	-1.67E-03 ~	(1.19E-03)	-9.55E-05	(8.04E-04)	-3.73E-03 *	(1.95E-03)
Total nr of turns to jobs in 10 min walking radius	-3.52E-01 ~	(2.75E-01)	7.76E-02	(1.69E-01)	-2.05E-02	(1.14E-01)	7.98E-02	(2.13E-01)
Total nr of intersections to jobs in 10 min walking radius	1.36E-01	(1.48E-01)	2.22E-02	(9.06E-02)	-6.32E-03	(6.08E-02)	-4.85E-02	(1.15E-01)
Built volume in 10 min walking radius	9.20E-05	(6.29E-04)	-2.55E-04	(3.86E-04)	2.59E-04	(2.58E-04)	-5.10E-04	(5.07E-04)
Total distance to built volume in 10 min walking radius	1.44E-06	(2.02E-06)	-5.30E-07	(1.28E-06)	-6.50E-07	(8.30E-07)	1.12E-06	(1.56E-06)
Total nr of turns to built volume in 10 min walking radius	1.75E-04	(1.62E-04)	-7.21E-05	(9.74E-05)	-1.90E-05	(6.71E-05)	-6.94E-05	(1.22E-04)
Total nr of intersections to built volume in 10 min walking radius	-2.59E-04 **	(1.18E-04)	1.43E-04 *	(7.44E-05)	1.54E-05	(4.85E-05)	4.04E-05	(9.02E-05)
Betweenness (radius n)	6.50E-05 ***	(1.38E-05)	8.97E-06	(8.06E-06)	8.04E-06 ~	(5.68E-06)	4.01E-05 ***	(1.05E-05)
Building Height	-7.07E-04 ***	(1.25E-04)	-4.43E-05	(7.60E-05)	-2.44E-04 ***	(5.13E-05)	-2.05E-04 **	(9.64E-05)
Building footprint area	5.90E-07 ***	(7.00E-08)	5.30E-07 ***	(5.00E-08)	6.00E-08 **	(3.00E-08)	3.00E-07 ***	(6.00E-08)
Sidewalk Width	1.29E-03 ***	(3.03E-04)	2.61E-04 ~	(1.84E-04)	-3.59E-04 ***	(1.43E-04)	8.65E-04 ***	(2.34E-04)
Road Width	-4.64E-05	(1.08E-04)	4.14E-05	(6.55E-05)	-2.35E-05	(4.43E-05)	-8.24E-05	(8.36E-05)
Rigth of Way (set back of buildings from street)	-8.51E-05 ~	(6.49E-05)	3.31E-05	(3.92E-05)	1.02E-04 ***	(3.04E-05)	-6.95E-05 ~	(4.91E-05)
Parcel Type (# of streets the building directly facces: 1-5)	1.32E-02 ***	(8.49E-04)	2.60E-03 ***	(4.90E-04)	9.13E-04 ***	(3.37E-04)	5.12E-03 ***	(6.27E-04)
R^2	**0.043**		**0.158**		**0.069**		**0.143**	

Significance level ~p<0.75, *p<0.10, **p<0.05, ***p<0.01

Cell etries are coefficients, standard errors in parenthesis

Spatial lag+error model parameter estimates for location choice variables of individual three digit NAICS retail and food establishment categories in Cambridge/Somerville (n 27,023)

Dependent Variable:	NAICS 452 (n= 39) General Merchandise Stores		NAICS 453 (n= 186) Miscellaneous Store Retailers		NAICS 722 (n= 618) Food Services & Drinking Places	
Independent Variables:						
ρ (rho)	-0.653 ***	(0.133)	0.650 ***	(0.100)	0.583 ***	(0.052)
λ (lambda)	4.61E-07 ***		-4.99E-06 ***		-2.54E-05 ***	
Nr of other types of retailers in 10 min walking radius	4.41E-05 ~	(3.19E-05)	2.37E-04 *	(1.39E-04)	1.14E-03 ***	(2.62E-04)
Total distance to other types of retailers in 10 min walking radius	-1.70E-07 *	(1.10E-07)	-4.30E-07 ~	(3.40E-07)	-2.61E-06 ***	(6.50E-07)
Total nr of turns to other types of retailers in 10 min walking radius	-1.17E-05	(1.07E-05)	-1.59E-05	(2.69E-05)	-5.46E-05	(5.48E-05)
Total nr of intersections to other types of retailers in 10 min walking ra	9.22E-06 ~	(6.82E-06)	-3.90E-06	(1.62E-05)	2.10E-05	(3.62E-05)
Constant	2.53E-03 *	(1.63E-03)	-7.59E-03 **	(3.48E-03)	-3.74E-02 ***	(5.66E-03)
Distance to nearest bus stop	-4.61E-06 *	(2.99E-06)	-1.15E-06	(6.50E-06)	1.94E-05 *	(1.04E-05)
Turns to nearest bus stop	-1.48E-04	(3.01E-04)	-2.23E-04	(6.52E-04)	5.50E-04	(1.04E-03)
Intersections to nearest bus stop	1.08E-04	(2.01E-04)	4.76E-05	(4.37E-04)	-7.99E-04 ~	(6.99E-04)
Distance to nearest subway stop	5.60E-07	(6.10E-07)	-2.17E-06 *	(1.29E-06)	-2.64E-06 ~	(2.07E-06)
Turns to nearest subway stop	-2.62E-04 ***	(1.03E-04)	2.23E-05	(2.17E-04)	-3.26E-04	(3.55E-04)
Intersections to nearest subway stop	-6.05E-05 ~	(4.91E-05)	1.43E-04 ~	(1.05E-04)	2.49E-04 *	(1.68E-04)
Nr of residents in 10 min walking radius	1.306 *	(0.821)	0.312	(1.783)	-1.425	(2.880)
Total distance to residents in 10 min walking radius	-5.05E-03 *	(2.71E-03)	8.97E-03 *	(5.88E-03)	5.95E-03	(9.43E-03)
Total nr of turns to residents in 10 min walking radius	3.24E-01 ~	(2.52E-01)	3.92E-01	(5.48E-01)	-3.01E-01	(8.77E-01)
Total nr of intersections to residents in 10 min walking radius	3.76E-02	(1.86E-01)	##### ***	(4.05E-01)	-4.49E-01	(6.42E-01)
Nr of jobs in 10 min walking radius	1.33E-01	(3.20E-01)	1.27E+00 *	(7.12E-01)	2.95E+00 ***	(1.12E+00)
Total distance to jobs in 10 min walking radius	-5.75E-04	(8.45E-04)	-1.34E-03	(1.87E-03)	-8.98E-03 ***	(2.98E-03)
Total nr of turns to jobs in 10 min walking radius	1.82E-01 *	(1.20E-01)	-6.83E-01 ***	(2.58E-01)	2.85E-01	(4.15E-01)
Total nr of intersections to jobs in 10 min walking radius	-3.70E-02	(6.43E-02)	9.94E-02	(1.38E-01)	-1.85E-02	(2.22E-01)
Built volume in 10 min walking radius	-6.22E-04 **	(2.72E-04)	-9.10E-04 *	(5.88E-04)	4.69E-04	(9.53E-04)
Total distance to built volume in 10 min walking radius	1.75E-06 **	(8.70E-07)	-2.90E-07	(1.89E-06)	-2.23E-06	(3.10E-06)
Total nr of turns to built volume in 10 min walking radius	-1.63E-04 **	(6.92E-05)	2.34E-06	(1.50E-04)	1.19E-04	(2.44E-04)
Total nr of intersections to built volume in 10 min walking radius	4.03E-05	(5.02E-05)	2.14E-04 **	(1.09E-04)	1.11E-04	(1.74E-04)
Betweenness (radius n)	1.33E-05 **	(5.82E-06)	1.60E-05 ~	(1.23E-05)	1.85E-04 ***	(2.15E-05)
Building Height	-8.41E-05 *	(5.42E-05)	-2.60E-04 **	(1.18E-04)	-9.12E-04 ***	(1.89E-04)
Building footprint area	3.70E-07 ***	(3.00E-08)	6.60E-07 ***	(7.00E-08)	1.01E-06 ***	(1.10E-07)
Sidewalk Width	-7.31E-05	(1.33E-04)	2.54E-04	(2.89E-04)	2.54E-03 ***	(4.55E-04)
Road Width	-1.77E-04 ***	(4.67E-05)	8.76E-05	(1.01E-04)	-2.73E-05	(1.62E-04)
Rigth of Way (set back of buildings from street)	9.86E-05 ***	(2.77E-05)	-6.95E-05 ~	(6.06E-05)	-1.75E-04 *	(9.48E-05)
Parcel Type (# of streets the building directly facces: 1-5)	2.09E-03 ***	(3.47E-04)	8.68E-03 ***	(7.65E-04)	2.83E-02 ***	(1.25E-03)
R^2	**0.073**		**0.080**		**0.153**	

Significance level ~p<0.75, *p<0.10, **p<0.05, ***p<0.01

Cell etries are coefficients, standard errors in parenthesis

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