Why retailers cluster: An agent model of location choice on supply chains

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ABSTRACT

This research investigates the emergence of retail clusters on supply chains comprised of suppliers, retailers, and consumers. An agent-based model is employed to study retail location choice in a market of homogeneous goods and a market of complementary goods. On a circle comprised of discrete locales, retailers play a non-cooperative game by choosing locales to maximize profits which are impacted by their distance to consumers and to suppliers. The findings disclose that in a market of homogeneous products symmetric distributions of retail clusters rise out of competition between individual retailers; average cluster density and cluster size change dynamically as retailers enter the market. In a market of two complementary goods, multiple equilibria of retail distributions are found to be common; a single cluster of retailers has the highest probability to emerge. Overall, my results demonstrate that retail clusters emerge from the balance between retailers' proximity to their customers, their competitors, their complements, and their suppliers.

Acknowledgement

My interest in complex systems emerged in 2006 when I attended the Santa Fe Institute Complex Systems Summer School. Before I attended the summer school, I was puzzled about what I should do in research. While having degrees in automatic and computer engineering, I felt that I think more like a social scientist. The problems in the world are complex, and maximizing or minimizing certain narrowly-defined objectives from the engineering point of view—while may be beautiful in mathematical terms—does not often seem to provide reasonable and acceptable solutions for the society. Yet in this summer school, I was amazed by how people from a variety of academic backgrounds (such as sociology, biology, and engineering) can work together to examine systems from a holistic perspective that would not have been otherwise possible. Also during this period of time, I, along with other graduate students worldwide, finished a project of analyzing the topology of Chinese airline networks. I sensed that there was more work to do to better our transportation systems and city life from a new perspective. After the summer school, I further read some books on complex systems and network theory, including Roger Lewin's *Complexity: Life at the Edge of Chaos*, and Duncan Watts's *Small Worlds*. I was completely drawn to the world of complexity.

When I started to search for Ph.D. programs, I focused on interdisciplinary programs on complex systems, transportation, urban policy, and urbanization. I found that Prof. David Levinson has done lots of work in this field, and therefore I applied to his program. I was lucky to be admitted, so here I am. One may wonder why a seemingly inconsequential event (such as attending a summer school) can have such an important and irreversible influence on one's career. My past experience perfectly attests to the theory of path dependence.

The greatest impact on my research and my working style comes from my advisor Prof. David Levinson, who gives me the freedom to work on the topics I am interested in. Moreover, we've had lots of discussions on research not just in weekly meetings but also in daily emails. I am very appreciative of his support. In particular, I am grateful for his patience and open-mindedness for my sometimes unusual ideas and curiosity.

In the past two years I spent most of my time in Office 275 of the Nexus research group. This is a fun group of people to work with. Many interesting discussions or debates are happening here every day, not just on research, but also on other parts of life. While we do not always agree with each other, I have learned a lot from each of them.

Many thanks go to my friends at the University and at my church, whose love, encouragement, and care have enormously strengthened me in almost every aspect of my life. I am blessed to have them around. Also, I want to thank my dear mom and dad who always tell me to finish what I have started. This work is as much theirs as it is mine.

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Chapter 1

Introduction

The locations of human activities shape travel behavior and have consequent outcomes on air pollution, noise, and safety, and overall social welfare. Hierarchical distributions of economic activities and resources occur in almost every region and nation. Famous examples are the US carpet production industry, disproportionately concentrated in Dalton, Georgia (Krugman, 1991) and the Italian textile industry in Prato (Porter, 1990). Within cities, there are different business clusters; to illustrate, Kappabashi, or Kitchen Town, in Tokyo is a district of competing businesses supplying cookware. Friedmann (1986), in his seminal work about the network of world cities, argued that inter-city relations lead to a complex spatial hierarchy of world cities. Sassen (1991) identified New York, London and Tokyo as leading examples of world cities and suggested that despite their different provenance, each city had experienced the same economic processes and resultant social change.

Contemporary globalization, pushed by fast-developing communication technology and decreasing transport cost, leads to two seemingly contradictory yet complementary spatial phenomenon: agglomeration of economic activities and decentralization (Taylor, 2004). On the one hand, we are impressed by the flourishing of the Silicon Valley as a major global Information Technology R&D center. On the other hand, a large proportion of the large-scale materials-intensive forms of manufacturing that formerly clustered near the core of the metropolis has decentralized to suburban and peripheral areas (Scott, 1988). Two questions naturally follow this: what can we learn from these phenomena? How should planners and transportation engineers respond in such a context for the betterment of social welfare? Policy makers are eager to know how to react in an economic system with inherent clustering characteristics, how to respond to win “founder’s advantage” in global competition, and how to behave if they are initially in a disadvantaged position. Properly answering such questions is vital for policy makers to make the world a better place to live.

The world economy has become increasingly connected, and almost all business activities worldwide can be seen as interlinked in terms of technology, capital, labor, demand, or supply. When almost all business activities worldwide are interlinked in terms of technology, capital, labor, demand, or supply, to disentangle the cause-and-effect relationship of daily phenomenon poses a great challenge. It is even more so for economic geography studies due to its complexity at both temporal and spatial dimensions. The lack of understanding about the principles of the distribution of human economic activities often results in ill policy-makings.

While acknowledging regional differences *a priori*, this research seeks to find an underlying mechanism that leads in some cases to spatial concentration of seemingly competitive economic activities, and in others to their dispersal. By building simulation models, I hope to better understand the “invisible hand” that directs the spatial distribution of business activities.

The reminder of this thesis is organized as follows. Chapter 2 describes my motivation for this research and the research questions. Also, I review the literature on business location choice and the agent-based approach in examining transportation and land use systems. Chapter 3 introduces the agent-based model of retail location choice on supply chains. Chapter 4 displays and analyzes the simulation results. The last chapter discusses the implications of the results and concludes the thesis.

Chapter 2

Problem statement and literature review

2.1 Motivation and Problem Statement

Retail clusters are geographic concentrations of competing, complementary, and interdependent stores. Rules governing the agglomeration and dispersion of retailers depend on numerous factors that may impact retail distribution patterns and consumer preferences. Traditional studies on retail geography and spatial clusters - while providing insights about the factors influencing retail location choice - often neglect complex interactive behavior among agents and heterogeneous population. From a systems perspective, urban areas are not only concentrations of places and people, but also “systems of organized complexity” where a large number of quantities vary simultaneously and “[interrelate] into an organic whole” (Jacobs, 1961).

Adopting a similar view, this research attempts to understand what can promote the concentration of human activities. This understanding suggests two insights I need to consider in modeling this phenomenon: first, numerous supply chains are interwoven in the urban milieu; second, structural and behavioral patterns of cities result from all kinds of economic agents’ interactions. My interest in the micro-foundation of the clustering of business activities leads me to study retailers’ relationships with suppliers and consumers, and their impacts on large-scale clustering patterns.

The research questions are: how do retailers select locations on supply chains in a context of consumers, retailers, and suppliers? What spatial distribution patterns we can obtain given different economic and behavioral conditions? What are the policy implications?

2.2 Literature on business location choice

Business clustering patterns have been a topic of extensive study. Traditional economic geography theories have explained production structures and spatial distributions mainly through differences in underlying characteristics (geography, labor, products) (Ottaviano and Puga, 1998). von Thünen (1826) studied the relationship between land rent, yield of land, market price of product, and transport cost. Weber (1909) proposed a theory of industrial locations where industrial organizations locate to minimize costs of transport and labor. Central place theory (CPT) posited a hierarchy of communities in terms of a variety of stores, where goods of higher order tend to stay farther away from each other than goods of lower order in that they serve a larger threshold population (Christaller, 1933). CPT also argued that higher-order places offer all the goods offered at the lower-order ones, but not vice versa. Lösch (1940) suggested that the distribution of manufacturing production could self-organize into honeycombs of regular hexagons. Marshall (1890) proposed a threefold classification of the reasons for industrial agglomeration: first, concentration can improve specialization and service; second, it builds a market for skilled workers; third, it facilitates cooperations with technological spillovers. However, such findings cannot explain how and why such spatial patterns emerge.

When researchers began to search for the "invisible hand" that leads to agglomeration, they resorted to the micro-explanations with different hypotheses about the causes. Micro-explanations for spatial economic theories perhaps begin with Hotelling (1929), who analyzed competitive firm location choice of duopoly in a linear market with homogeneous products. In this model, the players are two firms who maximize individual profits by changing location and price. His approach was to model firms' decision-making sequentially: choosing location first, then prices; the solution depended on the nature of transport costs and pricing policy. d'Aspremont et al. (1979) further showed that with linear transportation costs, no pure strategy equilibrium exist in a price stage game (assuming locations are fixed). Eaton and Lipsey (1982) modeled spatial distribution of retail firms, assuming that different goods are worth traveling different distances to acquire. Quinzii and Thisse (1990) extended Eaton's framework and found that the socially optimal configuration of firms involves the agglomeration of firms selling products of order 1 and order 2. Fujita and Ogawa (1982) considered wages, land prices, and equilibrium allocation of land in production and housing, and found that cities could experience drastic structural changes when transport costs and other key parameters change. By assuming some goods are complements in demand, Fujita et al. (1988) showed that a spatial hierarchy can emerge from economies of scope.

2.3 Retail geography

Previous Retail geography studies have examined the geography of retail centers (Frankowiak, 1978), store locations (Davies and Rogers, 1984), trading area (Huff, 1964; Huff and Rust, 1984), and the retail environment (Halperin et al., 1983; Jones and Simmons, 1990). In the subfield of supermarket business (food stores), some practical work has been done to measure and evaluate store trading area (Applebaum, 1940, 1960), consumer spatial behavior (Bacon, 1984), and retail location strategies (Brown, 1989; Laulajainen, 1987). While such work delved into different aspects of location strategies for retailers, there is still a lack of understanding about the interplay between consumer behavior and retail location choice from the microscopic perspective. Further, the implication of the geography of retailing and consumer travel behavior on urban planning theory and practice has not been fully investigated.

Retail change is an inherently spatial process, which is closely related with shopping trips and consumer preferences. Yim (1993), studying food shopping trips in Seattle, Washington, argued that transportation systems and food retail systems constantly adjusted to each other. It was also found that retail development over long periods has affected consumer choice and travel (Clarke et al., 2006); other studies reveal that transport access impacts firm location choice (Leitham et al., 2000; Targa and Clifton, 2006). Therefore, to capture the development path of retail clusters calls for a comprehensive understanding of consumers' shopping preference, residential preference, and travel behavior. A plethora of studies have found the relationship between non-work trips (such as grocery shopping) and urban forms (Handy, 1996; Schwanen et al., 2004), the built environment (Handy et al., 2005), and urban ecological and environmental issues (Dale and Sjoholt, 2007; Handy et al., 2004). Nevertheless, they were mostly done at the regional level or based on control experiments of stated preference. Jackson et al. (2006) argued that the consumer choice must be assessed at the local level, where the effects of competition are experienced by consumers on the ground. But such studies are limited by the lack of individuals' daily travel path data.

2.4 Previous urban simulation models

Since 1960s, many computerized prototype models have been built to assist planning and policy development in metropolitan areas. Most are mathematically or behaviorally based. Examples include the highly disaggregated EMPIRIC model (Hill et al., 1966), the Detroit prototype of the NBER Urban Simulation Model (Ingram et al., 1972), the TRANUS model (de la Barra et al., 1984), the ITLUP model (Putman, 1991), the MEPLAN model (Hunt and Simmonds, 1993), the California urban futures (CUF) models (Landis, 1994; Landis and Zhang, 1998) (see Wegener (2004) for a historical review). Yet such models do not adequately tackle the increasing complexities of the interactions between a variety of components in urban systems. To meet this challenge, some new planning supporting systems have been developed. Notable examples are the UrbanSim software which incorporated the interactions between land use, transportation, environment, and urban policies by modeling the behavior of urban agents at different levels (Waddell, 2002; Waddell et al., 2003) and the SIGNAL (a Simulator of Integrated Growth of Networks And Land-use) software which modeled the co-evolution of land use and transport networks (Levinson et al., 2007).

2.5 Agent-based modeling in transportation and land use

Traditional analytical models in economic geography, while characterizing the equilibrium status of the system, cannot shed light on what happens outside equilibrium and how equilibrium is reached. Arthur (1990) argued that economy should be portrayed as a complex, path-dependent, organic, and evolving system with positive feedbacks. He performed a theoretical analysis of the probability of location of business firms in urban development, and indicated that the pattern of cities cannot be explained by economic determinism alone (Arthur, 1989). Further, Martin and Sunley (2006) and Arthur (1989) identified path dependency as an important feature of economic landscape. The evolutionary approach has been adopted to examine the spatial evolution of sectors and networks as a dynamic co-evolutionary process. One key feature of this approach is that firms' decision-makings are modeled both in spatial and temporal frameworks, considering an underlying stochastic process to reflect innovation (Boschma and Frenken, 2006; Arthur, 1989; Gabaix and Ioannides, 2004; Andersson et al., 2006).

The agent-based modeling approach, focusing on the interactive behavior of the agents, has been used to model strategic interactions among economic agents. In recent years, agent-based models have gained popularity in revealing the complexity of spatial interactions, dynamics, and self-organization (Portugali, 1999; Parker et al., 2003). It is found that complex system properties can emerge out of simple interactive rules among the agents. Some recent studies have applied the agent-based approach to land use/cover change and the dynamic behavior. Examples include the agent models simulating the evolution of environmentally based land-cover systems (Wu and Webster, 1998, 2000; Brown et al., 2005; Webster, 2003; Evans and Kelley, 2004) and of humans' settlement patterns (Sanders et al., 1997). In addition, there are some models focusing on residential development modeled in a grid-cell environment (Manson, 2000; Berger, 2001; Berger and Ringler, 2002; Parker and Filatova, 2008).Other microscopic modeling approaches include fractal growing (Batty, 1991; Batty and Xie, 1999) and space syntax (Peponis et al., 1998; Batty and Rana, 2004).

Whereas such models have provided different insights on the self-organization of urban clusters, they have not seriously addressed transport costs. Dealing with transport costs in a more rigorous and mature way, while likely adding to the complexity of the model, is necessary to gain a better understanding of the effects of networks on spatial locations.

Chapter 3

The agent-based model

By explicitly tackling business interactions on supply chains, I employ the agent-based approach to explain the emergence of retail clusters from a microscopic perspective. The agents, connecting on supply chain networks, are consumers, retailers, and suppliers. This research appropriates and applies the notions of centripetal and centrifugal forces in economics (Krugman, 1991, 1996), implying that urban space can self-organize into order and pattern even based on simple and decentralized decisions of individual firms and consumers.

3.1 Model structure

My model aims to understand and visualize how retailers choose locations on supply chain networks. The general model structure, shown in Fig. 3.1, has three categories of agents: suppliers, retailers, and consumers. Products flow from suppliers, via retailers, to consumers, while cashes proceed in the opposite direction. The outputs include retail business networks, retail firm profits, and retail spatial patterns.

Two kinds of markets are tested based on this framework: first, a market of homogeneous goods; second, a market of two complementary goods where exists consumers' trip chaining behavior in shopping. The computational models are programmed in the Java language, where each agent is modeled as an object. In the beginning of each round, consumers patronize retailers based on their rules to meet their needs on the product; after consumers finish shopping, retailers calculate their profits (revenue - cost) and assess the profitability of other locales. At the end of each round, given others are fixed, each retailer moves to the locale that can provide the highest profit. The parameters used in this research are listed in Table 3.1.

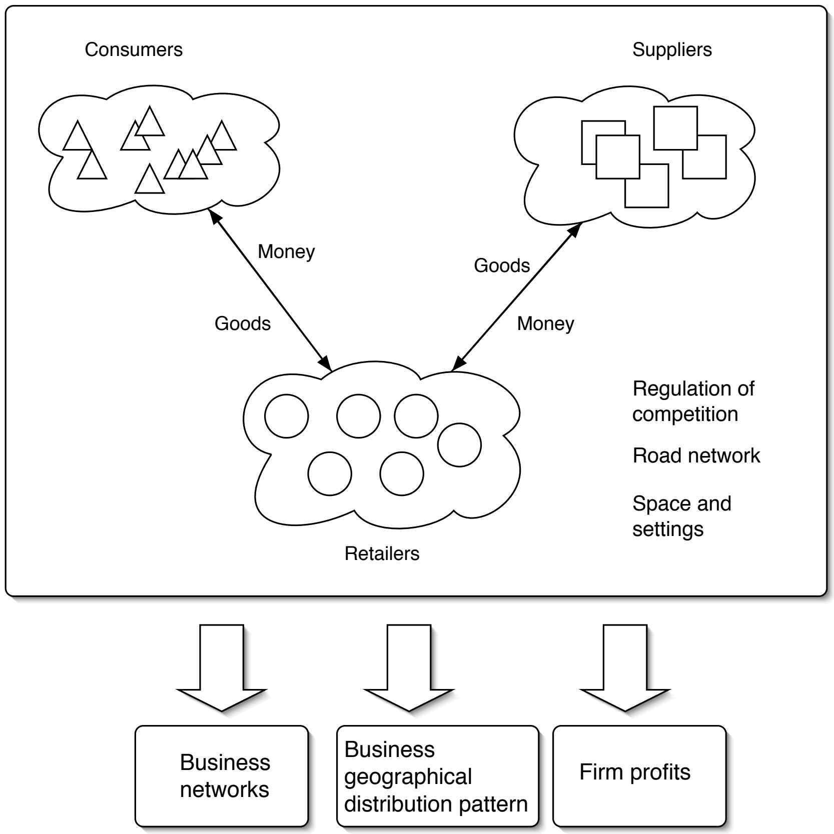

Figure 3.1: Model structure

3.2 Assumptions and definition of cluster

On a simplified three-layer supply chain, products flow from suppliers, via retailers, to consumers; cashes proceed in the opposite direction. All agents are presumed to own perfect information; they locate at a circular area of discrete locations. The idea of a circle, probably first adopted in Hotelling (1929), has the following advantages: (1) one-dimension (which simplifies the model and highlights the embedded economic mechanism); (2) providing an enclosed area (which is similar to a *de facto* geographical region and limits location choices for retailers).

Table 3.1: List of parameters used in the models

Variables	Descriptions
α_i	# of retailers in cluster i
β	exponent of distance decay
M	total # of clusters
τ_i	# of locales covers by cluster i
k_1	constant
C	# of locales on the circle
N	# of consumers
K	# of suppliers of x
L	# of suppliers of y
W_x	number of retailers of x
W_y	number of retailers of y
u	unit shipping cost per locale distance ($)
θ_x	retail unit sales price of x ($)
θ_y	retail unit sales price of y ($)
δ_x	supplier unit sales price of product x ($)
δ_y	supplier unit sales price of product y($)
λ_x	individual consumer demand on x
λ_y	individual consumer demand on y
ρ_{pi}	probability for consumer p to patronize retailer i
W_x	number of retailers of product x
W_y	number of retailers of product y
A_{pi}	attractiveness index of retailer i for consumer p
d_{pi}	shortest travel distance between consumer p and retailer i
γ_{mk}	dummy variable, equaling 1 if retailer in locale m patronizes supplier k
Π_{xm}	expected profit for retailer R_{xi} at locale m

Two kinds of markets are tested based on this framework: first, a market of homogeneous goods; second, a market of two complementary goods where exists consumers' trip chaining behavior in shopping. The computational models are programmed in java, where each agent is modeled as an object. In the beginning of each round, consumers patronize retailers based on their rules to meet their needs on the product; after consumers finish shopping, retailers calculate their profits (revenue - cost) and assess the profitability of other locales. At the end of each round, given others are fixed, each retailer moves to the locale that can provide the highest profit. The locales and profits of retailers are updated for each round; retail distribution patterns in equilibrium are visualized by the *Pajek* software (Batagelj and Mrvar, 2009).

Before elaborating the agents' rules, it is important to define a cluster for this research. A cluster is defined as an agglomeration of retailers which are geographically adjacent or co-located. The density of a cluster is calculated as the number of retailers in a cluster divided by the number of locations in the cluster. The average cluster density of n retailers, φ_n, is formulated as:

$$\varphi_n = \frac{1}{M} \sum_{i=1}^{M} \frac{\alpha_i}{\tau_i} \tag{3.1}$$

where α_i is the number of retailers in cluster i; τ_i is the number of locales covered by cluster i; M is total number of clusters. Some examples of calculating cluster density can be found in Fig. 3.2.

3.3 Consumers

In a market of homogeneous goods (named x) with W_x total number of retailers, a consumer selects a retailer to patronize based on its attractiveness, which depends on the observable shortest distance between the consumer and the retailer and other unobservable factors. For example, for consumer p, the attractiveness index A_{pi} of Retailer R_{xi} (the ith number of retailers of product x) is represented as:

$$A_{pi} = k_1 \cdot d_{pi}^{-\beta} + \epsilon_p \tag{3.2}$$

Where d_{pi} is the shortest distance between consumer p and retailer i; k_1 and the scaling

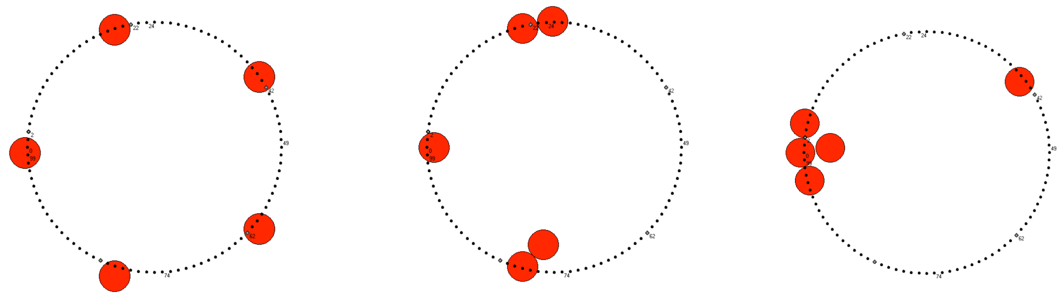

Fig.3.2-1 Fig.3.2-2 Fig.3.2-3

Figure 3.2: Exemplary retail distribution patterns on a circle of discrete locales. Fig. 3.2-1 has five clusters, each of which has only one retailer; therefore average cluster density equals 1. Fig. 3.2-2 has three clusters, one cluster has two adjacent retailers; one cluster has only one retailer; the rest one has two co-locating retailers. The average cluster density equals (2+1+1)/3 = 1.33. Fig. 3.2-3 has two clusters; one cluster has only one retailer, while the other has four retailers covering three locales. The average cluster density equals (1+4/3)/2=1.17.

parameter β are positive constants. The function indicates that longer travel distance would generally diminish consumers' willingness to patronize. White noise ϵ_p shows a certain degree of randomness.

In a market of two complementary goods sold by two kinds of retailers, let R_{xi} indicate retailer i of product x, and R_{yj} indicate retailer j of product y. A trip is defined as a round-trip for a consumer from home to visit R_{xi} and R_{yj}. Given W_x number of R_{xi} and W_y number of R_{yj}, there are in total $W_x \cdot W_y$ trip candidates.

The utility for consumer p to patronize retailer R_{xi} and R_{yj} (indicated by Pair t) equals:

$$A_{pt} = \sum_{t=1}^{W_x \cdot W_y} k_1 \cdot d_t^{-\beta} + \epsilon_p \tag{3.3}$$

After calculating all retailers' attractiveness indexes, a consumer probabilistically selects a retailer to patronize. In a market of homogeneous goods, the probability for consumer p to patronize retailer R_{xi} (indicated by ρ_{pi}), is calculated based on a simplified version of Huff's model (Huff, 1964):

$$\rho_{pi} = \frac{e^{A_{pi}}}{\sum_{i \in W_x} e^{A_{pi}}} \tag{3.4}$$

In the market of two complementary goods, the probability for consumer p to visit R_{yj} can be similarly calculated.

The Roulette Wheel selection method is adopted for a consumer to select a retailer in each round. This approach indicates that retailer i with higher ρ_{pi} for consumer p has a greater chance to be selected by this consumer. A consumer's probabilities of patronizing all retailers comprise a wheel of selection, which is updated for every round. A spin of the wheel selects a retailer; once a retailer is selected, a consumer buys all needed products from this retailer. The sequence for consumers to patronize retailers is randomly decided for each round.

3.4 Retailers

Retailers connect suppliers and consumers on supply chains. In each round, a retailer evaluates expected profits of all locales and moves to the locale of the highest profit. For example, retailer R_{xi}'s expected profit in locale m, Π_{xm}, is calculated as:

$$\Pi_{xm} = (\sum_{p=1}^{N} \lambda_x \cdot \rho_{pm}) \cdot [\theta_x - \sum_{k=1}^{K} (\delta_x + u \cdot \sigma_{mk}) \gamma_{mk}] \tag{3.5}$$

Where λ_x indicates individual customer's demand on product x (with total N customers); ρ_{pm} stands for the probability for consumer p to patronize the retailer in locale m; θ_x means retail unit sales price of product x (a constant in the model); δ_x means suppliers' unit sales price of x (a constant); u is the transport cost per unit distance per product; σ_{mk} indicates the shortest distance between supplier k of product x and locale m; γ_{mk} is a binary variable, which equals 1 if a retailer in locale m patronizes supplier k. $\sum_{p=1}^{N} \lambda_x \cdot \rho_{pm}$ represents total expected sales of products in locale m. The part in brackets refers to expected profit per product, equaling sales price minus cost. A retailer's cost includes the purchasing cost of products from a supplier and the shipping cost which is proportional to shipping distance and quantity of products. Here we assume a retailer patronizes its closest supplier. After evaluating profits of all C locales on the circle, retailer R_{xi} moves to the locale that provides the highest expected profit Π_{xi}, given others are geographically fixed at that time.

Each retailer can only move once per round; the sequence of moving is randomly decided.

3.5 Suppliers

We assume that all suppliers keep the same unit sales price. Moreover, they are evenly distributed on the circle and are fixed in all rounds. Further, in the market of two complementary goods, suppliers of the two products co-locate. It is presumed that suppliers can always produce enough goods to meet market demand.

Chapter 4

Results and analysis

4.1 The market of homogeneous goods

4.1.1 Base case

The basic setting is a circle of 100 discrete locales, where 5000 consumers and 5 suppliers are evenly distributed at their locales. Different scenarios are tested with different numbers of retailers ranging from 2 to 100. The parameter values in this model (Model 1) are shown in Table 4.1. We examine retail geographical distribution patterns when stable patterns emerge (i.e. no retailers change their locales). Typically, after 2 or 3 rounds a stable pattern emerges, which is an equilibrium where an individual retailer cannot improve its profit by unilaterally changing its locale, given the same is true of other retailers.

Fig. 4.1 shows the numbers of clusters and cluster densities given different number of retailers. As can be seen, as the number of retailers increases from 2 to 10, the number of clusters rises to 5 (the same number as suppliers). In particular, when 10 retailers partake in the game, retailers double up at supplier locales; the average cluster density therefore becomes two. As more retailers enter the market, the number of clusters remains flat; retailers in the clusters stay adjacent to each other while centering around suppliers. The average cluster density declines to one, while the distribution pattern remains almost symmetric. As the number of retailers approximates 100, which equals the total number of locales on the circle, all clusters connect with each other and each cell is occupied by one retailer. Some examples of retail distribution patterns are illustrated in Fig. 4.2.

Table 4.1: Values of parameters (Model 1: homogeneous goods; Model 2: complementary goods)

Variables	Descriptions	Model 1	Model 2
β	exponent of distance decay	1.0	1.0
k_1	constant	1	1
C	# of locales on the circle	100	100
N	# of consumers	5000	5000
K	# of suppliers of x	5	10
L	# of suppliers of y		10
u	unit shipping cost per locale distance ($)	0.02	0.02
θ_x	retail unit sales price of x ($)	2.5	2.5
θ_y	retail unit sales price of y ($)		1.5
δ_x	supplier unit sales price ($)	1.5	1.5
δ_y	supplier unit sales price ($)		1.0
λ_x	individual consumer demand on x	20	20
λ_y	individual consumer demand on y		10

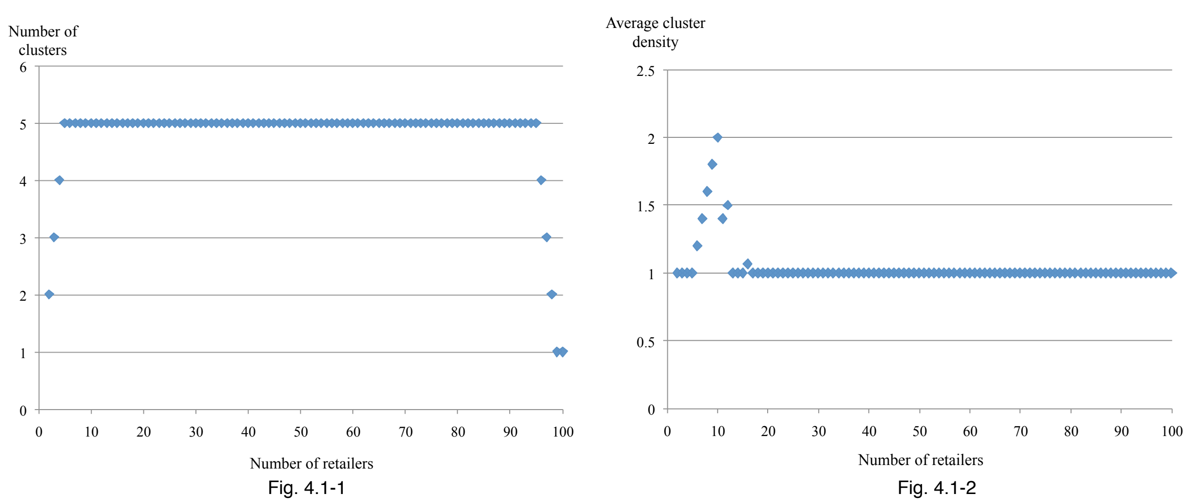

Figure 4.1: Number of clusters and average cluster density. Fig.4.1-1: Number of clusters emerged as the number of retailers increases from 2 to 100; Fig.4.1-2: Average cluster density as retailers rises from 2 to 100.

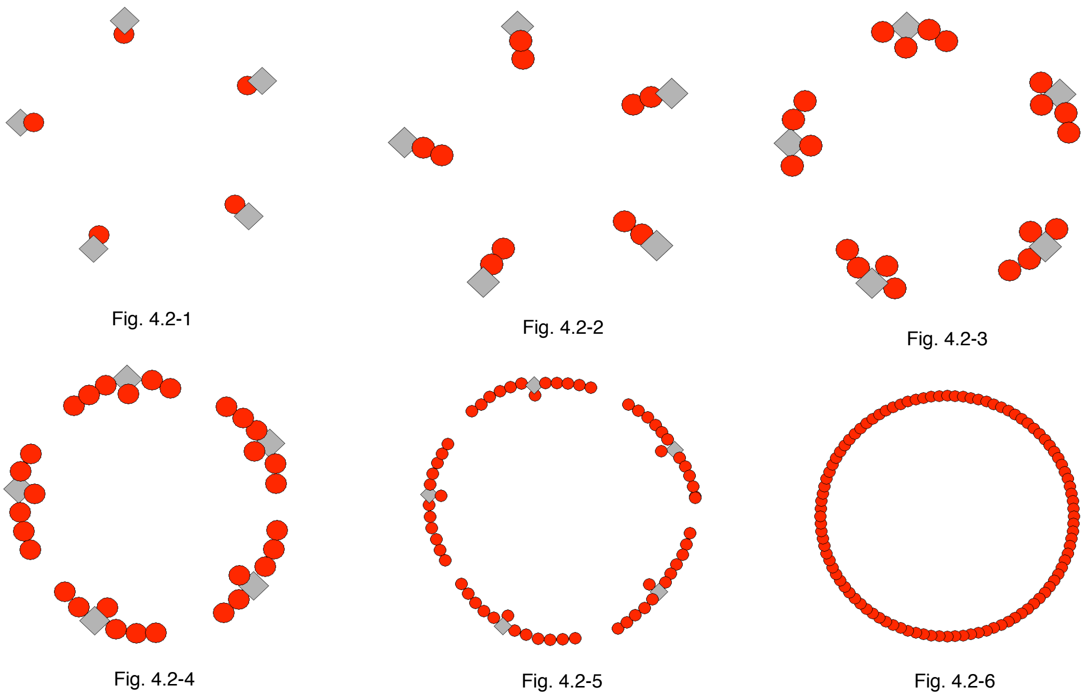

Figure 4.2: Examples of retail distribution patterns for different numbers of retailers in a market of homogeneous goods (plotted in *Pajek* (Batagelj and Mrvar, 2009)). (Red circles stand for retailers, and gray diamonds represent suppliers. Objects sitting on top of each other mean that they share the same locale; adjacent objects indicate that they are geographically adjacent.). Fig.4.2-1 displays the distribution pattern of 5 retailers. Fig.4.2-2 shows the pattern of 10 retailers. Fig.4.2-3, Fig.4.2-4, Fig.4.2-5, and Fig.4.2-6 respectively exhibit retail spatial patterns for 20, 30, 60, and 100 retailers.

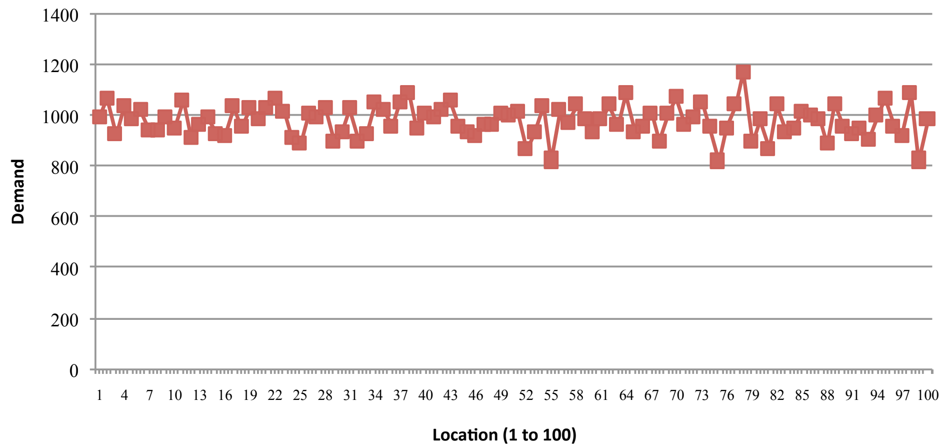

Figure 4.3: Demand in different locations, with individuals' demand following normal distribution (mean value equals 20 and st. dev. equals 10).

The above analysis indicates that when the number of retailers is no more than 10, the centripetal force (proximity to suppliers) induces them to double up at supplier locales, while the centrifugal force (proximity to customers) keeps the distribution pattern symmetric. As the number of retailers continues to grow, retailers tend to disperse themselves along the circle; the existence of centripetal force, however, keeps them near suppliers. Different numbers of retailers in the competition beget different distribution patterns.

4.1.2 Heterogeneous population

What if individuals demands on product x are different? How would the final retail distribution patterns change? Here I test the scenario where individuals' demand on product x follows normal distribution, with average 20 and standard deviation 10; the number for each consumer's demand is randomly generated based on this distribution. There are 50 customers in each locale; the total demand in each location can be found in Fig. 4.3. The high demand is equals 1171 at locale 78, and the lowest demand equals 830.

The find retail distribution pattern is shown in Fig. 4.4. Five symmetric retail clusters show up around supplier locales; yet different from the previous result, the case where every two retailers double up does not show up. The cluster density equals 1.

I further examine the case where the demand follows power-law distribution, assuming that individual's demand on product x ranges from 0 to 60 and that the scaling parameter

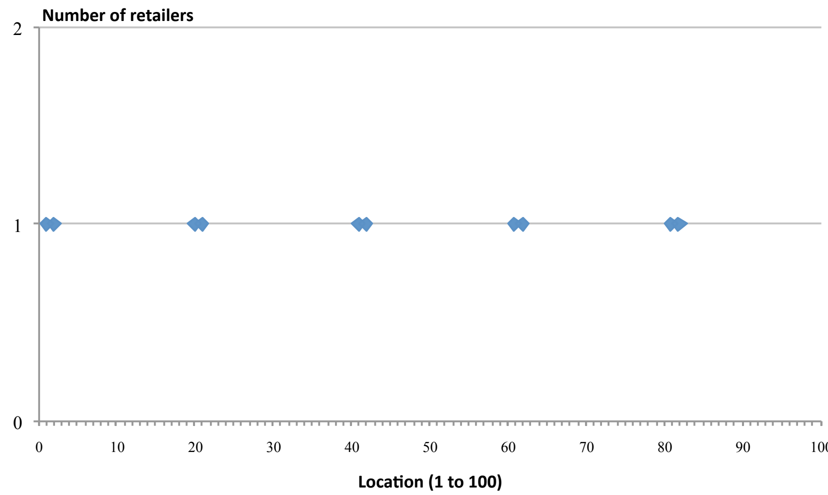

Figure 4.4: Retail distribution pattern in equilibrium, with individuals' demand following normal distribution.

equals -0.8. The demand distribution is shown in Fig. 4.5. The retail distribution pattern in equilibrium, shown in Fig. 4.6, is the same as in Fig. 4.4. While each cluster's locale is slightly different, it covers a supplier locale. Retailers stay close to suppliers to minimize costs and keep the density low to reach out to population with heterogeneous demand. It further shows that heterogeneous population can impact retail location distribution.

4.1.3 Sensitivity tests

To further explore the effects of the centripetal and centrifugal forces on retail distribution patterns, sensitivity tests are performed on β and u. When examining different values of β or u, we set other parameters to be the same as in Table 4.1.

First, we test the value of β from 0 to 2.0 (with step size 0.25) and for each case run the number of retailers from 2 to 30. Fig. 4.7 presents cluster densities for different values of β. We observe that when β is larger than 0.5, retail distribution patterns are similar to the base case ($\beta = 1.0$) described above. When β equals 0 or 0.25, retail geographical distribution patterns considerably differ from other cases. When β equals 0, retailers are evenly distributed and only locate in supplier locales for all scenarios of different numbers of retailers. This is because as β equals 0, consumers are indifferent to travel and retailers therefore stay at supplier locales to minimize cost. It is interesting to see that all retailers

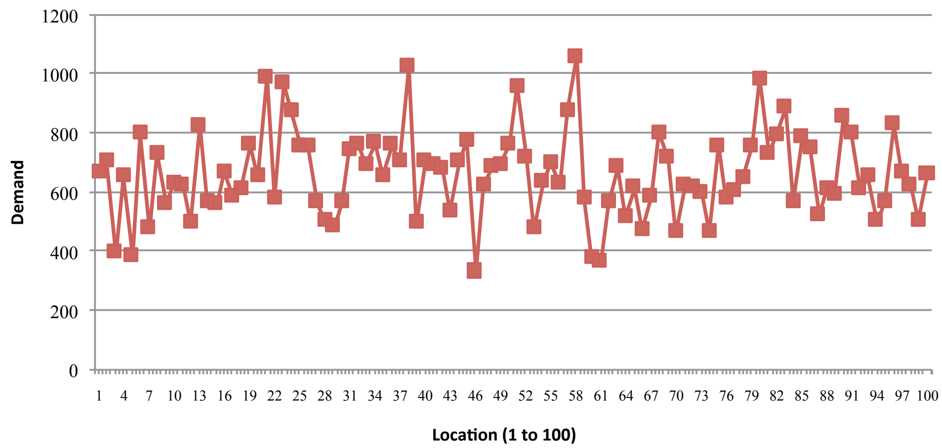

Figure 4.5: Demand in different locations, with individuals' demand following power-law distribution (the scaling parameter equals -0.8).

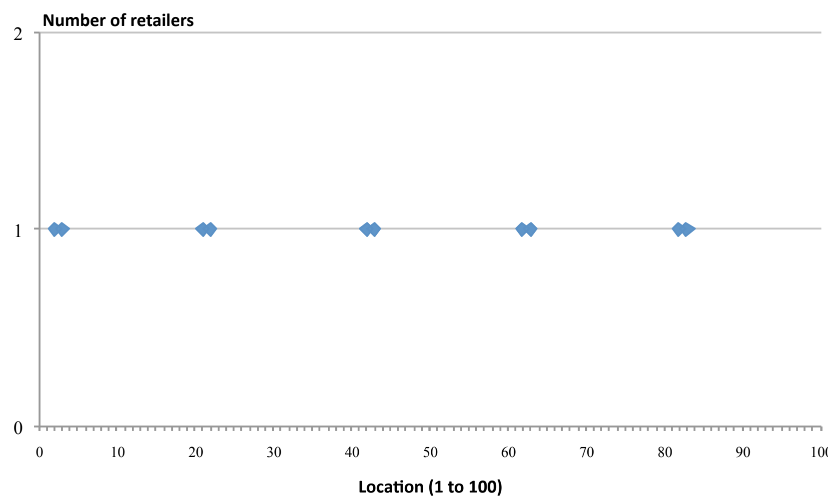

Figure 4.6: Retail distribution pattern in equilibrium, with individuals' demand following power-law distribution (the scaling parameter equals -0.8).

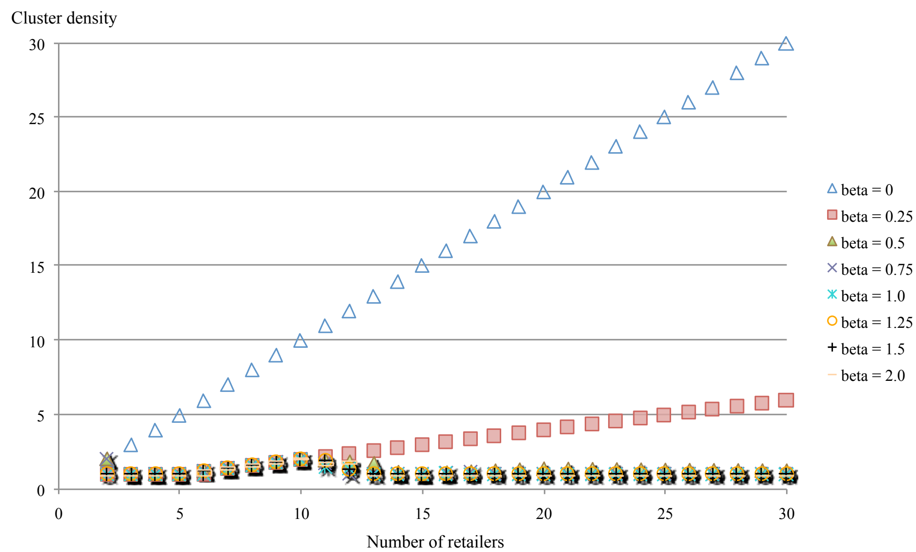

Figure 4.7: Average cluster densities for the scenarios with retailers ranging from 2 to 30: results of sensitivity tests on β (scaling parameter).

amass at only one supplier locale; cluster density therefore equals the number of retailers. This is an artifact of the simulation model that retailers choose the first most profitable locations and don't consider alternative locations of exactly equal profits. They might just as easily cluster uniformly or non-uniformly on any supplier locale.

I change the value of u from 0 to 0.16, with step size 0.02. Fig. 4.8 shows cluster densities for different values of u. When u is larger than 0.08, retailers tend to double up on suppliers, as their number booms from 2 to 10. However, as the number of retailers rises to 15, only the case of u equaling 0.16 shows continuing accumulation of retailers at supplier locales, which is different from the result of our base case (where u equals 0.02). In particular, in the case of 15 retailers, every three retailers stay at a supplier locale. When u equals 0.16, although the cluster density curve gradually falls as the number of retailers continues to increase, a rising trend of cluster density can still be noticed when the number of retailers ascends from 20 to 25.

I also examine the case where consumer demand can fluctuate. Since retailers' sales price is fixed, we relate consumer demand with retailers' attractiveness. Consumer p's demand

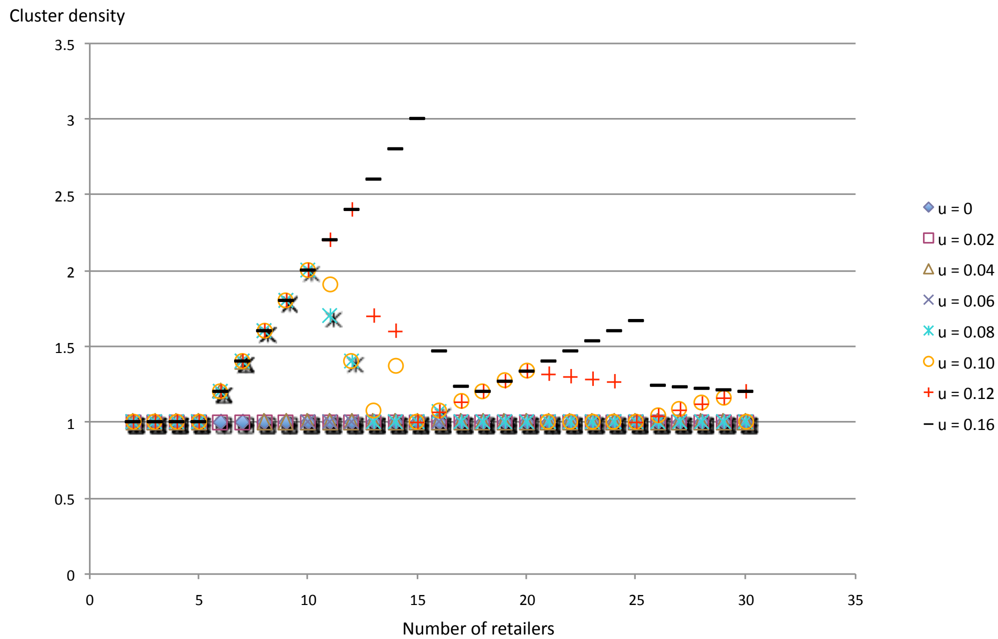

Figure 4.8: Average cluster densities for the scenarios with retailers ranging from 2 to 30: results of sensitivity test on u (unit shipping cost).

on product x, λ_{xp}, is measured as:

$$\lambda_{xp} = \alpha_0 + \alpha_1 \cdot \sum_{i \in W_x} e^{A_{pi}} + \epsilon_p \tag{4.1}$$

Where $\sum_{i \in W_x} e^{A_{pi}}$ is a function of accessibility to retailers, as introduced in Eq.(2); the error ϵ_p term is an i.i.d. with zero mean value. This expression originated from studies on evaluating accessibility of location in transportation research (Ben-Akiva and Lerman, 1985). It indicates that the maximum utility of all alternatives in a choice set is a measure of a consumer's expected demand associated with this situation. While α_0 and α_1 are assumed to be the same for all consumers, this function reflects the variation of the demands of consumers in different locales and different rounds and for different scenarios.

In this simulation, α_0 is set to be 10, representing a consumer's basic demand on product x; α_1 equals 1.75, indicating a consumer's demand elasticity with respect to accessibility to retailers. Other parameters are the same as in Table 4.1. An increase of the number of retailers generally induces the growing of consumers' demand. Yet, here we set an upper limit of 60 on an individual consumer's demand on product x. We compare the results of different numbers of retailers ranging from 2 to 100. The resultant retail distribution pattern with elastic consumer demand is basically the same as the base case wherein demand is inelastic.

Fig. 4.9 further shows the curve of individual consumer demand for different numbers of retailers in the market. In the very beginning, consumers' average demand gradually rises with the increase of retailers; it stops growing when more than 26 retailers are in the game, after it reaches the upper limit of individual consumer demand. It implies that as more retailers partake in the competition, the implicit product and price differentiation as well as the explicit lowered transportation costs increase demand in the first stage of the survival curve of the product. Fig. 4.10 compares retail average profits with and without consumer demand elasticity. We can see a steeper declining curve of average profits for the case with consumer demand elasticity, which is a direct consequence of competition. The profit gap is particularly salient when the number of retailers is between 5 and 40. As the number of retailers continues to increase, the two curves get increasingly closer. The implication is that as a new product is in its full swing of development in the market, a market with consumer demand elasticity offers greater financial returns than one without. Yet, as the product reaches its mature stage, retail profit decreases over time, and there is probably no big difference between the market with demand elasticity and without demand elasticity.

4.2 The market of complementary goods

4.2.1 Base case

In the market of two complementary goods, we first examine the scenario of 10 suppliers of x and 10 suppliers of y, every two of which co-locate and are evenly distributed around the circle. Table 4.1 shows the values of the parameters used in this experiment (Model 2). We first set 20 retailers (10 retailers of product x, 10 retailers of product y). Since multiple equilibria are possible, 200 different retail initial location patterns (seeds) are examined.

Given different seeds, our model produces multiple stable patterns, which can be grouped into three categories by the number of clusters (although each individual retailer's final

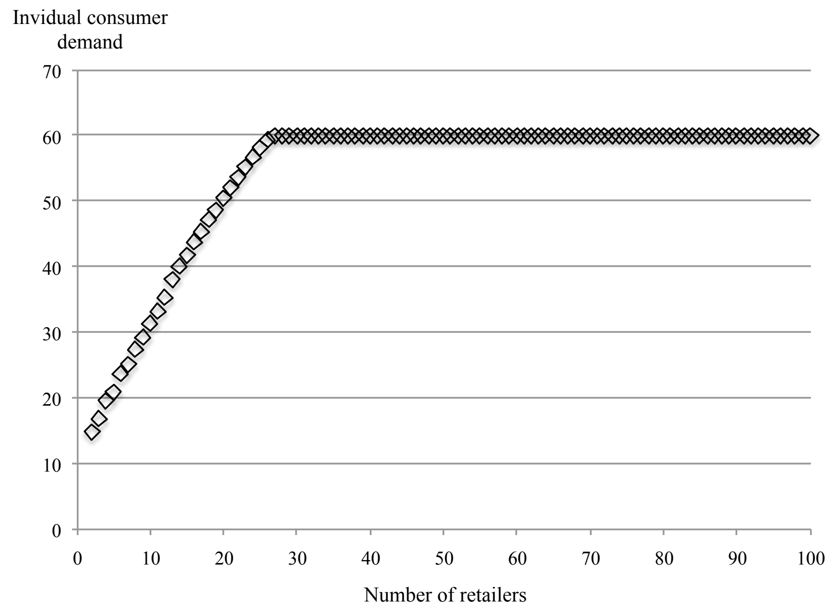

Figure 4.9: Individual consumer demand on product x increases with the rising of the number of retailers, yet does not exceed 60. When the number of retailers exceeds 26, average consumer demand reaches 60 (the upper limit of individual consumer demand) and stays constant thereafter.

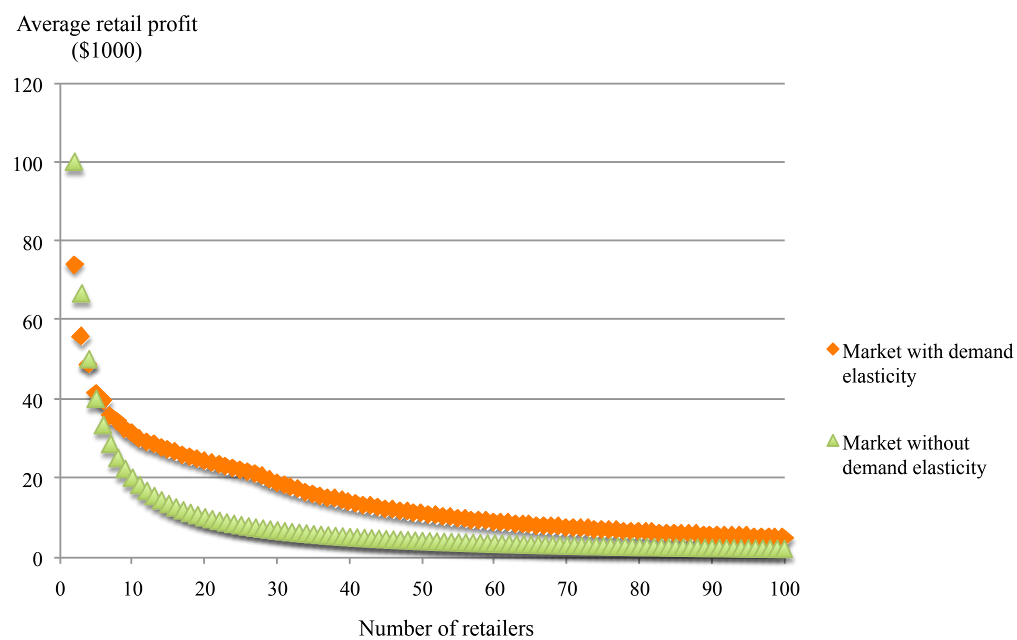

Figure 4.10: A comparison of retail average profit with and without consumer demand elasticity for the number of retailers from 2 to 100. The curve of retail average profit without demand elasticity (base case) goes under the curve with demand elasticity; the profit gap is particularly salient when the number of retailers is between 5 and 40.

locale may vary in different outcomes). The most common pattern is only one cluster (with probability 0.725), where all retailers accumulate at a supplier locale; the patterns of two clusters and three clusters emerge with probability 0.24 and 0.036. All the retail distribution patterns share two features: (1) retailers only stay at supplier locales; (2) the same number of retailers of x and retailers of y co-locate, indicating that they constitute pairs. It is interesting to notice that the evenly distributed pattern of retailers—every one retailer of x and every one retailer of y double at a supplier locale—does not appear in this experiment. To further explore this possibility, we intentionally set the initial distribution pattern to be very similar to the evenly distributed one, which ultimately results in the evenly distributed pattern of retailers.

4.2.2 Sensitivity tests

To understand the impact of the number of retailers on retail distribution patterns, we further vary the total number of retailers from 4 to 40 while keeping the same number of retailers of x and the number of retailers of y; other parameters are set to be the same as the base case. After testing 200 seeds for each scenario, except for the case of 4 retailers, our simulation results reveal multiple hierarchical retail distribution patterns for all cases. Fig. 4.11 shows the probabilities for different retail clusters. It is interesting to notice that the result of only one cluster has the highest probability to appear for all cases. Moreover, by observing the trend of the histograms of one cluster for different numbers of retailers, we can notice that the greater gap between the number of retailers and the number of suppliers (which is 10 for each category of products), the more likely that all retailers tend to accumulate in one cluster. The largest number of resultant clusters is 4; the probability of its happenstance nonetheless never exceeds 0.05.

But what if we have different numbers of retailers of complementary goods? We vary the number of retailers of product y from 2 to 16 while fixing the number of retailers of x to be 10. 200 seeds are also tested for each scenario. The probability distribution for different numbers of cluster is shown in Fig. 4.12. Overall, I find that the greater gap between the number of retailers of product x and the number of retailers of y, the more likely fewer clusters will emerge. Like the previous results, the case of one cluster has the

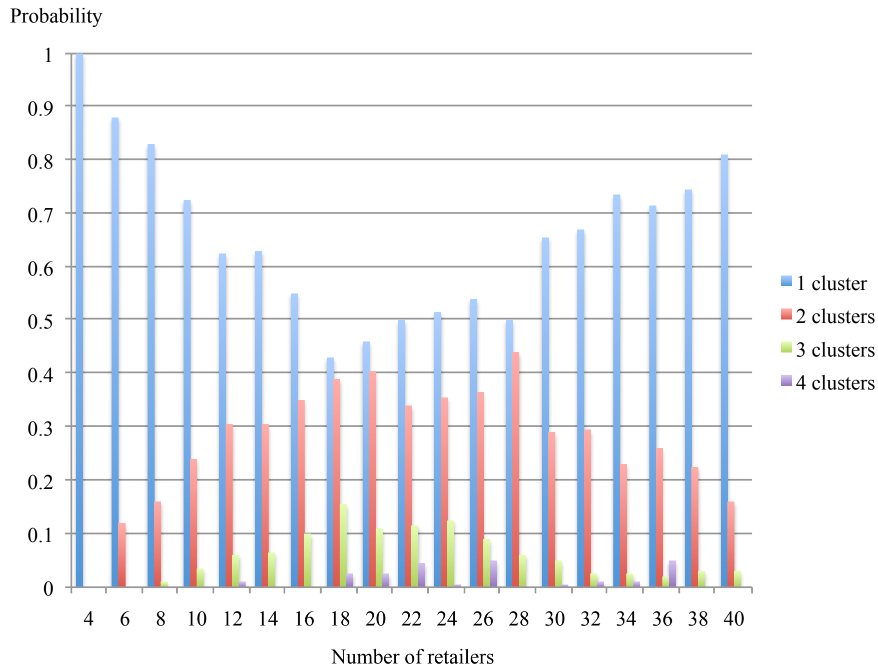

Figure 4.11: Probability distribution of the numbers of clusters with retailers ranging from 4 to 40 (where the number of retailers of x equals the number of retailers of y), with total 20 suppliers (10 suppliers of x and 10 suppliers of y). The case of one cluster has the highest probability to appear of all the cases.

highest probability to emerge and retailers only locate at supplier locales. Moreover, when there are more than one cluster in a retail distribution pattern, the ratio of the number of retailers of x to retailers of y in each cluster is very close. To illustrate, Fig. 4.13 shows some retail distribution patterns for the case of 10 retailers of x and 15 retailers of y. Such interesting phenomena may indicate that retailers of complementary goods can self-organize themselves into clusters of similar structures.

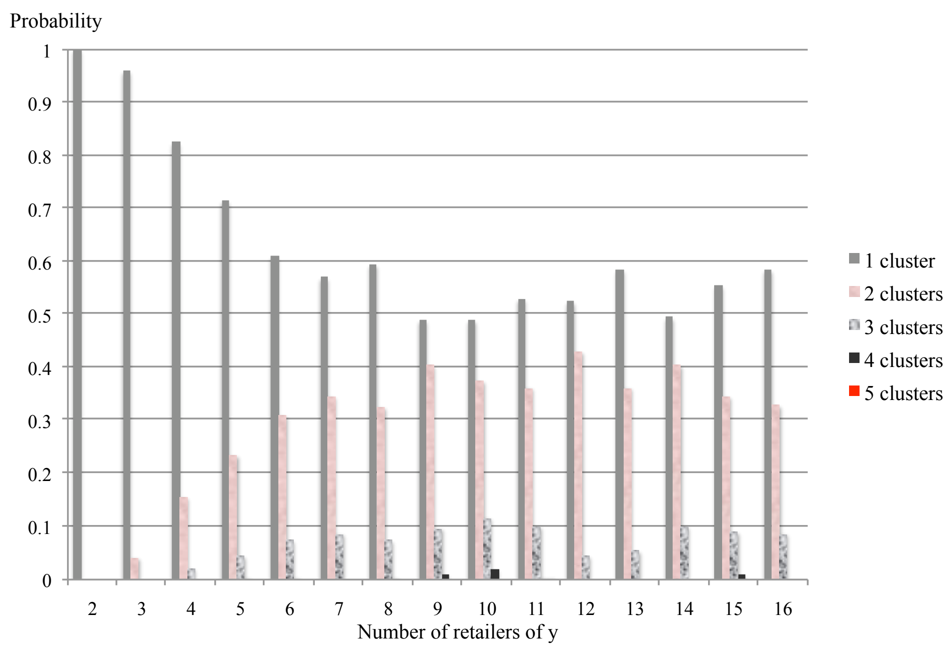

Figure 4.12: Probability distribution of the numbers of clusters with 10 retailers of product x and the number of retailers of product y ranging from 2 to 16 (shown in the horizontal axis). The case of only one cluster has the highest likelihood to emerge. The greater gap between the number of retailers of product x and the number of retailers of product y, the more likely that the case of fewer clusters will emerge.

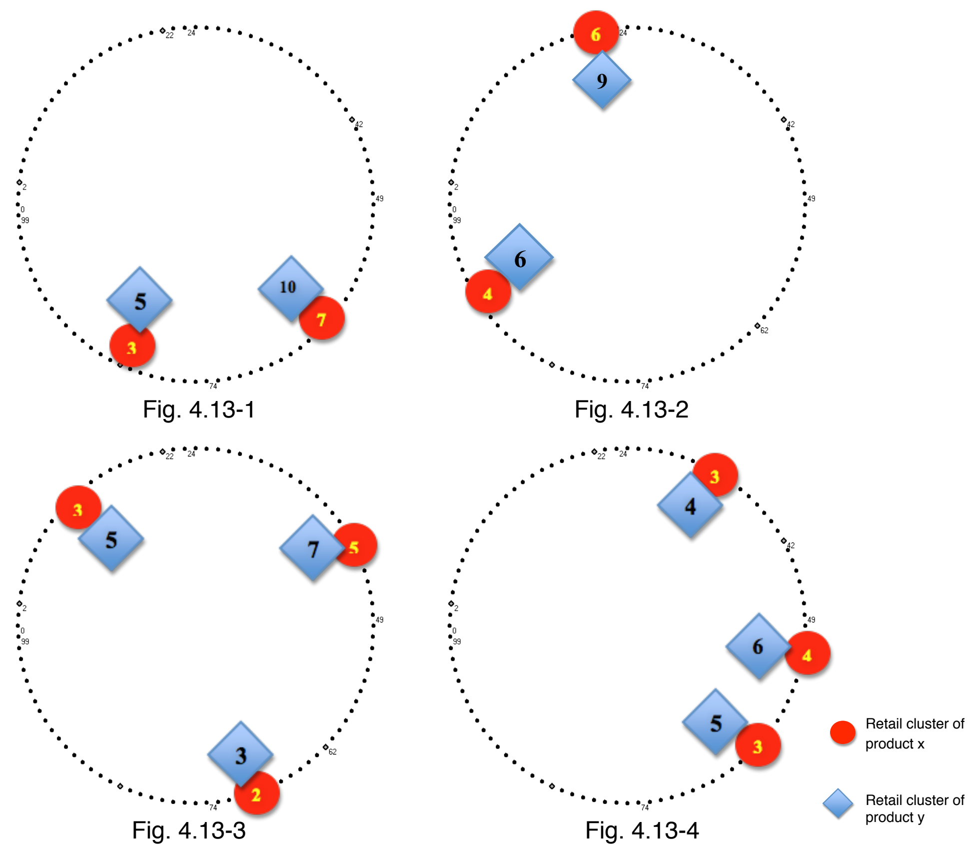

Figure 4.13: Some retail distribution patterns (with more than one cluster) in equilibrium for 10 retailers of x and 15 retailers of y (plotted in *Pajek* (Batagelj and Mrvar, 2009)). A red circle stands for a retail cluster of x; a blue cross represents a retail cluster of y. Two shapes laid together show that they co-locate. The number in each shape indicates the number of retailers. All retailers stay at supplier locales. In Fig.4.13-1, the ratio of the number of retailers of x to the number of retailers of y for the two clusters respectively equals 3:5 and 7:10. In Fig.4.13-2, the ratios the number of retailers of x to the number of retailers of y for the two clusters are identical, equaling 2:3. In Fig.4.13-3, the ratio respectively equals 3:5, 5:7, and 2:3 for the three clusters. In Fig.4.13-4, the ratios for the three clusters are: 3:4, 3:5, and 4:6.

Chapter 5

Discussion and conclusions

5.1 Discussion

Our agent model in the market of homogeneous goods and the market of complementary goods produces the emergence of retail clusters. In a market of homogeneous goods, clusters tend to be symmetric. When retailers are few, they accumulate in suppliers' locales; as the number of retailers increases, they spread out around suppliers and incrementally occupy the whole circle. Moreover, a larger scaling parameter (absolute) value for consumers tends to make the retail pattern more spread out, and higher unit shipping cost makes retailers more concentrated around suppliers. Such results exhibit the balance between proximity to the market and proximity to suppliers which impacts the retail distribution pattern.

In the market of two complementary goods, multiple equilibria of retail distribution patterns are found to be common; nevertheless, the case of only one cluster—where all retailers accumulate in a supplier locale—is most likely to emerge. Moreover, the greater gap between the number of retailers of x and the number of retailers of y, the more likely dense clusters are to emerge. A further extrapolation suggests that in the market of homogeneous goods, the case of one cluster cannot be stable in that some retailers in the big cluster can easily move to an open space on the circle to occupy a larger market. In the model of complementary goods, however, since consumers consider total travel distance for buying both goods, retail location choice depends not only on their distance to suppliers and consumers, but also on their distance to retailers of complementary goods. Additionally, for the patterns with more than one cluster, our results imply that emergent clusters, however different in size, tend to have a similar composition in terms of the ratio of retailers of complementary goods.

In central place theory, Christaller (1933) claimed that in the areas with population and resources which are evenly distributed, settlements have equidistant spacing between centers of the same order; high-order services are farther away from low-order services. Yet, this research demonstrates that even in a market of two equally important products, hierarchical distribution patterns can also autonomously emerge. This comports with the notion of retail districts found in many cities, such as the Kappabashi district of Tokyo specializing in kitchen equipment (and plastic sushi) along with similar examples of clustered competitors (Levinson and Krizek, 2008). In our model of complementary goods, although the evenly-distributed pattern of retailers can occur under certain circumstances, to achieve this each cluster requires a very specific timing, which has a high requirement for initial seeds and the sequence of location choice. Therefore it is much less likely to naturally emerge than the hierarchical patterns. Overall, our results find autonomous emergence of retail clusters; the hierarchical distribution patterns (in particular, the pattern of only one cluster) appear with a high probability.

5.2 Conclusion

This thesis builds an agent-based model to examine retail location choice on a supply chain network of consumers, retailers, and suppliers. In a market of homogeneous goods, we find symmetric retail distribution patterns, and average cluster density changes dynamically as retailers join the market. These patterns are affected by shipping cost and consumers' willingness to travel. Our findings demonstrate that the development of a market does not always lead to condensed agglomeration of business locations. Moreover, the balance between transportation cost and market size considerably impacts the size and density of clusters.

In a market of two complementary goods, assuming suppliers of the two products co-locate and evenly distribute themselves, we find self-organizing retail clusters with features different from the results of the first model. First, multiple equilibria of retail distributions are common. Second, co-locating of retailers of complementary goods appears with a high probability. Moreover, the likelihood of clustering increases with the gap between the number of retailers of complementary goods and the gap between the number of retailers and the number of suppliers. Third, when more than one cluster occurs, however different in size, the ratio of the number of retailers of one product to the number of retailers of the other product tends to be close for the emergent clusters. Our results illustrate that competition among retailers on supply chains (especially when considering trip chaining for complementary goods on the part of the customer) is sufficient to produce clustering, and other mechanisms (such as the desire of customers to comparison shop) are not required, but may also be additional source of clustering behavior. We have not identified whether there is a necessary assumption to produce clustering.

Future research should address the efficiency of such self-organized retail patterns in terms of social welfare, as opposed to a more evenly distributed one (such as posited in central place theory). Empirical studies should also test the hypotheses presented in this research.

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