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ORIGINAL PAPER

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Emergent macrostructures of path-dependent location adoptions processes of firms

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Abstract Agglomeration of firms in a regional context is a complex process that cannot be tamed easily using traditional economic models. Instead, in this paper, I conducted computer simulations to observe under the assumption of increasing returns how firms choose among competing locations to form regional agglomeration. By designing simple rules of firms' spatial choice behavior, I observed through such simulations how firms moved across and within regions. The findings showed that firms tended to lock-in a particular region, that is, that region dominated all others in the firms' movement, reminiscent of market domination of a technology among competing technologies. The emergent macrostructures were surprisingly orderly in that the distributions of sizes of spatial clusters in relation to frequencies followed a logarithmically linear form or a power law. Unpredictability, path dependence, and small events were present in the simulations and can be explained in the context of regional development. Useful insights as to how macrostructures of agglomeration emerge through microbehaviors of firms can be gained through the simulations.

JEL Classification R00 · R10 · R14

1 Introduction

On a website of the department that I am currently affiliated with, a bulletin board is constructed so that any student can post a message to express opinions. There are two pieces of information in each of the message: the subject of the message and the number of people who have read the message. Presumably, a student visiting the website would select a message to read based on the two pieces of information:

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whether the message subject attracts him or her and how many other students have read that message. An interesting question is: Would the distribution of the numbers of students who have read the messages follow a particular pattern? I conducted a regression analysis on the logarithmic scale of the numbers and the ranks of these numbers.[1] What I found was that the rank–size relation as depicted by Zipf (1949) applied to this case with an R^2 value equal to 0.89 and a slope of −1.1715. The surprising finding leads me to speculate that what Professor Krugman (1996a) named the mystery of urban hierarchy and explained as order from random growth (Krugman 1996b) resembles the formulation of the above phenomenon of what I call the bulletin board mystery. Consider each message on the board as a potential location from which a student as a firm is to select to read. The firm's preferences for locations depend on two components: geographical benefit and agglomeration benefit reminiscent of the curious student in selecting a particular message to view based on the inherent attractiveness of the subject and the popularity of the message in terms of the number of people who have read it. Indeed, Arthur (1990) has constructed mathematical models to analyze what spatial patterns would emerge from firms entering into alternative locations under the assumption of increasing returns. The results are insightful in that a monopoly outcome is to emerge, but which location would win is unpredictable.

Cities are spatial agglomerations of individual agents acting in particular facilities and buildings. It is still in debate as to how these spatial agglomerations come about and how they evolve. There are at least two camps of such explanations: deterministic and path-dependent (Batten 2001). On the one hand, traditional models of urban economics assume homogeneous agents that share some common behavioral assumptions, such as rationality in terms of profit or utility maximization (O'Sullivan 1993). These models can at best depict in a static way that regional spatial agglomerations are equilibriums or solutions of economical models built on such assumptions, ignoring the dynamic trajectories of the economic systems in spatial evolution. One condition under which such spatial equilibriums exist is decreasing returns or diminishing marginal rate of substitution functions. Decreasing returns are without a doubt present in many economic activities such as agricultural land cultivation, but in some economic activities such as technological competition, increasing returns or positive feedback are the driving force of market domination (Arthur 1994).

On the other hand, the market-sharing processes of competing technologies are subject to increasing returns resulting in multiple equilibriums, and which of these equilibriums emerges depends on small events (Arthur 1994). The path dependence models describing the market competition of technologies can readily be transposed into models depicting spatial competition of locations. This has been done by Arthur (1990) through a mathematical model to describe the stochastic processes of firms in choosing locations under the assumption of increasing returns to agglomeration economies. In his model, Arthur concludes that where there is no upper bound to locational increasing returns due to agglomeration, there will indeed be a dominant outcome, and that where there is an upper bound to

[1] The numbers of students viewing the 53 messages were, in descending order, 680, 185, 159, 153, 148, 147, 134, 124, 122, 110, 102, 92, 87, 87, 85, 83, 83, 81, 80, 75, 72, 69, 66, 61, 60, 59, 57, 54, 49, 46, 45, 44, 41, 41, 40, 40, 38, 36, 36, 35, 34, 33, 32, 29, 27, 27, 26, 23, 19, 18, 16, and 14.

increasing returns due to agglomeration, either dominance by one region or regional sharing of the industry exactly as if the agglomeration effects were absent could occur.

In the present paper, I follow the second camp of explanations of agglomeration, reminiscent of choices among technologies. The immediate question following the increasing returns and path-dependent model is: What macrostructures of locations of agglomeration would emerge from microbehaviors of agents that give rise to small events? The result derived from Arthur's model simply argues that there is a dominant location depending on the entry order of firms to form the industry, but no claim is made as to what properties the emergent locational patterns have. If there exists an envelope of certain properties within which all the emergent locational patterns fall, and we could trace the mechanisms based on which small events in the increasing returns regime are accumulated to lead the system to the envelope of all locational patterns, then that insight should enhance our understanding of how and why cities form and scatter spatially the way they do.

The present paper is not to provide such an answer, but through two sets of simulations designed under some plausible assumptions, it attempts to throw some light on the question. In short, the simulation results strongly suggest that increasing returns to agglomeration lead not only to a dominant outcome of locational patterns (which is consistent with the result of Arthur's theoretical model) but also to a locational pattern that is close to a power law of frequency–size distribution of cities. "Power law, increasing returns, and spatial evolution" reviews current work on the power law distribution of cities and depicts the relationship between increasing returns and spatial evolution. "Research design" introduces the research design of the computer simulations. "Results" shows the results. "Discussion" discusses some relevant issues. "Conclusions" concludes.

2 Power law, increasing returns, and spatial evolution

The fact that the size distribution of metropolitan areas is regular in relation to the ranking of the sizes is not a new story. Zipf (1949) found out the regularity about half a century ago. The regularity indicates that the population of a city is inversely proportional to its rank. The rank–size rule seems very stable over time regardless of technological and economical transformations. Krugman (1996a,b), confronted by the mystery of urban hierarchy, attempted to search for a plausible explanation of the mechanisms underlying the regularity. Specifically, he traced back to Simon's (1955) earlier work on probability mechanisms underlying five such empirical distributions: distributions of words in prose samples by their frequency of occurrences, distributions of scientists by number of papers published, distributions of cities by population, distributions of incomes by size, and distributions of biological genera by number of species. All these five examples show a commonality of underlying probability mechanisms, based on which

Krugman (1996b) attempted to explain the emerging power law of city sizes distribution of what he called order from random growth.[2]

In his seminal work on competing technologies, Arthur (1994) argues that when returns to choosing among two technologies, say A and B, are increasing, the technology that would dominate the market is unpredictable depending on small events that occur in the process of the competition. When these returns are decreasing, it is possible that the two technologies coexist with respective market shares over time. Increasing returns to additional adoptions of a particular technology are proportional with respect to the number of previous adoptions of that technology. More specifically, it is assumed that there are two types of agents, R and S, and two technologies to adopt, A and B. The payoff table for the market is as follows (Table 1).

In the payoff table, a_R, b_R, a_S, and b_S are the initial payoffs for the R and S agents adopting A and B, respectively; n_A and n_B are the numbers of agents already having adopted A and B, respectively; and r and s are rates of returns which can be increasing, diminishing, or constant, depending on whether r and s are positive, negative, or zero simultaneously.

Assuming increasing returns to agglomeration in the spatial context, this formulation can be readily transformed into spatial choices of two types of firms among two competing locations. We can relabel the Technology row as Location in Table 1.

Although one might argue that the adoption of agent among competing technologies is distinct behaviorally from the choice of firms among competing locations, the similarity of the formulations of the two decision problems is so obvious that at a higher level, the two problems could indeed bear some resemblance. The literature on urban economics or scale economics implies that urban agglomeration results in part from externalities of firms' moving nearby each other (O'Sullivan 1993). These phenomena are called order from random growth (e.g., Krugman 1996b). Regardless, the research design described in the next section considers the payoff table in Table 1 as the behavioral basis for the firms to locate themselves. By conducting computer simulations through varying the values of the parameters in the locational model, we can observe how regional agglomerations emerge and, more importantly, how lawful macrostructures would emerge from such simple rules as depicted in Table 1.

3 Research design

In the research design, I conducted two types of computer simulations, one across regions while the other within regions. Considering four regions on an island (Taiwan), two types of firms, R (basic industry) and S (nonbasic industry), have individual different initial locational preferences among the four regions. The firms enter into these regions in a random order.

[2] Krugman notes one example of order from random growth as Bak's (1996) earthquake model of self-organized criticality. A more widely known metaphor is a sand pile growing in height because of external dropping of grains of sand on top of it, which results in different scales of avalanches, whose frequency is inversely proportional to its scale logarithmically, an apparent case of a power law phenomenon.

Table 1 Returns to choosing A or B given previous adoptions

	Technology A	Technology B
R agent	a_R+rn_A	b_R+rn_B
S agent	a_S+sn_A	b_S+sn_B

3.1 Moving across regions

The first type of simulations of firms' choosing locations across regions was based on the following payoff table (Table 2).

The variables and parameters in the payoff table are modified slightly to reflect differences in locations and firms. For example, the initial payoffs for R and S firms to choose locations A, B, C, and D are different with respect to firms and locations, i.e., π_{RA}, π_{RB}, π_{RC}, π_{RD}, π_{SA}, π_{SB}, π_{SC}, and π_{SD} are distinct, and so are rates of returns, i.e., r_a, r_b, r_c, r_d, s_a, s_b, s_c, and s_d are distinct. Drawing on the random and empirical data of the two types of firms in basic and nonbasic industries over a period of 21 time steps (years in real data), and given different values of these parameters, I conducted a set of simulations of the firms' movement among the four regions. The random data were generated by a random number generator, hence the probability distribution of these numbers was uniform.

A decision rule of movement or immigration among the four regions is given. Consider a firm originally located in region A, in speculating whether to move to the other regions, the firm must take into account two cost: a distance cost that prohibits it from moving if the distance between the two regions is too great and an opportunity cost that is incurred because the firm, on deciding to move, must give up the payoff of residing in the original region. After considering these two costs for each target region, the net payoff is computed by subtracting these costs from the payoff of moving to the target region. The firm should then move to the region resulting in the maximum positive net payoff. Mathematically, let $\pi_{net(A\rightarrow B)}$ denote the net payoff for the firm located in region A that intends to move to region B, so that

$$\pi_{net(A\rightarrow B)} = \pi_B - \pi_A - C_{AB} \tag{1}$$

where π_A and π_B are the initial payoffs of the firm located in regions A and B, respectively, according to the payoff functions in Table 2, and C_{AB} is the cost of moving from regions A to B indicating distance cost. The decision rule for moving becomes

Table 2 Returns of firms to choosing locations (regions) A, B, C, or D given previous decisions

	Region A	Region B	Region C	Region D
R firm	$\pi_{RA}+r_a n_{RA}$	$\pi_{RB}+r_b n_{RB}$	$\pi_{RC}+r_c n_{RC}$	$\pi_{RD}+r_d n_{RD}$
S firm	$\pi_{SA}+s_a n_{SA}$	$\pi_{SB}+s_b n_{SB}$	$\pi_{SC}+s_c n_{SC}$	$\pi_{SD}+s_d n_{SD}$

$$\text{Max}\left[\pi_{net(A\to B)}, \pi_{net(A\to C)}, \pi_{net(A\to D)}\right], \text{ for all } \pi's \text{ greater than zero.} \tag{2}$$

Note that the cost of moving is referred to as the one-time cost of moving in the period in which the move occurs during a time step of the simulation. In the context of the real data, a time step can be thought of as per annum; thus, whenever the net payoff of moving for a firm is greater than zero during that year, the firm will move.

3.2 Moving within regions

Once certain firms have decided to move into a region, it is interesting to observe how these firms are distributed spatially. To simplify without losing generalizability, in this experiment, I incorporated the notion of increasing returns into a cellular automata simulation, but not in the geographic context of Taiwan. More specifically, in a grid system of $100 \times 100 = 10,000$ cells, initially the sequence of the firms moving to the region is randomly located. The initial assignment was random, hence the probability distribution among the cells of being occupied was uniform. But once a firm is located in a cell, the payoffs or values of the eight neighbors surrounding that cell would increase according to the payoff functions shown in Table 2. For example, in Fig. 1, two types of firms, shown as a dark and a gray cells, are located nearby with their neighbors overlapping, each with a distinct rate of returns, i.e., r_i or s_i. The payoff of their neighbors is the sum of the rates of returns associated with these firms, i.e., r_i+s_i. Therefore, the more firms located nearby that form clusters, the more attractive these clusters are to newcomers. This formulation is conceptually equivalent to the payoff functions depicted in Table 2, but it can be shown spatially. The movement of the firms among clusters is again based on the decision rule shown in Eqs. 1 and 2, with regions replaced by clusters.

0	0	0	0	0	0
0	0	**r_i+s_i**	**r_i+s_i**	**r_i+s_i**	0
0	**r_i+s_i**	**r_i+s_i**		**r_i+s_i**	0
0	**r_i+s_i**		**r_i+s_i**	**r_i+s_i**	0
0	**r_i+s_i**	**r_i+s_i**	**r_i+s_i**		0
0	0	0	0	0	0

Fig. 1 Payoffs resulting from emerging clusters

4 Results

4.1 Moving across regions

In the first set of experiments, I manipulated the values parameters of distances, initial payoffs, rates of returns across regions, and regional and technological differences in terms of rates of returns to simulate real regional and technological change as exogenous conditions. Note, however, that these values do not connote any realistic meanings, because they are assigned without referring to any specific units. They are determined only to show how sensitive the simulation outcome is to variation of the values of the parameters. For example, there is a decremental variation in the distance cost from 700 to 0 with other parameters being set at unity. It does not mean that the distance cost is unrealistically high relative to rates of return, but that it indicates how decremental changes in distance cost would affect the simulation outcome. All simulations were conducted using two sets of data, random and real numbers of firms in basic and nonbasic industries in Taiwan from 1977 to 1997 (see Tables 3 and 4). Each year stood for a time step in the simulations, and the numbers of the firms measured in hundreds in the data represented the sequence based on which the firms entered into the market. The lock-in effects were calculated according to the locational decision rule based on the sequence.

Table 3 The random data of firms entering the market (from 1 to 40 in hundreds)

	North		Central		South		East	
	Basic	Nonbasic	Basic	Nonbasic	Basic	Nonbasic	Basic	Nonbasic
1977	9	12	13	11	12	34	11	28
1978	36	26	3	30	24	17	8	22
1979	28	29	32	10	2	27	5	6
1980	32	18	13	31	19	20	6	9
1981	2	40	18	4	9	33	14	31
1982	24	1	35	7	15	18	34	16
1983	27	14	1	33	13	5	13	29
1984	14	15	28	32	36	12	32	28
1985	40	32	10	36	35	35	23	4
1986	3	5	21	19	27	28	16	28
1987	18	5	25	9	14	29	20	21
1988	7	29	24	32	6	20	30	20
1989	26	16	20	23	29	25	5	24
1990	2	37	22	8	28	22	30	23
1991	4	17	19	12	17	32	1	9
1992	18	34	10	38	16	37	21	12
1993	35	20	16	8	9	23	13	13
1994	14	6	4	6	15	7	3	31
1995	29	25	15	7	8	28	25	4
1996	11	30	29	33	34	24	4	25
1997	19	24	4	25	28	0	3	9

Table 4 The real data of firms entering the market (in hundreds)

	North		Central		South		East	
	Basic	Nonbasic	Basic	Nonbasic	Basic	Nonbasic	Basic	Nonbasic
1977	4	62	3	31	0	156	0	6
1978	0	73	0	29	0	30	0	4
1979	5	89	7	44	1	57	0	8
1980	5	101	6	55	3	77	0	11
1981	2	108	10	47	2	75	0	10
1982	3	109	5	49	0	45	0	9
1983	4	134	3	0	51	78	0	10
1984	9	108	1	100	0	62	0	7
1985	2	114	3	445	1	60	0	5
1986	7	88	8	39	7	65	0	5
1987	6	100	7	37	4	59	0	6
1988	2	88	2	37	2	42	0	1
1989	2	46	0	8	0	23	0	3
1990	0	38	1	16	0	12	1	6
1991	0	20	2	36	2	23	1	7
1992	4	88	1	43	8	70	1	7
1993	0	61	1	32	12	65	1	8
1994	4	19	2	28	10	54	1	9
1995	2	30	0	0	0	4	0	0
1996	0	39	0	14	0	3	0	1
1997	0	38	0	30	0	31	0	6

The geographic map of how the four regions, i.e., north, central, south, and east, are delineated in Taiwan is shown in Fig. 2.

When distance cost changed from 700 to 0, firms tended to agglomerate in region north for both random and real data, given that the rates of returns and the initial payoff were set to unity. In particular, for the random data, the four regions coexisted until the distance cost dropped from 700 to 30 (see Table 5).

With the initial payoffs for regions central, south, and east increasing from 1 through 50, the firms would agglomerate in the respective regions where the associated initial payoffs increased, given that rates of returns and distance cost were set to unity. This was true for both the random and real data sets, with only one exception, where the increase in the initial payoff for region east using the empirical data set resulted in agglomeration in region south instead of region east (see Table 6).

When the rates of returns across region increased from 1 through 50, reflecting economic growth, the random data set resulted in agglomeration in region north, while the empirical data resulted in region south, given that the initial payoff and distance cost were set to unity (see Table 7).

When the rates of returns in regions central, south, and east increased, respectively, holding the rates in the other regions constant, reflecting regional differences, agglomeration occurred in the respective regions both for the random and real data sets, given that the initial payoff and distance cost were set to unity (see Table 8).

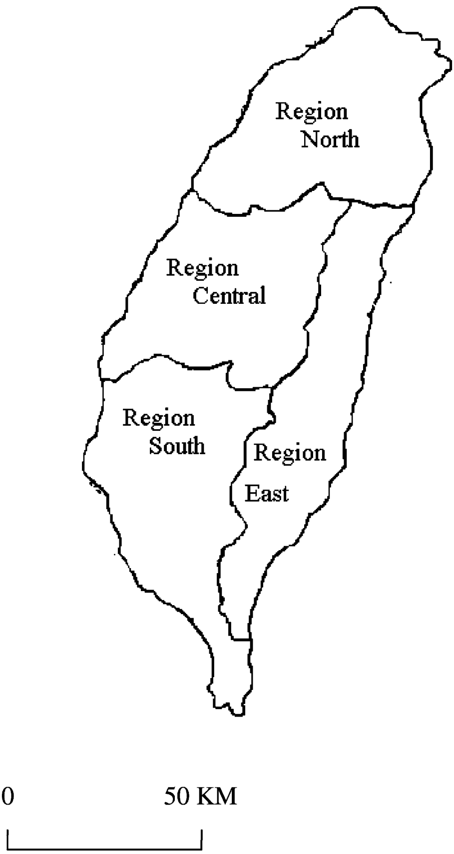


Fig. 2 A map of delineation of regions in Taiwan

When the rate of returns associated with the firms of an industry, say basic industry, increased, holding the rate of the other industry constant, reflecting technological change, agglomeration occurred in region north, except that with the increase in the rate of returns for nonbasic firms, the use of the empirical data set resulted in agglomeration in region south (see Table 9).

In short, the behaviors of agglomeration were apparently different between the two data sets, and exogenous factors indeed changed such behaviors. This implies that small events that created the history of how the firms entered into the market as manifested in the real data matter, in contrast to the random data where no historical meanings of the numbers exist. As to realism, the results coincide somewhat the

Table 5 Lock-in regions for the random and real data with different distance costs

Distance cost	0	1	5	10	30	40	50	100	300	500	700
Random data	N	N	N	N	–	–	–	–	–	–	–
Real data	N	N	N	N	N	N	S	S	S	S	S

– Means no regions dominate, *N* stands for north, *S* for south

Table 6 Lock-in regions for random and real data with different initial payoffs by regions

Initial payoffs		1	2	3	4	5	6	7	8	9	10	15	20	25	30	35	40	50
Region central	Random	N	N	N	N	N	N	N	N	N	N	N	N	N	C	C	C	C
	Real	N	S	S	S	S	S	S	S	S	S	S	C	C	C	C	C	C
Region south	Random	N	N	N	N	N	N	N	N	N	N	S	S	S	S	S	S	S
	Real	N	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S
Region east	Random	N	N	N	N	N	N	N	N	N	N	N	N	E	E	E	E	E
	Real	N	N	N	N	N	S	S	S	S	S	S	S	S	S	S	S	S

N stands for north, *C* for central, *S* for south, *E* for east

regional development situations in Taiwan. For example, the Taipei metropolitan area, the largest on the island, is located in region north. The second largest metropolitan area, Kaoshung, is located in region south. The simulation results clearly show the comparative advantage of the two regions. The explanations of the subtle differences in the simulation results in terms of shifts in lock-in regions as a result of the change in parameter values are beyond the scope of the paper. My main purpose here is, however, to show how regions are locked in based on the decision rule of Eqs. 1 and 2 and how sensitive they are to the change in the values of the parameters in these equations. Note that there were no multiple equilibriums in all conditions where more than one region existed.

4.2 Moving within regions

Once located in a particular region, it is interesting to observe how firms mutually adjusted to each other spatially and whether orderly patterns would emerge. Again, in this set of simulations, I used two behavioral models of spatial choices, random and increasing returns. In the former model, the firms chose randomly the cells in the grid system to locate themselves in sequence, whereas in the latter model, firms chose the cells to locate themselves according to the decision rule of Eqs. 1 and 2. Setting the rates of returns to unity for both types of firms in the two industries and increasing the distance cost from 0 to 50, I found that in the random model, no spatial patterns emerged. More specifically, the locations where the firms chose scattered evenly in the grid system. However, in the increasing returns model, clusters of the firms emerged and the greater the distance cost was, the more scattered the clusters were. One of the intriguing findings was that the spatial patterns showed a tendency of self-organization in that the size of clusters linearly correlated with the numbers of clusters in logarithmic scale. Figure 3 shows the R^2 values of the power law functions generated by the random and increasing returns models plotted against distance cost. The increasing returns model apparently resulted in higher R^2 values than the random model, meaning that the linear form is

Table 7 Lock-in regions for random and real data with different rates of returns

Rates of returns	1	2	3	4	5	6	7	8	9	10	15	20	25	30	35	40	50
Random	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Real	N	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S

Table 8 Lock-in regions for random and real data with different rates of returns by regions

Rates of returns		1	2	3	4	5	6	7	8	9	10	15	20	25	30	35	40	50
Region central	Random	N	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C
	Real	N	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C
Region south	Random	N	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S
	Real	N	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S
Region east	Random	N	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E
	Real	N	S	S	S	S	S	S	E	E	E	E	E	E	E	E	E	E

more significant in the former. Because I was interested in the resulting power law in general, and not in any specific one with a coefficient at −1 that Zipf found, I did not investigate to what extent the coefficients derived from the simulation deviate from that of Zipf's law, i.e., −1. Such attempts have been done and reported elsewhere (e.g., Yu and Lai 2005).

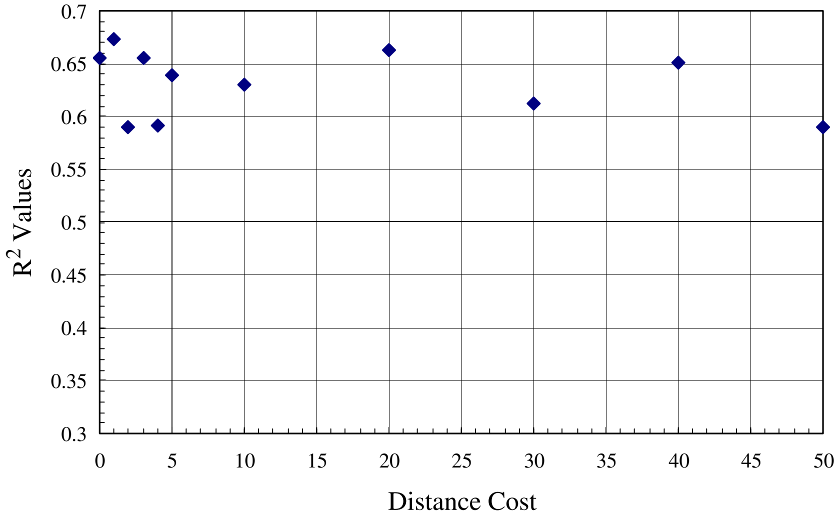
5 Discussion

It might be arguably true that the behavioral model of firms in choosing locations depicted here is too simple. In particular, the direct translation of the decision rule for technology choices into that for location choices might seem irrelevant at first, because in the latter, transportation costs and the spatial distribution of buyers matter. However, in both types of simulations, the locational factors of transportation costs and the spatial distribution of buyers are considered to some extent by including a distance cost in Eq. 1 and taking into account the effects of spatial distribution of clustering as shown in Figs. 1 and 2. The crux of the research design is, however, to show that complex phenomena may result from simple rules, a theme of an emerging science of complexity (Simon 1998). Although the spatial configurations used in the simulations were assumed homogeneous without features of a real landscape, such as rivers, hills, and transportation networks, it may be argued that most, if not all, such factors could be reflected in the distance cost, hence the model may be robust regardless of the variations in the landscape. Similar modeling approaches were adopted elsewhere (Krugman 1996b).

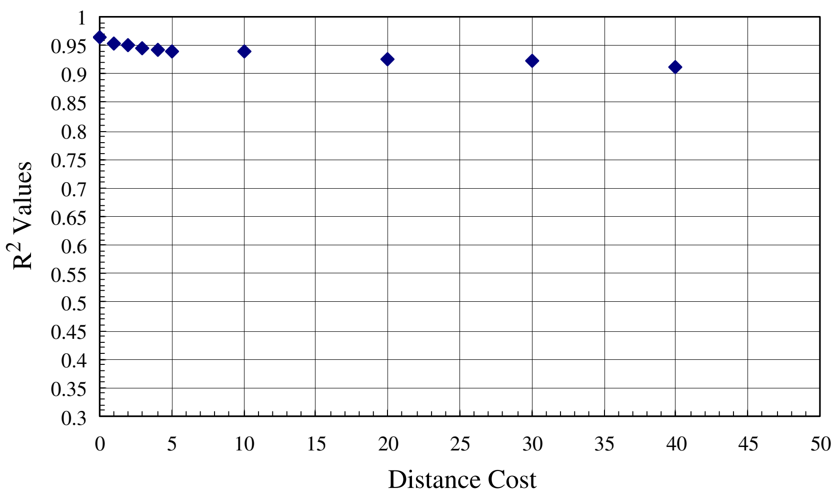
In the simulations of the firms' movement across regions, agglomeration in one region is essentially a lock-in phenomenon in Arthur's original model of agents' choosing among competing technologies. Under the assumption of increasing returns, when the number of agents adopting one of the technologies is greater than those of other technologies, that technology might eventually dominate the market.

Table 9 Lock-in regions for random and real data with different rates of returns by industries

Rates of returns		1	2	3	4	5	6	7	8	9	10	15	20	25	30	35	40	50
Random data	Basic	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
	Nonbasic	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Real data	Basic	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
	Nonbasic	N	N	N	N	N	N	S	S	S	S	S	S	S	S	S	S	S



a Random Model



b Increasing Returns Model

Fig. 3 Two plots of the R^2 values in relation to distance costs for the random and increasing returns models

In our transformed model of regional development, regions are considered as technologies and firms as agents. The lock-in processes imply that eventually all firms would reside in a particular region forming a sweeping agglomeration where all firms move into that region. Similar implication can be derived from considering the firms' spatial behavior within regions. The lock-in processes imply that there would be a super metropolitan area that attracts all firms to that area. But in reality, no such metropolitan area exists. That super metropolitan area can only be found in the simulations when the distance cost is set to zero. With the increase in the distance cost, the resulting clusters scatter in a more fragmented pattern. Except for the case of subsidy policies where movement is encouraged, in most cases in the real world, the distance cost is nothing but positive, and the sweeping metropolitan area cannot exist. We could infer from the simulation results that spatial agglomeration is path-dependent and unpredictable in that we cannot predict where agglomeration would occur except for explaining the process *after the fact*. Small events of firms choosing locations would be magnified over time resulting in agglomeration in particular locations. More importantly, the results of the simulations using the empirical data of firms resemble to some extent the real regional development in Taiwan, hence we could argue that the path dependence characteristic of the model is already embedded in the data. Note, however, that small events are referred to here as those events that cannot be modeled explicitly in the clustering process, i.e., they are invisible in the model. For example, decisions in a firm concerning hiring and budgeting at various times might not be directly related to location choices, but the effects of a sequence of such small events might propagate and eventually affect the firm's locational choices.

When examining more closely the patterns of particular agglomerations or clusters of firms, I found a power law relation between the numbers of clusters and their sizes. Similar patterns were found in simulations elsewhere (Lai and Gao 2001), but the underlying interactions among agents are different. In the simulations conducted here, the interaction among the firms is mainly based on increasing returns as a function of cluster sizes. In other simulations designed by Lai and Gao, the agents interacted through a payoff table according to a questionnaire survey and learned over time the best land development strategy contingent on the development pattern in the neighbors of the site. Based on the empirical data of land uses in Taipei, Lai and Lin (1999) also found the power law relation between the numbers of clusters and the cluster sizes in fractal scales. These findings strongly support the hypothesis that simple, reasonable interacting rules among the agents result in the spatial patterns that bear significant similarity, regardless of how the rules are constructed. There is no accepted theory yet to explain the fact that the complex spatial systems of interacting agents tend to self-organize themselves, such as a power law relation, but the increasing returns and cellular automata models might indeed share a common underlying mechanism yet to be found.

6 Conclusions

I have conducted two simulations focusing on how the firms would choose locations to form agglomeration as a way of observing spatial evolution both across regions and within regions. Instead of investigating in depth the behavioral rules of the firms' movement, I concentrated on how simple behavioral models of the firms interacting with each other give rise to complex but orderly spatial patterns. Based on the principle of increasing returns to choosing among competing locations, agglomeration of the firms is explained as a function of the initial payoffs of the regions as well as the opportunity and distance costs of moving. By manipulating the values of parameters of the model to reflect the change in exogenous factors, the simulations of the firms' moving across the regions based on the real data resulted in lock-in processes of agglomeration distinct from that using random data. In the second set of simulations considering the firms' moving within regions, I found that distance cost played an important role in the agglomeration of the firms. The evidence of self-organization in terms of a power law relation prompts me to speculate that there may be a common, underlying mechanism yet to be found, whether in an urban or regional context. Similar attempts have been made (e.g., Simon 1955). To yield results useful for understanding spatial evolution, we should aim at uncovering such a mechanism in a formal, rigorous way.

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