Growing Silicon Valley on a Landscape: An Agent-Based Approach to High-Tech Industrial Clusters

Junfu Zhang[1]

Public Policy Institute of California

500 Washington Street

San Francisco, CA 94111

E-mail: zhang@ppic.org

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Abstract

We propose a Nelson-Winter model with an explicitly defined landscape to study the formation of high-tech industrial clusters such as Silicon Valley. The existing literature treats clusters as the result of location choices and focuses on how firms may benefit from locating in a cluster. We deviate from this tradition by emphasizing that high-tech industrial clusters are characterized by concentrated entrepreneurship. We argue that the emergence of clusters can be explained by the social effect through which the appearance of one or a few entrepreneurs inspire many followers locally. Agent-based simulation is employed to show the dynamics of the model. Data from the simulation and the properties of the model are discussed in light of empirical regularities. Variations of the model are simulated to study policies that are favorable to the high-tech economy.

Do not regard Silicon Valley as some sort of economic machine, where various raw materials are poured in at one end and firms such as Apple and Cisco roll out at the other, but rather as a form of ecosystem that breeds companies: without the right soil and the right climate, nothing will grow.

— The Economist, March 29, 1997

1 Introduction

Silicon Valley is the most salient example of high-tech industrial clusters. Public policy makers throughout the world would like to learn the secrets of Silicon Valley in order to build their own high-tech economies. The existing literature on industrial clusters, which traces back to Marshall (1920), focuses on how firms benefit from locating in a cluster. It suggests that once a cluster comes into existence, it tends to reinforce itself by attracting more firms. However, a more important question is how to reach this critical mass in the first place. In contrast to the literature, evidence suggests that entrepreneurs rarely move when they found high-tech start-ups (Cooper and Folta, 2000). This contradicts the notion that location choice analyses lead entrepreneurs to a high-tech cluster.

A high-tech industrial cluster such as Silicon Valley is characterized by concentrated entrepreneurship. Following Schumpeter, we emphasize the fact that "the appearance of one or a few entrepreneurs facilitates the appearance of others" (Schumpeter, 1934). We propose an agent-based computational model to show how high-tech industrial clusters could emerge on a landscape where no firms existed originally. The model is essentially a spatial version of the Nelson-Winter model. Boundedly rational agents are scattered over an explicitly defined landscape. Each agent is endowed with some technology, which determines his firm's productivity if he has one. During each period of time, an agent with no firm would make a decision whether he wants to start one. This decision is mostly affected by the behavior of his social contacts, who are all his neighbors. If an agent's neighbors are successful in their entrepreneurial activities, the agent is more likely to found a firm himself. An entrepreneur makes business decisions according to some rules of thumb. When an agent does found a firm and makes some profit, he spends part of his profit on R&D to improve his productivity, part on imitating other firms' technology, and the rest on capital accumulation. Entrepreneurs who lag behind in the Schumpeterian competition will lose money and eventually fail; however, it is possible that they learn from their failures and try again.

We use agent-based simulation to show that Silicon Valley type industrial clusters will emerge spontaneously on the landscape. In addition, the model exhibits the following properties: 1) First mover's advantage: the first firm has a better chance to survive and grow; a region where firms enter the market early tends to capture a large piece of the industry. 2) Path dependence: the more firms a region has, the more it tends to have; once a cluster is formed, it can hardly be toppled. 3) Clustering of entrepreneurship: firms are continuously forming and dying within clusters. 4) Clustering of innovations: the productivity in clusters is much higher than elsewhere because of the collective learning within clusters through innovation and imitation.

Data from the simulation and the properties of the model are discussed in light of empirical regularities. We also explore variations of the model to study the factors that determine the location of emerging clusters. We learn two lessons from the model. First, the conventional knowledge-spillover literature may only tell part of the story; the contagion of entrepreneurship through peer effects seems to be an important mechanism through which high-tech industrial clusters emerge and grow. Second, while many scholars have recognized the importance of "seed capital" for a budding high-tech regional economy, our model suggests that "seed entrepreneurs" may be even more important because they serve as local role models and inspire new entrepreneurs.

The main contribution of this paper is the application of a novel methodological approach to study the formation of industrial clusters and related policy issues. While agent-based computational economics has introduced new tools for economic analysis, we have yet to see applications of this approach in policy analysis. This paper intends to fill in the blank. As our model shows, the agent-based approach is particularly useful for dealing with dynamic economic systems. It is also flexible for testing the effects of alternative assumptions.

The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 presents the model. The agent-based simulation of the model is described in Section 4. The last section concludes with some remarks.

2 Related Literature

Our model builds upon the intersection of several strands of the literature.

2.1 The Nelson-Winter paradigm

The term evolutionary economics has been used in different contexts and by various groups of economists, including institutional economists, evolutionary game theorists, and those who follow Nelson and Winter (1982). The Nelson-Winter paradigm of evolutionary economics is a synthesis that integrates three sources of work: Simon's concept of "bounded rationality," Nelson's and others' work on invention and innovation following Schumpeter, and Alchian's and Winter's work on "natural selection" in economic evolution.

A typical Nelson-Winter evolutionary model defines the state of the industry by a list of firm level state variables such as physical capital and productivity. Minimum environmental characteristics are specified, which may include input and output conditions, the space of innovations as well as the way innovative search takes place. Based on these, the activities of the industry in the current period are calculated and in turn generate new values of state variables for the next period. New technology or new rules may be adopted if they increase expected profitability. Calculations are conducted for a series of periods and are used to study the evolution of technology, the application of rules, and other characteristics of the industry (Anderson et al., 1996). The Nelson-Winter paradigm provides a powerful and general theoretical framework for studying variety-creation and variety-selection within a given economic sector. Up until now, researchers along this tradition have worked with very simple examples; the potential of the general schema is far from fully exploited. Nelson and Winter (1982) is a classic reference of their paradigm. Nelson (1995) gives a review of more recent developments in this area and related fields.

2.2 Agent-based computational economics

Agent-based computational economics is the computational study of economies modeled as evolving systems of autonomous interacting agents. It is an application of the basic complex adaptive systems paradigm to economics. Researchers in this field try to understand why certain macro-level regularities emerge and persist in decentralized market economies despite the absence of any forms of centralized coordination. For example, the agent-based computational approach has been applied to study business cycles, trade networks, market protocols, the formation of firms and cities, and the diffusion of technological innovations. Computer programs are heavily used to demonstrate constructively how those macro-level regularities might arise from the bottom up through repeated local interactions of autonomous agents. A methodological advantage of agent-based computational economics is that it enables social scientists to do "laboratory experiments" to test a theory, because computational models usually can be modified quite easily to study alternative socioeconomic structures and examine their effects on economic outcomes (Tesfatsion, 2001).

Using poker chips on a checkerboard, Schelling (1971) simulates the dynamics of racial housing segregation, which is generally recognized as the pioneering application of this approach in social sciences. In a groundbreaking work, Epstein and Axtell (1996) investigate how social structures and group behaviors arise from the interaction of individuals. With agent-based simulations, they show how fundamental collective behaviors such as group formation, cultural transmission, combat, and trade can emerge from the interaction of individual agents following simple local rules. Axtell (1999) presents a model in which heterogeneous agents form firms. Agents join firms or start up new firms when it is advantageous for them to do so. As firms grow, agents have less incentive to supply their efforts and tend to become free riders, which causes large firms to decline. At the micro level, firms grow and perish; at the aggregate level, the model produces data about firm sizes, growth rates, and related aggregate regularities that parallel empirical findings.

Epstein (1999) characterizes the agent-based computational approach with the following features: heterogeneous agents in terms of preferences, culture, social networks, etc.; decentralized autonomous behavior of agents; explicitly defined space; local interactions among agents; and bounded rationality. Because of these features, agent based modeling is particularly useful when the population is heterogenous, when interactions among agents are complex and nonlinear, and when the space is crucial.

2.3 Industrial clusters

An industrial cluster is a geographic area where many firms in an industry are located and interact with each other through competition and cooperation. Economists' interest in industrial clusters traces back to Marshall (1920), but we have seen a revival of this interest recently (see, e.g., Arthur, 1990;

Krugman, 1991; and Porter, 1998). This line of research emphasizes the net benefits to firms located in a cluster, which are determined by the benefits and the costs of agglomeration. Sources of benefits include pooled labor forces, specialized suppliers, access to capital, proximity to customers, and knowledge spillovers. Whereas, diseconomies of agglomeration stem from increased competition, congestion costs, and knowledge expropriation. If positive net benefits are expected from an industrial cluster, new entrants tend to arise in the cluster, further enhancing the geographic concentration.

Those works that focus on net benefits from agglomeration treat clusters as the result of firms' locational choices. Yet it is not clear whether firm owners or entrepreneurs engage in such searching and comparing exercises. Moreover, high-tech start-ups might have concerns different from manufacturing firms. Cooper and Folta (2000) point out that the primary determinant of a high-tech start-up is the prior location of its founder. In fact, entrepreneurs seldom move when they decide to start their new firms. This is understandable because, by staying where they are, entrepreneurs can utilize their existing network to seek investors, employees, customers, suppliers, and advisors; they can start on a part-time basis and defer full commitment until the start-up becomes more promising; and they may want their spouses to keep their current jobs. Given that entrepreneurs do not move, one doubts whether they intentionally take advantage of the benefits of geographic clusters.

Using data on U.S. manufacturing employment in the period of 1860-1987, Kim (1995) shows that industry localization patterns are negatively correlated with characteristics associated with external economies. In particular, high-tech sectors, which are believed to have more positive externalities than other sectors, are less agglomerated. This is inconsistent with the location choice literature.

Social scientists have long noticed that clusters, of individuals or firms, are the result of two types of behavior. One is a sorting process. For example, individuals' racial preferences could lead to housing segregation in which clusters of black or white residents are formed. The other is a behavior-adapting process. For example, smokers can convert their non-smoking friends into smokers, resulting in clusters of smoking behaviors. The existing literature on industrial clusters has studied the sorting process in which firms choose to locate close to other firms, but has neglected the other process. We argue that entrepreneurship may be contagious and that a person surrounded by entrepreneurs is more likely to start a firm himself. This provides an alternative theory of the formation of industrial clusters.

2.4 The Schumpeterian entrepreneur

The French economist, Richard Cantillon, first recognized the important role of entrepreneurs in economic life in the 18th century. The concept of the entrepreneur then appeared in the writings of many French economists including Quesnay, Turgot, and Say. Yet along the British tradition, the dominant classical school made no distinction between capitalists—who provide the means for investment in production—and entrepreneurs—who explore possibilities of innovation, seek profitable opportunities, and assume risks. Thus the followers of Smith and Ricardo excluded the entrepreneur from economic analysis.

Today's economists learn the theory of entrepreneurs mainly from Schumpeter (1934). Schumpeter starts by describing the economic system as a circular flow with a Walrasian-like general equilibrium. To him, economic development is driven by the activities of a class of entrepreneurs who take it upon themselves to disrupt the circular flow by introducing new products, reorganizing labor forces and capital, and rearranging the processes of business life in the hope of making a profit from the disequilibria they create. To answer what drives entrepreneurs to exercise their talents, Schumpeter might have given the most romantic reasoning in economics. He states that entrepreneurs choose their way of life because of the dream and the will to found a private kingdom, the will to conquer, the impulse to fight, to prove oneself superior to others, to succeed for the sake not of the fruits of successes but of success itself, and finally the joy of creating, getting things done, or simply of exercising one's energy and ingenuity. Schumpeter uses his concept of entrepreneur to explain business cycles. The introduction of new and untried products and processes causes "disturbances;" these disturbances that appear "in groups or swarms" constitute business cycles. And entrepreneurial activities appear in clusters because "*the appearance of one or a few entrepreneurs facilitates the appearance of others, and those the appearance of more, in ever-increasing numbers* [Schumpeter's italics]."

Schumpeter's theory of entrepreneurs has been renowned and influential. However, it is fair to say that its influence has remained outside of neoclassical economics. Schumpeter's entrepreneur is by definition an equilibrium-disturbing figure; his entrepreneurial activities constantly interrupt the tendency toward equilibrium in the economic system. Therefore, since neoclassical economics focuses on equilibrium analysis, there is no room for Schumpeter's entrepreneur. Yet, as we will see, the Schumpeterian entrepreneur plays a crucial role in our model.

3 The Model

Consider an $N \times N$ lattice graph, $\Lambda_N = (V, E)$, with periodic boundary conditions. V and E are the sets of vertexes and edges respectively. Each vertex $i \in V$ represents an agent. An agent i is endowed with some human capital (technology) h_i.

At time 0, all agents are born and each agent's endowment of human capital is determined by a random draw: h_i^0.

In each period of time, an agent with no firm has to make a decision whether he wants to be an entrepreneur and start a firm. If he wants to do so at time t, he will raise some money to buy capital K_i^t. If agent i has a firm, his production function is

$$Y_i^t = h_i^t (K_i^t)^\alpha, \qquad \alpha < 1, \tag{1}$$

otherwise, he produces nothing: $Y_i^t = 0$. Capital is always obtainable at a fixed unit cost c. For simplicity, we deal with the single-factor production and do not bother with labor. This simplification may be understood in this way: each unit of capital is attached with a certain amount of labor according to a fixed capital-labor ratio and abundant labor is supplied at a constant price which is already included in c.

Aggregate supply in this industry is

$$S^t = \sum_i Y_i^t. \tag{2}$$

Aggregate demand D^t is given exogenously. Market price at time t is decided by

$$P^t = \frac{D^t}{S^t}. \tag{3}$$

If agent i produces, his profit is

$$\pi_i^t = P^t Y_i^t - cK_i^t. \tag{4}$$

Agents are boundedly rational; they act according to some rules of thumb. When an agent makes some profit, he will put part of it into R&D and spend the rest on capital accumulation. The R&D fund will be split again, with part of it spent on technological innovation and the remainder on technological imitation. Each agent is born with two uniformly distributed random numbers $\gamma_i, \lambda_i \in (0, 1)$, which he takes as rules that govern his spending on technological innovation and imitation. If agent i makes profit $\pi_i^t > 0$, he puts aside $\gamma_i \pi_i^t$ for R&D. Among that amount, $\lambda_i \gamma_i \pi_i^t$ goes to technological innovation. Let IN_i and IM_i denote i's spendings on innovation and imitation, respectively. Then,

if $\pi_i^t > 0$, then

$$\begin{aligned} IN_i^{t+1} &= IN^t + \lambda_i \gamma_i \pi_i^t, \\ IM_i^{t+1} &= IM^t + (1 - \lambda_i) \gamma_i \pi_i^t, \\ K_i^{t+1} &= K^t (1 - d) + (1 - \gamma_i) \pi_i^t; \end{aligned}$$

if $\pi_i^t \leq 0$, then

$$K_i^{t+1} = K^t (1 - d) + \pi_i^t. \tag{5}$$

Here $d > 0$ represents the rate of capital depreciation.

Technological innovation and imitation are costly. In addition, the larger a firm is, the more costly to improve its technology. Whenever agent i's spending on innovation exceeds $f(K_i)$, he gets a chance to draw a new h_i from the distribution of technological opportunities $F(h,t)$. This distribution function is independent of i's current technology but its mean increases with time. If the new draw is greater than his old one, he will adopt the new one. Whenever agent i's spending on imitation exceeds $g(K_i)$, he gets a chance to copy the best technology from his neighboring firms. It is more costly for large firms to upgrade technology, so $f'(\cdot) > 0$ and $g'(\cdot) > 0$. i's neighboring firms are those started by surrounding agents:

$$B_i = \{j | d(i,j) \leq 2 \text{ and } K_j > 0\}, \tag{6}$$

where $d(i,j)$ is the distance between i and j, which is defined as the number of edges that constitute a shortest path between i and j. Therefore, the mechanism of innovation and imitation can be summarized as follows:

$$\begin{aligned} \text{If } IN_i^t &\geq f(K_i^t), \text{ then } h_i^{t+1} = \max\{h_i^t, h_i'\}, \text{ where } h_i' \sim F(h,t), \\ &\quad \text{and } IN^{t+1} = IN_i^t - f(K_i^t); \\ \text{if } IM_i^t &\geq g(K_i^t), \text{then } h_i^{t+1} = \max\{h_i^t, \max_{i' \in B_i} h_{i'}^t\}, \\ &\quad \text{and } IM^{t+1} = IM_i^t - g(K_i^t). \end{aligned} \tag{7}$$

If the firm simultaneously gets a random draw and a copy of the best technology in the neighborhood, the better one is adopted.

In addition, entrepreneurs learn from failures. Each time an entrepreneur fails, which means he keeps losing money and eventually does not have enough capital to operate, he earns a chance $\rho > 0$ to copy the best technology from his neighboring firms. For the sake of parsimony, we use a single parameter, h, to represent technology, which should be understood as a combination of both management skills and production technology. A failed entrepreneur is likely to learn some management skills from the practices of nearby successful entrepreneurs. Similarly, he will likely recognize the better production technology used by neighboring entrepreneurs. And this opportunity for a failed entrepreneur to copy a better technology from surviving firms could be interpreted as a chance for "zero-cost imitation." In this sense, we are assuming that imitation is easier for a re-starter than for an incumbent firm. Previous studies have shown that incumbent firms are less likely to adopt radical innovations because it is more costly for them to shift to a different technology standard (Foster, 1986; Christensen, 1997). But a failed entrepreneur who starts up a new firm faces no such costs.[1]

An agent's decision on firm-founding reflects his perception of risk and his evaluation of profitability. In turn, his attitude is affected by other agents in the society. We assume that social distance is proportional to physical distance and an agent's behavior is largely influenced by close neighbors. If many of his neighbors are entrepreneurs and make a lot of money, he will see the profitable opportunity and also get a psychological boost from their success. Hence he is likely to choose to be an entrepreneur himself; otherwise, it is less likely that he will do so. A distant successful entrepreneur has

[1] For example, it is quite easy for a fresh starter to imitate Amazon.com, but not that easy for a conventional bookstore because its on-line service could hurt its physical store. In this sense, it costs less for a failed bookstore owner to imitate Amazon's technology.

smaller effects on an agent's decision. Specifically, the probability that an agent chooses to start a firm is defined as follows:

$$\begin{aligned}
\Pr(K_i^{t+1} &> 0 \mid K_i^t = 0) = \phi(K_{j_1}^t, K_{j_2}^t, \ldots), \\
\text{and } \frac{\partial \phi}{\partial K_j^t} &\geq 0, \forall j \neq i; \quad \frac{\partial \phi}{\partial K_{j_x}^t} \geq \frac{\partial \phi}{\partial K_{j_y}^t} \text{ if } d(i, j_x) \leq d(i, j_y).
\end{aligned} \tag{8}$$

For simplicity, we have assumed that a failed entrepreneur has no negative effect on another agent's decision. Casual observation of the real world help justify this asymmetry between the social effects of success and failure. For example, the limited liability corporation system creates an asymmetry between success and failure: a successful entrepreneur is usually worth millions but a failed one almost never loses much. Also, the media always gives more attention to successes than to failures, which further magnifies the relative psychological impact of successes. Research shows that even in the peak years of the Internet revolution, a large number of high-tech firms went out of business in Silicon Valley (Zhang, 2003). However, even the local media rarely cover such failures.

4 Agent-Based Simulation

Our dynamic model represents a complex Markov Process. To analyze it rigorously is a formidable task. We will proceed with an agent-based simulation to learn the properties of the model.

4.1 Parameterization of the model

One way to calibrate our model is to search for a set of parameter values, using methods such as the Genetic Algorithm, so that the outcomes of the model replicate some pre-selected empirical regularities. Since we will focus on the qualitative properties of the model, such a sophisticated method seems unwarranted. Instead, we take a simpler approach by picking a set of "reasonable" parameters through a few trials on the computer program. As you will see, the model works fine. This partly proves the robustness of our basic setup. The model is parameterized as follows:

- $N = 100$. That is, we have a population of 10,000 agents.
- Technology h_i^t is drawn in the way such that $\sqrt{h_i^t}$ follows $U(0, 1+\frac{t}{2{,}500})$, a uniform distribution on $(0, 1+\frac{t}{2{,}500})$. That is,

  $$F(h,t) = \left(\frac{2{,}500h}{2{,}500+t}\right)^2.$$

  It looks like a truncated normal distribution, which makes it difficult to attain a very efficient technology. Over time, the distribution expands to the right. This implies that a draw today is expected to yield a better technology than a draw yesterday. Therefore, the investment in technology, just like the investment in capital, also depreciates.
- When agent i decides to start a firm, he simply takes money out of his savings and acquires capital $K_i = 5k$, where $k \in U(0,1)$. We impose an arbitrary minimum capital requirement such that if $K_i < 0.1$, the firm has to be shut down. The diminishing return to capital is captured by $\alpha = 0.995$.

- Aggregate demand is given exogenously to replicate the evolution of an industry that grows fast at an early stage and loses its momentum over time. We start with $D^0 = 10$. Its growth rate is declining over the life cycle of the industry. Specifically, we define

$$g^t = \begin{cases} 0.03 & \text{if } D^t < 2{,}000; \\ 0.02 & \text{if } 2{,}000 \le D^t < 10{,}000; \\ 0.01 & \text{if } 10{,}000 \le D^t < 20{,}000; \\ 0.005 & \text{if } D^t \ge 20{,}000. \end{cases} \tag{9}$$

We also define a cyclical parameter as $b^t = \frac{1}{100}\sin\left(\frac{2\pi t}{40}\right)$, which simulates business cycles that span 40 periods (quarters).

In addition, we introduce random demand shocks in the form $\epsilon^t \in U(-0.01, 0.01)$. The dynamics of aggregate demand follows

$$D^{t+1} = D^t(1 + g^t + b^t + \epsilon^t). \tag{10}$$

- If agent i is not producing at time t, the probability that he will choose to do so is

$$\Pr(i \text{ starts a firm} |\ K_i^t = 0) = \frac{1}{25}\sum_{j|d(i,j)=1}\frac{K_j^t}{a_j^t} + \frac{1}{50}\sum_{j|d(i,j)=2}\frac{K_j^t}{a_j^t} + \frac{1}{50{,}000}, \tag{11}$$

where a_j^t is the age of firm j at time t. It says that i may choose to be an entrepreneur independently with a low probability; if his neighbors accumulated a great deal of capital in a short time, he is more likely to found a firm himself. Notice that closer neighbors have bigger effects on an agent's choice and distant entrepreneurs have no effects.

- Profitable firms spend money on R&D and try to improve their technology through innovation and imitation. The parameters that affect the costs of R&D activities are $f(K_i) = 0.1(K_i)^3$ and $g(K_i) = 0.3(K_i)^3$. The chance of learning from failure is $\rho = 0.1$.

4.2 Main results

We start our simulation with a blank landscape with no firm. In this case, the emergence of the first entrepreneur is a pure chance event. He may not be an agent endowed with superior technology. But one thing is certain, he will make a big profit for his entrepreneurial move. Once the first entrepreneur emerges on the landscape, many of his neighbors will recognize the opportunity and follow suit; at the same time, others may start firms by chance. Those firms that make profits will upgrade their technologies. As more firms are founded and technology is improved, the market price decreases sharply. Many new firms are born around profitable firms. Before long, one or more clusters form in certain regions. Some firms are forced to exit because they cannot keep up with others in technological progress, which may result from lower R&D expenditure or continuous unlucky draws from the distribution of technology. In the long run, we see a spatial pattern of industrial clusters as shown in Figure 1.[2] In Figure 1, a green cell represents a small firm ($K_i \leq 10$); a red cell represents a medium firm ($10 < K_i \leq 100$); and a blue cell is a large firm ($K_i > 100$). A cluster generally hosts firms of all types.

In this model, firms in a cluster do benefit from knowledge spillovers as

[2] Interested readers may want to try the simulation by themselves. A Java Applet is available from the author upon request.

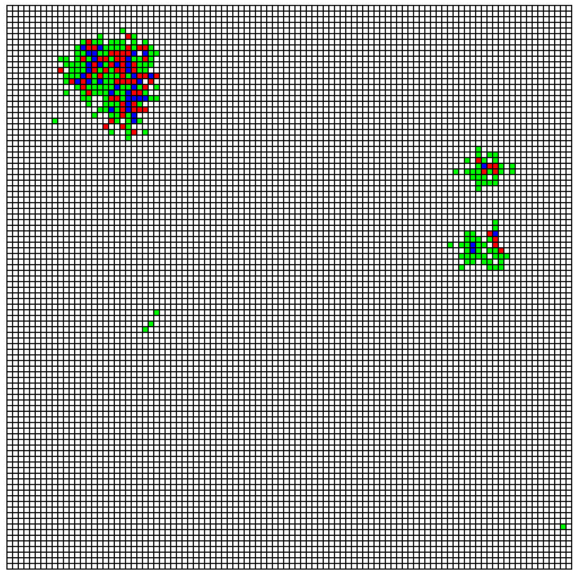

Figure 1: A Snapshot of Industrial Clusters

they can imitate better technologies possessed by nearby firms. However, we see that entrepreneurs do not move and they do not intentionally seek the benefits from knowledge spillovers. In fact, if it is cheap to improve the technology through independent research, industrial clusters still tend to emerge even if we shut down the channels for inter-firm transmission of technology.

Figure 2 shows the dynamics of market price. When the first firm enters the market, price is high. As capital is accumulated and production is expanded, market price is driven down quickly. Competition by entry of new firms continuously pushes the price down to the cost of production. There is a cyclical pattern in the price series, which reflects the cyclical movement we build in the demand.

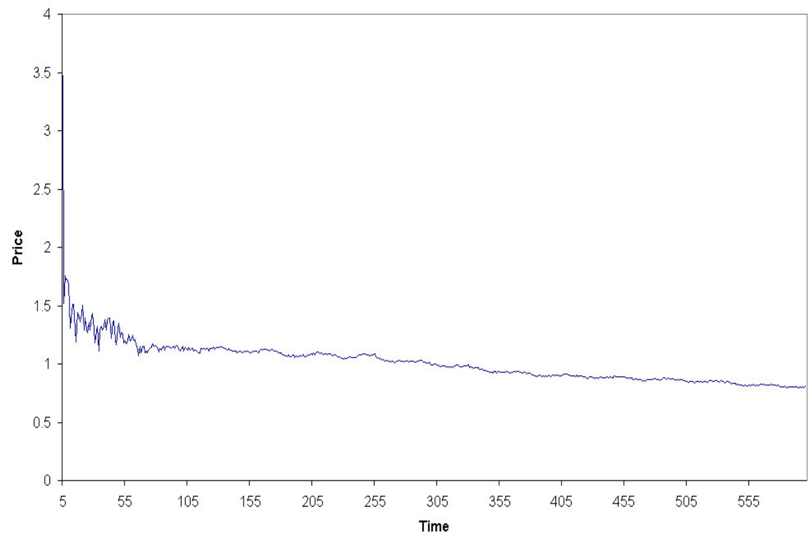

Figure 2: Price Series

Figure 3 shows the firm size distribution. Large firms are rare; small and medium firms dominate the industry. Here we use output level to measure firm size. An alternative measure, capital stock, gives similar qualitative results.

Since Gibrat's work in the early 1930s, it has been common practice to fit firm sizes with lognormal distributions (Sutton, 1997). A standard justification for the distribution is the so-called "law of proportional effect," which postulates that firms grow at random rates independent of firm size. This has now become well known as the "Gibrat's law." A lognormal distribution is skewed to the right. It means that firm sizes are concentrated on smaller values; in particular, the mean firm size is larger than the median firm size, and both of which are larger than the modal firm size. By definition, a log-

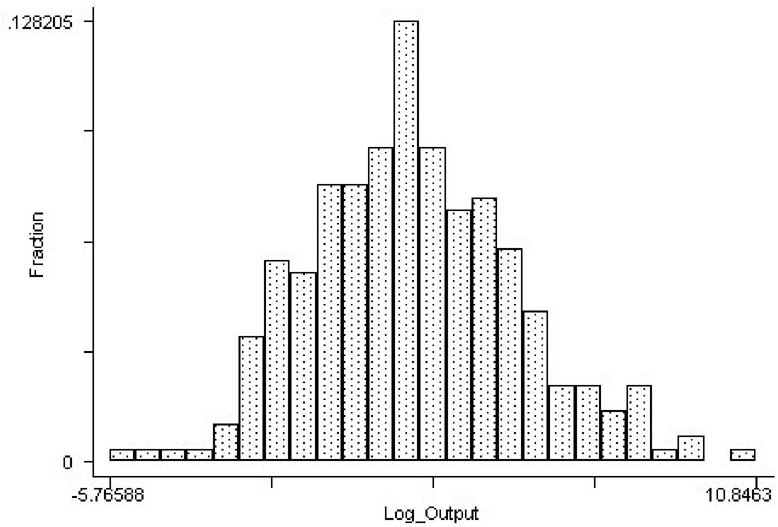

Figure 3: Firm Size Distribution

normal distribution of firm size implies a normal distribution of log firm size. Figure 3 roughly corresponds to a normal distribution.

The firm size distribution, especially its upper tail, has often been described by the Pareto law (Ijiri and Simon, 1977; Axtell, 2001):

$$sr^{\beta} = M, \tag{12}$$

where s is the size of a firm, r is its rank in an industry (or an economy) with the largest firm ranked 1, and β and M are constants. The power law implies a linear relationship between log firm size and log firm rank:

$$\log s = \log M - \beta \log r. \tag{13}$$

Figure 4 plots firm size over firm rank. Cutting off the lower quartile of the sample, we fit a straight line to the remaining data and obtain:

$$\log(firm\_size) = 12.33 - 2.11 \log(firm\_rank), \quad R^2 = 0.97. \tag{14}$$
$$(0.125)\ (0.028)$$

It is almost a perfect fit. To compare this with reality, we do the same exercise for the 211 U.S. high-tech firms on the list of Fortune 1000 largest firms. The firm size-rank plot is presented in Figure 5. Since this data is already truncated from below, we fit a straight line to the whole sample. The results are:

$$\log(firm\_size) = 13.14 - 1.09 \log(firm\_rank), \quad R^2 = 0.94. \tag{15}$$
$$(0.086)\ (0.019)$$

We see that the real data also fits a straight line very well, although its slope is smaller.

The curvature in Figure 4 corresponds to a feature that is repeatedly observed in real data. Ijiri and Simon (1977) propose two possible interpretations for the "departure" from the Pareto distribution: autocorrelation in firm growth rates and the effects of mergers and acquisitions. Our model does not allow for mergers and acquisitions, but we do have autocorrelated firm growth. Figure 5 only plots the upper tail of the real data, which gives no indication about how the lower tail behaves. However, based on what we know, we are able to get a rough idea about the profile of the complete sample. Assume the smallest high-tech firm has an annual revenue of $0.01 million. By equation 16, we predict its rank is higher than 11.7 million. That rank is even larger than the total number of U.S. firms.[3] Therefore, the lower

[3] According to the Census Bureau, the total number of U.S. establishments in 1999 is

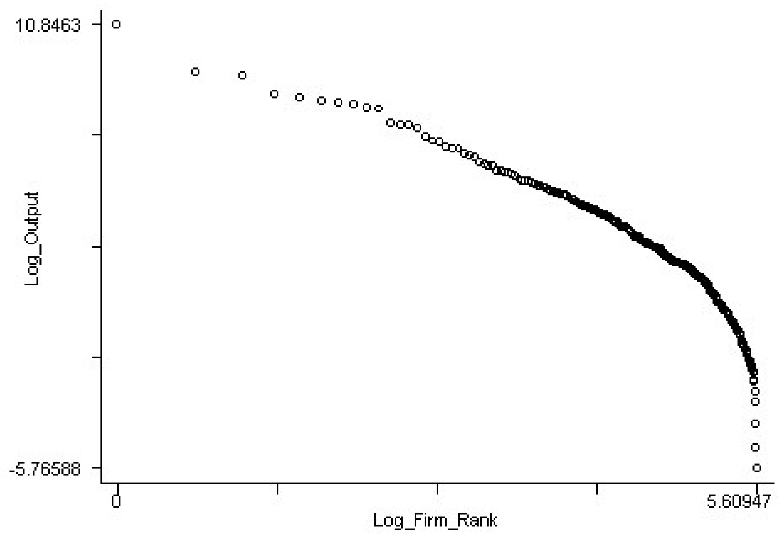

Figure 4: Firm Size-Rank Plot

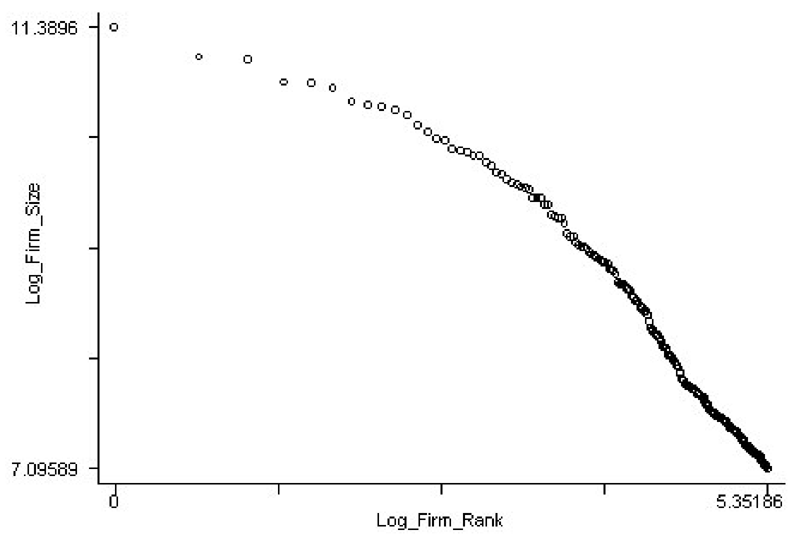

Figure 5: Size-Rank Plot for Fortune1000 High-Tech Firms

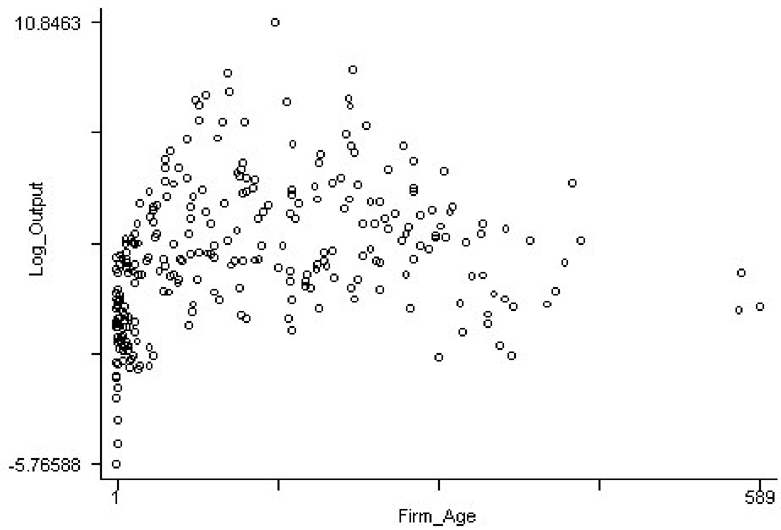

Figure 6: Firm Size-Age Plot

end of the real data must bend down like the simulated data.

By construction, a firm's growth rate is related to its size in our model. In particular, a small firm is assumed to be able to upgrade its technology more easily. This is a violation of the Gibrat's law. However, our model is able to generate firm size data that is qualitatively similar to empirical findings. It reminds us that the Gibrat's law is only one of the parsimonious interpretations of empirical data.

Figure 6 plots firm size over firm age. Interestingly, there is not a strong positive correlation between firm size and age. In fact, the largest firms are all relatively young. This is because once an old firm reaches certain size, it slows down in upgrading technology due to the high cost. But, remember, the distribution of technology moves to the right. A newcomer is drawing

7,008,444.

technology from a better space. Thus it is more efficient and will outgrow older firms under the same market condition. This reflects what happens in the high-tech sector in the real world. For example, in Silicon Valley, more than half of the top 40 technology firms in 2002 were not even founded two decades ago; only 4 out of 40 largest firms in 2002 were survivors from the top-40 list in 1982 (Zhang, 2003).

The model also exhibits the following properties:

The first mover's advantage

At the firm level, the first few entrepreneurs tend to make a lot of money and have good chances to grow up into large firms. However, their survival is not guaranteed. Some late comers may be endowed with better technology that can drive the pioneers out of the market; the first mover may follow a rule that spends very little profit on R&D and eventually lags behind in the Schumpeterian competition; the first mover may be so unlucky that his research efforts fail to generate superior technology before his followers do. Therefore, the first mover does enjoy some advantage, but only in a probabilistic sense.

At the economic region level, an area that enters the market early (with a few firms already operating at the early stage) tends to capture a large piece of the whole industry. In a variation of the model, we differentiate regions by assigning different innovation spaces to them. In one region, firms search new technology in $(0, 1)$, but in another, firms are only allowed to innovate in $(0, 0.99)$. We find that if the disadvantaged region first occupies the market, its first mover's advantage can overcome their technological disadvantage and sustain the regional economy for a long time. The reason is, firms in the disadvantaged region can innovate and learn from each other and approach their potential quickly. They drive the price to such a low level and leave a slim profit margin for new firms. Not all agents in the advantaged region are endowed with superior technology. Even if an agent has a very advanced technology to start with, he can make little profit, and an economic downturn may drive him out of business. Although the bigger firms in the disadvantaged region also lose money in the downturn, they will not go bankrupt and will recover during the next upturn.

Path dependence

A region with many firms, on the one hand, will have more agents thinking of starting up new firms, and on the other hand, will become more advanced in technology because of R&D. This property of "increasing return" tends to make the development of the industry locked into certain regions. Once clusters are established, other regions have little chance to catch up. In the real word, for example, it is very unlikely that other regions can surpass Silicon Valley in the semiconductor industry.

Clustering of entrepreneurship

Within the clusters, firms enter and exit the industry constantly. People in clusters try new ideas and found new firms. They may not succeed the first time but they will try again and learn from their failures. This is the reason why a cluster differs from other regions and has so many firms and becomes so technologically advanced. However, any snapshot of the industry tends to ignore the fact that cluster status is achieved through continuous learning by trial and error.

Clustering of innovation

Just like entrepreneurship is clustered, innovative activities are also unevenly distributed over the landscape. Firms in clusters spend a lot of money on R&D. They make technological progress through both innovative research and imitation. In the long run, almost all firms in clusters have mastered very advanced technology, which leave any firm outside clusters little chance of survival.

4.3 Location of clusters

The way we start our simulation implies that industrial clusters can emerge in any area. However, it is particularly interesting to know what factors may determine the location of clusters. To study that, we try simulations with different initial conditions.

Technological advantage

Our simulation shows that a region that is quicker at finding, learning, and imitating better technologies (the distribution of technology is further to the right, and/or lower values of f' and g') is more likely to develop into an industrial cluster. In reality, different regions do have different capacities in terms of research and innovation. For example, California and Massachusetts together house 14.3 percent of the U.S. population, yet 43.3 percent of the National Academy of Science members and 34.6 percent of the National Academy of Engineering members are based in these two states. Not surprisingly, California and Massachusetts lead the U.S. high-tech economy. Universities, research institutes and labs have always been a major source of technological advancement. The recent development of the biotech industry further proved the importance of academic research for a regional high-tech economy. Almost all biotech firms either are founded by academic researchers or get advice from them. At the same time, universities continuously provide high-quality laborers to the high-tech sector. It is safe to say that high-quality research universities are the necessary condition for a vibrant high-tech center, if not the sufficient condition.

Knowledge spillovers

Innovation such as superior technology is always first acquired by a lucky few. Other firms have to keep up with the pace of innovation through imitation. We find that regions where firms could easily "copy" advanced technologies (smaller g' and/or imitation allowed for more distant firms) tend to develop into an industrial cluster. In reality, a local culture that tolerates inter-firm knowledge and labor transfers allows firms to learn collectively, which is favorable for the development of a cluster (Saxenian, 1994). A legal infrastructure, such as the enforceability of "not to compete" covenants also has big effects on technology transfers (Gilson, 1999). Notice, the way we see knowledge spillovers is different from what the existing literature sees it. In our model, spillovers do benefit firms within clusters, but do not attract firms into clusters as the new economic geography literature suggests.

Seed capital and seed entrepreneurs

In a variation of our model, we assume that in some regions entrepreneurs have difficulties raising capital to start their businesses. In such regions, when agent i decides to start a firm, he acquires capital $K_i = 2k$ instead of $5k$ as in other regions, where $k \in U(0,1)$. Those capital-scarce regions are less likely to develop into industrial clusters. The availability of capital is important for fostering entrepreneurs, which is well recognized. Many scholars even suggest that local governments set up public funds to provide "seed capital" to potential entrepreneurs if the objective is to develop a high-tech regional economy.

In another variation of the model, we start by putting 4 "seed entrepreneurs" in 4 different regions and see whether that brings substantial advantage to those regions. Our simulation shows that, with a very high probability, one or more of the 4 regions will grow up into industrial clusters. In a different way, this proves first mover's advantage and path dependence. On the other hand, it also shows the importance of entrepreneurial leadership to a regional economy.

It is widely believed that the history of Silicon Valley traces back to the garage where Hewlett and Packard started their business in Palo Alto. Another frequently heard story is the departure of the "Traitorous Eight" from Shockley's Semiconductor Lab to found Fairchild. Those successes have inspired generations of entrepreneurs in the Valley. Almost every other high-tech center's history begins with legendary entrepreneurs, who serve as local heroes and role models that motivate others to pursue success in the same way. Famous examples include Ken Olson in Boston, Bill Gates in Seattle, and Robert Dell in Austin. It seems that the key to replicating the Silicon Valley model is to incubate such a heroic entrepreneur. Providing seed capital is certainly an important part of that game, but it is not sufficient. Although we know heroes in most cases spontaneously emerge, some local policies may facilitate their emergence. For example, local government may provide training program for those scientists and engineers who consider starting their own businesses. Favorable policies such as tax credits also help pioneers.

Trying, and learning by failing

A high-tech industrial cluster, by definition, is characterized by many successful firms. Our dynamic model allows us to see the other side of the story: clusters emerge on failures. Most successes are achieved through constant learning by trial and error. In fact, a region that does not tolerate failures (failed entrepreneurs not allowed to start over again or do not learn from failures ($\rho = 0$)) has a slim chance of success. Therefore, a cluster will most probably appear in a region where entrepreneurship is encouraged and failed experiences are valued (Saxenian, 1994).

5 Concluding Remarks

We have proposed a simplified Nelson-Winter model with an explicit space dimension to study how high-tech clusters emerge on a landscape where no firm exists originally. We use agent-based simulation to show the dynamics of the model.

Social scientists have long been interested in clustering behaviors, such as racial housing segregation, the concentration of poverty and unemployment in certain neighborhoods, the exceedingly high crime rates in certain areas, the extreme dropout rates in certain schools, etc. Mainly two types of explanations are raised for clustering behaviors. One contends that clusters result from a sorting process in which individuals alike choose to associate with one another. For example, the residential segregation phenomenon can be explained in this way. The other argues that peer effects cause individuals to conform to norms in a social group. Obviously, the two arguments are not mutually exclusive. In many cases, including all other examples mentioned above, the two arguments could work simultaneously. The existing literature on industrial clusters recognizes the sorting process in which firms choose to locate close to other firms in order to exploit the benefits from a cluster. However, it neglects the possibility that entrepreneurial spirit can spread among the people in a region through social effects. We believe this kind of social contagion story is close to the reality of high-tech industrial clusters that are characterized by concentrated entrepreneurship. Our model shows that one does not have to invoke the benefits of industrial clusters such as knowledge spillovers to explain the formation of clusters; the contagion of entrepreneurship through peer effects alone is able to account for the emergence of clusters.

Another point our model has highlighted is the importance of pioneering entrepreneurs for an emerging industrial cluster. Entrepreneurial life style is by definition creative and disruptive. It takes at least one charismatic, successful role model to demonstrate the profits of taking risks and the joy of "changing the world" through innovation. Such "seed entrepreneurs" that generate a swarm of followers locally can be identified in every major high-tech industrial clusters in the United States. We are aware that such pioneers are not picked beforehand; in fact, in most cases, it seems that those leaders had appeared by luck. However, we can certainly increase the chance of seeing such leaders by creating a favorable environment for entrepreneurial activities. Providing "seed capital" is one measure that may work, especially when entrepreneurs face binding financial constraint. Yet that is not enough. Given that high-tech firms are often founded by scientists and engineers, who do not necessarily have the impulse or knowledge to start as entrepreneurs, policies that help convert those people into entrepreneurs are useful.

Despite the simplicity of our theoretical model, it is beyond our capability to analyze it mathematically. For this reason, we resort to agent-based simulation to show the evolutionary dynamics of the model. We have built a prototype for studying the emergence of high-tech industrial clusters. The primary advantage of the simulation approach is that we are free to try many variations of the model. For example, some authors have recently shown that large incumbent firms are likely to spin off new businesses, which provide an alternative mechanism through which industrial clusters emerge and grow (e.g., Klepper, 2001; Klepper and Sleeper, 2002; Lazerson and Lorenzoni, 1999; Zhang, 2003). Although our model completely shuts off the spin-off channel, one can easily modify our simulation to incorporate such spin-off activities.[4] Our model can also be modified to allow firms to move into or out of clusters, to have more sophisticated agents, to introduce product inno-

[4] Indeed, early spin-offs in Silicon Valley, such as those from the Fairchild Semiconductor, inspired many employees at incumbent firms to follow suit and start their own businesses, which has been happening over many generations. This is an important thread of Silicon Valley's history (Saxenian, 1994).

vation in addition to new technology, or to test the consequences of different social network structures. We leave those for future work.

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