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A Percolation Model of the Product Lifecycle

By

Koen Frenken, Gerald Silverberg and Marco Valente

Danish Research Unit for Industrial Dynamics

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Koen Frenken
(Corresponding author)
Urban & Regional research centre Utrecht (URU)
Utrecht University
P.O Box 80115, NL-3508TC, Utrecht
The Netherlands
Tel: +31302532466
Fax: +31302532037
E-mail: k.frenken@geo.uu.nl

Gerald Silverberg
UNU-MERIT, Maastricht University, the Netherlands
IISA, Lazenburg, Austria

Marco Valente
Department of Economics, University of L'Aquila, Italy

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Abstract:
The product lifecycle model can be understood as a three-stage model of technological development associated with a particular product technology. In the explorative stage many different designs are developed, in the development stage products become standardized into a dominant design, and in the mature stage only incremental changes occur within the dominant design. Although the product lifecycle model is widely accepted and often applied in empirical research, innovation scholars have failed to develop systematic theoretical models that explain the different stages of technological development along the lifecycle. In this study, an attempt is made to contribute to product lifecycle theory by developing a theoretical model based on percolation dynamics. The model combines the concept of increasing returns to adoption with information diffusion among consumers within social networks. The main contribution of the model is that it replicates the three stages of the product lifecycle as an outcome of a single elementary process. The model also replicates the S-shaped diffusion curve and the occurrence of an industry shakeout.

Keywords: Percolation; diffusion; social networks; product lifecycle; dominant design

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1. Introduction

The product lifecycle model and the concept of dominant design have received a great deal of scholarly attention in industrial organisation and innovation studies for over three decades. Since Abernathy and Utterback (1978) first developed the concept of a dominant design from a study of the automobile industry, scholars have found the concept to be a useful tool for studying the evolution of products. Related concepts such as natural trajectories, technological paradigms and technological guideposts (Nelson and Winter 1977, Dosi 1982, and Sahal 1985, respectively) have also become central concepts in the innovation literature.

The product lifecycle model can be understood as a three-stage model of technological development associated with a particular product technology. In the first, explorative, stage product innovation is dominant as many firms explore the new technology in various directions. During the development stage, standardization on a dominant design causes a fall in product innovation and opens the way for increased mechanization of the production process. During this stage, many firms are forced to exit the industry, causing a 'shake-out' (Klepper 1997). Finally, in the mature stage, only incremental innovations occur within the dominant design to customize the product for specific user groups. A new cycle may be initiated by the introduction of a radically new technology.

Though the product lifecycle model is widely accepted and often applied in empirical research, innovation scholars have failed to develop systematic theoretical models that explain the different stages of technological development along the lifecycle. Exceptions are the industrial dynamics models that have focused on the shake-out leading to the emergence of an oligopoly (Jovanovic and MacDonald 1994; Klepper 1996). Yet, these 'industry lifecycle' models remain silent on the innovation dynamics that occur during the product lifecycle.

In this study, an attempt is made to contribute to the product lifecycle theory by developing a theoretical model based on percolation dynamics (Solomon et al. 2000). The model synthesises the concept of increasing returns to adoption and information diffusion within social networks. Increasing returns to adoption stem from the benefits that consumers enjoy from adopting the same dominant design due to the positive externalities in common use (Arthur 1989). Information diffusion processes within social networks capture the role of word-of-mouth and demonstration effects among consumers regarding the properties of new products (Rogers 1962). Combining these two features of innovation in a percolation model is shown to be sufficient to replicate the aforemonetioned three stages of the product lifecycle.

We proceed as follows. In section 2 we will first discuss the product lifecycle model and the empirical insights that have been derived from it. In section 3 we turn to the standard percolation model. In section 4, we introduce increasing returns to adoption and competing technologies to elaborate the percolation model into a product lifecycle model. Section 5 concludes.

2. The Product Lifecycle Model

The product-life cycle concept was first developed as a concept in marketing in the 1960s (Klepper 1997: 146-147). In the 1970s, the concept was further refined into a stage model of industrial innovation (Utterback and Abernathy 1975; Abernathy and Utterback 1978). Three stages are generally distinguished: the explorative stage, the development stage, and the mature stage. Williamson (1975: 215-216) characterized the three stages of development along a product lifecycle as follows:[1]

[1] As quoted in Klepper (1997: 146-147).

> "Three stages in an industry's development are commonly recognized: an early explorative stage, an intermediate development stage, and a mature stage. The first or early formative stage involves the supply of a new product of relatively primitive design, manufactured on comparatively unspecialized machinery, and marketed through a variety of exploratory techniques. Volume is typically low. A high degree of uncertainty characterizes business experience at this stage. The second stage is the intermediate development stage in which manufacturing techniques are more refined and market definition is sharpened; output grows rapidly in response to newly recognized applications and unsatisfied market demands. A high but somewhat lesser degree of uncertainty characterizes market outcomes at this stage. The third stage is that of a mature industry. Management, manufacturing, and marketing techniques all reach a relatively advanced degree of refinement. Markets may continue to grow, but do so at a more regular and predictable rate … (e)stablished connections with customers and suppliers (including capital market access) all operate to buffer changes and thereby to limit large shifts in market shares. Significant innovations tend to be fewer and are mainly of an improvement variant."

The theoretical contribution of the product lifecycle model lies not so much in its description of three stages of technological development, but in its explanation of the interplay between product innovation and process innovation. After an explorative period of product innovation, increasing returns to adoption render one design approach dominant (David 1985; Arthur 1989). Both firms and consumers incur increasing returns from adopting a single design incorporating standardised features. Product standardisation in turn opens up opportunities for process innovation in large-scale production technologies. More efficient process technologies allow for lower sales price of the popular design, accelerating its dominance in the market. The two trends of product standardisation and process mechanisation can be mutually reinforcing, which would explain the sudden transition from technological variety to product standardisation in what is called a “dominant design” (Abernathy and Utterback 1978).

The first systematic empirical study of product lifecycles was carried out by Gort and Klepper (1982) and examined the history of 46 products using data on entry, exit, patents, prices and output, as well as counts of major and minor innovations. It can still be regarded as the most comprehensive study of the subject. They broadly confirmed the basic product lifecycle pattern in terms of expanding output through falling prices and demand only saturating in the later stages of the product lifecycle. Using the distinction between major and minor innovation, they also found that, on average, the rate of major innovations peaked earlier than the rate of minor innovations. In so far as major innovations can be considered as early product innovations, and minor innovations as later incremental extensions of a dominant design, the results may be interpreted as consistent with the predictions of the product lifecycle model.

The second systematic study of product lifecycles was done by Malerba and Orsenigo (1996), who speak of the Schumpeter Mark I regime when referring to the entrepreneurial stage of the product lifecycle, and the Schumpeter Mark II regime in referring to the mature oligopoly stage of the product lifecycle.[2] They distinguish 49 technological classes, which have been grouped according to classes of patent statistics. On the basis of this classification, they found that the majority of classes could be characterized as either Mark I or Mark II. The former group contained industries with small-sized firms, high entry, low concentration, and low stability in the ranking of innovators (the explorative stage in the product lifecycle). The second group contained industries with large firms, low entry, high concentration, and high stability in the ranking of innovators (the mature stage of the product lifecycle). In a follow-up study, Breschi *et al.* (2000) related the Schumpeter Mark I and Schumpeter Mark II regimes to

[2] Malerba and Orsenigo (1996, p. 452) also recognised these similarities between their terminology and the product lifecycle.

indicators that characterize the properties of the technology to test whether these patterns of industrial organization can indeed be related to a particular stage in technological development. The indicators include the size of technological opportunities, the degree of cumulativeness of innovations, the degree of appropriability of innovations, and properties of the knowledge base. Following the product lifecycle model, the Schumpeter Mark I regime is characterized by high technological opportunities, a low degree of cumulativeness and appropriability, and a knowledge base predominantly based on applied science. The Schumpeter Mark II regime is characterized by low technological opportunities, a high degree of cumulativeness and appropriability, and a knowledge base predominantly based on basic science. Breschi et al. (2000) indeed found that Schumpeter Mark I patterns of industrial organization can be explained by the signs of the four indicators characterizing the first regime, and that Schumpeter Mark II patterns of industrial organization can be explained by the opposite signs of the four indicators characterizing the second regime.

Many other empirical studies have been carried out mostly focusing on specific products. In their reviews, Klepper (1997) and Murmann and Frenken (2006) conclude that, despite the growing body of empirical literature, systematic evidence on the product lifecycle model is still limited. This is due to the lack of common methodologies and definitions as well as a lack of formal models providing predictions of the specific innovation dynamics that are to be expected given particular sets of industry characteristics.

In the following we propose a simple theoretical framework based on percolation models from complex systems theory. The model simulates the explorative stage when many different designs are developed, the development stage when one dominant design emerges, and the mature stage when only incremental changes occur within the dominant design. The main contribution of the model is that is replicates the three stages of the product lifecycle as an outcome of a single elementary process. We do so by combining two concepts: technologies exhibit increasing returns to adoption (Arthur 1989) and information diffusion among consumers within social networks (Solomon et al. 2000). The generality of the model can be easily adapted to account for more specific dynamics characterizing individual product technologies.

3. Adoption as Percolation

Economists have traditionally studied the choice behaviour of consumers as a rational choice process in which an individual consumer weighs the benefits and costs of alternative product bundles. Outside the field of theoretical economics, applied researchers as well as company managers have long acknowledged the relevance of agent interactions in understanding innovation diffusion. The owner of a given product is a powerful demonstration able to induce similar purchasing decisions by people in his or her social circle. Still, individual people also have personal preferences. The sports car used by a playboy, however attractive, may be of little interest to the father of four, or the new Internet-enabled mobile phone shown off by a jetsetting manager may not interest a housewife. A model of adoption should thus incorporate both individual preferences and social imitation.

One such model is the social percolation model, which makes use of a powerful tool developed in mathematical physics and was recently introduced into the social sciences to model diffusion dynamics (Solomon et al. 2000). Percolation, as its name suggests, was originally developed to analyse whether a material can be traversed by a fluid or not.

In the model, we have agents connected by social relations to other agents. We assume the social network to be regular in that all agents are symmetrically connected to four neighbours on a lattice. This assumption is useful to avoid the possibility that certain model results are driven by the specific asymmetries in the network structure.[3]

Percolation in adoption means that an agent becomes aware of a novel product only when a neighbour buys it for the first time. At this moment, the agent considers whether to adopt him/herself. That is, in our model word-of-mouth is the only medium for agents to gain information about new products. Whether the agent subsequently adopts the product is dependent on the agent's preferences as indicated by its "minimal requirement", a level of value-for-money below which the agent refuses to buy the product. Conversely, any product about which the agent becomes aware with a value-for-money index above the minimum threshold will be purchased.

To assign preferences to agents, we follow the standard percolation model in assigning a random number drawn from a uniform distribution on the interval [0,1).[4] These values represent the minimal requirement demanded by an agent before adopting the product.

A simulation consists in assigning a product an exogenous value-for-money index level, defined as a value q in the interval [0,1). The initialisation consists in choosing randomly a few agents, and offering them the product. They will buy it only if the value-for-money index q of the product is above the agent's minimal requirement. For each subsequent simulation time step t the agents neighbouring those who made a purchase at t-1 will have the opportunity to buy a product, and the purchase will be made only if the product exceeds the agent's minimal requirement.

[3] The model set-up allows any network structure to be implemented. For example, network structures can be drawn from empirical research in specific product industries and can reflect quite different topologies with properties such as small worlds or scale-free.

[4] Other distributions could of course be employed, such as lognormal to reflect income distribution (cf. Cantono and Silverberg 2008).

A simulation run represents the diffusion of a novel product in a market. Clearly, all agents whose minimal requirements are higher than q will never buy it. However, it is also possible that agents with requirements lower than q will not adopt, because in the absence of previously adopting neighbours they never get a chance to evaluate the product. Since preferences are randomly drawn from a uniform distribution on the interval [0,1), the maximum extent of diffusion of a product with value-for-money index q is exactly equal to q. For example, a product with q=0.9 will be adopted by at most 90 percent of all agents, since ten percent of the agents will have a minimum requirement exceeding 0.9.

The mathematical properties of percolation models are such that there exists a critical value-for-money index q^* such that for product with values above q above the critical value q^*, the diffusion rate will be close to their value-for-money index, and for values of q below the critical value q^*, the diffusion rate will be significantly lower than their value-for-money index. In the former case, information about the existence of the new product almost fully percolates through the social network thus triggering nearly all potential customers to adopt the product. In the latter case the information does not percolate, causing many potential adopters not to adopt the product because they never become aware of it through contact with other adopters.

Figures 1 and 2 report the diffusion of a product in a market consisting of 160,000 agents on a lattice of 400 x 400 cells.[5] The same results are obtained for lattice of different sizes. Dark cells are agents who did not buy the product, while brighter ones are agents who did. Both snapshots are taken at the end of the simulation runs, i.e., when no more purchases take place. In both cases 10 cells selected at random are initially offered the opportunity to buy the product, and then, in subsequent time steps, the model evolves iteratively as described above.

[5] The model has been implemented in the Laboratory for Simulation Development (LSD) available via http://www.business.aau.dk/~mv/Lsd/lsd.html. See also Valente (2008).

In the case reported in Figure 1 the product's value-for-money index is set at q=0.55, below the known critical value threshold for two-dimensional site lattices, q*=0.593. As can be expected, only some of the initial agents buy the product. These early adopters manage to "infect" their neighbours, spreading the information about the existence of the novel product. But each of these cases hits, sooner or later, against clusters of too demanding agents, that is, agents with minimal requirements higher than the product's value-for-money index. Therefore, the diffusion of the products is stopped before the vast majority of agents have the opportunity to consider the product. Conversely, Figure 2 reports the same simulation when the product value-for-money index is set to q=0.6, above the critical value q*. In this case the diffusion of the product may be slowed by groups of highly demanding consumers, but the vast majority of willing consumers have the opportunity to make their purchase. Consequently, close to 60 percent of all consumers will adopt the new product. The simulations thus show that raising the value-for-money index of the product only slightly from 0.55 to 0.60 leads to a sudden increase in the rate of the product's diffusion, a phenomenon known in physics as a phase transition.

The phase transition property of percolation to produce a qualitative change in system behaviour above the critical value is well known and was employed by Solomon et al. (2000) in a model of product adoption as a hit or flop phenomenon. The percolation model thus explains the fine line between success and failure of new products, and the inherent difficulty for firms to predict success and failure. In the following section we extend the standard percolation model to include increasing returns and competing technologies, as a model of the product lifecycle.

4. The Model

What is characteristic of the product lifecycle model is the sudden emergence of a dominant design. David (1985) and Arthur (1989) suggested that the emergence of a dominant design, which often takes the form of a technological standard, is due to increasing returns to adoption. The benefits of adopting a new technology increase with the number of adopters due to lower prices resulting from scale economies for producers and higher utility, due to wider availability of complementary products. Even though these benefits are diverse, we capture the increasing returns in our value-for-money index q.

In the following, we assume that there are several technologies competing on a product market, with each technology being offered by a single firm. We further assume that their value-for-money index q is not fixed (as in the original percolation model), but increases as a function of the number of adopters as follows:

$$q_{i,t} = 1 - \left(1 - q_{i,0}\right)\left(\frac{N_{i,t}}{k}\right)^{-a} \qquad (1)$$

where $q_{i,t}$ is the value-for-money index of product i at time t; $N_{i,t\text{-}1}$ is the number of adopters of product i at time t-1; k and a are positive parameters.[6]

We set the initial value-for-money index levels, $q_{i,0}$, for all products identical and to a value well below the critical value q^* so that we know the market will not be automatically invaded. Yet, as early adopters generate increasing returns and thus raise the product's value-for-money

[6] These parameters govern the "speed" of reaction of quality to the increment of number of adopters of a given product. Setting different levels for these parameters allow us to increase or decrease the effects of new consumers on product quality, as well as change the shape of the relation. The effect of these parameters also depends on the extent of the market considered, i.e., the number of agents.

index endogenously, the market may eventually be invaded. We can observe something akin to a network externalities effect: the higher the share for one specific product, the higher will be its rate of growth of value-for-money index, thus allowing for still higher sales growth in the future. Since all products are initially identical in terms of their value-for-money index, any product can, by pure chance, attain an early advantage that competitors have no way of overcoming later.

In assuming that products compete on the market and differ solely in value-for-money index, we abstract from substitutability between products. In general, different products, however distinct in their specific characteristics, can nonetheless be compared along some dimensions in characteristics space (following Hotelling 1929). We assume products to be ranked along a single, unspecified variable, so that products closer in their ranks are considered more similar than products with very different ranks. The ranking variable is independent of the value-for-money index variable, which evolves with the increasing returns function as described above.

The ranking variable can be interpreted as a stylised representation of different technological patterns, or paradigms, where nearby products have more similar technological characteristics then far away products. Any product has the possibility to be developed to provide higher and higher value-for-money index. However, consumer behaviour can restrict the technological area that is actually explored, because only through adoption the value-for-money index of a product will be improved as specified in formula (1).

From our model, it follows that an agent who is informed by a neighbour about the existence of a new product, is actually informed about the existence of the particular variant of the product that the neighbour purchased. If the agent then decides to purchase the new product, the agent will adopt the same product variant as its neighbour, or – as we will assume – a variant technologically similar. This widening of options can be considered as reflecting the fact that choices of agents are only partially influenced by their peers. We modify agents' behaviour as follows. Once an agent considers buying a product with rank *r* (because a neighbour bought it the previous period), he will choose among all products with rank between *r* - τ and *r* + τ, where τ is a non-negative integer. Of these products, all of those with a value-for-money index below the agent's minimal requirements are removed from the list of potential choices. Among the remaining ones, probabilities of being chosen decrease the farther the products rank differs from *r*. The probability is controlled by a parameter $\beta \in [0,1]$ in that for each product whose rank *i* is in the range τ from the "triggering" firms *r* we compute the indicator $x_i = \beta^{|r-i|}$. The probability of being chosen is then this indicator normalized by the sum of all the indicators:

$$x_i^* = \frac{x_i}{\sum_j x_j} \quad (2)$$

5. Results

Figure 3 reports the total number of agents adopting each of the ten products over time for an example run, while figure 4 shows the lattice for the same run. The model starts with a small percentage of all the agents that choose randomly one product. These initial purchases, scattered across the lattice, then triggers the process of diffusion.

We first analyse the results for $\tau = 0$, thus assuming that consumers purchase the exact same products as their peers. The results in figure 3 and 4 show that increasing returns do play a crucial role in determining the overall success of the introduction of a new product, but also influence the eventual structure of the market, in terms of which agents choose which product. Our results show that earlier fluctuations may generate one single firm dominating the whole market, or a few of them reaching a level of q_i sufficient to expand in smaller niche areas of consumers' space. In this manner, we can not only replicate the outcome of the lock-in model of Arthur (1989)[7], but also produce different competing dominant designs among different clusters of consumers. The same results are obtained with different parameter values and across different runs. For example, if the initial value-for-money index level $q_{i,0}$ is even lower than 0.3, it simply takes longer before the dominant design emerges. And, if k is higher, the dominant design emerges quicker.

Figure 4 shows a run of the model in three dimensions (market share vs. time and firms offering a ranked product). Initial value-for-money index is low ($q_{i,0}$=0.1) reflecting the embryonic stage of product development at the start of a new product lifecycle. The low initial value-for-money index means that only a few, rare, consumers make a purchase, and generally no neighbour actually follows this lead. For presentation purposes, we show the simulation results from step 100 onwards, because during the initial period of 100 iteration steps, no product manages to gain more than a few consumers. Over time, there will be one design profiting from the increasing returns, thus increasing its value-for-money index and appealing to the majority of consumers. This sudden transition is reflected in the rapid increase in the market share of a particular product. After the dominant design emerged, however, products that are similar to the dominant design also become popular due to the fact that consumers do not necessarily perfectly imitate the product purchased by their neighbours as reflected in a positive value of tau ($\tau = 1$).

To understand the evolution of the variety of designs in a more precise manner, we computed the entropy of the market shares of the 100 products in Figure 5 as well as the total number of adopting agents. Entropy here reflects the variety in designs.[8] The figure shows that entropy during the initial period of limited diffusion is very high.[9] The high level of variety can be

[7] A similar model has recently been proposed by Hohnisch et al. (2006).
[8] Entropy is a measure of variety and is given by $H = -\Sigma s_i \log_2 (s_i)$ where s_i stands for the share of product i in the population of products.
[9] Considering that the maximum entropy for 100 products equals $\log_2 (100) = 6.64$.

understood from the random drawing of agents and products. In the second stage, entropy falls as a single cluster starts to dominate the market as increasing returns set in. During this phase, the dominant design emerges and a mass market is created. In the final stage, the dominance of the most popular product diminishes as similar products are being purchased as well. In this mature phase, the dominant design is still in place, but has taken the form of a family of similar products. The emergence of a family of products is indeed in accordance with empirical evidence as summarised by Murmann and Frenken (2006).

The model also replicates two other stylised facts (Rogers 1962). The adoption curve in Figure 5 is S-shaped, which is typical for innovation diffusion processes. Second, it takes a long time for a new product to diffuse after it is introduced. For example, before cars became mass products, they were used for decades only by a small group of people.

If we further assume that each product variant is produced by a different firm, the entropy curve in Figure 5 reflects the evolution of market structure as well. The sudden drop in entropy reflects the sudden dominance of one or few firms, leading to an industry shake-out as it is common in product industries (Klepper 1997). The slight increase in the number of producers after the dominant design emerges, reflected by the slight increase in entropy in the final phase, is also confirmed by empirical evidence that in maturing markets, remaining niches become filled by small niche players (Carroll and Hannan 2000).

The patterns shown in Figures 4 and 5 are robust across simulations, yet which design becomes the dominant design is indeterminate. Thus, one can explain the general pattern of product evolution without being able to predict which of the 100 designs will become the dominant design (David 1985; Arthur 1989).

The qualitative pattern reflecting the three-stage development of the product lifecycle shown by the simulations is also robust against changes in the parameter values of β and τ.[10] The possible values of β lie between 0 and 1, where the simulation results that are shown, are generated for β=1. Lowering the value for β yields a similar pattern of development, though narrowing the family of firms composing the dominant design. The parameter τ can only assume positive integer values, where the simulation results shown, are generated for τ=1. Increasing τ to 2, 3 or 4 yielded the same qualitative pattern, generating larger "clusters" of technologies in the dominant design, while further increasing τ would be theoretically unrealistic.

The range of *k*-values that produces the product lifecycle pattern is more limited. This can be understood on the basis of the model formulation itself. Given that we assume very low initial value-for-money index levels ($q_{i,0}$=0.1), a too low value for k will not trigger a sufficient amount of increasing returns, so that a dominant design will not emerge. Such low values can be associated to invented products that fail to diffuse. A too high value of k, by contrast, will immediately lead to a dominant design as the increasing returns rapidly increase the value-for-money index of the product. Such products can be associated with the (rare) products that diffuse instantaneously.

6. Concluding Remarks

Using only a few assumptions, the theoretical model replicates the three-stage product lifecycle model developed by Abernathy and Utterback (1978). The first stage in the theoretical model is characterized by a high level of variety of different products, each with its own small clusters of like-minded agents that are socially connected ('niches'). This stage

[10] Results can be obtained upon request.

corresponds to the explorative stage in the product lifecycle theory. In the second stage, one design suddenly emerges, thereby reducing variety and making the product available for the mass market. This stage corresponds to the development stage of the product lifecycle during which a dominant design emerges. And, assuming single-product firms, the occurrence of a dominant design also leads to an industry shake-out. In the third stage, small modifications of the dominant designs are being explored incorporating only minor modifications of the dominant design. This stage corresponds to the mature stage of the product lifecycle during which the dominant design is elaborated in different variants.

The main contribution of the model is that is replicates the three stages of the product lifecycle as an outcome of a single elementary process, while also producing the S-curve of product diffusion and the industry shake-out. The model can be easily adapted to account for more specific dynamics characterizing individual product technologies. For example, we did not consider the case in which consumers repurchase the product several times in their lifetime (which might reinforce the dominance of the dominant design as consumers abandon their initial choice and follow the crowd later on). For many products this is a relevant factor. Another possible modification of the model is to allow for multi-product firms.

For individual industries, empirical evidence on product lifecycle patterns and industry dynamics might be used to validate the theoretical model empirically in specific contexts. We leave this for future research.

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Appendix - Figures

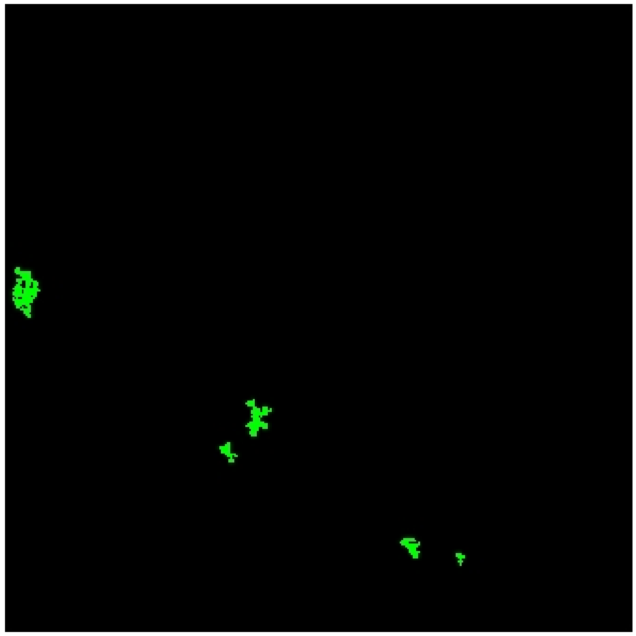

Figure 1. Diffusion for a single product with value-for-money index q=0.55 on a square lattice containing 400 x 400 points and initialising 10 randomly chosen cells. Lsd configuration file: **SIM1.LSD**.

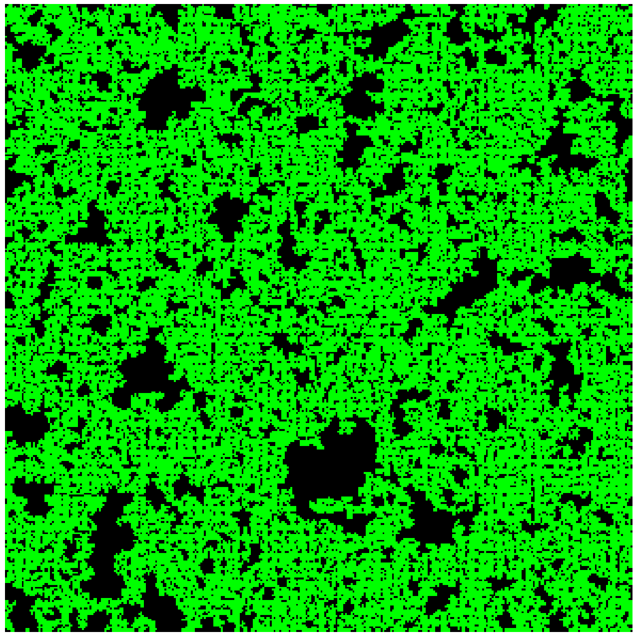

Figure 2. Diffusion for a single product with value-for-money index q=0.6 on a square lattice containing 400 x 400 points and initialising 10 randomly chosen cells. Lsd configuration file: **SIM2.LSD**.

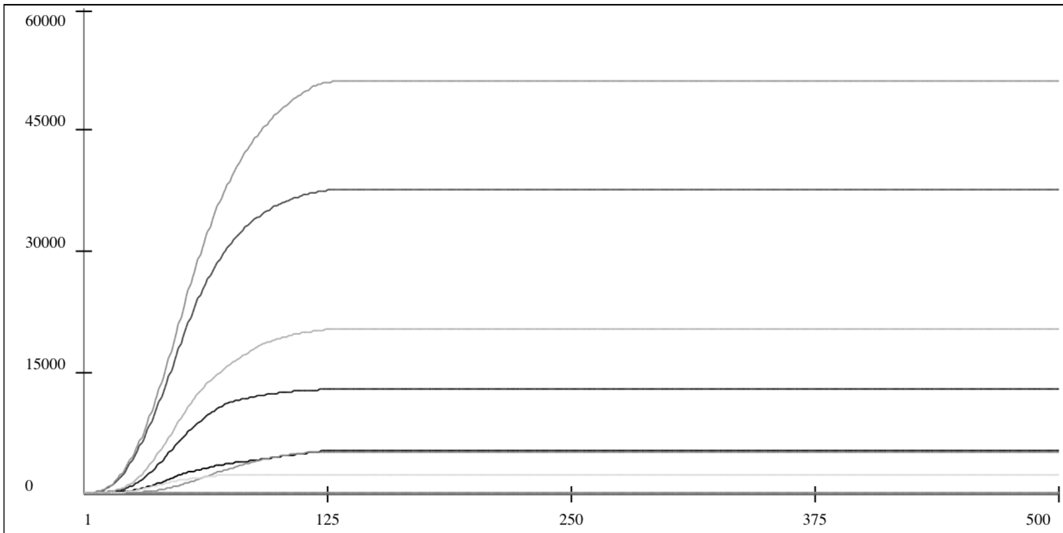

Figure 3. Time series for number of adopters among consumers on a 400 x 400 lattice of 10 different products. Initial price-performance index q_0=0.1; *k*=1; *a*=0.2; initial adopters 0.2 %.

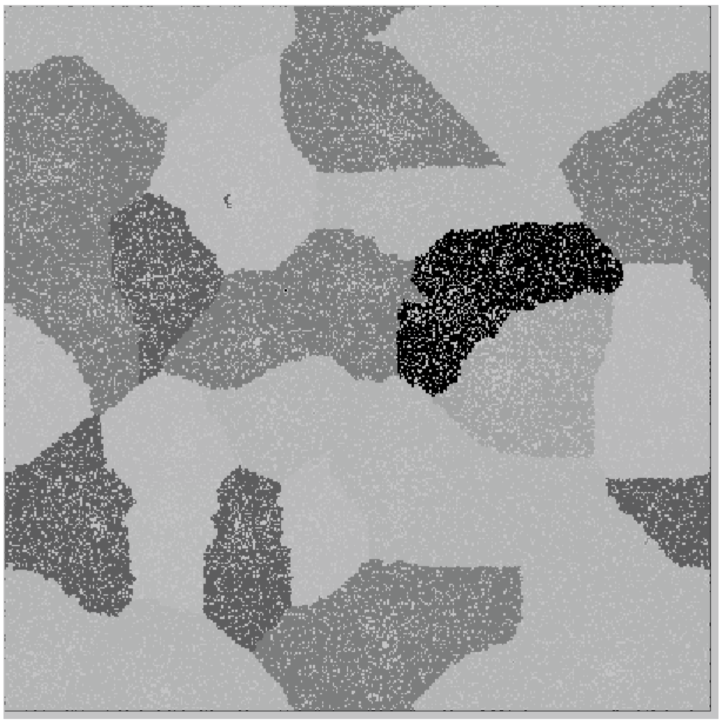

Figure 4. Lattice of adopters among consumers on a 400 x 400 lattice of 10 different products.

Initial price-performance index q_0=0.1; *k*=1; *a*=0.2; initial adopters 0.2 %.

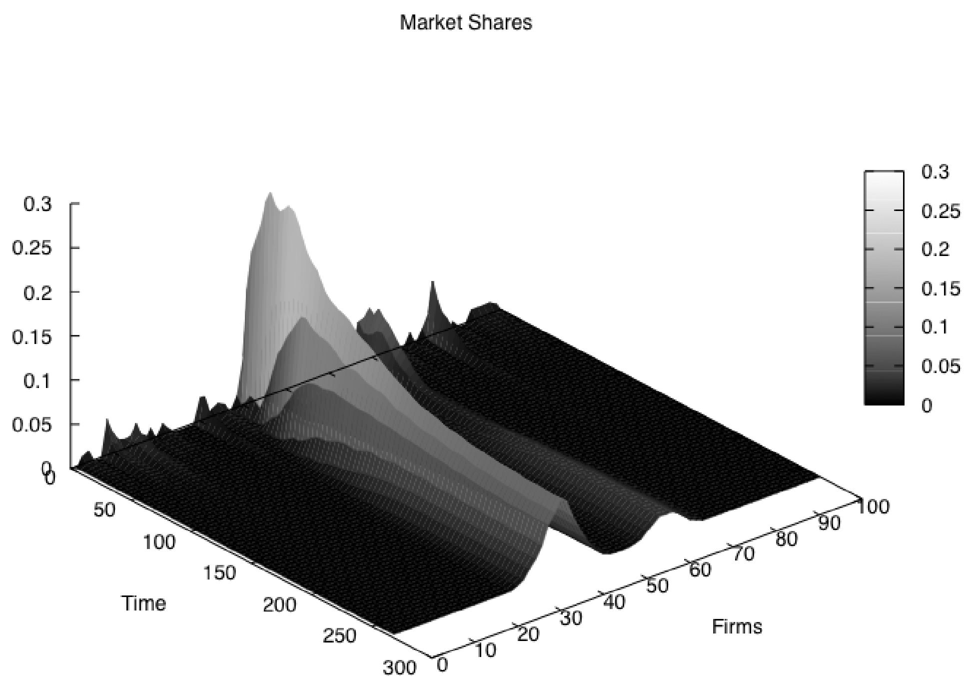

Figure 5. Time evolution of market shares for 100 ranked products. Consumers form a 400x400 lattice; τ=1 and β=1; initial price-performance index $q_{i,0}$=0.1; a=0.2 and k=1; initial adopters 0.5%.

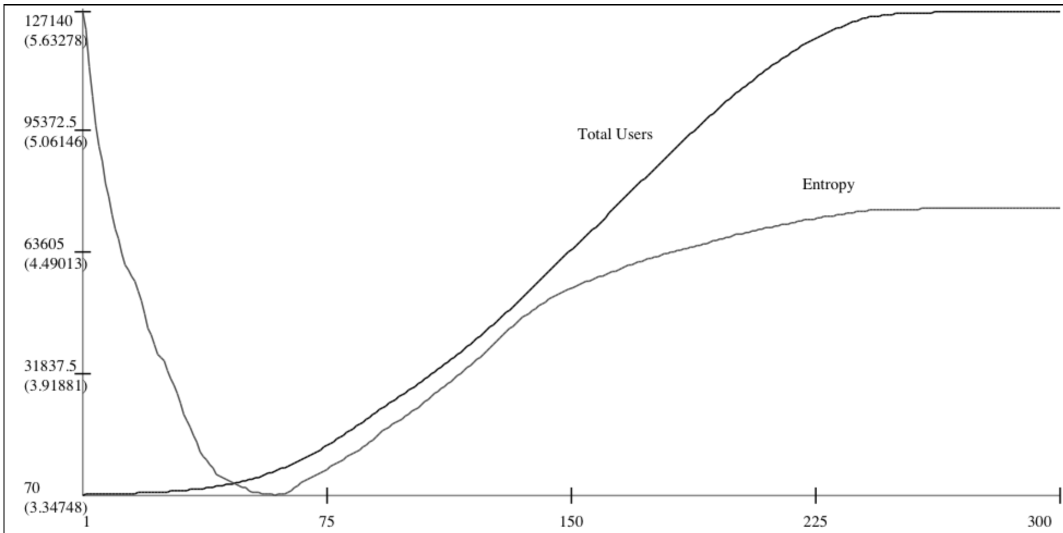

Figure 6. Total number of consumers who adopted a product and entropy values. On the vertical axis the upper values refer to the number of adopters and the lower figures in parentheses refer to the entropy measure. Parameter values for the simulation are as described in Figure 5.

Appendix – Model Description

The model has been implemented using Lsd, and is available upon request to replicate the results presented in the paper or test other configurations.

The model contains a set firms, assigned some parameters, like an initial value-for-money index and a ranking index. The model includes several routines computing accounting values and the consequential upgrade of the value-for-money index, as described in the main text. A routine **Init** perform some general initializations at the starting of a simulation run. The main steps of a simulation cycle are composed by three variables: **Action**, **Choose** and **Spread**.

Init is used only to create the model's data structure and is executed only at the first time step of the simulation. It generates several matrices concerning descriptive states for the consumers. In particular, one of these matrices describes the states of the consumers which may be one of the following three values: currently using a product; considering the purchase of a product; unaware of the existence of such products. The **Init** routine sets all consumers to the state "unaware", but for a small number (as defined in the model configuration) of randomly chosen consumer that are set to "considering".

The routine **Action** scans all consumers. Those marked as "considering" are evaluated by the routine **Choose**. If this routine returns a positive value (i.e. they actually purchased a product), then the same consumers are evaluated by the routine **Spread**. For consumers marked as "unaware", the routine **Action** draws a random variable, which, with a small probability, switches their state as "considering".

Routine **Choose** applies to a specific consumer that is evaluating whether to make a purchase. The routine considers the products consumed by the four neighbours of the evaluating consumer. One of these products (randomly chosen, if they are more than one) is selected as "focal" product. If no neighbouring consumer is actually using any product, or, in general, if the evaluating consumer was not put in state of "considering" by the routine

Spread, the focal product is chosen randomly among all existing products. The routine then assigns the probability of products to be chosen, in the following way. The routine assigns an index 1 to the focal firm, say having rank *r*. For all firms with rank *i* within a range τ from the focal firm, the probability index is $\beta^{|i-r|}$. All firms are then assigned a probability index zero if scoring a value-for-money measure below the threshold of the evaluating consumer, or if they have a ranking further than τ from the focal firm. If no firm remains with positive probability, the routine returns a null code, and the evaluating consumer is re-set to the "unaware" state. Otherwise, the positive probability indexes are normalized, and a random choice according to these indexes is performed. In this latter case, the chosen firm is assigned a new consumer, the evaluating consumer is set to the state "using a product", and the product's code (a positive value) is returned to the calling routine **Action**.

The routine **Spread** is activated on a specific consumer. All the neighbours of this consumer are set to the state "considering", signalling which product has been just purchased by the consumer specified for the routine. The consumers set in this state at time step *t* will activate the routine **Choose** only at time step *t+1*.