

Knowledge creation and diffusion in user and producer networks:

a simulation analysis of technological succession

## 1.0 Introduction

We present a multi-agent simulation model that attempts to incorporate interdependencies between a user network and a population of self-organizing producers in an innovation system. In particular, we look at the formation and evolution of a network of knowledge-producers and their interaction with a user network located on a two dimensional lattice.

Technological succession refers to substitution of an existing technology by a new one: in this paper we view a succession as a transformation in the knowledge accumulation patterns of users and producers of the substitutable technologies. As a result, process of knowledge creation and diffusion, or learning by heterogeneous agents about the existing and the new technology, plays a central role. We assume that a part of this learning process occurs through interaction between heterogeneous agents linked in social networks.<sup>1</sup> Further we focus on the diffusion of technologies that possess network externalities i.e., a user's decision to adopt a given technology depends upon the technology used by her neighbours (Katz and Shapiro 1985; David 1985). We model scenarios where occurrence of a succession or escaping a lock-in from an established knowledge accumulation regime is difficult to achieve due to high switching costs among users and producers of the technology. The switching costs are high due to network externalities and stabilised learning pathways on the user side, knowledge and capability endowments more suited to the existing technology regime in the producer network, and the mutually reinforcing effect between these two factors.

This paper is structured around two core questions. First, why existing technological regimes persist for long periods of time in the face of competition from new emerging technologies, and second, what types of inducement mechanisms can be provided or how the co-evolutionary process between users and producers can be modulated for creating new desirable transition paths. Broadly speaking, answering the first question requires an understanding of the processes that sustain a lock-in or 'path dependence' (see David 1984; Arthur 1987; Cowan 1991) and the second is related to 'path creation' (see Garud and Karnøe 2001 for some recent conceptual developments along these lines). Understanding path dependence requires an analysis of the social context in which technologies are embedded, developed and diffused. Social network analysis allows one to represent and study the social embeddedness of the knowledge processes in a relatively simple manner. An analysis of 'path creation' on the other hand involves studying

the provision of attractive socioeconomic incentives to selected agents and strategic niche management. Here a niche is sometimes referred to as a technological niche which is essentially a protected space, in terms of a small number of users and producers, for learning and knowledge accumulation in the new technological regime (Rip and Kemp 1998; Levinthal 1998). The role of user-producer interactions in stabilising a new nascent design in a niche is akin to ‘learning by interacting’ as outlined in Lundvall (1992), and others, in the innovation systems literature. In section 2, we present the model description, identifying the role of network effects related to lock-in as barriers to new technology adoption and focus on learning processes involved in producing and using a technology. Section 3 is a discussion of the results from a simple version of the model. In section 4, we outline some plausible future directions of work and improvements to the model.

## **2.0 Model Description**

In section 2.1, we outline the producer side of the model with network formation through matching, and emergence of different social communities of producers through deliberate actions of the agents. The emergent network structures on the producer side depend upon the knowledge sharing and absorption capabilities of individual agents on the one hand, and on the adoption of the produced technologies in the user network. In particular, the proportion of the user population using each technology impacts the matching among producers for knowledge integration and sharing (equation 5 below). The users are connected to each other on a two-dimensional lattice and each user possesses a few long distance links. Small changes to the user network structures can be made by modulating the long distance links (see Kleinberg 2001).

### 2.1 The producer network

Consider a population of knowledge producing agents of size,  $N$ .<sup>2</sup> Each agent is initialised with a knowledge endowment which is represented as a knowledge vector,  $\mathbf{K}^i$  of size  $M$ . The knowledge vector is randomly assigned to all agents at initialisation. An agent’s *expertise* is in the knowledge type she knows most in. Each agent produces and develops one technology using a combination of different knowledge types. The intensity of each knowledge type used in the production of a

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<sup>1</sup> Members of a social or business network may not necessarily share knowledge with each other, as demonstrated by Giuliani (2005) in a study of wine clusters. Therefore, a knowledge or learning network as distinct from a traditionally defined social network may be a more precise term for what we are referring to.

<sup>2</sup> We will refer to the producer agents, simply as agents in the remainder of this section. The producer side of this model is based on Ozman (2005).

technology  $s$  is given by a vector of size  $M$ . We refer to the elements of this knowledge-intensity vector as  $\gamma$  parameters,

$$\sum_{i=1}^M \gamma_{s,i} = 1 \quad (1)$$

Initially, each agent is engaged in the production of the same technology. The vector of knowledge intensity ( $\gamma$ ) parameters is used to determine the breadth and depth of the technology (Wang and von Tunzelmann 2000; Ozman 2005). Breadth is given by the number of knowledge types  $i$  that correspond to a non-zero value of  $\gamma_i$  i.e., it signifies the number of different knowledge types used in producing a given technology. Depth refers to the extent to which one knowledge type dominates in the technology and is given by the standard deviation of the sample of non-zero  $\gamma$  parameters. Using these two dimensions of knowledge base of a technology, we compute its complexity index as,

$$\Omega_s = \text{depth}_s * \text{breadth}_s / M \quad (2)$$

At time  $\tau$ , a new technology is introduced with a different set of  $\gamma$  parameters. As a result, the new technology will have a different complexity index associated with it. The two different sets of  $\gamma$  parameters for the old and the new technologies are used to determine the knowledge relatedness among the two technologies using the cosine index (Breschi et al. 2003; Ozman 2005). If we refer to the old and the new technologies as  $s_1$  and  $s_2$  respectively, knowledge relatedness between them is given by,

$$X = \frac{\sum_{i=1}^M \gamma_{s_1,i} \gamma_{s_2,i}}{\sqrt{\sum_{i=1}^M \gamma_{s_1,i}^2} \sqrt{\sum_{i=1}^M \gamma_{s_2,i}^2}} \quad (3)$$

Upon introduction of the new technology, a small number of niche producers,  $l^*N$ , acquire knowledge in the types which are more intensive in the new technology.<sup>3</sup> This exogenous increase in knowledge occurs such that the expertise of the niche producers switches to a knowledge type,  $i$ , for which  $\gamma_{s_2,i} > \gamma_{s_1,i}$ . These niche agents become producers of the new technology and do not switch back to producing the old technology.<sup>4</sup>

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<sup>3</sup> This niche may also be viewed as entry by producers of the new technology, accompanied with an exit by the weakest producers of the old technology. The way we define weakest is explained below. Here,  $l$  is a parameter we vary in the simulations.

<sup>4</sup> In general, in this model we assume that once an agent has switched to the production of the new technology, she doesn't revert to producing the old technology.

### 2.1.1 Interaction among agents

An agent can produce a technology as a singleton or in combination with other agents in the population. In each time step, an agent decides whether to produce alone or by integrating her knowledge with that of another agent. Each agent then compares her knowledge-output as a singleton in the technology she produces ( $y^j$ ) to her output as a member of a pair with every other agent in the population.<sup>5</sup> If two agents producing two different technologies form a pair, we assume that they produce both technologies. The output in each technology is weighted by the fraction of user population using, or intending to use, that technology. In other words, for the same amount of knowledge endowment, it is more attractive to match with other agents who produce the technology used by a bigger share of the user population. In addition, the weighting ensures that learning by doing happens faster in the technology with a bigger market share. This faster learning causes a greater reduction in price of the dominant technology, as discussed later in this section.

For integration of knowledge types in a pair, we assume that if two agents  $i$  and  $j$  producing different technologies form a pair, their joint knowledge in type  $u$  is given by (Ozman 2005),

$$K_u^{pair} = \max(K_u^i, K_u^j) \quad \forall u = 1 \dots M \quad (4)$$

This joint knowledge value in each type is used to determine the output of the pair in each time period. Denoting the joint knowledge vector by  $\mathbf{K}^{pair}$ , each agent's share of the joint output at time  $t$  is given by,

$$y_{s_1, s_2}(\mathbf{K}^{pair}, t) = \frac{\phi_{s_1} y_{s_1}(\mathbf{K}^{pair}) + \phi_{s_2} y_{s_2}(\mathbf{K}^{pair})}{2} \quad (5)$$

where  $\phi_{s_2}$  is the fraction of the user population that has already made the decision to switch to the new technology, and  $\phi_{s_1} = 1 - \phi_{s_2}$ . All variables on the R.H.S. of equation (5) are taken at the previous time step,  $t-1$ . The intuition behind Equation 5 is as follows. When two agents come together, they decide what proportion of each good to produce based on the current market shares of the goods.

For making the decision to collaborate or not, each agent compares her share of the joint output  $y_{s_1, s_2}(\mathbf{K}^{pair})$  with every other agent to her output as a singleton,  $y_{s_1}(\mathbf{K}^i)$  or  $y_{s_2}(\mathbf{K}^j)$ . Based upon this comparison, an agent produces a preference listing of other agents according to the output level

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<sup>5</sup> By output, we are referring to the amount of knowledge created in a time period, which is then assimilated through learning. Here learning by doing as a singleton is compared to the result of 'learning by doing and interacting' in a pair.

in a pair with this agent. The listings are used to select pairs such that no individual agent prefers to produce as a singleton over producing with her current partner.

### 2.1.2 Knowledge creation and learning

The output of each agent,  $y$ , is determined using the Cobb Douglas production function where the inputs are the different types of knowledge. We assume that agents create knowledge through the integration of their existing knowledge and while engaged in producing a given technology. In accordance with the assumption of  $\sum_{i=1}^M \gamma_i = 1$ , the use of the Cobb Douglas function implies constant returns to scale (accumulated knowledge). If an agent's accumulated knowledge doubles in all types used in a technology, her output also doubles. We assume that integration of different knowledge types and changes in expertise made by the agents offsets any decreasing returns that may otherwise come into play as more knowledge is accumulated in a specific technological regime. Thus, the output of any agent engaged in producing a technology  $s$  at time  $t$  is given by,

$$y_s(\mathbf{K}, t) = \prod_u (K_u(t))^{\gamma_{s,u}} \quad \forall u = 1 \dots M \quad (6)$$

where  $\gamma_{s,u}$  is the intensity of knowledge type  $u$  in producing/developing a technology  $s$ . Using this output, the knowledge levels of agents are updated in each time period as follows (Ozman 2005),

$$K_u^i(t) = K_u^i(t-1) + \phi \theta_i y(t) g(t) \quad (7)$$

$$g(t) = \delta_i(t) \frac{K_u^i(t-1)}{\max(K_u^i(t-1), K_u^j(t-1))}$$

where  $\phi$  is the share of the user population using the technology that agent  $i$  produces,  $\theta_i$  is the combinative capability of agent  $i$ ,  $\delta_i(t)$  is an uncertainty parameter picked randomly within fixed limits and  $K_u^i(t)$  is agent  $i$ 's knowledge in type  $u$  at time  $t$ . In addition, the function  $g(t)$  accounts for learning by individual agents in case of joint production in a pair. If agent  $i$  knows more than her collaborating agent  $j$  in knowledge type  $u$ , then the amount learnt by her through joint production is equal to the product of her share of the output  $y(t)$ , her capability and the uncertainty parameter. Therefore, apart from the uncertainty parameter, the only factor limiting an agent's learning is her own capability. On the other hand, if agent  $i$  knows less than her

partner in knowledge type  $u$ , the amount learnt by her is further multiplied by the ratio of her knowledge to the knowledge of her partner.<sup>6</sup>

### 2.1.3 Prices and quantities

We assume that each agent supplies the technology it produces to the same number of users. This number is equal to the ratio of the user-population size to the producer-population size ( $n/N$ ).

Each technology carries a proxy for price which influences the users' decision to switch to the new technology. This price index is a function of the combined knowledge. The combined knowledge of a producer  $i$  in a technology  $s$  is determined by weighting her accumulated knowledge stock in all types by the corresponding  $\gamma$  parameters. At time  $t$ ,

$$\omega_s^i(t) = \sum_{u=1}^M \gamma_{s,u} K_u^i(t) \quad (8)$$

where  $\omega_s^i(t)$  is the combined knowledge of agent  $i$  in a technology  $s$  at time  $t$ ,  $\gamma_{s,u}$  is the intensity of knowledge type  $u$  in  $s$  and  $K_u^i$  is the accumulated knowledge level in type  $u$  of agent  $i$ . Now, denoting the sub-population of producers of a technology  $s$  at time  $t$  by  $N_s(t)$ , the price index of  $s$  is then given by,

$$p_s(t) = \min_i \left( \frac{1}{\log_{10}(\omega_s^i(t))} \right) \quad \forall i \in N_s(t) \quad (9)$$

Note that this definition of the price index ensures that no agent makes a loss in the sub-population producing each technology. We assume that there is a collusion among the agents in a sub-population that enables them to charge this price as long as there is a market for the technology they produce. However, if size of the market for the old technology declines due to decisions to switch to the new technology by users, this collusion among the producers of the old technology breaks down. The weakest producer of the old technology is then selected out, thereby reducing the production of that technology. This weakest producer switches to the new technology if there is sufficient demand for it. Details of the switching decision of producers (and users) are discussed in section 3.3.

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<sup>6</sup> For more details on this part of the model, see Ozman (2005).

## 2.2 The user network

The social network of users is modelled as a square lattice of the type shown in Figure 1. The size of the user population is  $n$ , so the size of the lattice is  $\sqrt{n} \times \sqrt{n}$ . Each user, located at a lattice point, is linked (incoming and outgoing links) to her immediate neighbours on the lattice. In addition, each user gets  $q$  incoming links from distant users. The mechanism for making the distant connections is based upon Kleinberg (2000). The  $q$  directed links received by a user  $u$  are constructed using random trials: a link originates from another user  $v$  with a probability proportional to  $d(u, v)^{-r}$ , where the parameter  $r \geq 0$  and  $d(u, v)$  is the lattice distance between the two users  $u$  and  $v$ .<sup>7</sup> A probability distribution for a lattice point is generated through normalisation by  $\sum_v [d(u, v)]^{-r}$ . Different user network structures can now be created by changing the parameter  $r$ . For  $r = 0$ , the originating nodes of the distant connections are uniformly distributed over the lattice. At greater values of  $r$ , the originating nodes get clustered around the receiving node i.e., the length of the distant links reduces with increasing values of  $r$  (Kleinberg 2000).

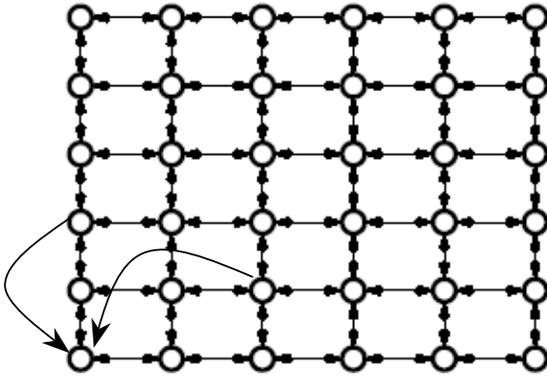


Figure 1. User network on a two dimensional lattice with two ( $q=2$ ) distant connections among users.

### 2.2.1 User knowledge

Each user possesses a knowledge vector,  $\mathbf{k}^i$  of size two. This vector holds the user's use-knowledge of the two substitutable technologies. As on the producer side of the model, at initialisation, each user is assigned the same technology. The users possess a certain use-knowledge of this technology which is randomly assigned initially. In each time period, every user augments her knowledge through by learning by using (accumulation of experience with the

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<sup>7</sup> If each point on the lattice is represented as a vector  $(i, j)$ , where  $i$  and  $j \in \{1, 2, \dots, \sqrt{n}\}$ , and if users  $u$  and  $v$  are located at points  $(i, j)$  and  $(k, l)$  respectively, the lattice distance  $d(u, v)$  is given by  $|(k-i)| + |(l-j)|$  (Kleinberg 2000).

technology over time) and learns from one of the other users that she receives an incoming link from. In the remainder of this paper, we refer to all users  $j$  that send incoming links to user  $i$  as neighbours, or the ball  $b^i$ , of  $i$ . The learning algorithms are discussed in more detail later in this section.

As on the producer side at time  $\tau$ , a small number of niche-users  $l^*n$  obtain knowledge about the new technology. Here  $l$  is the fraction of the producer (and user) population that produce the new technology at time  $\tau$ . The use-knowledge in the new technology of the niche users is made equal to their use-knowledge in the old technology. We assume that the niche users acquire this knowledge as a result of some external support or training, which is not explicitly modeled in the present paper.<sup>8</sup> Finally, the niche users switch to the new technology immediately after the exogenous increase in their use-knowledge is introduced.

### 2.2.2 Learning by using

Users learn as they accumulate experience in using a technology. Following Rosenberg (1982), we call this self-learning process of the users as ‘learning by using’. We assume that learning in a technology becomes harder as more knowledge is accumulated along its trajectory: there are dynamically decreasing returns in learning along a particular technological trajectory. Further, the use-knowledge in each technology has an upper limit ( $\Psi$ ).<sup>9</sup>

Self-learning in one time period in the technology used by a user  $i$  (at time  $t$ ) is given by the following inverse exponential function,

$$sl^i(t) = (1 - \Omega) * \eta^i \left( k^i(t-1) - \frac{(k^i(t-1))^2}{\Psi} \right) \quad (10)$$

The L.H.S. of equation (10) is the amount learnt in one time period by user  $i$  in the technology used by her at time  $t$ .  $\Omega$  is the complexity index of the technology defined in equation (2),  $\Psi$  is the upper limit in use-knowledge in a technology and  $k^i(t-1)$  is the use-knowledge of user  $i$  in the technology at time  $t-1$ .  $\eta^i$  is a parameter that represents the learning capability of user  $i$ : values

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<sup>8</sup> This assumption may be viewed as instantaneous formation of a market niche for the new technology. In this paper, our aim is not to explore the phenomenon of niche formation but to study processes that lead to expansion or multiplication of the small initial niche.

<sup>9</sup> The upper limit in use-knowledge of a technology brings about a (quasi-)stagnation in learning possibilities for users despite continued (incremental) knowledge creation in that technology on the producer side. This stagnation may also be interpreted as problems encountered by users with a technology.

are assigned randomly over the user-network lattice within fixed limits. Each user accumulates knowledge through learning: the amount learnt in a time period is added to the total knowledge of the user as discussed in more detail below. A user's learning capability determines the slope of her knowledge accumulation curve. See Figure 2 for the shape of the knowledge accumulation curve with only self-learning for different values of  $\eta$ .

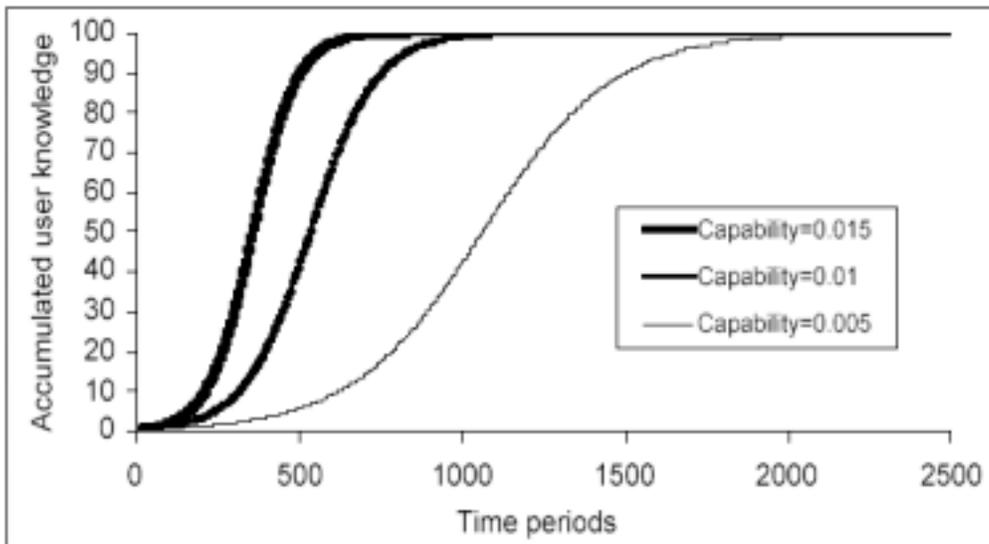


Figure 2. User knowledge accumulation due to self-learning (learning by using).

### 2.2.3 Learning from others

Each user learns from *one* of her neighbours. A user compares the amounts that she can learn from each of her neighbours and picks the neighbour from whom the maximum amount can be learnt in one time period: Here the assumption is that there is significant overlap in contents of what a user can learn from each of her neighbours.

In each time period, a user  $i$  can learn about both available technologies from other users in her ball,  $b_i$ . If users of both technologies exist in  $b_i$ , the user  $i$  learns about the old technology from a user of that technology *and* about the new technology from one of its users. A user  $i$  only learns from a neighbour  $j$  if the knowledge level of  $j$  is greater than that of  $i$ . The amount learnt in a technology by user  $i$  from a connected user  $j$  is a function of the difference between the knowledge levels of  $i$  and  $j$  in that technology. This knowledge difference vector between two users  $i$  and  $j$  is given by,

$$\Delta \mathbf{k}^{ij}(t) = \mathbf{k}^j(t-1) - [\mathbf{k}^i(t-1) + s^i(t)] \quad (11)$$

Note that the R.H.S. in equation (11) avoids overlap in the content of self-learning and learning from others. Further, the amount learnt from others also depends upon the knowledge relatedness between the two technologies if users  $i$  and  $j$  use different technologies. Therefore, if  $i$  uses the new technology and  $j$  uses the old,  $i$  learns about the old technology from  $j$ ,

$$nl_s^i(t) = \max_j \left( X\eta^i \cdot \left( \Delta k_s^{i,j}(t) - \frac{(\Delta k_s^{i,j}(t))^2}{\Psi} \right) \right) \quad \forall j \in b_s^i \quad (12)$$

where  $\Delta k_s^{i,j}(t)$  is the difference between the knowledge levels of  $i$  and  $j$  at time  $t$  as defined in equation (11), and  $b_s^i$  is the set of users of the old technology in the ball of  $i$ . The subscript  $s$  can refer to either of the two available technologies. As described earlier, in equation (12), the amounts learnt by user  $i$  from every other user of technology  $s$  (in  $b_s^i$ ) are compared to each other and the maximum is picked. Here  $X$  refers to the relatedness among two technologies as defined earlier in Eq. 3. See Figure 3 for an example of the profile of the learning curve for learning from others: a user  $i$  learns the highest amount from a user  $j$  if the difference between their knowledge levels is at an intermediate level. If their knowledge levels are equal to each other, no learning takes place. Similarly, if  $j$  knows much more than  $i$ , the amount learnt by  $i$  is very small (this learning scheme is based upon the concept of cognitive distance)<sup>10</sup>. If both users  $i$  and  $j$  use the same technology  $X=1$  in equation (12).

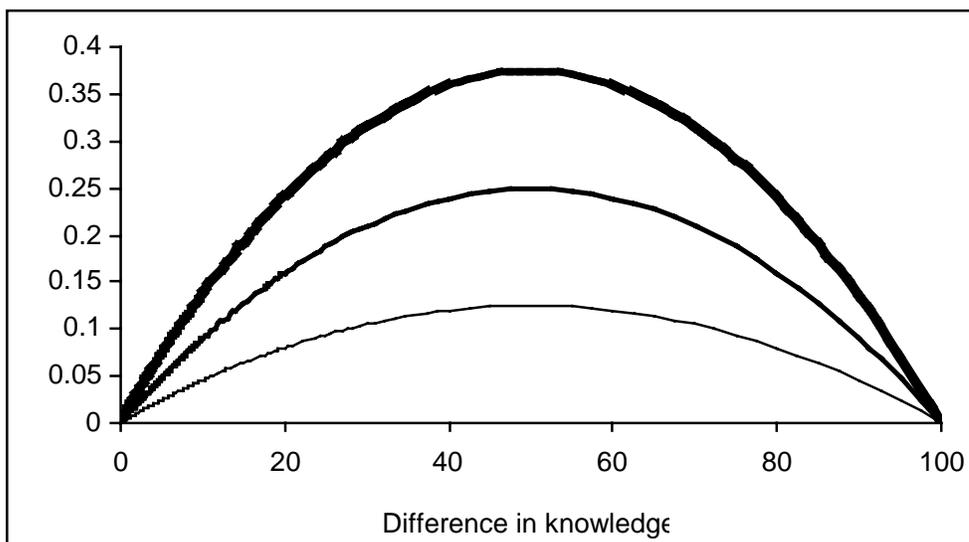


Figure 3. Learning from others as a function of knowledge difference between the two interacting users.

<sup>10</sup> See also Cowan et. al (2005) for the functional relationship.

Finally the use-knowledge values of all users  $i$  in each technology is updated as follows,

$$k^i(t) = k^i(t-1) + \left( sl^i(t) + nl^i(t) \right) \cdot \varepsilon \quad (13)$$

where  $\varepsilon$  is an uncertainty parameter picked randomly between 0.90 and 1.1. That is, we allow a maximum of 10% uncertainty in learning by the users. An example of the knowledge accumulation curve is shown in Figure 4.

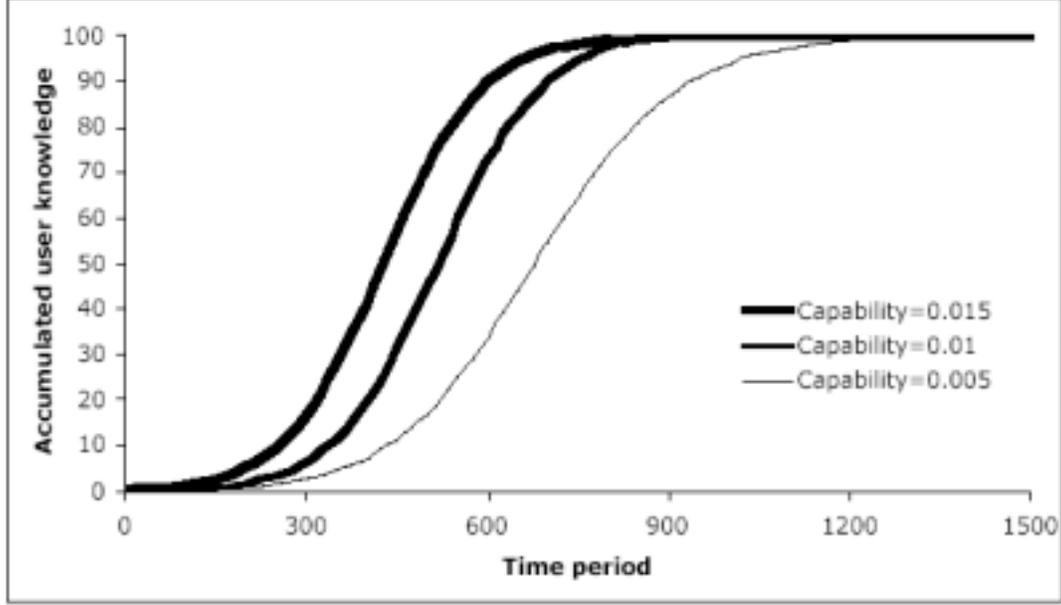


Figure 4. Examples of user knowledge accumulation curve due to self-learning and learning from others.

### 2.3 Switching decision of users and producers

At the end of each time step after the introduction of the new technology, each user of the old technology decides whether to switch or not.<sup>11</sup> The profitability of a technology to a user  $i$  depends upon her knowledge of that technology, the fraction of her ball  $b^i$  which uses that technology and the price set by the producers (defined in equation 9 above). Then profitability of a technology  $s$  is given by,

$$\pi_s^i(t) = \kappa(k_s^i(t))^{(1-\beta)} \left( \frac{b_s^i(t)}{b^i} \right)^\beta \frac{1}{p_s(t)} \quad \text{if } ku_s^i < 1 \text{ and } \beta < 1 \quad (14a)$$

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<sup>11</sup> In the present version of the model, we don't allow the set of early adopters (the new-technology users) to switch back to the old technology, repeated switching between the two technologies is not allowed for this set of users. This may be viewed as a result of the provision of niche-protection incentives or policies.

$$\text{else, } \pi_s^i(t) = \kappa(k_s^i(t))^\beta \left( \frac{b_s^i(t)}{b^i} \right)^\beta \frac{1}{p_s(t)} \quad (14b)$$

where  $\beta (\leq 1)$  is the weight of use-knowledge relative to the weight of the neighbourhood composition (in terms of the proportion of new- or old-technology users in the neighbourhood) in determining the technology's profitability at time  $t$  for a user  $i$ . Below we present results for  $\beta = 1$  and thus use only equation (14b) to determine the profitability of a technology, which is reduced to a simple product of knowledge, neighbourhood composition and inverse of its price.<sup>12</sup> The switching decision of a user  $i$  then depends upon the relative profitability of the new technology w.r.t the old ( $s_2$  vs.  $s_1$ ), and is given by,

$$r\pi^i = \frac{\pi_{s_2}^i}{\pi_{s_1}^i} \quad (15)$$

A user  $i$  makes the decision to switch to the new technology if  $r\pi^i \geq 1$ . However, this only reflects a user's intention to switch to the new technology. As discussed below, the actual adoption of the technology will depend upon its availability from the producer network. After this decision by the users, we calculate the fractions of the user population using, or intending to use, each technology,  $\phi_{s_1}$  and  $\phi_{s_2}$ . These fractions are passed as a signal to the producer network, where they are used in the matching algorithm in the next time step (see equation 5 above).

### 2.3.1 Adoption of the new technology by users and producers

The actual adoption of the new technology by a user  $i$ , for whom  $r\pi_i \geq 1$ , depends upon the availability of the new technology from the producer network. As discussed in section 2.1.3, each producer can supply its technology to a constant number of users ( $=n/N$ ). We assume that the weakest producer of the old technology (the one with the lowest combined knowledge) switches to the new technology if there is sufficient market for it at any time period  $t$ .<sup>13</sup> That is, there exist at least  $n/N$  users  $r\pi^i \geq 1$  at time  $t$ . We allow only one producer to switch in any time period

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<sup>12</sup> However, a more realistic scenario with different values of  $\beta$  implies that the relative importance of use-knowledge and neighbourhood may be different for the two substitutable technologies. Further, for a knowledge-intensive technology like integrated pest management (IPM), both use-knowledge and network effects may be more important than the alternative technology (pesticides). Such scenarios can be modeled by taking different values of the parameter  $\kappa$  for the two technologies. In the results presented below,  $\kappa = 1$ . Finally, the upper limit ( $\Psi$ ) of use-knowledge may also be different for the two technologies. A lower upper limit in one of the technologies may imply that a user encounters problems with that technology, such as pesticide resistance among pests (see also note 9).

<sup>13</sup> After the switch, the knowledge of this producer is made approximately equal to the knowledge of the weakest producer of the new technology so that the price of the new technology is unchanged for the time being.

and the switch is irreversible. After the switch by a producer,  $n/N$  users with  $r\pi_i \geq 1$  switch to the new technology as now more of this technology is available. Now, the neighbours of these users can learn from them about the new technology according to equation (12) above.

Once a user has adopted the new technology, she cannot switch back to the old technology. However, before the actual adoption, she may change her decision to switch if the old technology becomes more profitable (i.e.  $r\pi_i$  becomes less than 1), during the time that a user is waiting for enough of new technology to become available (i.e. the time duration required for a producer to switch to the new technology). This time duration starts when the new technology becomes more profitable for the *first* of the  $n/N$  users and ends when a producer switches (i.e.  $r\pi_i \geq 1$  for *all* of the  $n/N$  users).

### 3.0 Preliminary simulation results and discussion

In this technology succession model, first we must ascertain the time period  $\tau$  at which the old technology regime becomes stable and embedded in the user producer networks. By stable and embedded, we imply that users possess close to the upper limit of knowledge in the (old) technology they use. Similarly, in the producer network significant amount of knowledge, in types relevant to the old technology, must be accumulated by time period  $\tau$ . This knowledge accumulation on the producer side makes producers of the old technology more attractive in the matching process, according to equations 5 and 6. The new technology is introduced at time  $\tau$  for studying transition scenarios away from the locked-in old technology.<sup>14</sup>

For the range of user capability values used in the simulation results presented here, knowledge accumulation curves are shown in Figure 4 above: a user with the lowest possible capability of 0.005 possesses close to the upper limit of use-knowledge by the 1000<sup>th</sup> time period.

Accumulation curves of producers' combined knowledge ( $\bar{\omega}$ ) in the types active in the old technology are shown in Figure 5. Here, a producer with the lowest capability possesses a combined knowledge of approximately 100 by time period 1000.

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<sup>14</sup> If we allowed switches to any of the two substitutable technologies, at smaller values of  $\tau$ , we get closer to scenarios of technology-competition between two technologies that are not yet locked-in (see Arthur 1988 and David 1985 for classic studies on technology competition). In this paper, we focus exclusively on technological transitions from an old locked-in technology to a new one. However, in Appendix II below, we briefly present results for  $\tau=100$  and 500, when the old technology may be considered as partially embedded or weakly locked-in.

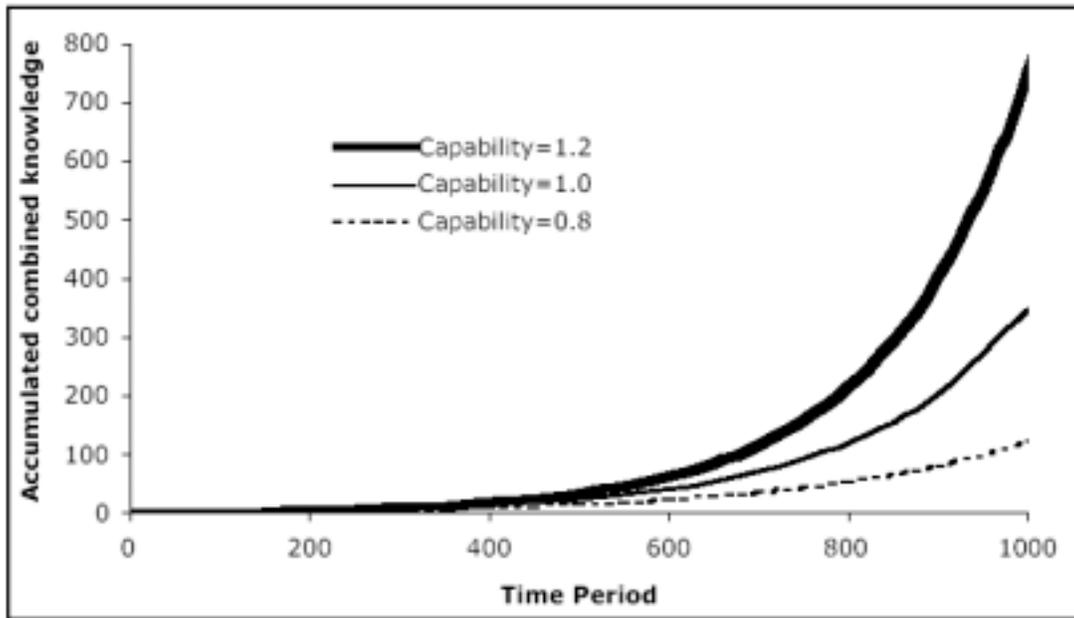


Figure 5. Examples of combined knowledge ( $\bar{\omega}$ ) accumulation by producers.

In the remainder of this section, we search for parameter settings that lead to a technological succession or ‘transition’ to the new technology in the user and producer networks. By transition we imply a full adoption of the new technology in the user network (number of new technology users  $\geq n-1$ ) and corresponding switches by the producers to the new technology. In section 3.1, under different niche selection scenarios, we vary the number of early adopters, both among users and producers.<sup>15</sup> The parameter we modulate is the fraction of the user and producer population who are early adopters,  $l$ . The user and producer population sizes are 100 and 20 respectively. Further,  $\tau=1000$  for all simulation runs. In section 3.2, we explore a different user network structure by allowing links among distant users.

### 3.1 Niche selection

We select a group of users and producers from each population and make them switch to the new technology at time  $\tau$ . Following Rip and Kemp (1998), we refer to this set of early-adopters as the ‘technological niche’. Here we explore the possibility of a transition to the new technology for different niche sizes ( $l$ ) and niche structures (the location of niche users on the user network lattice). At the time of niche selection ( $\tau$ ), knowledge of the selected users in the new technology is made equal to their existing knowledge in the old technology. Similarly, niche-producers are

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<sup>15</sup> The user-network structure is a plain lattice with no distant connections here i.e.  $q=0$  in these runs.

made experts in one of the types active only in the new technology at time  $\tau$ .<sup>16</sup> In subsequent time periods, other users and producers can learn and exchange knowledge from the niche users and producers respectively. If at any time  $t (>\tau)$ , the new technology becomes profitable for  $n/N$  non-niche users, the weakest old-technology producer switches to the new technology followed by the  $n/N$  users. After switching to the new technology, users and producers cannot switch back to the old technology.

In this section, we present results from simulation runs with user network as a simple 2-D lattice. We tried four different scenarios for selecting niche users and producers in the two networks. All plots shown in this section are average values of ten simulation runs. In §3.1.1, we present results for different values of  $l$  with the early adopters randomly selected in the user and the producer network. Next we look at clustering of early adopters in the user network with the producers still being randomly selected. In §3.1.3, the niche-users are the ones possessing the highest learning capability values. In §3.1.4, both early-adopter users and producers are the ones with the highest capability values in their respective populations. In all four scenarios, we simultaneously analyse the network structures created on the producer side (see Ozman 2005 for network structures emerging on the producer side with self-organization driven by matching for knowledge-sharing without an input from technology adoption decisions by a user network). In these simulations, we use a high value of knowledge relatedness (0.84), and low complexity index (0.062 using a knowledge depth of 4 and breadth equal to 0.078.), for both technologies to ensure high learning rates among users (see equations 10 and 12 for the dependence of user learning rate on complexity index and relatedness respectively).<sup>17</sup> The knowledge intensity (gamma) parameters used to produce these values of knowledge relatedness and complexity index are shown Table 1.

Table 1. Knowledge intensity parameters used for getting  $\Omega=0.062$  and  $X=0.84$ .

	$\gamma_1$	$\gamma_2$	$\gamma_3$	$\gamma_4$	$\gamma_5$
Old technology	0.237219	0.359351	0.176155	0.227275	0
New technology	0	0.35382	0.232686	0.248041	0.165452

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<sup>16</sup> A small random number ( $<5$ ) is added to the knowledge level of the niche producer in its existing expertise subject. The niche-producers' knowledge in the subject-types common to both technologies remains the same as before the switches. As discussed by numerous scholars of transition and history of technology, development of new technologies very often depends upon existing capabilities and knowledge accumulated in the older technological regimes.

<sup>17</sup> We examine the impact of product relatedness and complexity index on niche size in a later study.

### 3.1.1 Randomly selected early adopters

In this set of simulation runs, we select a fraction of the existing user and producer populations and make them switch to the new technology at time  $\tau$ . This set of early adopters (or technological niche) is randomly picked from the two populations. Since each producer supplies a technology to  $n/N$  users, for each selected producer there are  $n/N$  niche users. Number of users who have made the decision to switch to the new technology at different time periods are shown in Figure 6. Each curve is an average of results from ten simulation runs with the same parameter setting: The user network is a simple two-dimensional lattice with no distant links. User and producer capabilities are randomly initialised within the limits  $[0.005, 0.015]$  and  $[0.8, 1.2]$  respectively, and held constant for the ten runs at each  $l$ . The uncertainty parameter in the learning equations is restricted to  $[0.90, 1.10]$ . User and producer capability values, and their initial knowledge endowments, are kept constant for the ten runs at each  $l$ . Whereas niche users and producers were randomly selected from their respective populations in each run. The smallest niche size required for a transition is at  $l=0.45$ , i.e. 45 users out of a total of 100 and 9 producers out of 20.

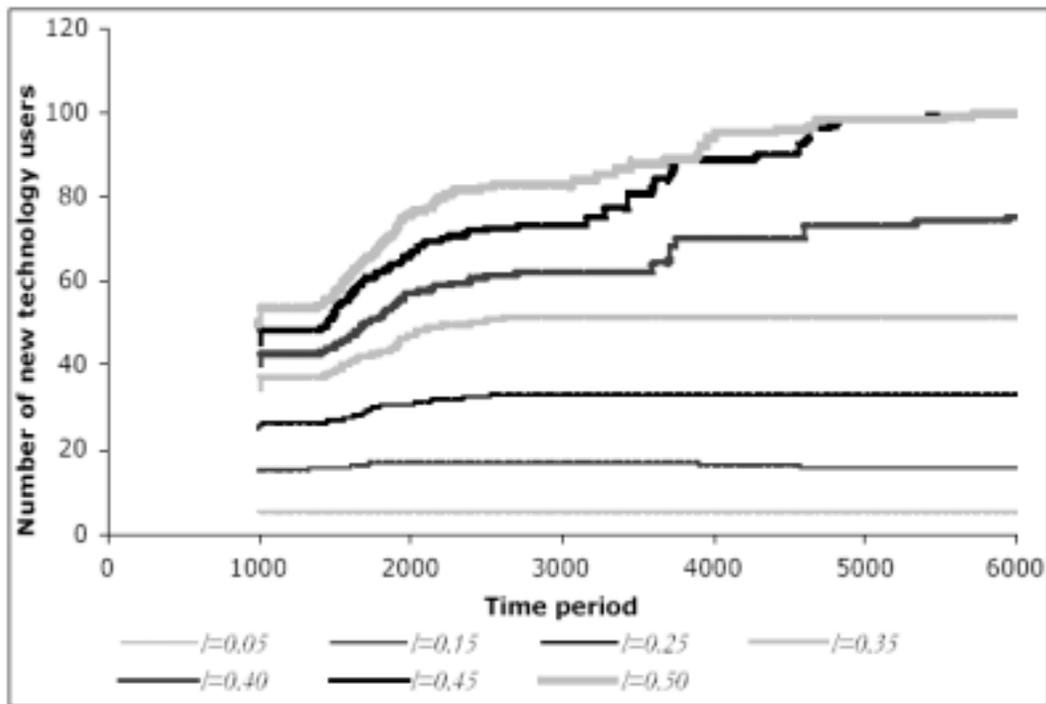


Figure 6. Niche size for transition scenarios with with niche users randomly selected over the user network lattice.  $\tau=1000$ .

Networks of producers are created over time as producers match and form pairs in each time period. The knowledge produced by an agent in a time period, either as a member of a pair or

alone, is used to augment her knowledge according to equation (7). The combined knowledge values of producers in each sub-population, at the end of a simulation, are shown in Figure 7.<sup>18</sup> Here, agents in the same sub-population produce the same technology. In the Figure, there are ten data points, one for each simulation run, at each value of  $l$ . In cases when a transition does not occur (the clearest example is  $l=0.05$ ), producers' possess greater combined knowledge in the old technology. On the other hand, when a transition occurs (for example,  $l=0.50$ ), there is more accumulated knowledge of the new technology in the producer population.

The total amount of knowledge created is a function of the niche size. If a transition does not occur and a majority of the user population keeps on using the old technology (as in the case for  $l=0.05$ ), there is no substantial break in the knowledge accumulation pattern. At  $l=0.05$ , only one producer has switched to the new technology, the remainder of the producer-population keeps on accumulating knowledge in the old technology, thereby continuing on the same knowledge accumulation path as before the introduction of the new technology. As a result, the highest absolute knowledge values are achieved in the simulation runs with  $l=0.05$ . Highest levels of knowledge accumulation in the new technology are obtained at  $l=0.50$ . However, the difference between the knowledge levels in the two technologies are not as acute as at  $l=0.05$  since substantial knowledge in the old technology exists before the new technology is introduced. Also, knowledge in the old technology accumulates until a transition occurs because switching to the new technology by producers (and users) is a gradual process involving knowledge sharing and learning. At  $l=0.35$ , accumulated knowledge levels in the two technologies are comparable. Here the number of users of the old and the new technology are approximately equal, after  $t=2000$  (see Figure 6). We present the average combined knowledge in the new technology as a function of the number of new technology users in Figure 8. All values plotted are those at the end of a simulation.

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<sup>18</sup> Knowledge accumulation in the old technology stops if a transition occurs in a simulation run. Therefore, in cases where a transition occurs, value of combined knowledge in the old technology at the time of transition is plotted in Figure 7.

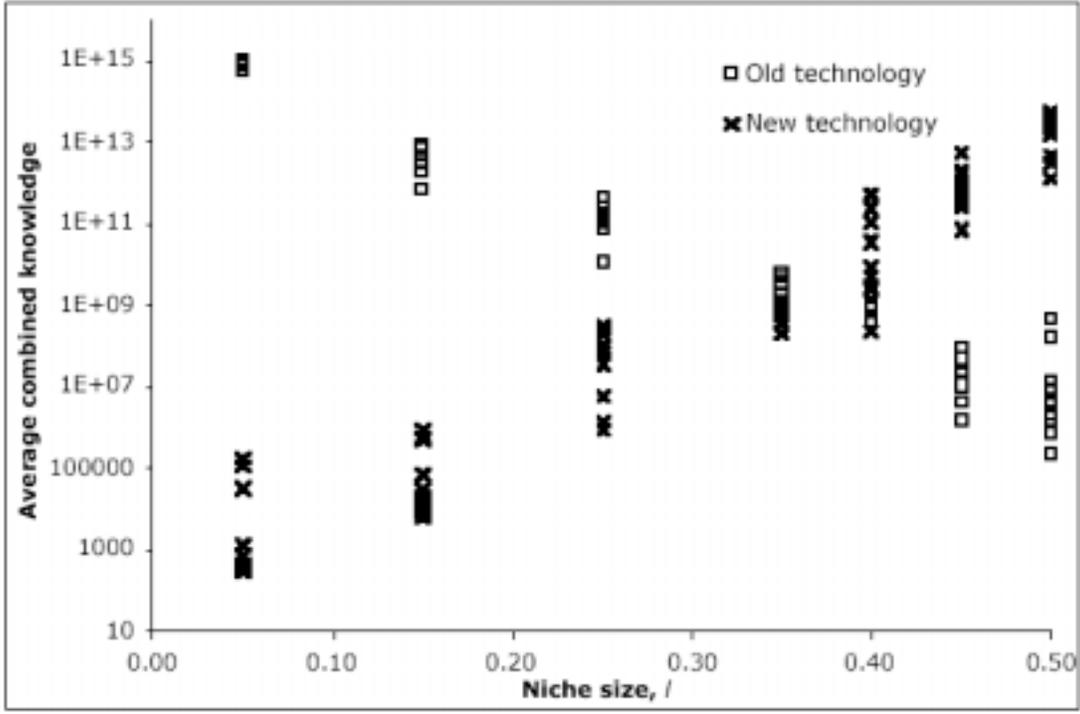


Figure 7. Average combined-knowledge of producers at the end of a simulation.

An adjacency matrix of size  $N \times N$  is created in each time period as a result of matching among the producers. We generate a frequency matrix by adding the adjacency matrices every 500 time periods. This frequency matrix shows the number of times two agents form a pair with each other in the last 500 time periods Ozman (2005). Using a frequency matrix, we calculate the density of the producer network generated in different 500 time-period durations over the course of a simulation run. This density is given by,

$$D = \frac{\sum_{i=1}^N \sum_{j=1}^N x_{ij}}{N(N-1)} \quad (16)$$

where  $x_{ij}=1$  if a link is formed between two agents  $i$  and  $j$  in the 500 time periods, and 0 otherwise and  $N$  is the size of the producer population. Results from the frequency matrix generated in the last 500 periods of a simulation run are shown in Figure 8.<sup>19</sup> It is clear from the figure that there is greater networking among the agents when one of the two available technology dominates, i.e. when majority of the agents produce the same technology. In other words, knowledge sharing among agents producing different technology, and thus having different knowledge assets, is lower. As shown in Figure 9, networking among the agents is the

<sup>19</sup> We use the frequency matrix from the last 500 periods to make sure that the system has attained stability.

lowest when the number of agents producing the new technology is approximately equal to those producing the old.

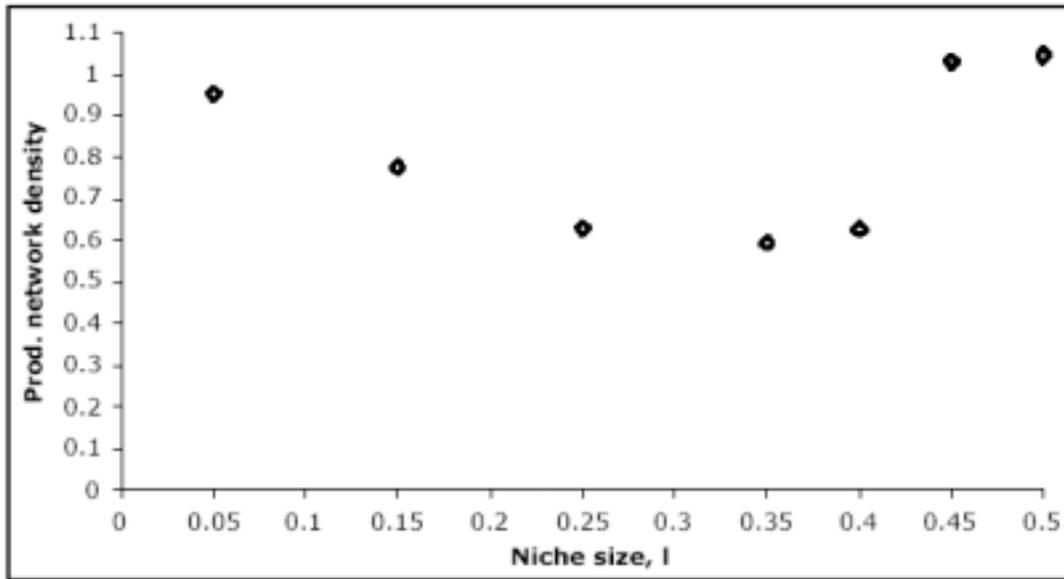


Figure 8. Density of the producer network at the end of a simulation averaged over ten runs for each niche size.

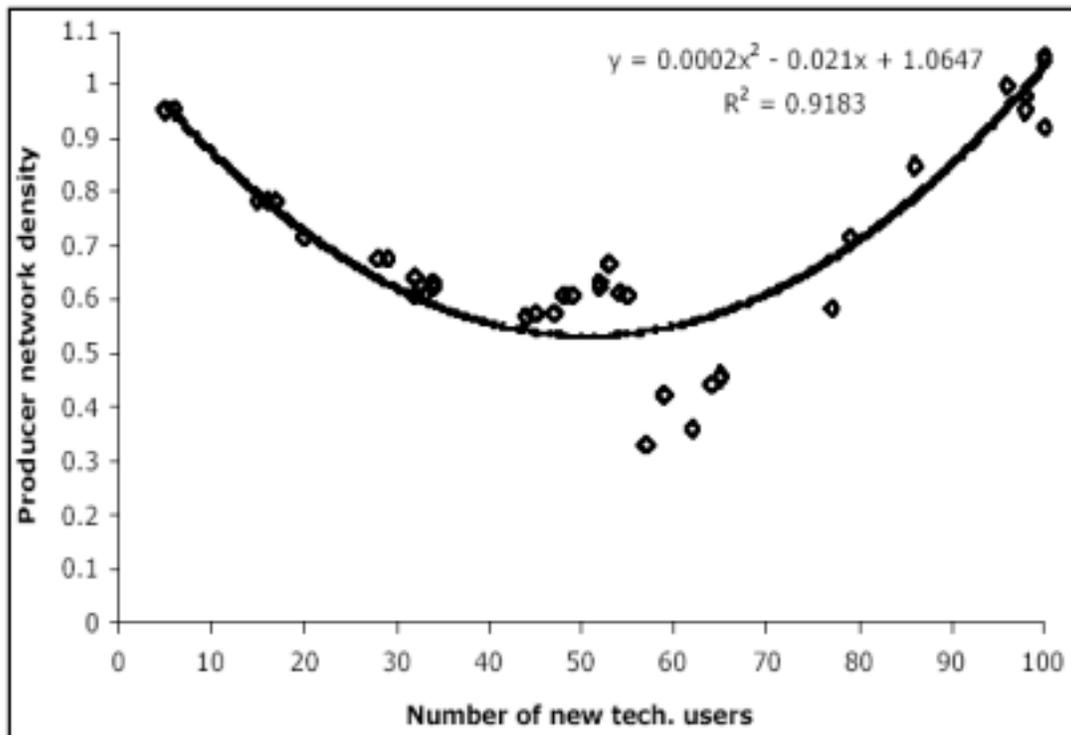


Figure 9. Producer network density as a function of the number of new technology users at the end of a simulation.

### 3.1.2 Clustered early-adopter users

Here the early adopters in the producer population are randomly picked whereas in the user population, they are clustered in the middle of the lattice network. We pick a user in the center of the lattice and her closest lattice-neighbours  $v$  as niche users. For example, to select 5 niche users ( $l=0.05$ ), we pick a user  $u$  and her four immediate neighbours. These four immediate neighbours lie at a lattice distance equal to 1 from user  $u$ , i.e.  $d(u,v)=1$ . Similarly, to select 10 niche users ( $l=0.10$ ), we select the first five as above and the remaining five are situated at a lattice distance of 2 from user  $u$ . Here, preference is given to users who are at a diagonal distance of two from user  $u$ , rather than the ones on the same line as user  $u$  (see Figure 1 and note 7 above). To select 15 or more lead users, after exhausting all users lying at distance 2 from user  $u$ , we pick the users at distance 3 and so on.

Results for the number of new technology users for different niche sizes are shown in Figure 9. Once again, each curve is an average of ten simulation runs. The smallest average niche size required to achieve a transition increases to  $l=0.60$  in this clustered scenario. Capabilities are randomly assigned in each run so that users with different capability are selected as part of the niche each time. The clustering of niche users causes the formation of closed enclaves of users of the new technology who learn from each other about the new technology. But only a small number of users of the old technology have niche users as their neighbours. As a result, majority of the old technology users are unable to learn about the new technology at smaller niche sizes. However, if we allowed links among distant users on the lattice, the results might have been different. Scenarios with two long-distance links among the users are presented later in the section.

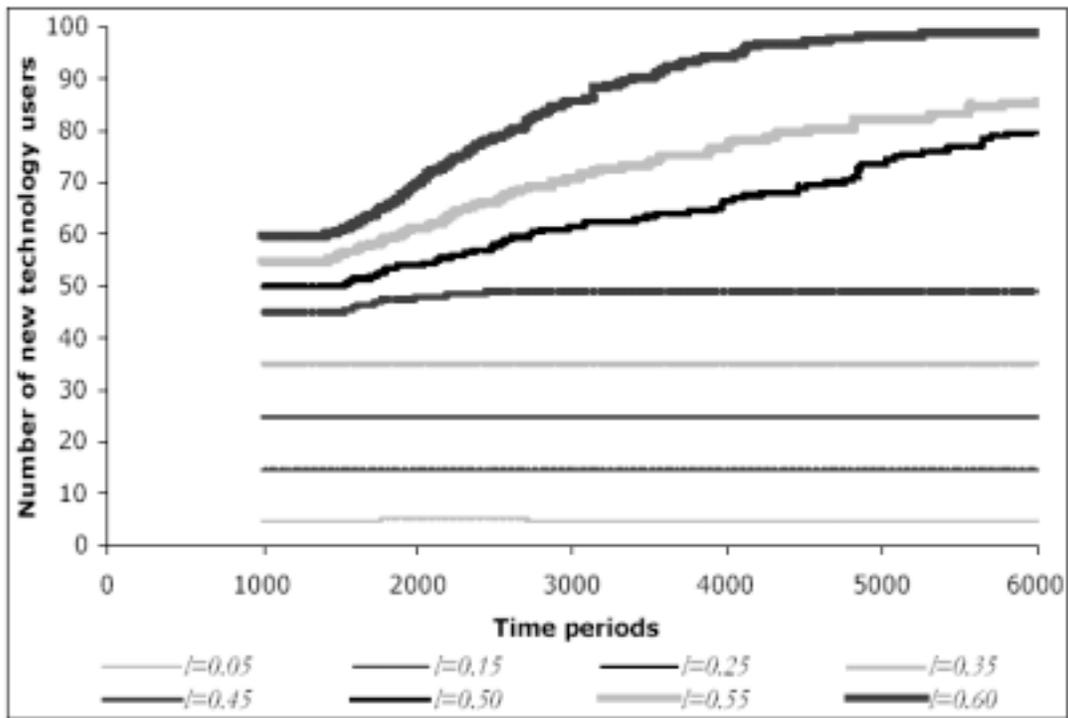


Figure 10. Niche size for transition with low complexity (0.064) and high relatedness (0.84). Niche users clustered in the middle of the user network lattice.

### 3.1.3 High Capability early-adopter users

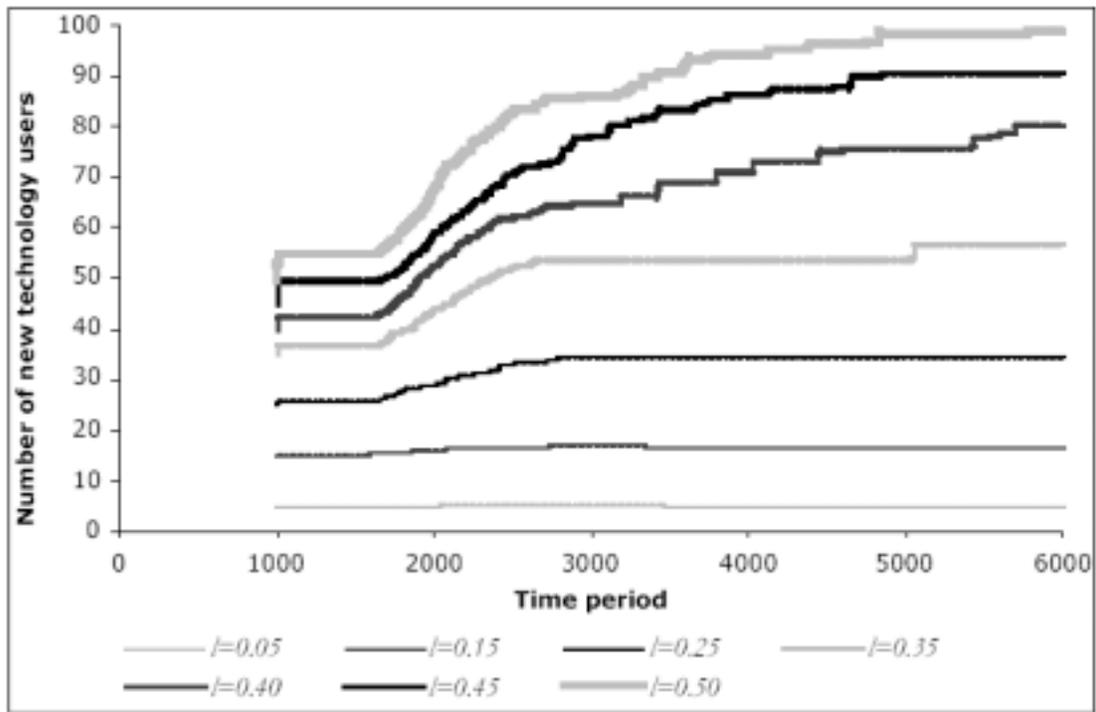


Figure 11. Niche size for transition with low complexity (0.064) and high relatedness (0.84). Niche users possess highest capability values in the user-population.

### 3.1.4 High capability early-adopter producers and users

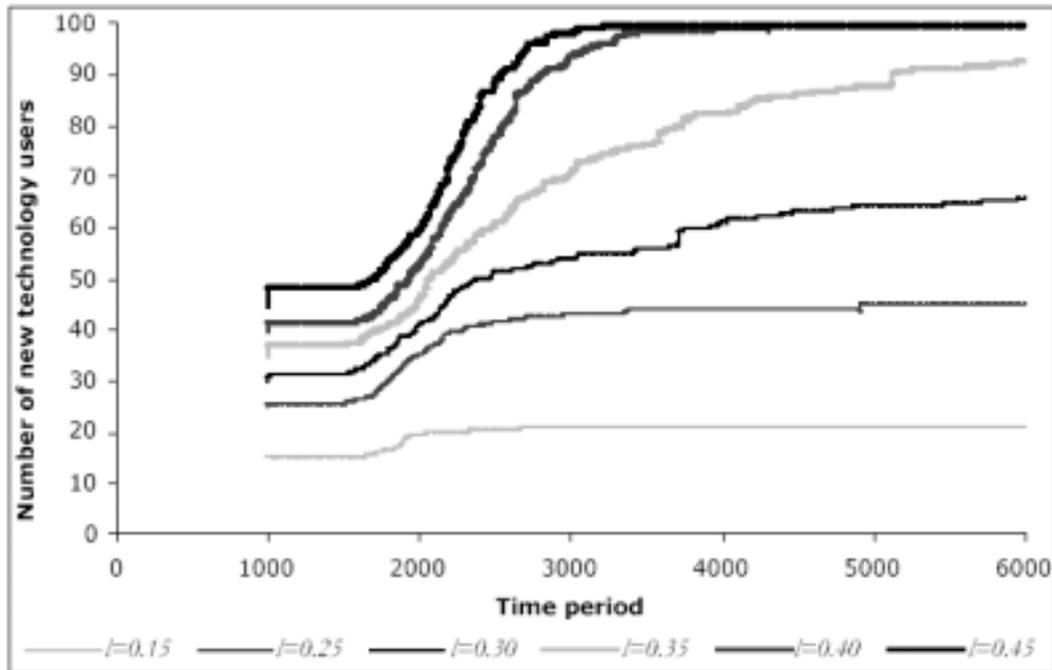


Figure 12. Niche size for transition with low complexity (0.064) and high relatedness (0.84). Niche users (and producers) possess highest capability values in the population.

The smallest niche size required for bringing about a transition is 0.40, i.e. 40% of the user and producer populations. Both users and producers in this niche possessed the highest capability values. If niche members are randomly selected in the two networks, the smallest niche size required for transition is 0.45. Other configurations we tried for niche selection require bigger niches for transition. The user network is a simple lattice in the simulation results presented above. Below, we present results for niche sizes under different user network structures but restrict the niche selection scenarios to random and highest capability users and producers.

### 3.2 User network density

Results for niche sizes for transition under different user network structures are presented in this section. Users and producers for the niche are either selected randomly or possess the highest capability values. The other two niche selection scenarios are not explored in this section as they yielded bigger niche sizes in the simulations with the simple lattice user-network (see section 4.1).

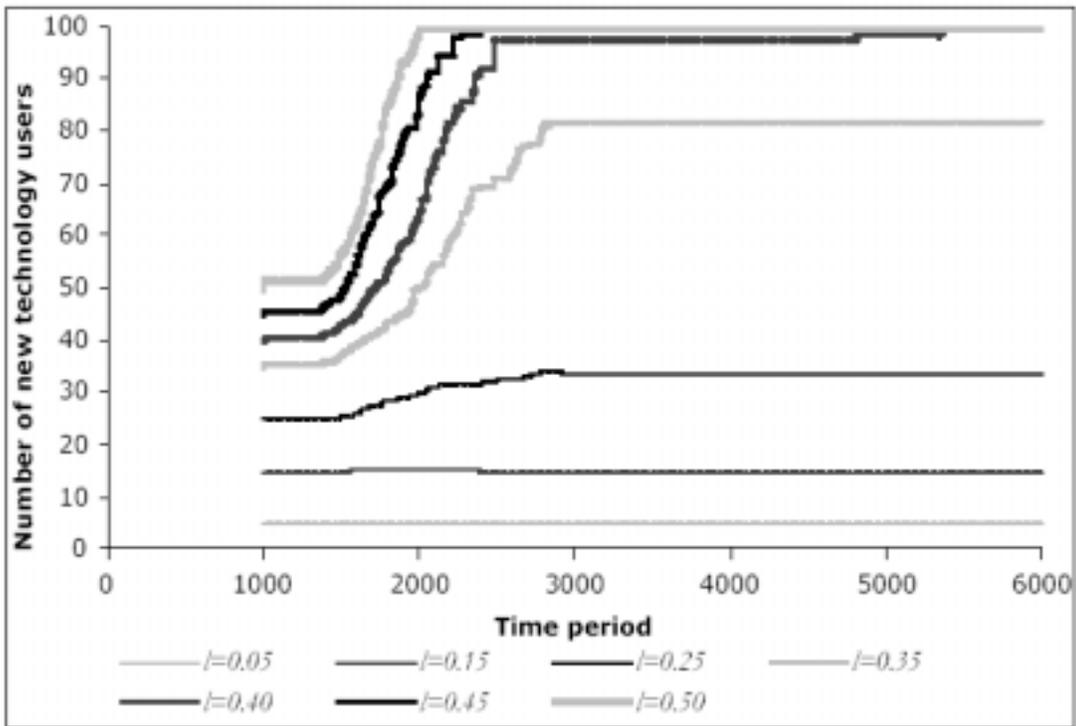


Figure 13. Niche size on a user lattice with two distant neighbours,  $q=2$ . Compare this to Figure 6 where the user network is a simple lattice.

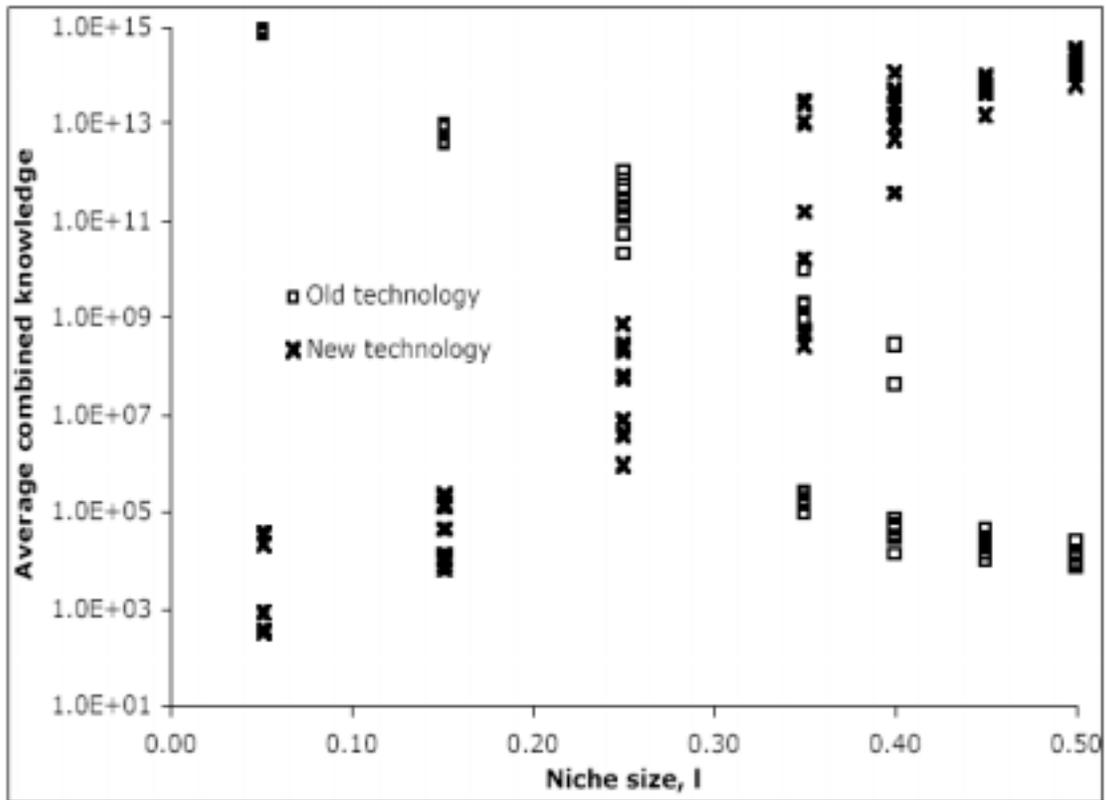


Figure 14. Average producer knowledge values with two distant links on the user network lattice.

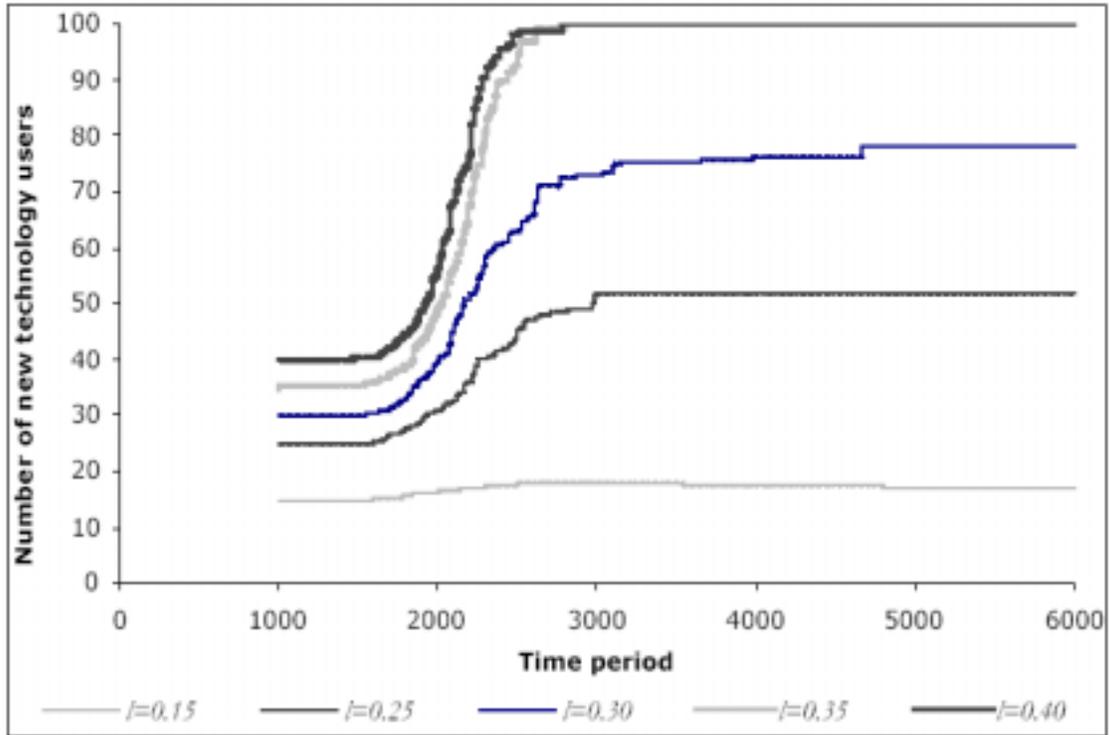


Figure 15. Niche size on a user lattice with two distant neighbours,  $q=2$ . Compare to Figure 10 where the user network is a simple lattice. Niche users (and producers) possess highest capability values in the population.

#### 4.0 Future work

In future work as a continuation of this paper, we will focus on locating simulation settings that minimize the niche size for technology succession, dividing this work into two parts: first, we will investigate the impact of provision of incentives to users and producers and second, we will examine strategic niche management scenarios based upon insights from extant literature (see for example Rip 1992; Kemp et al. 1998; Rip and Kemp 1998 on strategic niche management).

Further, we will explore different combinations of knowledge intensity ( $\gamma$ ) parameters of the new technology, generating different values of the complexity index  $\Omega$  and knowledge relatedness  $X$ . These two parameters affect the rate at which users learn in the new technology. Finally, we will examine scenarios with different combinations of weights for network effects and knowledge levels in the switching decision of users.

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