InventSim: An Agent-Based Model of Product Invention

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Abstract

This study develops an agent-based simulation model (*InventSim*) of the process of product invention. Invention is conceptualised as a search on a landscape of product design possibilities, by a population of payoff-seeking agents (inventors). The agents employ a set of search heuristics in searching this landscape which embed individual & social learning, and expectations of future payoffs to proposed product inventions. In the simulation, agents compete for payoffs and co-evolve based on each other's actions. The simulation experiments examine the impact of agent's search heuristics on the societal rate of inventive progress. The results indicate that the forward-looking heuristics of election and thought-experiments are crucial in driving forward the inventive process, even when payoff expectations for proposed product inventions are noisy.

Key Words: Agent-based modelling, Product invention, Search heuristics.

1 Introduction

Given the economic and social importance of the development of new products, questions of interest naturally arise concerning the dynamics of the process of invention, and these form the research domain of this study. Fleming and Sorenson [8] note that the processes of commercial diffusion of new goods have attracted substantial study:

> '*...however, we lack a systematic and empirically validated theory of invention.*' (p. 1019).

Insight into the process of invention is important for several reasons. Without a robust model of invention, the ability of managers to create organisations which encourage inventive practices is constrained, and policy-makers risk making sub-optimal decisions regarding how best to encourage invention in society in order to promote long-term economic growth.

The lack of a theory of invention leaves open the question *how do inventors actually invent*? In product invention there are a huge number of possible choices of components and related component attributes. This renders the dimensionality of product design spaces vast, and makes any attempt to engage in enumerative invention futile. Two interesting questions which naturally arise from this observation are: *what methods do inventors employ to simplify their task*? and *what are the implications of these methods for the rate of inventive progress in a population of inventors*?

One way inventors seek to simplify their task is by employing search heuristics. Search heuristics are widely used in every-day decision making, either because of the impossibility of determining and evaluating all possible solutions to a problem, or because the benefits from obtaining the best, rather than a good, solution to a problem are outweighed by the extra costs of obtaining the optimal solution. This study examines the effect of a number of inventor's search heuristics on the rate of product advance.

2 An Evolutionary Metaphor for Invention

Evolutionary algorithms such as the GA [11, 9] draw metaphorical inspiration from biological evolution in order to simulate the adaptation of a population of entities over time. *Prima facie*, the framework of the GA has the potential to incorporate several salient aspects of the process of product invention, namely: a population of entities (product designs) which adapt over time, competition for resources amongst inventors (payoff-seeking behavior), reuse of previously invented components (imitation), and trial-and-error experimentation.

The environment (market) favors (selects) the better inventions from those discovered to date, and through feedback mechanisms such as realised profit and increased funding for research, encourages further related invention through adaptation and imitation of current product designs. The concept of invention as the directed recombination (or partial imitation) of existing technology fragments in novel ways has a long pedigree in studies of economic innovation [23].

Although there are parallels between biological evolutionary processes and the process of invention, there are also important differences. The most significant of these differences concern the consciousness of economic agents. Unlike biological evolution, economic agents such as inventors *intentionally* direct their search efforts in order to achieve the greatest expected payoff [2].

2.1 Conceptual Model of Invention

The conceptual model of invention underlying the simulation experiments is outlined in Figure 1. The model is embedded in a general evolutionary process, but this is adapted for the salient characteristics of the process of product invention.

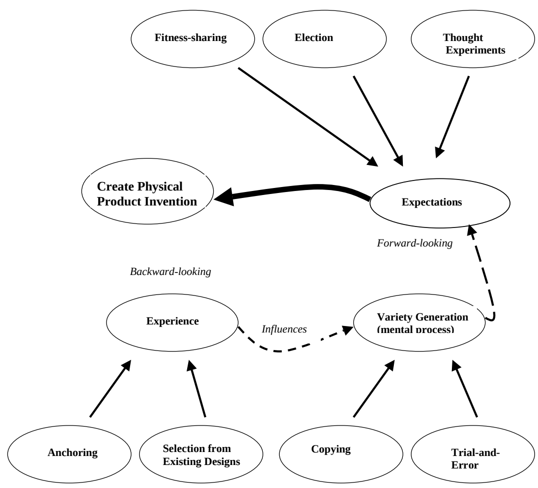

Figure 1. Model of product invention.

The conceptual model contains the general evolutionary search heuristics of selection, imitation and trial & error experimentation, and these are supplemented by the additional heuristics of anchoring, thought experiments, election, and fitness sharing. In the model, inventors are conceptualised as starting from their existing product design in each inventive trial (an anchoring heuristic). The generation of novel proto-product ideas (defined as mental product design ideas in the heads of inventors) in an effort to improve existing product designs, arises from a combination of copying elements of existing product designs (an imitation heuristic), and incremental trial and error invention.

In each inventive trial, an inventor is considered to generate multiple proto-product ideas (a thought experiment heuristic). The expected payoff to the best of these thought experiments is compared with the expected payoff to the inventor's current product, and if higher, the proto-product is physically made and replaces the inventor's current product (an election heuristic).

All the expected payoffs are discounted by considering the expected degree of competition that a proposed product idea will face (a fitness-sharing heuristic). The heuristics of anchoring, election, thought experiments and fitness sharing are discussed in more detail in the following subsections.

2.1.1 Anchoring

Product invention is strongly influenced by, and anchored within, the population of currently existing product designs. Heavy reliance is placed on historical experience by inventors, and the results of past searches become natural starting points for new ones [19, 24]. From a technical stand-point, as populations of engineers and designers build up experience and absorption capacity [7] with current product architectures and design elements, they will tend to draw on this experience when faced with future design decisions, rather than re-examining all possible alternatives *ab initio* in each inventive trial. Existing products also embed past learning concerning knowledge of customer needs. Hence, it is plausible to assume that inventors employ an anchoring search heuristic, and start their inventive activity from current product designs.

2.1.2 Election Heuristic

Payoff-seeking inventors will not discard their current product design until they uncover one which they expect will produce even higher returns. This represents a search heuristic 'do not give up a good idea until a better one comes along'. The economic interpretation of this heuristic is that the inventor carries out a mental simulation [4, 15]. If the expected payoff to the new product design idea appears unattractive, the 'bad' idea is discarded, and the inventor stays with his current design. In the election step, inventors compare the expected return from the proposed proto-product design idea with that of their current physical product and if it is less, the proto-product idea is discarded and is not physically created. Examples of election mechanisms abound in business, ranging from formal project appraisal systems, to procedures for monitoring the performance of on-going product development projects.

2.1.3 Thought experiments

Inventors do not typically consider a single product-design idea in each inventive trial before they attempt to physically create a new product [21]. Thought experiments represent the heuristic 'generate several mental product ideas, and pick the best of these'. These mental simulations can include the construction of computer simulations and mock-ups [20]. Thought experiments can be considered as corresponding to the *openness* of an inventor to new ideas. The greater the number of mental thought experiments which inventors consider when creating new products, the more open they are considered to be to new ideas.

2.1.4 Fitness Sharing

A key factor which impacts on the return to any product is the degree of competition it faces from similar existing products. If there are several very similar products in the marketplace, they compete for the same customer segment, and the returns to each product are likely to be lower than they would be in the absence of competition. In the model of invention it is assumed that inventors employ a heuristic of 'take account of expected competition' (payoff sharing) when forming their expectations as to the likely payoff to a product idea. The fitness-sharing mechanism is based on that of [18], and is defined as follows:

$$f'(i) = \frac{f(i)}{\sum_{j=1}^{n} s(d(i,j))} \qquad (1)$$

where $f(i)$ represents the original raw payoff of product design i (the payoff to the design is calculated using the NK landscape - see section 3.1) which exists in the marketplace. If this design suffers competition from other very similar products which are active in the market, its realised payoff is reduced. $f'(i)$ represents the shared (reduced) payoff of design i, and corresponds to its original raw payoff, reduced by an amount which is determined by a *sharing function* s.

The (sharing) function s provides a measure of the *density* of active product designs within a given neighbourhood of design i on the landscape. For any pair of designs (i, j), the sharing function returns a value of '0' if the two designs (i, j) are more than a specified distance ('t') apart, and therefore are not considered to be competing for the same market niche, a value of '1' if the designs are identical, and a scaled value between 0 and 1 otherwise. The form of the sharing function adopted in this study was taken from [18]:

$$s(d) = \begin{cases} 1 - \left(\frac{d}{t}\right)^{\alpha} & \text{if } d < t; \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

where t is the neighbourhood within which designs are considered to compete, d is the actual distance between two designs, and α is a scaling constant.

Fitness-sharing impacts on the expectations of inventors as to the likely payoffs to proto-designs, and acts to discourage inventors from closely imitating products which are already subject to significant competition. In the simulation experiments, all payoffs are assessed by inventors using a shared fitness heuristic. Therefore, election and selection (for imitation) decisions are based on shared rather than raw payoff values. The idea of fitness sharing embeds a co-evolutionary aspect in the model, as payoffs are a function of the actions of multiple as well as individual inventors.

3 Simulation Model

A relatively recent development in the analysis of complex economic systems is the use of agent-based modelling (ABM) [3, 16, 1]. In ABM, the complex system of interest is split into artificial adaptive agents. The interactions, information flows, and decision processes of these agents can then be modelled using computer simulation. This study uses an ABM approach, wherein the agents are inventors, and the activities of these inventors are simulated under different conditions, in order to obtain insight into the implications of the rules (search heuristics) governing their behavior.

The use of a simulation-based methodology offers particular advantages when:

- The system of interest has stochastic elements. These generally make it difficult to evaluate a system analytically.
- The system of interest is long-lived. Simulation allows the study of such systems in a compressed time-frame, a particular advantage when studying systems with an evolutionary component.
- The intention is to examine the *sensitivity* of system output to changes in system inputs.

These issues arise in this study. Product invention is an on-going, stochastic process, and the intent of the simulation experiments is to examine the sensitivity of the rate of inventive advance in a population of inventors (the output of the system), to particular sets of search heuristics (the inputs).

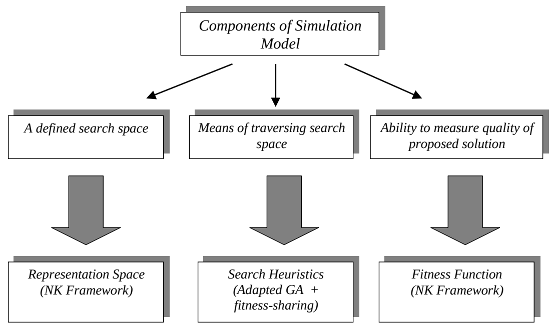

Figure 2. Components of simulation model.

The simulation framework for this study is drawn from [6]. In order to operationalise the conceptual model for the simulation experiments, it was mapped into a synthesis of two general frameworks drawn from the literature of complex adaptive systems, Kauffman's NK model, and Holland's genetic algorithm (see Figure 2). The NK model was used to define a product-design landscape (the environment). The GA framework was adapted (as outlined in section 2.1) to encompass inventor's (agent's) search heuristics.

3.1 Product Design Landscape

The product design landscape is defined using Kauffman's NK model, and a detailed description of this model can be found in [12, 13]. The NK model considers the behavior of systems which are comprised of a configuration (string) of N individual elements. Each of these elements are in turn fitness-interconnected to K other of the N elements (K<N). In Kauffman's operationalisation of this general framework [13], the number

of states for each element is restricted to two (0 or 1). Therefore the configuration of N elements can be represented as a binary string. The parameter K, determines the degree of fitness interconnectedness of each of the N elements and can vary in value from 0 to N-1. In one limiting case where K=0, the contribution of each of the N elements to the overall fitness value (or worth) of the configuration are independent of each other. As K increases, this mapping becomes more complex, until at the upper limit when K=N-1, the fitness contribution of any of the N elements depends both on its own state, and the simultaneous states of all the other N-1 elements, describing a fully-connected graph.

Physical product designs are characterised as consisting of N attributes [17]. Each of these attributes represents a choice of design attribute, that an inventor faces. Hence, a specific design configuration **s** is represented as a vector $s_1, \ldots, s_N$ where each attribute can assume a value of 0 or 1 [22]. The vector of attributes represents an entire product design, hence it embeds a choice of physical components, ancillary choices concerning these components (such as their colour or finish), the choice of configuration of the components (their tolerances, directional orientation, physical linkage structure), and the choice of production technologies required to manufacture the product design [14]. Good consistent sets of components and attributes, correspond to peaks on the product design landscape.

3.2 Pseudo-code for Simulation Model

The pseudo-code for the *InventSim* simulator is presented below. An overview of the simulation experiments undertaken is provided in Figure 3.

```
Repeat ‘A’ times Create Product Landscape

Repeat for each string (active product design)
   in the population

    Take string ‘i’
    Calculate fitness values for each string
    in the population

        For x=1:a  (‘a’ thought experiments)
            Select another design ‘j’ in the population
            Recombine design ‘i’ and ‘j’
            to produce new design ‘k’
            Apply mutation operator to new design ‘k’
            If design ‘k’ is best design of thought
              experiments so far, store design ‘k’ in
              design ‘best’
        End (for loop)

        If design ‘best’ is better than the original
           design ‘i’,replace design ‘i’ with design
          ‘best’(election operator)

End (Repeat for each string loop) (end of generation)

Output results for simulation run End (Repeat ‘A’ loop)
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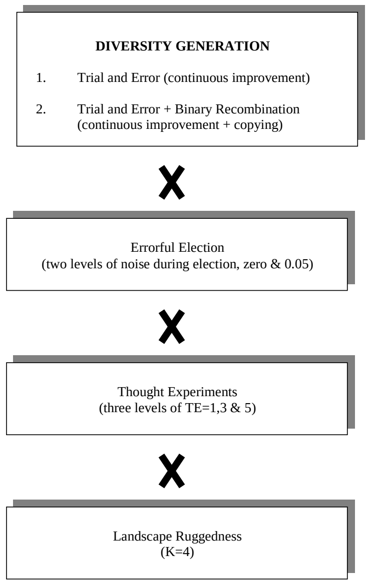

Figure 3. Overview of simulation experiments.

In the simulations the inventor has a very limited knowledge of the worth of locations on the product design landscape when undertaking each inventive trial. The inventor knows the worth of his (her) current product design, and stochastically selects other currently active product designs for imitation based on their observed payoffs. The inventor forms an expectation of the payoff of the proto-designs generated by his thought experiments, and also uses these expectations of payoff when making an election decision. The inventor does not have knowledge of the potential payoffs to any other product designs during his inventive trial.

4 Results

All results are averaged across 30 separate simulation runs, and in each run the NK landscape is specified anew, and the positions of the initial product designs are randomly selected. A value of N=96 and a K value of 4 were selected in defining the landscapes. The imitation operator (binary crossover) is applied with a probability of 0.60, and the trial and error (mutation) rate is selected to produce an expected mutation of one bit in each product design string during each inventive trial. In all the simulations, the number of inventors is held constant at fifty.

Both the election and thought experiment heuristics rely on an inventor's ability to make estimates of the likely payoff to a proposed product design. However, making accurate estimates is problematic, and *ex-post* the expectation may found to be incorrect. The majority of new products introduced each year fail [10], indicating that real-world inventors find it difficult to assess the likely worth of new products. In particular, the ability of inventor's to assess the likely payoff to a proposed product will vary depending on the nature of the underlying product market. For example, the accurate estimation of payoffs for product ideas is likely to be particularly difficult in rapidly changing markets for technological goods.

The long-run impact of noisy payoff assessment on the process of invention is unclear. It could act to retard development of promising product ideas, or by producing occasional *wrong way* choices by product inventors it could allow inventors to escape a local optima in product design space. Hence the simulations also examine the utility of the heuristics of thought experiments and election under conditions of different levels of noisy payoff assessment when making the election decision. Two levels of noise are considered, zero and 0.05. In the latter case, the noise level applied to a payoff assessment during an individual inventive trial is modelled as a random draw from a gaussian distribution, with a mean of zero and a standard deviation of 0.05.

4.1 Trial and Error

Figure 4 shows the comparative curves of average product-payoff advance in a population of inventors for the scenarios where there is zero noise in assessing the payoffs to proto-products and the case where the noise-level=0.05, for three levels of thought experiment (1,3 & 5), and for K=4. Payoffs graphed are those after the first iteration (generation), and thereafter every tenth iteration up to 200 iterations.

In each case, inventors only use a trial-and-error variety generating heuristic (they do not use imitation). Figure 4 indicates that the introduction of noise (moving from zero noise to noise=0.05) into the assessments of the payoffs of proto-designs which are used in the election process, reduces the level of average product payoffs attained at the end-point of 200 iterations (difference is statistically significant at the 5% level). Noisy payoff assessments lead to slower product invention progress than would occur absent the noise. Hence, there is no evidence that noisy payoff assessments by inventors can play a useful role in the process of invention by allowing inventors to escape from locally optimal product designs, by means of wrong-way moves on the product design landscape.

The introduction of noise into inventor's elections does not alter earlier findings [5] concerning the importance of thought experiments in determining the rate of inventive progress. Even with the introduction of noise, the undertaking of more than one thought experiment leads to increased average populational payoffs by the simulation end-point of 200 iterations (difference is statistically significant at the 5% level). It is also noted that the effect of noisy election in reducing the level of average populational payoffs is greatest when inventors undertake a limited number of thought experiments. As the number of thought experiments increases, the impact of noisy election is reduced.

In assessing the results from the differing levels of thought experiments, it is useful to remember that the thought experiments mechanism does not require that inventors can make perfect assessments of the payoffs of several potential product designs *ex-ante* their testing in the marketplace. Rather it only requires that inventors can assess the *relative payoffs* of the designs. A similar comment can be made in respect of the election heuristic, in that inventors only need to be able to identify whether the new product design is better than their existing design. It is not necessary that inventors are able to precisely assess the worth of the new design. Once inventors can make reasonably accurate assessments of the relative payoffs of proto-product designs, average populational payoff advance is assured under a simple trial and error search heuristic when inventors use an election mechanism, or when they engage in multiple thought experiments.

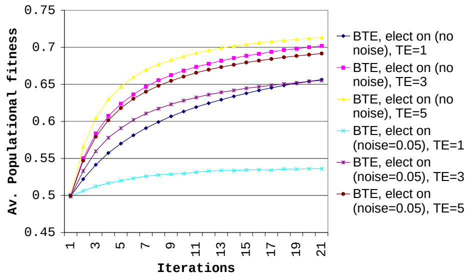

Figure 4. Trial and error + election (no noise) vs trial and error and election (noise=0.05).

4.2 Trial and Error + Imitation

Figure 5 shows the comparative curves of product payoff advance for the scenarios where there is zero noise and the case where noise=0.05, for three levels of thought experiment (1,3 & 5), and for K=4. In both cases, inventors use a trial and error and an imitation heuristic when generating novel products. Figure 5 suggests that the introduction of noise (moving from zero noise to noise=0.05) into the election evaluation for new product designs, leads to a reduction in the level of average populational product payoffs obtained after 200 iterations (difference is statistically significant at the 5% level).

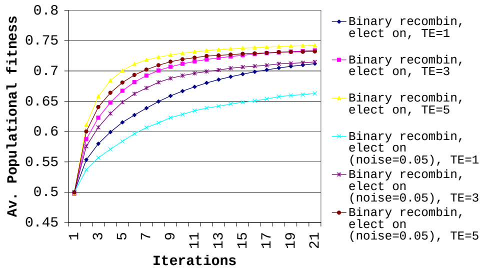

Figure 5. Imitation + trial and error with election (no noise) vs imitation, trial and error, and election (noise=0.05).

In summary, the simulation results for both forms of variety-generation heuristic (trial and error vs imitation & trial and error) indicate that:

- Noisy election generally leads to slower rates of inventive progress than would occur without noise.
- The negative impact of noisy election on the rate of populational payoff advance advance is lessened as the number of thought experiments increases. The gap in the rate of product inventive progress between noisy and noise-free election is generally greatest when the number of thought experiments is 1, lessening when the number of thought experiments increases to 3 or 5.
- Election and thought experiments, in other words inventor's expectations, matter, and remain an important driver of the process of product invention even when inventor's payoff assessments are noisy.
- The results do not suggest that inventors should bias their choice of search heuristics depending on their ability to accurately assess the payoffs to proposed products.

5 Conclusions

In order to investigate the role that search heuristics play in the inventive process for physical products, a conceptual model of the process of product invention was developed, and operationalised in a series of simulation experiments.

The results highlight the importance of expectations as to payoffs in product invention and suggest that an essential role of the inventor, and by analogy managers in organisations, is to supply direction to the variety-generating process. Successful product invention is not a matter of monkeys sitting at typewriters! The results also underscore the importance of formal product evaluation procedures in organisations, and the importance of generating multiple product ideas when inventing new products. Methods of promoting the openness of organisations to multiple product ideas include diverse hiring, and allowing staff to devote a portion of their time to personal research projects.

The developed *InventSim* simulator allows the modeller to alter a wide-variety of parameters which govern the simulation. The generalisability of the findings of this study across different rates of trial and error & imitation, different values of K, and varying levels of other parameters of the conceptual framework, will be tested in future work.

References

[1] Arifovic, J. (1994). Genetic Algorithm Learning and the Cobweb Model, *Journal of Economic Dynamics and Control*, 18(1):3-28.

[2] Baldwin, C. and Clark, K. (2000). *Design Rules: The power of modularity*, (vol 1), Massachusetts: MIT Press.

[3] Bell, A. (2001). Reinforcement learning rules in a repeated game, *Computational Economics*, 18(1):89-110.

[4] Birchenhall, C. (1995). Modular Technical Change and Genetic Algorithms, *Computational Economics*, 8(3):233-253.

[5] Brabazon, A., Silva, A., Ferra de Sousa, T., O'Neill, M. Matthews, R. and Costa, R. (2005). Agent-Based Modelling of Product Invention, *in Proceedings of the Genetic and Evolutionary Computation Conference (GECCO 2005)*, Eds. Beyer, H., O'Reilly, U. et al., Washington, USA, June 25-29, 2005, 1:129-137, New York: ACM Press.

[6] Brabazon, A. (2005). *Product invention as a complex adaptive system: An investigation of the impact of inventors' search heuristics on the rate of invention*, Doctoral Thesis, Kingston University, London.

[7] Cohen, W. and Levinthal, D. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation, *Administrative Science Quarterly*, 35(1):128-152.

[8] Fleming, L. and Sorenson, O. (2004). Science as a map in technological search, *Strategic Management Journal*, 25(9):909-928.

[9] Goldberg, D. (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*, Boston, USA: Addison Wesley, Longman.

[10] Goldenberg, J. and Mazursky, D. (2002). *Creativity in Product Innovation*, Cambridge: Cambridge University Press.

[11] Holland, J. (1992). *Adaptation in Natural and Artificial Systems*, (originally published in 1975), Ann Arbor, USA: University of Michigan Press.

[12] Kauffman, S. and Levin, S. (1987). Towards a General Theory of Adaptive Walks on Rugged Landscapes, *Journal of Theoretical Biology*, 128:11-45.

[13] Kauffman, S. (1993). *The Origins of Order*, Oxford, England: Oxford University Press.

[14] Kauffman, S., Lobo, J. and MacReady, W. (1998). Optimal Search on a Technology Landscape, *Santa Fe Institute Working Paper, 98-10-091.*

[15] Kennedy, J., Eberhart, R. and Shi, Y. (2001). *Swarm Intelligence*, San Mateo, California: Morgan Kauffman.

[16] Klos, T. and Nooteboom, B. (2001). Agent-based computational transactions cost economics, *Journal of Economic Dynamics and Control*, 25(3-4):503-526.

[17] Levinthal, D. (1997). Adaptation on Rugged Landscapes, *Management Science*, 43(7):934-950.

[18] Mahfoud, S. (1995). Population size and genetic drift in fitness sharing, in *Foundations of Genetic Algorithms 3*, Whitley, L. and Vose, M. (eds), pp. 185-223, San Francisco: Morgan Kauffmann.

[19] Nelson, R. and Winter, S. (1982). *An Evolutionary Theory of Economic Change*, Cambridge, Massachusetts: Harvard University Press.

[20] Nooteboom, B. (2000). *Learning and Innovation in Organizations and Economies*, Oxford: Oxford University Press.

[21] Otto, K. and Wood, K. (2001). *Product Design: Techniques in Reverse Engineering and New Product Development*, Upper Saddle River, New Jersey: Prentice-Hall.

[22] Rivkin, J. (2000). Imitation of Complex Strategies, *Management Science*, 46(6):824-844.

[23] Schumpeter, J. (1934). *The Theory of Economic Development*, eighth printing, 1968, Harvard Economic Studies, Volume XLVI: Harvard University Press.

[24] Stuart, T. and Podolny, J. (1996). Local Search and the Evolution of Technological Capabilities, *Strategic Management Journal*, 17(Summer Special Issue):21-38.