The emergence of a market: what efforts can entrepreneurs make?

Shuyuan[1] and Anthony Brabazon[2]

[1] Department of Management Faculty of Business, AUT University, Auckland, New Zealand. shuyuan.wu@aut.ac.nz
[2] Natural Computing Research and Applications Group, UCD CASL, University College Dublin, Dublin, Ireland. anthony.brabazon@ucd.ie

Summary. This chapter, using a complex adaptive systems (CAS) approach, models how entrepreneurs create markets for a new, disruptive, technology through an effectuation process. Starting from dispersed knowledge components held by both the demand and supply sides, a market emerges from the interactive learning behaviours of entrepreneurs and potential customers. The CAS approach enables investigation of both system-level emergence and the process of dynamic co-evolution at the individual level. The results indicate the process of market creation is significantly impacted by factors including exploration tendency, alertness, and participant prior knowledge.

1 Introduction

Complex and adaptive systems have interacting components whose individual behaviours and interactions lead to system-level emergent phenomena [49]. Economies, and individual firms within economies, present a rich ecology of interacting processes. Schumpeter [42] pictures an economy as a complex system with existing and emerging industries undergoing creative destruction leading to continual adaptation within the economy. Adopting a firm-level unit of analysis, Penrose [35] presents the firm as a system of wealth production and knowledge application, with the firm's productive resources being the components of this system. In a general sense, organisational scientists have long treated firm-level organizations as complex adaptive systems, the components of which are internal decision-making mechanisms [8, 54]. To investigate firm-level organisational changes, simulation models have been developed to treat strategic adaptation and punctuated equilibrium as results of subsystem interactions via basic learning processes [5, 26, 27]. This study takes a similar approach to examine the creation of markets.

Markets entail the interaction of multiple buyers and suppliers with each influencing the behaviour of the other. For a market to exist, the demand side has perceive that there is value in the suppliers offering and in turn, this requires that the suppliers have some understanding of customers' needs. In this sense we can see a market as a body of knowledge, having converged from the two sides. The supply side configures a *value proposition*, a combination of technology and other components which promise to satisfy customers' needs; on the demand side, *customer perceived value* (CPV), the customers' assessment of a solution's overall capacity to meet their needs, comes as a composite of multidimensional concerns and evaluations [25]. Knowledge components originate from both sides and evolve in an entangled way. For example, the creation of a telephone which is 'mobile' and 'wireless' was realised by supply side decisions on combining the enabling technology components - wireless communication, microelectronics, telephony, to name just a few. Meanwhile the concept of a 'mobile-phone' was perceived as providing value by customers as they evaluate and compromise between various issues in concern, including, for example, sound quality, the size and weight of the handset, battery life etc.

Knowledge '*never exists in concentrated or integrated form, but solely as the dispersed bits of incomplete and frequently contradictory knowledge which all the separate individuals possess*' ([20], p. 519). No matter which side initiates it, the innovation or market creation journey is a process by which the social needs and technological possibilities meet and shape each other to converge [3, 56]. From the perspective of a supply-side firm starting its market creation journey with a new technology, answering the question of what values to propose and for whom involves critical decisions under uncertainty. As what the end-solution should be is unknowable to both the supply and demand sides, the answer is to be agreed through an *effectuation* process, '*a process that continually transforms existing realities into possible markets*' ([40], p. 544). This process occurs through the commitments of individuals to networking [39] so that technical possibilities and needs are reconfigured and refined through social interactions. So in general, market creation is the collective learning process of solution-formation.

To combine dispersed and incomplete knowledge components, of what is needed with what is possible, into an end-solution a decision-maker from either the demand or supply side starts the learning process with what she currently knows and has, involves other stakeholders whose knowledge components are recognised as relevant, and with them (collectively) bounds the uncertainty out in the environment 'by deeming irrelevant a wide variety of information that may be available' ([40], p. 534). So individuals and firms from the demand and supply sides commit to the effectuation process, learning about and from each other in order to create a market as an institution of bounded cognition under uncertainty [40]. Such a community temporarily agrees on what needs are most relevant and how this need is to be satisfied [39]. The construct of such institutions or communities takes interactive learning and transformation.

Sarasvathy and Dew [40] describe the emergence of a new market as setting a thin interface (an artefact) between two hierarchical levels of complex adaptive systems ([40], p. 550):

> The new market, however, gets fabricated, not through the designs of any one person, but as a chain of interactive commitments that form the interface between the inner environment of the effectual network [of committed members forming the community], and the outer environment ...

To create a 'market' as bounded cognition - an artefact to which the firm and its customers are committed, the effectuation process from the point of view of a supply-side firm is a learning process: learning to expand knowledge and to converge constraints [40]. By involving and interacting with the demand side, an option of what value to create, and for whom to create it, is taken by suppliers.

This chapter investigates how a new technology competes with its older predecessor, and how a market is created for the new technology via an effectuation process involving potential customers. This process brings about a technological disruption when new effectuation networks emerge, producing a new system attractor, as suggested by Rosenkopf and Tushman ([38], p. 404):

> This community of organizations evolves as new organizations introduce technological discontinuities, as coalitions form around technological substitutes, as incumbent organizations resist these efforts as substitution, and as interorganizational processes of compromise and accommodation affect a dominant design.

CAS provides a set of tools and frameworks for investigating emergent phenomena. Unlike for example, laboratory-based sciences, it is not possible to 'rerun' the creation of a real-world market under different circumstances in order to assess the influence of different variables or different market structures. Indeed, the emergent nature of the process of market creation would render such attempts at 'understanding' problematic. Hence, a simulation Agent-based Modelling (ABM) approach provides a good methodology in or attempts to understand the complex process of market creation.

We investigate the emergence new markets, by modelling the behaviour of a population of individual learning agents (suppliers and users). These agents can learn from each other and we can examine the outcome of these interactions - the emergence of a viable market. An artificial fifty dimensional (50D) problem space is generated within which the agents can interact. The traits and behaviours of the agents are modelled by synthesizing concepts from bounded cognition, individual learning processes and marketing. In the simulations we will observe how the agents can co-evolve so as to combine their knowledge components in new ways leading to a new (higher) customer perceived value (CPV). The constructed ABM simulator is used to test the influence of some fundamental factors on market emergence, including: individual learners' exploitation and exploration tendency; their alertness in searching for relevant information; and their prior knowledge.

The remaining sections in the chapter are organized as follows. We initially review the literature of organisational learning and technology entrepreneurship to identify and synthesize key factors influencing the cognitive behaviours. The construction of our simulator and the implementation of individuals' learning behaviours in this simulator are then reported. Next we provide the simulation results and discuss these. Finally we conclude the chapter.

2 THE BUILDING BLOCKS AND PROPOSITIONS

A complex phenomenon at any level can only be explained by studying the entities and their interactions at one level down the hierarchy (components or subsystems). To understand how a machine or living body works, we study its component parts and investigate how they interact. Likewise, to understand how a market is created, we need to see how learners from the potential demand-side and supply-side come to understand each other. To understand how the CPV of a radically new technology emerges, we need to study the sub-product level knowledge components to see how they are brought together.

From the point of view of individual actors or components, the future of any complex adaptive system is unpredictable as the path to the future is stochastic. However, system level order emerges from individuals' actions and interactions [52, 53]. An entrepreneurial firm with a new technology as its core resource, the customers whose needs are satisfied by what the firm offers, and competitors offering similar solutions constitute a market or technological community:

> The lags (temporal or otherwise) between any invention and the creation of new economic welfare enabled by it, require not only the ability and alertness to recognize, and the perception and perseverance to discover opportunities for the achievement of pre-determined goals such as increasing profits and larger market shares, but also necessitate decisions and actions based often only on human imagination, and human aspirations, that may or may not in time lead to new products, firms and markets. ([41], p. 159)

Widget X

A technology entrepreneurial firm begins its effectuation journey from the local reality of its initial conditions - its technology core - and some prior knowledge about established markets and the customers within them. Sarasvathy and Dew [40] illustrate the uncertainty of market creation for new technologies with Goodman's ([16]) *grue paradox*.[1]

The effectuation process starts with some knowledge component(s) - or 'widget X'. In general, widget X can be any component of a future market including demand side elements (such as needs and wants), or supply side components (such as inventions, ideas about product and/or service, as well as institutional structures of a market such as channel, regulatory infrastructure, or standards bodies) ([40], p. 547). Using the 'grue' paradox as an analogy, future grass cannot be predicted to be green or blue. Widget X can be further developed into either green or blue (or for that matter, any other colours) end-products and thus 'the history of technological invention is full of unanticipated economic consequences' ([41], p. 142). To the extent that end product from (any) widget X is unformed and negotiable, the market is not to be 'discovered' but rather will *emerge* through transformation. The entire process is driven by interactions, with stakeholders learning about the existence of 'relevant' components and negotiating on what the end-product from widget X's should be like.

When an effectual network or technological community is being formed around providers of key components for the development of widget X, an opportunity is created and a market emerges. With the new artefact having been set, the behaviors of suppliers, customers and related institutions are 'boxed' within this inner environment, until the next gale of creative destruction enters to shake and reshape the system(s). The vital point of new artefact formation, as Simon ([48], p. 12) puts it:

> is the possession of relevant skill and knowledge, and at certain key periods in the history of science and of other domains, the relevant knowledge comes from a field other than the one to which it is applied

Critical to new market creation seeded by widget X, then, is the capability of capturing, evaluating, and utilizing 'outside' knowledge components. An entrepreneurial owner of a knowledge component (widget X) needs to learn about other relevant knowledge components, in order to make decisions on what and how to combine them into a commercially successful solution. Through the interactive learning activities of entrepreneurs and their potential customers, novel combinations of technical components are developed into vehicles of customer values, and thus new paradigms for wealth generation are set [11, 42].

[1] The Grue paradox flows from the observation that multiple hypotheses could be supported by any set of empirical data. Goodman illustrated this paradox with the sample hypothesis that 'All emeralds are green.' A physical examination of a sample of emeralds will, of course, support this hypothesis. However, consider an alternative hypothesis that 'All emeralds are grue' where grue is defined as being green before (say) the year 2200 and blue after that date. Obviously, this hypothesis cannot be disproved by examining the colour of a sample of emeralds today!

To commit to and negotiate a green or blue widget X, the two parties (customers and entrepreneurs) have to sense the existence of each other, learn about the widget X's that each one carries, recognise one another as relevant or not, and commit to negotiations (interactive learning). Given the complex and uncertain environments that entrepreneurs are required to navigate through, they need to possess, at a minimum, essential individual characteristics that deal with and benefit from information asymmetries: prior knowledge endowments, the level of alertness to distant knowledge, and some tendency for exploration in face of uncertainties.

Prior Knowledge

Prior knowledge enables connections to unfamiliar domains and hence influences the generation and nature of the business ideas [43, 46]. Shane [43] suggests that prior knowledge about

1. the potential market(s),
2. the way to serve the market, and
3. customer problems, enables entrepreneurial alertness.

Shane and Khurana [45] hypothesized that prior knowledge accumulated through careers of entrepreneurs are important not only for forming social ties [18], but also as a means of learning. It provides a framework that can be used to process information [13, 21]. Cohen and Levinthal [9] emphasize that learning is self-reinforcing by nature, and thus the ability to absorb new knowledge is a function of the breadth of current knowledge stock. The broader the prior knowledge stored, the easier it is for a learner to evaluate and acquire new 'relevant' knowledge components. Newly acquired components may not be well utilized for a while, until the appropriate contextual knowledge is obtained. Simon [48] suggests that the possession of relevant knowledge 'chunks' is the precondition for learning, innovating, and problem-solving. These chunks give rise to insights or intuitions necessary for the evaluation and further application of new knowledge. Therefore we propose:

> **H1.** Prior knowledge equips technology entrepreneurs to capture new knowledge components and thus positively influences the emergence of a new market.

Alertness coefficient

When seeking relative information to form solutions, alert learners are 'quick' in recognizing relevant knowledge components, and are quick in transforming and applying them. Within this context, scholars have postulated that the level of entrepreneurial activity within an organization is a function of available information and entrepreneurial alertness [33, 12, 45]. Ray and Cardozo [36] see alertness as a state of awareness or a propensity to notice and to be sensitive to information about objects, incidents, and patterns of behavior in the environment, with special sensitivity to problems, unmet needs and interests, and novel combinations of resources. Minniti [33] conceptualizes alertness as a parameter that controls how well different learners can take advantage of information asymmetry. In other words, alertness is the extent to which a learning entity makes use of its current knowledge endowment to acquire new knowledge. Equipped with the same prior knowledge, different learners may have different levels of alertness which leads to different learning performances. The different alertness coefficients of agents in a market underscores the proposition that all cannot be explained by prior knowledge endowments. Entrepreneurs not only need to possess the basic endowments of their prior knowledge but also need to take advantage of the information asymmetries [33]. The alertness coefficient thus may be an important predictor of the market creation performance of technology entrepreneurs:

> **H2.** Higher level of alertness leads to better market creation performance.

While prior knowledge and alertness combine to create alert learners, these learners need to be bold enough to commit to the learning journeys under uncertainties and this is considered in our next hypothesis.

Exploration vs. Exploitation

Market creation and development require aspiration for explorative learning. An organization or individual person with a tendency towards exploration searches for new ideas and conducts experimentation to deliver novelty, while exploitative learners focus on tweaking existing knowledge [30]. Of course, bold exploration in a sea of uncertainty may not produce profit, with March [31] noting that often, bold learners' explorations are driven by 'the heroism of fools and the blindness of true believers'. Similarly, [27] observe that the acquisition and processing of distant knowledge components 'takes place in a relatively costly process of search, frequently conducted under conditions of ambiguity.' ([27], p. 48). So, to achieve organisational changes, convergence and reorientation, exploration is necessary and through the process of experimentation the organisation recognises new goals or means to achieve goals, finds new ways of assembling responses or connecting stimuli to responses, and integrates 'new constructs into existing cognitive structures.' ([27], p. 49). In contrast, exploitation, or first-order learning is 'a routine, incremental conservative process that serves to maintain stable relations and sustain existing rules'. We examine the significance of *Exploration Tendency* (ET) for the process of market creation.

> **H3.** ET motivates commitments to new knowledge acquisition under uncertainty and positively influences market creation performance.

Hence, the above hypotheses are examining whether learning activities are initiated by alertness, informed by prior knowledge and motivated by ET. The hypotheses are tested using our simulation model. The following section explains the simulation model in detail.

3 Methodology

To simulate the behavioral processes leading to changes in complex systems, an ABM simulator [19] generates agents, endows them with various traits including specifying the simple rules their behaviours follow, and observes them interacting with one another. The behaviour of the system arises out of the interactions among these individual agents. For example, a modeller can specify the rules of behaviours of thousands of individual ants and then observe the resulted colony-level patterns. The emergence of any new colony-level structure (system level emergence) is not designed or programmed, but can be observed [37]. On observing the emergence of a new system structure, the researcher may check who among the individual agents initiated and/or benefited from the structural changes, and even trace the individuals' journeys to investigate what features and/or contingencies have led to such 'successes'. At this stage, statistical analysis can also be used to study whether there are factors significantly influencing the individual performance and system behavior. In this sense, an ABM simulator may also be seen as a special data generator for longitudinal case survey. When a theoretical focus is longitudinal, nonlinear, and processual (as is technological disruption, or the emergence of a new CPV), simulation modelling provides a robust method for theory development [10]. Particularly for studies on multiple interdependent processes operating simultaneously [19] collecting large scale empirical data may be impossible. In such cases, simulation may be a rigorous alternative to generate data for theory development through statistical analysis.

In this study, a simulation methodology is used for data generation to test the propositions that predict a pattern of market emergence. A set of agents representing individuals or organisations from both the demand and supply sides of the market are generated. Their activities are governed by simple rules of learning and differences among their (individual) features are governed by a probability distribution [27, 32].

3.1 Simulator Construction

In this model, new market(s) will emerge endogenously as a combination of the knowledge components initially owned (but not initially shared) by agents from the demand and supply sides. As knowledge is shared, a new CPV (or body of shared knowledge), is built and agreed concerning individuals' needs and how these needs can be satisfied. A CPV as shared knowledge emerges in the 50 dimensional space when a new effectuation network is being formed around a technology-based entrepreneur and potential customers committed to developing their individual 'widget X's'. Therefore, at the system level, we expect to observe agents from different subpopulations converging together on their shared knowledge. The market creation performance of an entrepreneur is measured by counting the customers who are committed to further developing her widget X. Specific details of the simulator construction are reported below.

The space for system level emergence

Customers require a solution to 'get a job done' and a valuable solution has a set of specifications. It is believed that for any given job (e.g., transportation, cutting wood, or growing corn), customers collectively apply 50 to 150 metrics to measure the performance of a technical solution [55]. We model the 'knowledge space' for emergent customer-values as having 50 dimensions: supply-side technology possibilities and the demand side concerns on which customer values are to be perceived. In this 50D space of knowledge, an agent's coordinates represent its 'knowledge-profile', represented as a 50 dimensional vector bearing the agent's level of knowledge on each individual dimension. Individual agents initially have knowledge on their widget X's one core dimension but possess little information on the remaining dimensions. However, they will typically build up knowledge about other dimensions during the effectuation journey. In this sense, each of the agents is in an open and evolving world and this reflects the real-world impact of information asymmetries, or bounded rationality.

Agents carrying knowledge-components move around in the knowledge space, and can potentially sense the existence of other agents, decide whether other agent's knowledge is relevant and learn from/about each other. Knowledge about a new dimension, once captured, is taken into an agent's updated knowledge-profile (it's 50D vector). Dispersed knowledge components from various agents can therefore be integrated to finally create a market [20].

Among the 50 dimensions of possible future customer values, some are connected with others. So knowledge on one dimension may lead to the recognition of the existence of other dimensions. For example, the weight of a laptop computer, its memory capacity and its computation speed are all interconnected features and hence customers' perceived value about these features comes as a compromise. The interconnections among the dimensions actually make this 50D space a twisted torus, somewhat similar to an N-K landscape [5, 22, 28]. In other words, adding a new dimension to a possible solution may activate or change the agent's knowledge about another K dimensions. If customers, for example, start to believe that a mobile-phone handset should have a camera function as an improvement, they then expect new applications and specifications such as a large data storage space and on-line picture-sharing.

Scales on the dimensions and initial locations of agents

Goldstein and Gigerenzer [15] suggest that there are three levels of knowledge. First, one may have no knowledge of an issue at all, so the existence of such a dimension has been ignored or unrecognized. At the second level, knowledge about some dimensions/ issues is merely recognized based on prior knowledge. At the third level of knowledge, one can provide all sorts of additional information about an issue - a dimension on which one has deep expertise. An example of the latter in this simulation is the information that each agent initially possesses on their knowledge core (their widget X).

For this study, we use 0, 1, and 2 to denote respectively the three levels of knowledge (ignorance, some prior knowledge, and the knowledge core). At any point in time, the location of an agent in the 50D space reveals its knowledge profile. At the starting point of learning, agents carry partial and dispersed knowledge components of some (potentially) enabling technologies (supply side) or demand-side customer problems/concerns (demand-side). Each agent's knowledge is limited to a few dimensions known to it. For example, an individual technology-based entrepreneur (denoted as a 'techie' in the rest of this chapter) ('techie 31' from the simulator) has a knowledge profile as (2 2 0 0 2 0 1 0 0 0 1 0 0 0 0 1 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0). This means that this technology-based entrepreneur has expertise on dimensions 1, 2, and 5 (e.g., cooking expertise the cook possesses as her widget X [40]); prior knowledge about some potential market domains on dimensions 7, 11, 16, 17, and 23 (e.g., knowledge about a grocery store owned by a friend with whom this cook might start a deli business; or, about a popular media for whom she might produce cooking videos (Sarasvathy and Dew 2005)). In the meantime, other dimensions are unknown to this techie; in other words, her point of view is one from a little corner of the 50D space.

Taking an example from the demand side, one of the 200 customers, Customer 7, is initially located at (0 0 0 0 0 1 0 0 1 0 0 1 0 1 0 0 0 0 0 2 0 0 0 1 0 2 0 0 2 0 0 2 2 0 0 0 0 1 0 0 0 0 0 0 1 2 0 2 0 0) sharing little knowledge with techie 31.

An incumbent organization (denoted as *incum* in the remainder of this chapter) (for example, organisation 2) at (0 0 0 0 0 1 0 0 0 0 0 1 1 2 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 2 0 2 1 2 0 2 2 0) is an established supplier in an extant market, and it has more dimensions of expertise, some of which respond to customers' existing needs. Although initial conditions are critical to agents, none of the agents can predict *a priori* what/how the future is to be, which dimensions from the unknown may occur to them and to be agreed on. Yet the future is reachable through transformation and effectuation.

Boundary-spanning organizations

To make it possible for agents to learn distant knowledge, we randomly planted in the 50D space 50 boundary-spanning organizations (denoted as

Spanners). For new technologies, boundary-spanning organizations could be 'research labs, patent agencies, regulatory bodies, professional societies, trade associations, consortia, and other types, depending on technological and political contexts' ([38], p. 411). Rosenkopf and Tushman [38, 39] believe that boundary-spanning actors (which are composed of representatives from multiple organizations) create cognitive linkages across organizations in different technological communities. Dosi [11] (p. 229) suggested that these bridging institutions may have a key influence on the early stage of innovations. From the supply-side point of view, [50] suggest that firms, in order to overcome the tyranny of served markets, build cognitive ties broadly with suppliers, businesses in different industries, consultants, universities, and government agencies. In this simulator, Spanners are set to have various levels of knowledge randomly, for example, one (Spanner 52) stands at the point (0 0 0 0 0 2 1 1 2 1 0 2 2 2 2 0 1 1 1 2 2 1 0 1 1 1 0 0 2 0 0 0 1 0 0 0 0 0 0 0 0 0 0 2 0 2 1 2 1 0). All the spanners are randomly planted as such in the knowledge space.

Behaviours of the learning agents

In the 50D knowledge space, an agent's location denotes its current knowledge-profile and its movements are learning activities as time goes by. At each time-step (tick) of the algorithm, learners are displaced from their current positions by applying a velocity vector to them [23]:

$$X_i(t+1) = X_i(t) + V_i(t) \tag{1}$$

The magnitude and direction of an agent's velocity at each step are determined by simple rules: whom a learner decides to move toward (learn from), and how large this step can be. The simple rules for each population of agents are as follows:

Techies: may move towards the closest spanner and/or a tentatively identified lead user (a customer close enough in the knowledge space to it, thanks to their prior knowledge on the same dimensions, or indirectly, through some bridging spanners);

Incums: if they are sufficiently 'explorative', they may learn from distant customers (customers whose needs have not been identified/served). If they are not explorative, they stay with committed customers to elaborate on current solutions based on shared knowledge;

Customers: learn about a supplier, a techie or an incum, having sensed its existence; and/or having learnt from a close neighbor, if the neighbor is happier (having more dimensions of its needs served).

In a natural ecosystem, predators have to make foraging decisions with little, if any, knowledge of present resource distribution and availability. The likelihood of a learner to sense distant knowledge elements is similar to the encounter rates with prey in heterogeneous natural environments [47]. We model this likelihood as a decreasing exponential function of the distance [56]:

$$C = Ae^{-bD} \tag{2}$$

where D is the Euclidean distance in the knowledge space between the locations of an agent and the source of the knowledge element to be recognized. The alertness coefficient, b, represents the extent to which such a distance obstructs the learning activity - in other words, the extent to which an agent can take advantage of information asymmetry. For an alert learner, $b < 1$. Since the 'intelligence was guided by will towards the solution of envisaged problems' ([40], p. 535), A is ET, the exploration tendency, or the 'will' of committing to new learning under uncertainty. For the implementation of ET concept, we adopt a 5 point Likert scale, with 1 being the lowest in ET and 5 the highest. Combining Eq. (1) and (2), the learning behaviours of the three types of agents are expressed by the following equations:

Techies:

$$\begin{aligned} &V_i(t+1) = A_i e^{-b_i D_i}(leaduser(t) - X_i(t)) + A_i e^{-b_i D_i^*}(P_{closest}(t) - X_i(t)) \\ &D_i = EuclideanD(leaduser(t), X_i(t)) \\ &D_i^* = EuclideanD(Spanner(closest), X_i(t)) \end{aligned} \tag{3}$$

Incums:

$$V_i(t+1) = (1 - A_i e^{-b_i D_i})(customer(t) - X_i(t)) + A_i e^{-b_i D_i}(leaduser(t) - X_i(t)) \tag{4}$$

Customers:

$$V_i(t+1) = \alpha(lbest(t) - X_i(t)) + A_i e^{-b_i D_i}(heard(t) - X_i(t)) \tag{5}$$

where α is random number drawn from $U(0, 1)$ representing a customer's exploitation tendency (its tendency to learning only from close neighbours in the 50D space); *lbest* is a neighbour customer who is recognized as being happier (having more dimensions of need served); and heard is either a techie or an incum, whose existence has been recognized by this customer.

If an agent has '0' level of knowledge on a dimension before making a step of movement, it may after learning from others, flip the knowledge to '1'. This is governed by:

$$Sgmd(V) = \frac{1}{1 + e^{-|V|}} \tag{6}$$

When the sigmoid function of the velocity on a dimension is larger than a random number $U(0, 1)$, knowledge on that dimension flips from '0' to '1' [4].

After recognizing a dimension as relevant, the knowledge-gain along the dimension is cumulative from ‘1’ to ‘2’. An agent can ‘unlearn’ (or forget) about a dimension by unloading its knowledge from ‘2’ continuously down to ‘1’, but not from ‘1’ back to ‘0’. After recognizing the existence of a dimension, one cannot be ignorant of its existence any more. Taking into account the interconnectedness of dimensions, if a learner’s knowledge level on one dimension is higher than 1, there is a chance for this learner to recognise the existence of other K dimensions.

If customers and supplier(s) (either incum or techie) have built sufficient shared knowledge to come close to each other, a new effectuation network emerges in the 50D space. Customers whose needs are satisfied by an incum will paint their shared patches green whereas those who are happy with a techie’s widget X (and are willing to commit further to its development) paint their patches blue. Normally, as incums have initially more shared dimensions of knowledge with customers, some green patches emerge very early in the simulation. These become extant markets in the disruptive techies’ eyes. Still, we are unable to predict the colour of future patches (therefore all markets are ‘grue’).[2] From running the simulation model, the emergence of green or blue patches can be observed. Simulation experiments are conducted to collect data for testing the hypotheses on individual learning behaviours of the agents and their market creation performance.

3.2 Model Validation

To simulate means to build a likeness. The validation issue of a simulation model addresses the question of how accurate that *likeness* is [24]. Although there are arguably diverse approaches through which a researcher can validate a simulation model [24], empirical validation- comparing generated data with longitudinal case studies is the most direct approach [10]. Alternatively, staying in accordance with ‘expert opinion and professional acceptance can be as good validation’ ([24], pp. 1089-1090). As we have to leave empirical validation for future studies, the current model construction complies with the widely accepted principles for building agent-based models ([23], p. xx). Each agent has strategic choices in making its movements in the knowledge space for each time step. Specifically, to test whether the model renders a reasonably wide array of behaviors, we draw a sample of 104 technology-based learners randomly by running the simulator in various system conditions such as different levels of prior knowledge, different involvement with boundary spanning organizations, and different levels of explorative behaviours of the incumbent organizations.

[2] The NetLogo code is available from the authors on request. Please contact Shuyuan Wu.

4 The Simulation Results

This section presents the simulation results. We initially describe the results of this simulator by demonstrating the system level emergence and secondly, we examine the behaviours and performance of individual agents.

System Level Emergence: Markets are Grue

Fig. 1 shows a simulator snapshot of the development of green and blue patches within the system. It was captured after 300 ticks (iterations) of one run of the simulator. In this figure, green patches are technological communities around green solutions developed from the widget X's of incums. On the blue patches are effectuation networks created by techies together with their committed customers. White patches represent mature markets developed from green or blue patches). Yellow figures represent customers, red circles with dots are spanners, blue happy faces are techies, and grey pillars are incums. The picture shows the emergence of blue and green patches, as the results of the commitments of agents in their learning journeys.

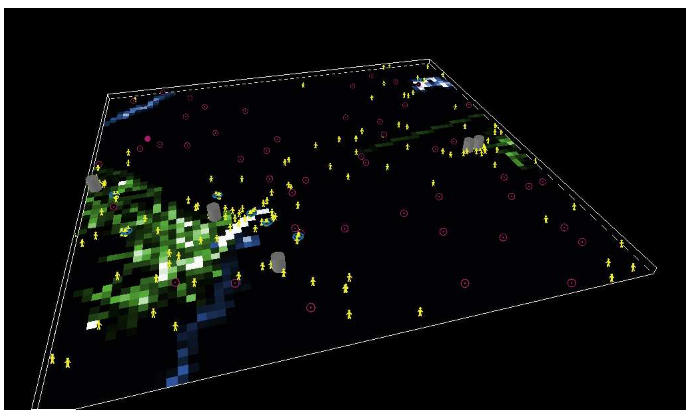

Fig. 1. Markets are Grue

Fig. 1 demonstrates the existence of blue or green patches that have emerged from the learning activities of the agents. From this figure, we can observe the results of the movements and commitments of the agents in creating a new markets for/from their 'widget X's'. Within this landscape, a variety of markets are created. We find that there are established markets (green patches which are set earlier by incums and their customers during the running of simulation, new markets (blue patches showing where previously unsatisfied customers have interacted with techies to create new markets for their new-to-the-world widget X's), and well developed markets (when the blue or green solutions have been well refined and accepted and those markets are maturing).

Fig. 2 shows dynamically the technological disruption. We can observe that green patches appear at iteration 5 (very early on in the running of simulation). Sharing more dimensions of knowledge with customers at the starting point, incums are able to interact and negotiate with customers to establish solutions to their needs quite quickly. However the green line up to 303 iterations shows that the number of green patches and mature markets from them (markets for the former technology) tend to stay fairly constant over the running of the simulation, indicating that extant markets of established solutions continually attract, retain, and sometimes lose customers. This can be contrasted with the emerging blue patches, which began to become noticeable at iteration 62. As can be seen from Fig. 2, the number of blue patches increases steadily after iteration 62. This indicates that more and more customers are committed to develop new solutions together with techies as their shared knowledge expands. At iteration 79, the number of blue patches overtakes the number of green patches indicating that the new markets have begun to overtake existing markets. This indicates the success of disruptive technologies [7, 1, 6]. In creating its markets, a new disruptive technology at its inception is inferior to mainstream solutions along the recognized dimensions of performance. Therefore at that stage their early development only serves niche segments which value their non-standard performance attributes, however, subsequently along their development, these technologies are able to raise the performance attributes such that they begin to involve more and more customers. Fig. 2 graphically displays the competition between green and blue solutions being developed, the result of which was the emergence and dominance of blue widgets (or blue markets being created). At iteration 303 (the end of the simulation experiment), customers with techies have created 82 blue patches, while there were 39 green patches in comparison (i.e. the new technology is dominating).

The system-level emergence demonstrates a number of issues of significance for theory advancement in market creation. Firstly, the results of the system-level emergence in the simulation provide evidence that markets are indeed *grue*. Technology entrepreneurs need not know the future in order for new markets to emerge. Rather, the collective learning and interactions of entrepreneurial entities, customers and others give rise to opportunities for market creation. The various agents within a system work through commitments to exchange and combine their knowledge components without a complete knowledge about the future. These results demonstrate the importance of learning and transformation (the accumulation and sharing of knowledge resources) that entrepreneurs and customers are required to commit to in order to create new CPV.

Our second theoretical insight is the emergence and dominance of disruptive innovations. While preliminary at this stage, the results of our simulation suggest that the success of disruptive innovations is due to the combination

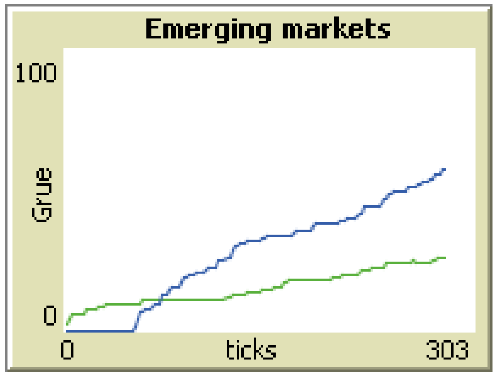

Fig. 2. The emergence of blue patches. The blue line crosses the green line after approx. 79 iterations and remains above the green line thereafter. The x-axis (ticks) are iterations of the simulation, whereas the y-axis denotes the number of green and blue patches respectively

of knowledge, and interactive learning activities with customers [6, 14, 17]. However, in order to examine the complex and adaptive behaviours of this system level emergence, we need to examine the micro-level interactions of the entrepreneurial agents.

What Efforts Can a Techie Make?

Individual agent's movements are recorded automatically during the running of the simulator. With this data we can trace the learning journey of individual agents and also test the influence of each individual's traits on their performance. Longitudinal cases can be drawn from the datasets as abstract versions of market creation journeys. Each can be compared with market-creation case examples of technology-based entrepreneurs that began with new-to-the-world 'widget Xs' (for example, molecules such as Kevlar [51] and Surlyn [34] invented by Du Pont).

In general, the learning journey for individual techies is uncertain. They go through a stochastic process of expanding resources (the techie's knowledge, in this model) and converging on constraints constructed together by the supply and demand sides [40]. Most of the techies end up having no customers staying with them, even if they attracted customers at times during the simulation run. This parallels the high failure rate for real-world product development. Some succeed in having more and more customers committed to their widget X because of their strong wills to make use of what they know and push the boundary of the unknown. They 'move' actively, even after being frustrated during earlier time steps and they are alert to identify distant knowledge elements so that they expand knowledge resources to realise a shared body of CPV together with customers.

The journey to success is not smooth. It is difficult to sense the existences of potential customers and attract their attentions to new widget X': on average it takes more than 45 iterations to observe blue patches showing up. It seems even harder to keep customers' commitment because there are multiple competing widget X's being developed at the same time. For example, we traced an alert and extremely bold (exploratory) techie, 'techie 4' with $b = 0.5$ and $A = 5$. Being narrowly specialised in its expertise and having only 3 dimensions of prior knowledge, it had no potential customer within mind-sight range. It learned about a few dimensions from Spanner 225, then Spanner 241, and hence after 3 iterations saw Customer 70. However, Customer 70 , committed to a green widget X with Incum 10, did not pay any attention to Techie 4. Techie 4 continued expanding its knowledge, learning from Spanner 441 and identified Customer 137 as a lead-user at iteration 9, but this customer decided not to go together with it either. At iteration 15, Customer 70 who had been involved with Incum 10 and then Techie 2 updated its knowledge-profile (on what is important to satisfy her needs) and the update took it closer to Techie 4. However, the first 'transaction' between these two did not happen till iteration 38, when Customer 70 felt happy to paint its patch blue, after a negotiation lasting 23 iterations. As a result of these, customer 70's need-profile was updated to [1 1.23 1.48 1 1 1 2 1 2 1 1 1 1 1 1 1 1 1 1 0 0 0 1 1 1 1 1 1 0 0 1 1 1 0 0 0 0 0 1 1 0 1 1 1 1 1 0 1 1 1] and the knowledge of techie 4 arrived at [1 2 2 2 0 1 1.4 1 1.18 1 1 1 1 1 1 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 1 1 1 1 1 1 0 0 1 0 1 1].

Until iteration 63, techie 4 had only been trading with customer 70, without expanding its knowledge resources at all and unfortunately Customer 70 left it during iteration 63. Afterwards, techie 4 learned from Spanner 241, Spanner 215, and Customer 102 to recognize dimension 17 and 22 so that it involved Customer 102 and recaptured Customer 70. By iteration 66 customer number has increased to 5 after Techie 4 took into its knowledge-profile dimension 5 and dimension 34.

The market kept expanding as Techie 4 learnt more about the needs of lead users, Customer 70, 102, and 137, and meanwhile potential customers were learning from each other. By iteration 96 it had involved 10 committed customers and the (sub)market size increased to 35 customers at iteration 121. Within 10 iterations the number of customers had increased to 66. The count of committed customers as the market creation performance of techie 4 reached 95 (47.5% of the customer population) at iteration 134 when we ended our observation on it.

In order to examine the importance of the three parameters in our model, we collected data from the simulator by running it under a variety of conditions. This dataset includes 104 techies and their market creation performances (counts of customers who are committed together with individual techies to develop future solutions). Multiple regression analysis tested the relationship between the number of customers involved (Customers) with a focal techie as its performance and the techie's exploration tendency (ET), alertness coefficient (Alertness), and the breadth of prior knowledge (PriorKw). The results show that ET, alertness, PriorKw together explained 20.7% (the R^2) of the variance in market-creation performances. The ANOVA analysis confirms the significance of this model, with p-value smaller than 1%. This means that the success of market creation was not totally by chance, but can be attributed to the individual traits of each techie agent, even though future is not predictable from initial conditions. PriorKw was positively correlated with the performance, with the coefficient being 0.56 ($p < 0.00$). This is consistent with hypothesis 1 that prior knowledge plays a highly significant part in the creation and development of CPV. Support for hypothesis 2 is also found as the alertness coefficient, b, was found to be negatively correlated (due to the implementation of the alertness concept in the simulator, the higher b is, the less alert an agent is) with techies' market creation performances. The effect is strongly significant ($B = -1.542$, $p < 0.001$). ET has a correlation of 0.5 at the significance level of 95% ($p < 0.05$) with the market creation performance, suggesting support for hypothesis 3. The result from our simulations supports an assertion that information asymmetries impact on the market creation process of technology entrepreneurs [43]. The ability to create markets is a function of the interaction of prior knowledge and alertness. Also ET, the aspiration to create future through commitments under uncertainties, is significantly important for the success.

The emergence of CPV is a function of the system in which individual agents interact and expand their knowledge. Entrepreneurs and customers act within their worlds of bounded cognition, partial knowledge and uncertainty [40]. During the effectuation process, stakeholders come together to commit to transforming extant realities into a new market. Therefore to a great extent, the creation of an effectuation network (and the eventual development of a market) is largely dependent on the interactions of who and what components have been seen as 'relevant' and hence has come on board during the process. In short, chance plays a large role.

5 Conclusions

This study shows that the interactive behavioral processes of market creation can be realized through computer simulation so that researchers can analyze both system-level behavior and the influence of individual factors on performance.

Taking the CAS approach, we simulate the market creation process for disruptive technologies. New markets emerge from the interactions between entrepreneurs and their potential customers. Starting with limited and dispersed knowledge components, these individual agents converge at artefacts of shared knowledge (CPV) on what is needed and how that need is to be satisfied. In expanding their knowledge profiles and negotiating their constraints, individual learners sense each other's existence, recognise relevant components, and learn about/from each other through commitments. The result showed that individual entrepreneurial traits including prior knowledge endowments, alertness, and exploration tendency are significantly influential in the market creation performance. However, because the effectuation process of individual agents is highly stochastic and complex, individuals' traits together explained only 21 percent of the variance of market creation performance.

It is not possible in a single set of simulation experiments to exhaustively examine every possible combination of settings for each parameter in the simulation model. Future work will extend the range of settings examined and will include further development of the simulator.

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