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RESEARCH REPORT

NEW VENTURES ON THE SEARCH FOR VIABLE BUSINESS MODELS: TAKING INTO ACCOUNT LEVELS OF UNCERTAINTY/AMBIGUITY

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New ventures on the search for viable business models:
Taking into account levels of uncertainty/ambiguity

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ABSTRACT

There exists evidence that most initial selections of business models by new ventures have to be adapted later on and that minor this need for adaptation stems from the high degrees of uncertainty and ambiguity new ventures are confronted with, both on the technology and the market level. The main research question of this paper is whether different levels of uncertainty and ambiguity have an effect on the appropriateness of different search strategies new ventures can use to adapt their business model; and if yes, what this effect is. We first present the relevant literature. We then put forward a simulation model - based on the model developed by Kauffman (1989, 1993) - as a formal basis for addressing our research question and analyze the simulation results. To conclude, these results are discussed in the light of existing research on entrepreneurship and innovation and some limitations of our research methodology are presented.

INTRODUCTION

One of the most pertinent questions in the field of entrepreneurship research, as suggested by Venkataraman (1997, p. 121) is *"...why, when and how some [entrepreneurial companies] are able to discover and exploit opportunities while others cannot or do not"*. Various authors have put forward that it is not the clairvoyance of the entrepreneur that determines this ability. Pitt and Kannemeyer (2000) question whether many entrepreneurs are able to define the concept correctly from the outset. To paraphrase Stoica and Schindehutte (1999: p. 1): *"Entrepreneurs start with a vision. ... When successful it is because they are able to translate this vision into a business concept that addresses a marketplace need. ... only in a minority of cases do entrepreneurs succeed because they define their concept correctly from the beginning, and rarely do they immediately achieve a good fit between the available opportunity and their approach to the business concept."* Or as Peter Drucker (1985: p. 189) has noted: "*When a new venture does succeed, more often than not it is in a market other than the one it was originally intended to serve, with products and services not quite those with which it had set out, bought in large part by customers it did not even think of* *when it started, and used for a host of purposes besides the ones for which the products were first designed."*

Existing research data confirms this. Chesbrough (2002), in his study of 35 Xerox spin-offs, found that the business model for many of these spin-off companies evolved substantially from the time of formation of each company to the time each company achieved significant value for its shareholders. Also Brokaw (1991), in her update of the twenty seven ventures that were profiled in Inc.'s 'Anatomy of a Start-up' series between the period of 1988 and 1990, found that by 1991, a large fraction of the surviving ventures had adapted their initial business model: *"What has made or broken many of the companies we've watched...is... the ability (or inability) to recognize and react to the completely unpredictable... To be flexible, and not just in response to small surprises but to really big ones- like discovering you're selling to the wrong customers or selling through entirely wrong channels. Some companies even find they have to revamp from top to bottom in order to survive. They discover they're in the wrong business"* (Brokaw, 1991: p. 54).

There thus exist evidence that most initial selections of business models by new ventures have to be abandoned later on (see also Tegarden et al., 1999; Chesbrough, 2003; Chesbrough & Rosenbloom, 2002) and that minor or major changes to the initial business model are needed. Furthermore, this need for adaptability apparently stems from the high degrees of uncertainty and ambiguity new ventures are confronted with, both on the technology and the market level (Pitt and Kannemeyer, 2000; Chesbrough, 2002; Chesbrough and Rosenbloom, 2002).

Although the importance of adaptation for new ventures is widely accepted, relatively little is known on the process of entrepreneurial adaptation itself and on the exact relationship between uncertainty/ambiguity and this entrepreneurial search for a viable business model. Some authors, such as Chesbrough and Rosenbloom (2002), indicate that we need to learn more about what facilitates or impedes (successful) adaptation in new ventures. The aim of this paper is to do this. More precisely, it wants to investigate in depth the effect that different levels of uncertainty and ambiguity have on the appropriateness of different search strategies new ventures can use to adapt their business model.

A first section discusses the difficulty ventures have in finding a viable business model. It suggests that they need to adapt their initial business model and that this need for adaptation is mainly due to high degrees of uncertainty and ambiguity in their environment. In a second section, we provide a formal basis for addressing these issues by developing a simulation model that examines the efficiency of different entrepreneurial search and adaptation strategies under varying degrees of uncertainty/ambiguity. We discuss the model, which is based on the model developed by Kauffman (1989, 1993) and analyze the simulation results. A third section discusses the results of our simulation model in the light of existing research on entrepreneurship and innovation.

LITERATURE OVERVIEW

New ventures on the search for viable business models

New ventures often start from a vision or from a technological capability. In both cases, the initial idea needs to be translated into the economic domain through the development of a business model (Chesbrough and Rosenbloom, 2002). The business model is then considered a construct that mediates the value creation process, by selecting and filtering technologies and ideas, and packaging them into particular configurations to be offered to a chosen target market. The functions of a business model are "*to articulate the value proposition, identify a market segment, define the structure of the value chain, estimate the cost structure and profit potential, describe the position of the firm within the value network, formulate the competitive strategy*" (Chesbrough and Rosenbloom, 2002: p. 533-534).

Because both technical and market uncertainty are involved in this translation and because environments may change rapidly, the set of all feasible business models is not foreseeable in advance. The difficult search for viable business models is largely due to the uncertainty and ambiguity new ventures are confronted with, especially in the case of technology-based ventures that are coping with high degrees of both technical and market newness (see also Morris et al., 1999; Shane and Stuart, 2002; Aldrich and Fiol, 1994). Nohria (1992) points out that in the creation of new ventures, different elements must be combined, taken apart and recombined (see also Baker and Faulkner, 1991) and that: "*successfully putting these puzzles together is no easy matter, given the [...] uncertainty inherent in the creation of a new enterprise*" (Nohria, 1992: 243).

Uncertainty has been defined in existing literature as characteristic of a situation in which the problem solver understands the structure of the problem (including the set of relevant decision variables), but is dissatisfied with the knowledge available on the value of these decision variables (Schrader et al., 1993). The relevant decision variables are known, but the organization does not know the exact values these variables should take. There thus is a difference between the amount of information available and the amount of information required to execute a task at hand (Galbraith, 1977). There hence exists an information asymmetry. On the other hand, under ambiguity, there is lack of clarity regarding the relationships between the variables and the problem solving algorithm and sometimes even about the set of relevant decision variables itself. Differing interpretations of the situation exist. It is unclear to the actors involved which information is needed to solve these differences (Van Looy, Debackere & Bouwen, 2001). There hence exist a lot of interpretation asymmetries as to what should be done. This relates directly to Daft and Lengel's notion (1986) of equivocality, which they define as *"... ambiguity, the existence of multiple and conflicting interpretations about a situation."*

Certainly during the early stages in its life, a technology-based venture is confronted with high degrees of both uncertainty and ambiguity while confronted with a limited knowledge base and experiencing restricted access to resources (see for example: Bhidé, 2000). When initially developing a business model, the venture faces uncertain innovation targets, unclear product performance requirements and ambiguous design criteria. Innovations are by definition only successful when they succeed in coupling a technological capability to a user need (Teubal et al., 1991). During this process, innovations face considerable selection pressures on their way to commercialization (Nelson and Winter, 1982). Not only is the nature and the outcome of their technical activities inherently unpredictable (Steensma et al., 2000), but also the market selection and commercialization process itself poses problems of uncertainty and ambiguity (Chesbrough, 2003; Chesbrough and Rosenbloom, 2002; Chesbrough, 2002). Utterback (1987) therefore distinguishes between technical and target uncertainty. The range of options - and problems - that founders of new businesses confront is vast. Entrepreneurs must continuously ask what application they want to strive for and what competencies they need to develop in order to accomplish that prowess (Bhidé, 1996). In emergent markets, technological options are at best marginally understood, distribution channels and sources of supply are problematic, market needs are not clearly defined, and hence, market viability cannot be proven a priori (see Abernathy and Utterback, 1975 & 1978; Debackere, 1997; Eisenhardt and Schoonhoven, 1990; Bhidé, 1992, 1994, 1996 & 2000; Teubal et al., 1991).

As a logical consequence, it is not possible for a venture to identify upfront what will be the most viable business model. Uncertainty and risk occasion many needs to change (Pitt and Kannemeyer, 2000). In general, high levels of uncertainty are known to require adaptive approaches to organizations (Timmons et al., 1990). Market signals may reveal information about the external environment that was unknown and or uncertain at the outset, indicating a possible need to change or adapt the initial business model (Stoica and Schindehutte, 1999). As Stoica and Schindehutte (1999) put it: *"The adaptive entrepreneur allows the* *business concept to develop over time as he/she gains experience with products, markets, suppliers, employees, and other key variables surrounding the enterprise"* (Stoica and Schindehutte, 1999: p. 1-2). In the context of new venture development, adaptation thus refers to the entrepreneur's willingness and ability to make appropriate adjustments to the business concept and marketing approach as the venture evolves from an initial idea or business plan through the early stages of the organizational life-cycle (Morris et al., 1999; Pitt and Kannemeyer, 2000).

MODEL[1]

Performance landscape

In their book 'The Innovation Journey', Van de Ven et al. (1999) used the analogy of a rugged fitness landscape to describe the development of an initial, vague idea into a concrete innovation. The purpose of the development process is *"...to cross the dark valley to reach the peak on the other side... To reach the other side we must explore the valley at the same time we are constructing a path to the other side"* (Van de Ven et al., 1999, p. 87).

In this paper, we will model ventures and their business models as searching a performance landscape. This landscape is based on the work of Kauffman (1989, 1993). It was originally developed in the context of evolutionary biology and devised to explore how organisms and proteins evolve. It was adapted by Levinthal (1997) to examine managerial search and has since then been used in a number of organizational studies (for a survey, see Sorenson, 2002). Most of these studies look at adaptation processes of organizational attributes. They study how the performance of various adaptation or search strategies is affected by the complexity of and changes in the landscape.

Principles

A venture's business model consists of different aspects. According to Chesbrough and Rosenbloom (Industrial and Corporate Change, 2002), the functions of a business model are to articulate the value proposition, identify a market segment, define the structure of the value chain, estimate the cost structure and profit potential, describe the position of the firm within the value network, formulate the competitive strategy. Pitt and Kannemeyer (2000) as well as Stoica and Schindehutte (1999) point out that several of

[1] An overview of the main programming algorithms is provided in Appendix 2.

these business model attributes – such as product/service offering, prices, advertising and sales strategy, target audience, location, customer service levels, financial structure, production/service delivery methods, and distribution channels - need to be adapted.

In our model, a business model consists of N attributes. For simplicity, this model assumes that each attribute can take on two possible values (0 or 1). This corresponds to a total of 2^N possible business models. A specific business model is then characterized by a vector $N\{x_1,x_2,...,x_N\}$, where each x_i takes on the value of 0 or 1. If a venture's set of choices is described by a vector of N attributes, then the performance landscape consists of N dimensions depicting the venture's alternatives along each dimension and an (N+1)th dimension depicting the performance associated with each vector of N choices. The performance landscape is thus the mapping of a function F that assigns a performance measure to every possible configuration.

The individual contribution of a given attribute x_i to the payoff of the business model is influenced by K other attributes. K captures the fact that the choice made concerning one decision may affect the marginal benefit or cost associated with another decision. If K equals zero, then the contribution of each attribute is independent of all other decisions. At the other extreme, if K equals N-1, then the individual contribution (C_i) of each attribute (x_i) depends on the value of all other attributes of the venture's business model. As a result, C_i, the payoff to a particular choice x_i, can be represented by the following expression: $f\{x_i| x_{i1},x_{i2},...,x_{iK}\}$. The contribution of each individual element in the N-length string may thus take on 2^{K+1} values depending on the value of the K other elements with which it interacts. In the model these different individual contributions are set between 0 and 1 by assigning a random number drawn from the uniform distribution from zero to one to each of the possible $f\{x_i| x_{i1},x_{i2},...,x_{iK}\}$ combinations. These individual contributions can then be used to calculate the overall payoff associated with the full vector of N values, $F\{x_1,x_2,...,x_N\}$. This is simply the average of the N individual contributions given the other choices; or

$$F\{x_1,x_2,...,x_N\} = \sum_{i=1 \text{ to } N} f\{x_i| x_{i1},x_{i2},...,x_{iK}\}/N$$

An example is given in Appendix 1. In our model, the K variables with which a given element interacts are specified as being the K adjacent elements. The payoff to a particular choice x_i, can then be represented by the following expression: $f\{x_i| x_{i+1},x_{i+2},...,x_{i+K}\}$. Another possibility would be to randomly choose K elements of the vector. This results in a similar performance landscape (Kauffman, 1989).

Levels of uncertainty/ambiguity

A venture, when searching for an optimal business model, is confronted with various sources of uncertainty and ambiguity. Both uncertainty and ambiguity can be translated into our simulation model.

Uncertainty

The model as previously used in management literature is inherently characterized by uncertainty. Companies or organizations are placed on the landscape. They are aware of the landscape's N dimensions, but they do not know a priori which values these N dimensions should take in order to reach optimal performance. Therefore, they 'walk' over the landscape by altering the decisions with respect to some or all of the N dimensions, trying in this way to constantly improve their performance level. This situation corresponds perfectly to the definition of uncertainty as characteristic of a situation in which the problem solver understands the structure of the problem (including the set of relevant decision variables), but is dissatisfied with the knowledge available on the value of these decision variables (Schrader et al., 1993). The relevant decision variables are known, but the organization does not know the exact values these variables should take.

Ambiguity

We adapted the Kauffman model to study the effect of ambiguity on entrepreneurial adaptation. When ventures search for a viable business model, they are not always aware of all the factors or attributes of the business model that are relevant for its performance. A lack of clarity about the set of relevant decision variables can be easily translated into our model. It means that a venture is only aware of the relevance of N1 decisions, where $N1 \leq N$. Its position on the landscape, i.e. its business model, will be determined by the N1 decisions it makes, but also by the materialization of the N-N1 remaining decisions. Since the venture is not aware of the existence or relevance of these N-N1 remaining decisions, it will not make any deliberate choices for these decision variables. Instead, it will take its position on these remaining decision variables purely by chance. For the simulation, this means that these remaining N-N1 decisions are randomly set to 0 or 1 at the beginning of each period.

So, in period t the venture assesses the performance for a specific business model (of which N1 decisions are consciously chosen and N-N1 are random) and then decides whether to move or not. When evaluating its N1-length decision vector, the venture thus sees the expected performance of these joint N1 choices given the randomly set values on the N-N1 remaining decisions for period t. Note that the actual performance for this business model in period t+1 will depend on a new set of values for the N-N1 attributes which are reset at the beginning of period t+1.

The number N1 of decision variables of which the venture is aware is specified by the modeler/researcher. For each venture, the computer will then randomly choose N1 decisions out of the total N decisions. Although ventures will be all aware of the same number N1 of decision variables, they will differ with regard to the precise attributes they are 'aware' and 'unaware' of.

Search strategies: looking for alternative business models

Off-line performance assessment

Ventures will first search for a (range of) alternative business model(s), and then assess the expected performance value of the business model(s). If this expected value is less than the maximum actual payoff achieved before, the venture will return to this maximizing business model for further search efforts. If the expected value is better than the maximum actual payoff achieved before, the venture will select this new business model. Only in the next period, the venture will experience the actual payoff for this new business model. Search in our model is always off-line, which we believe to be a realistic representation of managerial decision-making processes. Entrepreneurs will not experiment with options if they do not at least expect that these options might be successful. We consider this feature an improvement on existing managerial research using Kauffman landscapes.

Local search

In a process of local search, only business models in the immediate neighborhood of the existing business model are examined. A neighborhood is defined as those business models that vary from the current business model by only one attribute. Therefore if there are N attributes and each attribute can only take on two values, the each business model has N different business models in its immediate neighborhood. Search is local in that only one element of the N dimensions is varied at a time. In addition, only the N1 attributes of which the venture is aware can be varied. Although each business model has N different business models in its immediate neighborhood, only N1 of those can be searched.

Ventures are assumed to be able to a priori assess all alternative business models in their immediate neighborhood whose expected performance value is superior to their current level of performance (see Levinthal 1997). Furthermore, they are assumed to be able to modify the single attribute that differs between the two business models so as to achieve this higher level of performance. If the new business model's expected payoff is superior to the venture's actual performance, the venture adopts it. Alternatively, if the venture's performance is expected to decline, then the venture sticks with its current business model. Its performance in period t+1 will then be the actual payoff of this new business model (depending on N-N1 attributes randomly reset at the beginning of period t+1). The venture is assumed to remember which of the local experiments were unsuccessful. As a result of this local search strategy, the venture either identifies a new superior alternative or, after N trials, stops engaging in local search and persists in what is a local peak.

Search through random long-jumps

This search strategy is based on Levinthal (1997) and Gavetti & Levinthal (2000) and is again adapted for the possibility that ventures may not be aware of all relevant attributes. On-line experimentation through random long-jumps is modeled by assuming that each of the business model's N1 attributes of which the venture is aware are specified anew at random. Each period t, a venture draws at random new values for the N1 attributes it is aware of. The venture then compares the assessed performance value of this new business model (which depends on the values of N-N1 attributes randomly set at the beginning of period t) and adopts the new values of these N1 attributes if the assessed payoff is superior to the current performance level. Alternatively, if the venture's performance is expected to decline, then the venture sticks with its current business model for its subsequent search efforts. If the venture adopts these N1 new values, its performance in period t+1 will be the payoff of a new business model, depending however not only on the N1 values but also on the values of N-N1 attributes randomly reset at the beginning of period t+1. Unawareness about some decision variables may thus cause the actual payoff for a venture's choice to differ between periods. Also in this search strategy, the venture remembers which of the experiments were unsuccessful.

SIMULATION PROCEDURES

Firstly, the researcher needs to specify a number of parameters. Secondly, the computer will run a large number of simulations (e.g. two hundred) based on these pre-specified parameters and randomization. Thirdly, the average result of these multiple runs is reported.

Specifying parameters

The parameters N and K (which defines the complexity of the landscape) are specified by the modeler/researcher. The interaction patterns between decision variables follow an adjacent logic as explained above. The parameter N1 is set by the modeler/researcher. The modeler/researcher will assign different search strategies to different groups. He will specify the number of groups (in our study two groups) and the search strategy for each of these groups (in our study one group uses local search and one group used search through long-jumps). Each group of the population will consist of x ventures, where x is specified by the modeler/researcher. The modeler/researcher will specify the number of periods each simulation will run.

Running one simulation

The first procedures of the simulation initialize the performance landscape by specifying the interaction patterns between decision variables. As discussed above, this follows an adjacent pattern. Once this is done, the performance level of each of the 2^N possible business models is specified. The individual contribution of each element in the N-length string may take on 2^{k+1} values depending on the value of the K other elements with which it interacts. As explained earlier, these individual contributions are generated by assigning a random number drawn from a uniform distribution ranging from zero to one. Based on these individual contributions, the total payoff for each of the 2^N possible business models is calculated as explained above. The performance landscape, once specified, is fixed for that specific simulation run.

At the beginning (i.e. at t=0) of each simulation run, the initial population of ventures is specified by choosing each of the N attributes (either a one or a zero) at random, where there is an equal probability associated with the two possible values. This procedure is carried out for each venture in the population. In case the researcher/modeler has specified the existence of multiple subgroups, the computer has to make sure that these subgroups will be populated by exact clones with respect to their initial position in the landscape, to make the analysis as controlled as possible.

At the beginning (i.e. the start of period 1) of each simulation run, for each venture, the computer will randomly choose the N1 out of N decision variables of which the venture is aware. Ventures thus differ in their sets of 'aware' and 'unaware' decision variables.

Averaging the results of multiple runs

For each research question, this simulation procedure will be run repeatedly. For each of the simulation results discussed below, two hundred different landscapes and populations histories are examined. The pre-specified parameters remain the same for each of these runs, whereas the randomly generated inputs are generated anew for each run. For example, each of the landscapes has the same structure in terms of N and K but is seeded independently. The number N1 remains the same. The number of subgroups and the search strategy for each of these groups remains the same. The number of ventures in each group remains the same.

In addition, a new set of individual performance contribution values are created for each run. At the beginning of each simulation run, a new population is randomly distributed over the landscape. For each specific venture, the set of N1 decision variables are chosen anew.

The (average) results of all these different runs will then be averaged. Therefore, the answer to each research question, unless otherwise indicated, will reflect the average behavior of multiple (e.g. two hundred) runs of the simulation where for each run there is a distinct performance landscape and a distinct population of organizations.

ANALYSIS

Comparing performance

For 200 simulation runs, over 200 periods of time, we mapped the average performance of two sets of 15 companies, where one set is using a local search strategy and the other set is using long-jumps. The two sets are identical clones with respect to their initial position on the landscape. We ran these simulations with landscapes of different dimensions. The results shown in Figures 1a through 1d are for landscapes with N=10. A schematic overview of our results is given in Appendix 3. We ran simulations for all possible degrees of landscape ruggedness (i.e. different values of K) and degrees of ambiguity (i.e. different values of N1). For reasons of clarity, only some of these simulation results are shown in Figures 1a through 1d. However, our discussion of the simulation results is based on all simulations. As explained in Appendix 4, we also ran simulations for a different number of companies, a different number of simulation runs, and different values of N, N1, and K. Results were very similar.

In general, we find that the degree of ambiguity has a significant effect on the (average) performance of local search and search through long-jumps. Whereas a strategy of local search is superior under situations of low ambiguity, this effect is nullified and in some cases even reversed as ambiguity increases (i.e. as N1 decreases). For example, for K=0 (i.e. a smooth landscape with only one peak), for N1=8, local search scores significantly better than search through long-jumps. For N1=6, there is no significant difference between both strategies; and for N1=2, search through long-jumps scores significantly better than local search (see Figure 1a). Also for other values of K, we also see that the difference in performance between local search and long-jumps becomes less and less significant and even reversed if we move from situations with low ambiguity to situations with higher ambiguity.

The case of N1=10 deserves some special attention. After a large number of periods, search through long-jumps starts to outperform local search for N1=10, i.e. a situation in which the companies are aware of all relevant dimension of the landscape. In some cases, the same effect is found for N1=9. The explanation is that, if companies are aware of (almost) all relevant dimensions, the true value of an option will be the same as its assessed value. This means that companies have perfect assessment. If they search through long-jumps, they will only change position if they have indeed found a new and better peak on the landscape. They will always improve, never worsen in performance. However if companies adapt through local search, they will get stuck in a local optimum (a peak, but not the highest peak on the landscape). This also explains why we do not see this pattern for K=0 (i.e. a smooth landscape with only one peak); in that case, there are no local optima and local search continues to outperform search through long-jumps. It also appears that the higher K, the sooner search through long-jumps outperforms locals search. A higher value of K means that there are more local optima on the landscape. This increases the probability that ventures using local search get stuck early on.

- INSERT FIGURES 1a, 1b, 1c, and 1d ABOUT HERE -

Introducing selection mechanisms

Since the development of emerging markets and the related dominant product designs are difficult to predict, new ventures may not be able to access the financial resources required to cope with the large amounts of experimentation involved. Ventures that are not able to find an attractive business model rather quickly can loose the thrust of their investors (Eisenhardt and Schoonhoven, 1990). Selection processes in populations of young ventures are less due to a lack of sales or profits then to a lack of investors' interest and thrust. Indeed, most ventures do not generate significant revenues during the first years of their existence. Survival then becomes a matter of continuously attracting new investment. It is reasonable to say that ventures which on their search path come across better performing business models than the ones of their competitors, are more likely to continue receiving funding.

Consider a competitive ecology within the population of ventures, with ventures exiting and entering, and relatively poorly performing ventures tending to exit/die. The probability of mortality can be defined as $1 - F/F_{Max}$, where F is the focal venture's performance level, and F_{Max} is the performance level of the best performing venture in the population (Levinthal, 1997). Note that this F_{Max} is not necessarily the highest possible performance level in the landscape, but, rather, the maximal performance level obtained in the current period by a venture within the population. For different values of K and N1, the use of the above formula for the probability of mortality leads to mortality patterns similar to the one shown in Figures 2a and 2b. These mortality rates are relatively high. However, this corresponds to empirical findings of high start-up mortality (Timmons, 1994; Smilor & Gill, 1986; Bruno et. al., 1992: EC, 1993; Cooper et al., 1994; Bhidé, 2000).

- INSERT FIGURES 2a and 2b ABOUT HERE -

In the remaining analyses, the total number of ventures is assumed to remain constant over time. Ventures that exit/die are replaced by new ventures/entrants. These new ventures imitate existing ventures' business models and strategy. A new entrant imitates a certain incumbent with respect to the N1 attributes it is aware of; the remaining N-N1 attributes are randomly set to 0 or 1. The probability of a given form being replicated is determined by its relative performance in the population. More precisely, the probability of any one venture being replicated is equal to its performance level divided by the sum of the performance levels of all surviving ventures in the population (Levinthal, 1997).

Under this selection and replacement mechanisms, we look at the proportion of ventures using local search versus venture using search through long-jumps. Our simulations start with a population of 15 ventures using local search and 15 ventures using search through long-jumps at time t=0. A schematic overview of our results is given in Appendix 3. As can be seen in Figures 3a and b, we find that under high degrees of ambiguity (i.e. low values of N1), the proportion of both search strategies remains relatively constant over time. For higher values of N1, the proportion of local searchers increases over time, and this increase is higher for lower degrees of ambiguity (i.e. higher values of N1). This suggests that under high degrees of ambiguity, search through long-jumps is equally valid as local search, and that the former becomes less appropriate under lower degrees of ambiguity.

However, once the degree of ambiguity becomes sufficiently low (i.e. N1 equal to 9 or 10), we see that the proportion of ventures searching through long-jumps decreases as expected for the first 10 to 20 periods of our simulation, but that this trend becomes reversed afterwards: in the second part of the simulation, the proportion of ventures searching through long-jumps starts to increase. As in our comparison of venture performance earlier on, the reversal of the trend is due to the fact that companies adapting through local search can get stuck in a local optimum. The timing and magnitude of this effect depends on the ruggedness of the landscape. Under high values of K, the proportion of ventures searching through long-jumps initially decreases sharply, but starting from period 10 this search strategy completely takes over the ventures that use a local search strategy. Under lower values of K, this take-over is less drastic.

- INSERT FIGURES 3a and 3b ABOUT HERE -

DISCUSSION AND CONCLUSION

For our analyses, we borrowed heavily from Kauffman (1989, 1993) and Levinthal (1997). We elaborated on their model in a number of ways. Our main contribution is that we introduced ambiguity into the simulation model, by explicitly taking into account the number of decision variables of which the venture is aware and by allowing this number to be smaller than the total number of relevant decision variables. Other improvements were the off-line performance assessment and the fact that ventures using local search as well as ventures searching through long-jumps are given a memory which allows them to remember whether past experiments were successful.

Our results indicate that we need to discern between different types of adaptation. Indeed, new ventures can adapt their business model following a local search strategy or search through long-jumps. The first form of adaptation implies that they gradually refine and adapt their business model by changing only one (or in real life: only a couple of) aspects of the business model at a time. The second form of adaptation on the other hand implies that they try out unrelated business models. It is important to discern between these two types of adaptation since they yield different results under different circumstances. We found that a strategy of local search is superior in terms of performance and survival under situations of moderate ambiguity, but that search through long-jumps becomes more interesting as ambiguity increases. Or in other words: in situations characterized by moderate ambiguity, new ventures should adapt their initial business model through experimentation with closely related alternatives. In situations characterized by high ambiguity, it becomes more appropriate to look at opportunities that are far removed from the initial business model.

We believe that this finding adds significantly to the existing literature on venture development. The Abernathy-Utterback model (1975 & 1978) proposed that a venture should make relatively small investments before the dominant design has emerged and should augment the investment afterwards. The results from our simulation model in addition suggest that the type of alternative business models to invest in should also depend on the degree of ambiguity. We believe that this insight adds value to existing work on business model development, especially to the work by Van de Ven et al. (1999). They model the innovation process as a cyclical process consisting of two phases in a set sequence of divergent and convergent behavior. Divergence involves the exploration of new directions. According to the authors, it is triggered by the infusion of resources and it increases the complexity of a system. Convergence on the other hand implies testing and exploiting a given direction. According to the authors, it is triggered by external constraints (such as institutional rules) and internal constraints (including resource limitations and the discovery of a possibility that focuses attention). Van de Ven et al. literally relate their work to search on Kauffman landscapes. They indicate that it is the complexity or ruggedness of the landscape that warrants divergent search behavior. However, our simulation results show that although the ruggedness of the landscape has a significant influence on the performance level ventures can reach, it does not have an effect on the appropriateness of different search strategies. The results of our simulation model suggest that the underlying driver of divergence versus convergence is not the complexity of the problem, but in fact the degree of ambiguity. We see the presence of ambiguity as the trigger for divergent behavior (or search through long-jumps). The reduction of ambiguity can then trigger convergent behavior.

This interpretation corresponds to other suggestions in the literature on innovation project management. Some research shows that the appropriate approach to change/adaptation depends on the levels of uncertainty/ambiguity. As indicated by McGrath (2001), in her study of 56 projects launched by established firms, the choice between learning as more narrowly directed search (ex ante planning and control, limiting variety) on the one hand, and learning as serendipity (generating enough variations and then selecting through retrospective sense-making) on the other hand, depends upon how much existing organizational knowledge is applicable to the new situation[2]. In situations dominated by uncertainty, "traditional" project management is appropriate (Debackere and Van Looy, 2003; see also von Gelderen et al. (2000) on planning strategies in small business start-ups). The success of the innovation project depends on the speed and the resources with which all project phases are completed. Extensive use of clear goals and planning - using milestones and phases - can reduce uncertainty in the decision-making process and should reduce lead-times (see for example: Eisenhardt and Tabrizi, 1995). Since market and technology requirements are understood, the product concept can be frozen early and can then be developed during sequential or partially overlapping phases (i.e. "sequential" versus "concurrent" engineering methodologies). In situations marked by high levels of ambiguity, characterized by different interpretations on the nature and the scope of the application envisaged, the "traditional" approach of planning and intensive preparation of the product definition is not longer sustainable. Flexibility and adaptability (Iansiti, 1995; Verganti et al., 1998) allowing for the continuous inclusion of new information on market and technological developments until late in the development process (i.e. the pursuit of a "window of opportunity" as suggested by MacCormack, 1998), gathering and incorporating sufficient knowledge before committing to one specific product concept, delaying the final concept choice, and experimenting (i.e. solving problems through iterative, though intelligently pursued, trial and error) then become the dominant organizational themes (Eisenhardt and Tabrizi, 1995; Thomke et al., 1996; Verganti et al., 1998).

A second finding of our model was that <u>even in situations that are characterized by zero ambiguity, search through long-jumps becomes superior to local search in the long run</u>. We find this effect for N1=9 and 10. It is due to the fact that ventures using a strategy of local search can get stuck in local optima. This suggests that even in environments that are not characterized by ambiguity, companies should eventually start experimenting with alternative business models that are far-removed from their established business model. Similar propositions have been made in literature on product portfolio management. Portfolio management forces management to make the mission and nature of the organisation's innovation activity explicit. The framework developed by Wheelwright and Clark (1992) distinguishes between research, breakthrough, platform, and derivative projects. The strategic objectives of a firm's innovation efforts have to be balanced over time and it is important to understand how innovation activities can broaden and deepen a firm's business portfolio (e.g. Wheelwright & Clark, 1992; Roussel et al., 1992; Christensen, 1997; Miller & Morris, 1999; Van de Ven et al., 1999; Christensen & Raynor, 2003). Without active management intervention, what

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[2] Pich et al. (2002) have further elaborated on this contingency view by stating that the appropriateness of certain project management approaches depend on the (in)adequacy of the information available, and that this (in)adequacy is determined not only by the project's status as to uncertainty and ambiguity, but also by the complexity of the project's payoff function.

was once a breakthrough innovation will ultimately result in very incremental changes. As a consequence, managerial action has to continuously balance the need for short-term incremental improvement to its existing product-market platforms with the more long-term need for fundamentally new business development. One runs the risk of becoming locked into the path chosen; a path that will inevitably erode over time (Van Looy et al. in Raghu & Karnoe, 2001). Local search, which represents incremental changes to the business model, will eventually need to be complemented with the search for far-removed opportunities.

The use of a simulation model has advantages and disadvantages. It is an interesting tool for analysis and for the generation of hypotheses. However, it remains a simplified version of organizational reality. The realistic mortality rates and the similarity of our findings to issues put forward in literature on innovation and portfolio management, lead us to believe that our findings could be indeed very valuable for ventures' business model developments. Further research needs to test these findings in a real setting, through qualitative case studies or larger scale quantitative analysis of new ventures.

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Appendix 1: Example of performance contribution

This example is taken from Dosi et al. (2003).

Table 1 contains the random individual performance contributions of a landscape with N=6 binary elements. In this example, each of the six elements interacts with two other adjacent elements. Element 1 interacts with 2 and 3, element 2 interacts with 3 and 4, and so on until element 6, which interacts with 1 and 2. The values under for example f_1 represent the individual contributions of element 1, given the value of element 1 (provided in the column titled 'Bit') and given the values of its adjacent elements (provided in the column titled 'Block'). We read for instance that, if element 4 takes value 0 (f_4 for Bit=0), its performance contribution is 0.99 when elements 5 and 6 are both set to 0 (Block=00); 0.24 if element 5 takes value 0 and 6 takes value 1 (Block=01); 0.33 if they both take value 1 (Block=11), and so on.

Bit	Block	f_1	f_2	f_3	f_4	f_5	f_6
0	00	0.29	0.73	0.64	0.99	0.83	0.35
0	01	0.67	0.68	0.28	0.24	0.75	0.03
0	10	0.74	0.33	0.18	0.34	0.55	0.69
0	11	0.63	0.63	0.57	0.33	0.54	0.46
1	00	0.41	0.19	0.46	0.76	0.58	0.48
1	01	0.25	0.58	0.67	0.74	0.89	0.58
1	10	0.55	0.64	0.44	0.56	0.34	0.73
1	11	0.85	0.67	0.39	0.08	0.55	0.47

Table 1

We can then generate the landscape starting from the individual performance contributions. The global fitness of a string is computed as the average of the individual performance contributions, thus, for instance, string 011010 has the following performance value:

$$F = (0.63 + 0.64 + 0.67 + 0.34 + 0.58 + 0.03) / 6 = 0.482$$

Appendix 2: Main programming algorithms

This simulation model was programmed in Matlab, a mathematical programming package that is very powerful in dealing with matrices and vectors. This feature made it very suitable for programming the performance landscape and business models. The main programming algorithms are presented below.

I. SEARCH THROUGH LONG-JUMPS

I.1. Selection of business model for assessment

A matrix is generated with all possible combinations of values for the N1 dimensions of which the company is aware.

```
possibilities=Fbinary_counter(n1);
```

We then measure the number of rows (a) and the number of columns (b) of this matrix.

```
[a,b]=size(possibilities);
```

We then randomly pick a number between 1 and a, representing one row and thus one combination of values for these N1 dimensions.

```
choice=round(1 + (a-1)*rand);
vector(N1_1(s,:))=possibilities(choice,:);
vector(NminN1_1(s,:))=maxvector(i-1,NminN1_1(s,:));
```

This combination is then removed from the matrix to assure that later on it cannot be chosen a second time by the company.

```
possibilities(choice,:)=[];
```

I.2. Performance assessment and true performance

Performance assessment

Performance is estimated for a business model consisting of the combination of N1 values under consideration, and the N-N1 values as in the current business model.

```
estimated=landscape(Ffctconversion(vector));
```

But the true performance will depend on the randomly reset N-N1 attributes

```
truevector(N1_1(s,:))=vector(N1_1(s,:));
truevector(NminN1_1(s,:))=fctrandom(n-n1);
```

Decision to move and revelation of true performance

1. If the assessed value is higher than the current performance, the new application is chosen

```
if    estimated > truescoor_1(s,i-1)
maxvector(i,:)= truevector;
```

The performance of the chosen application is then:

truescoor_1(s,i:periods)=landscape(Ffctconversion(truevector));

2. If the assessed value is lower than the current performance, the venture sticks with the current application

   else maxvector(i,N1_1(s,:))= maxvector(i-1,N1_1(s,:));

   However, this will not yield the same performance as in the previous period, since the N-N1 attributes are randomly reset

   maxvector(i,NminN1_1(s,:))=fctrandom(n-n1);

   The performance of the application is then:

   truescoor_1(s,i:periods)=landscape(Ffctconversion(maxvector(i,:)));

II. LOCAL SEARCH

II.1. Selection of business models for assessment

The creation of a new business model for period i starts from the N1 known attributes of the current business model (i.e. the business model in period i-1).

```
testvector= maxvector(i-1,N1_2(S2,:));
```

All neighbour combinations of the current application are determined by toggling attributes one at a time.

```
for j= 1:n1
    localstestvector(j,:)=testvector;
    if testvector(j)==0
        localstestvector(j,j)=1;
    else localstestvector(j,j)=0;
    end
```

Check which of these combinations have been assessed before

```
if   localstestvector(j,:)== past(q,:)
remov=cat(1,remov,[j]);
end
```

Delete them from the list that needs to be assessed

```
localstestvector(remov,:)=[];
```

The N-N1 unknown attributes remain the same as in the current makret application

```
localstestvector(j,NminN1_2(S2,:))=maxvector(i-1,NminN1_2(S2,:));
```

For all neighbour combinations that need to be assessed (i.e. that have not been assessed before), we estimate performance.

```
for r=1:x
    testscore(r)=landscape(Ffctconversion(localsvector(r,:)))
```

All these combinations are then added to the list of combinations that have been assessed before .

```
past=cat(1,past,localstestvector);
```

Of all these combinations, the one with the highest performance is selected for further assessment.

```
if   r>1 & testscore(r)>max(testscore(1:r-1,:))
        position=r;
```

II.2. Performance assessment and true performance

Similar to long-jumps

III. SELECTION AND REGENERATION

III.1. Selection / dying of ventures

All ventures in the population are attributed a probability of surviving. This is calculated as

$$P(survival) = \frac{Current\ \ performance\ of\ \ the\ venture}{Average\ current\ \ performance\ of\ \ all\ ventures\ in\ the\ population}$$

Ventures that do not survive are added to a DELETE list.

```
if rand > (truescoor_1(q,i)/average)
DELETE_1=cat(2,DELETE_1,[q]);
end
```

All matrices used in the program are updated: arrays that refer to failed ventures, are emptied.

```
truescoor_1(DELETE_1,:)=[];
POSSIB(DELETE_1)=[];
MAXVECTOR_1(DELETE_1)=[];
N1_1(DELETE_1,:)=[];
NminN1_1(DELETE_1,:)=[];
```

III.2. Regeneration

All failed ventures are replaced by new entrants. These entrants all imitate a surviving venture (represented by its business model) in the population.

The probability that a certain business model is replicated is calculated as

$$P(replication) = \frac{Current\ \ performance\ of\ \ the\ venture}{Sum\ of\ \ current\ \ performance\ of\ \ all\ surviving\ \ ventures\ in\ the\ \ population}$$

We construct REPLICAMATRIX as a tool for producing replications. This matrix contains essential information on surviving ventures. It has three colums: probability of replication, position of the company in the TRUESCOOR matrix, and strategy (1=Longjumps, 2= Locals).

By adding the probabilities, we get an interval of length 1. This interval consists of various sub-intervals of different width. The width of each sub-interval represents the probability of a venture to be replicated. The higher this probability, the wider the sub-interval.

REPLICAMATRIX(:,1)=cumsum(REPLICAMATRIX(:,1));

We then generate a random number between 0 and 1. This will fall in one of the sub-intervals and the venture (and business model) that corresponds to this sub-interval will be replicated.

if random < REPLICAMATRIX(counter,1)

Then all characteristics of that venture are replicated (except for the N-N1 unknown attributes).

IV. GENERATING THE PERFORMANCE LANDSCAPE

As explained in appendix 1, the performance of each combination is calculated as the average of the performance of each attribute in that combination, given the values for its K adjacent attributes.

IV.1. Generation of the landscape

```
function [perform] = fctlandscape(k,n)
perform=zeros(2^n,1);
N=zeros(n,k,2^n);
K=zeros(n,k,2^n);
a=dec2bin(0:2^n-1);
y=a(:,1:n)/1-48;
y=cat(2,y,y(:,1:k-1));
K=a(1:2^k,n-k+1:n)/1-48;
K=K(:,:,ones(1,n));
score  = fctrandscore(k,n);

for p =1:2^n
   q_lus=0;
   z=y(p,:);
  for q=1:n
     l= 0+q:k-1+q;
     N(q,:,p)= z(l);
```

IV.2. Performance of individual attribute

This is (score(location,q));
where

location=Ffctconversion(N(q,:,p));

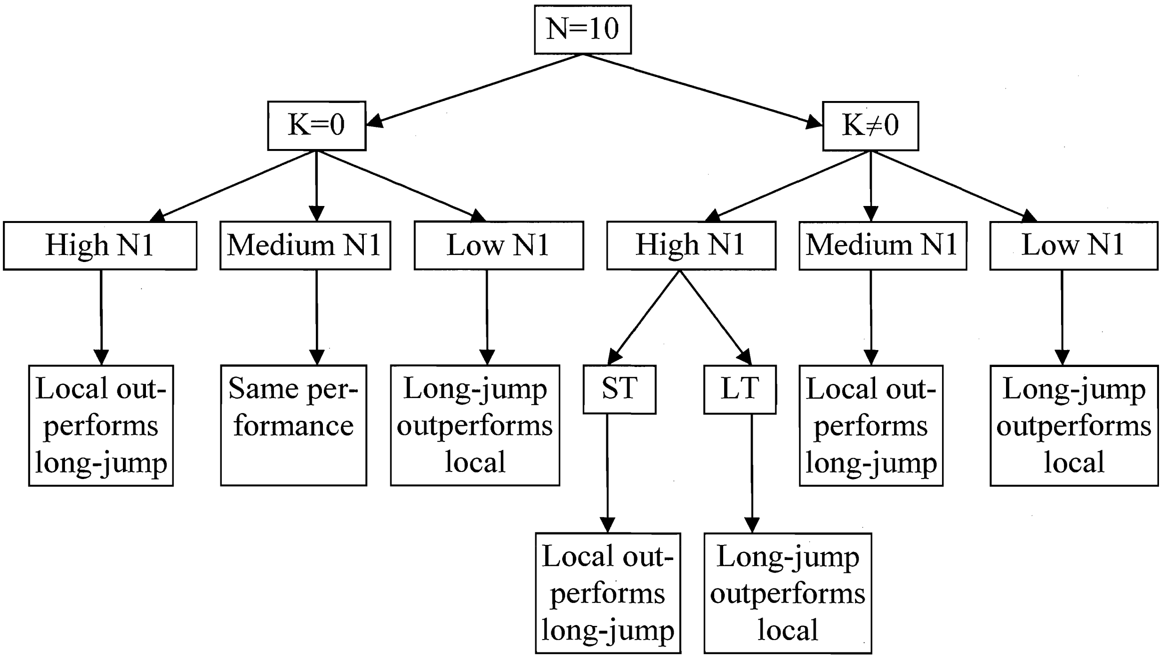
IV.3. Performance of combination

The average of the performances of all individual attributes is calculated

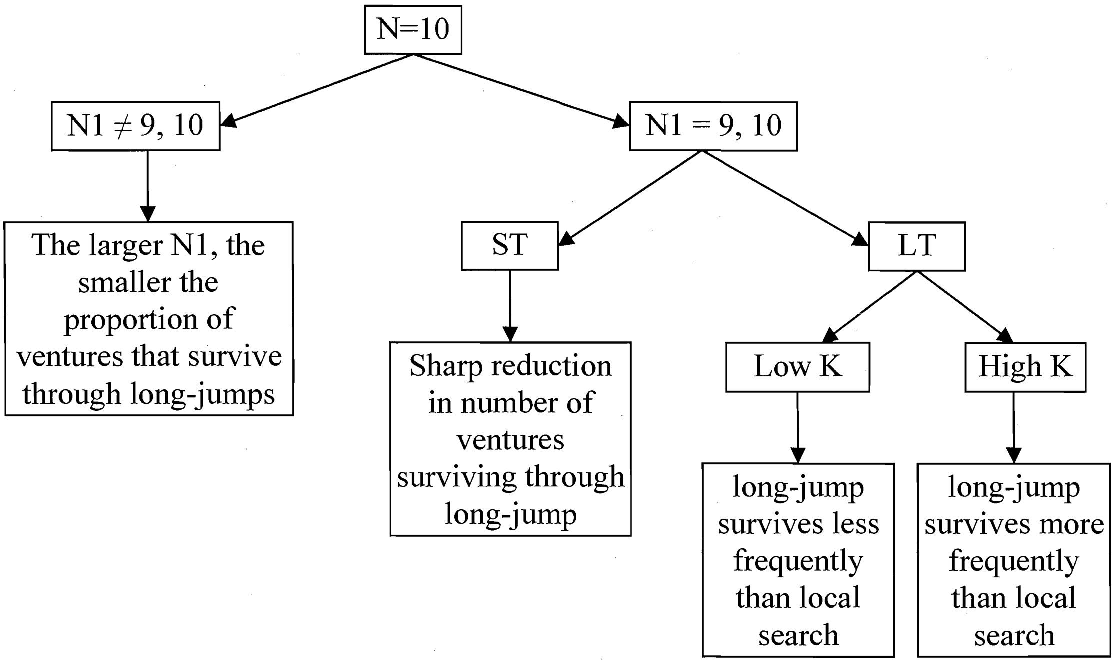
perform(p)= perform(p)+((score(location,q))/n);

Appendix 3: Schematic summary of simulation results

Pay-off



Survival



Appendix 4: Overview of additional simulations

In addition to the results mentioned in this paper, we have performed other simulations.

- The results presented are for two sets of 15 companies and for 200 simulation runs. We also ran simulations for two sets of 30 companies and for 100 and 150 simulation runs. This did not alter the results. We decided to present the results for two sets of only 15 companies, since the number of entrepreneurial companies working in the same space is often relatively small. For this total of 30 companies, we chose to do 200 simulation runs in order to obtain relatively smooth curves of the average performance and mortality rates. In general, the smaller the number of companies, the larger the number of simulations needed to smooth out the performance curves.

- The results presented are for landscapes with N=10. We also ran simulations for values of N ranging between 6 and 14. The results were very similar. However, the smaller N is, the smaller the range of possible values for N1 is, and the less detailed insights on ambiguity are. On the other hand, the higher N becomes, the more computing time is needed. We present the results for N=10 since they provide us with the same details as simulations with higher values of N, and at the same time do not require too much computing time.

- For N=10, we performed simulations for K ranging from 0 to 9 and for N1 ranging from 2 to 10. For reasons of clarity, not all these results are presented in this paper. However, these other results did not differ from the findings described above.

- Above, we define the probability of mortality as $1 - F/F_{Max}$, where F is the focal venture's performance level, and F_{Max} is the performance level of the best performing venture in the population (Levinthal, 1997). We also performed analyses with a less strict mortality criterion, where the probability of mortality was defined as $1 - F/F_{Avg}$, where F_{Avg} is the average performance level of all the ventures in the population. This lead to lower death rates. However, when introducing replacement mechanisms, the same trends as presented in Figures 3a and 3b were found, although over a slightly longer period of time.

FIGURES

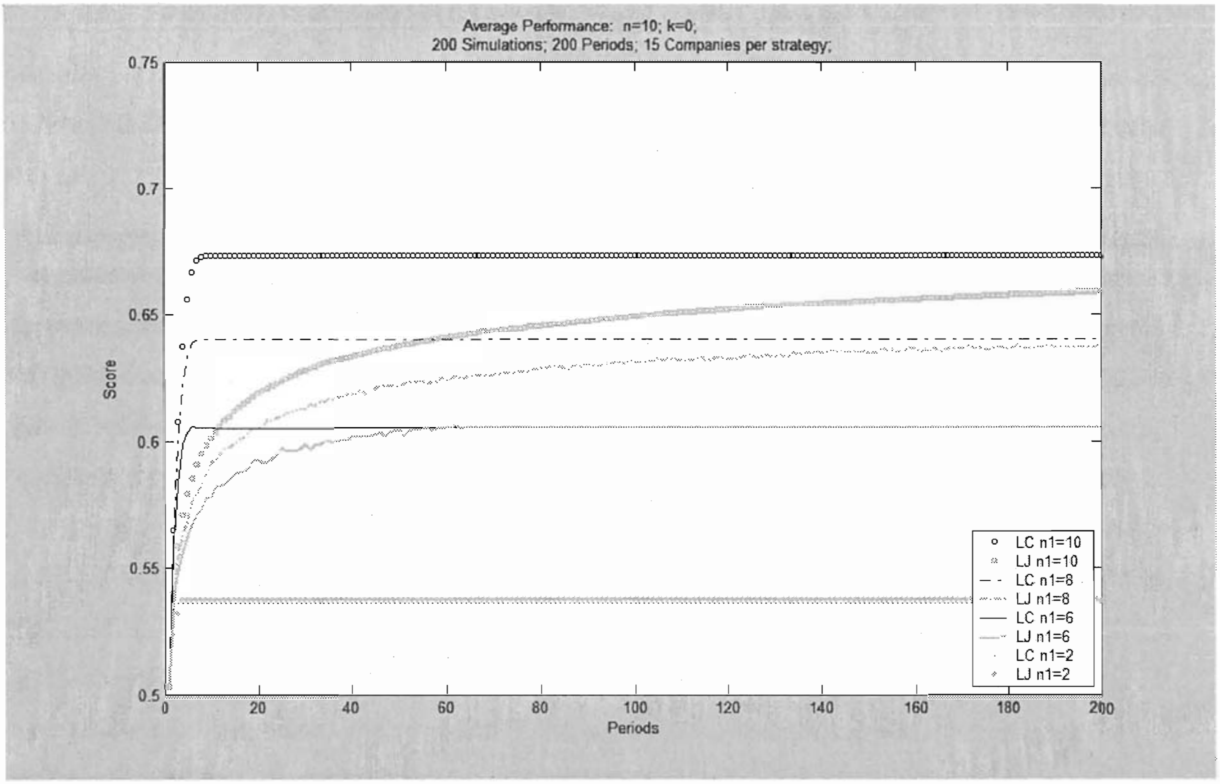


Figure 1a

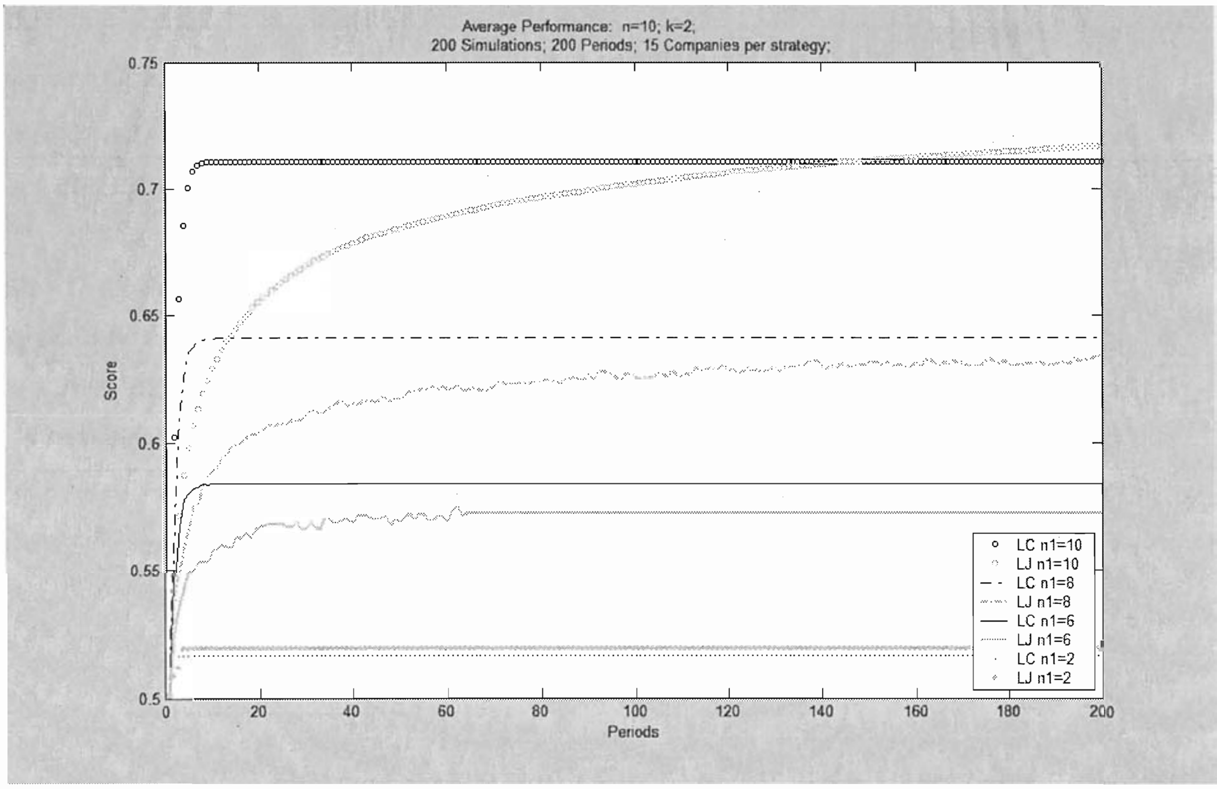


Figure 1b

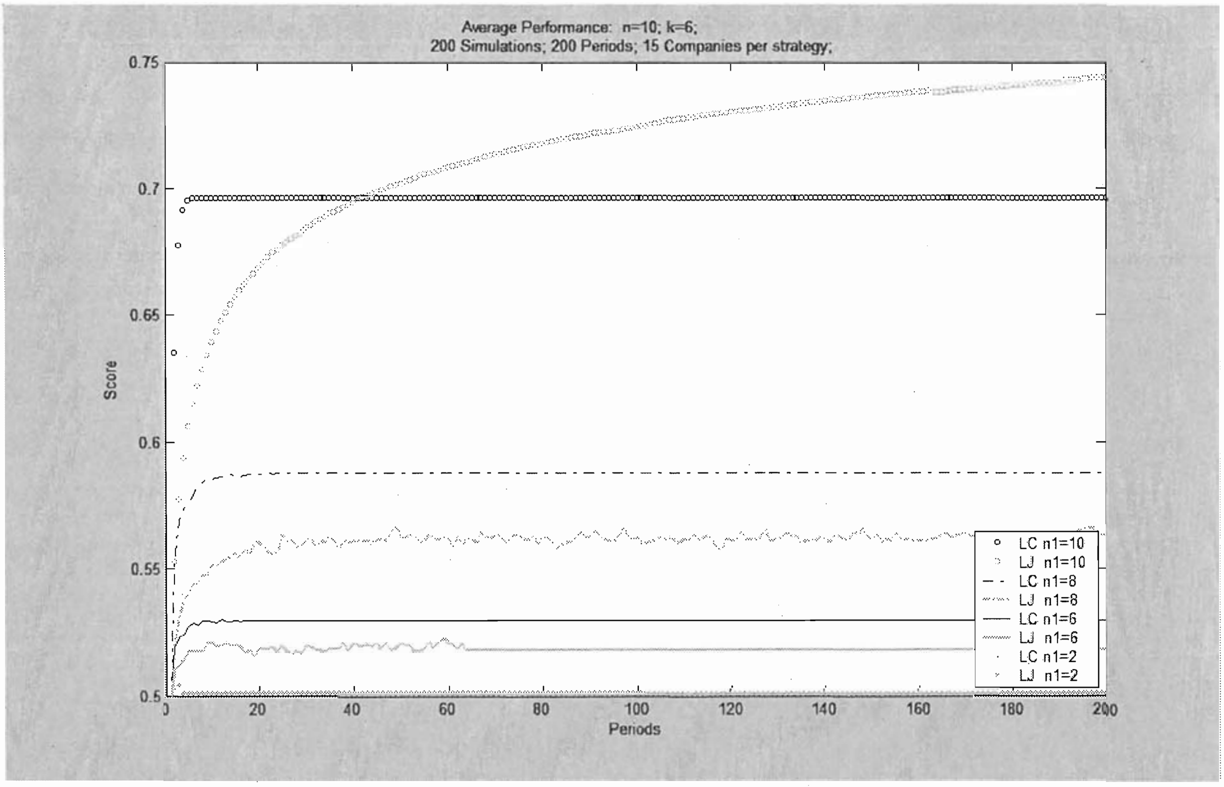


Figure 1c

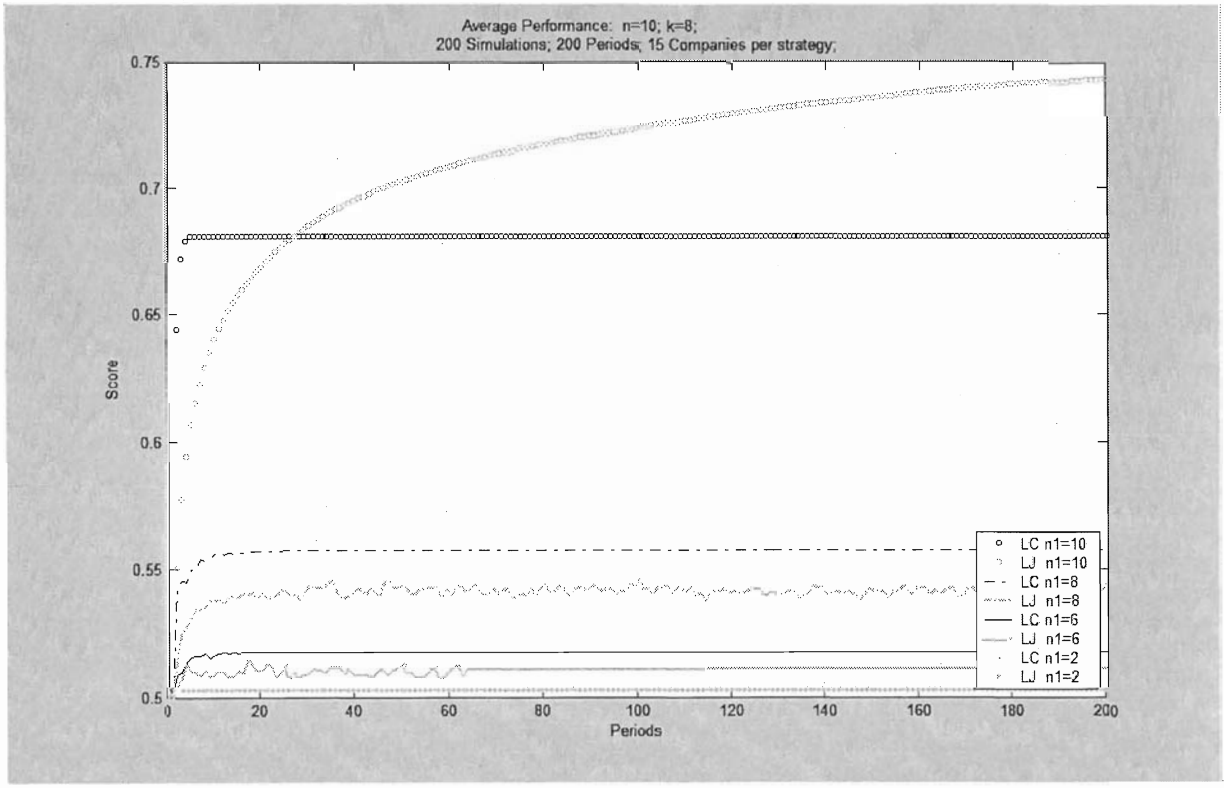


Figure 1d

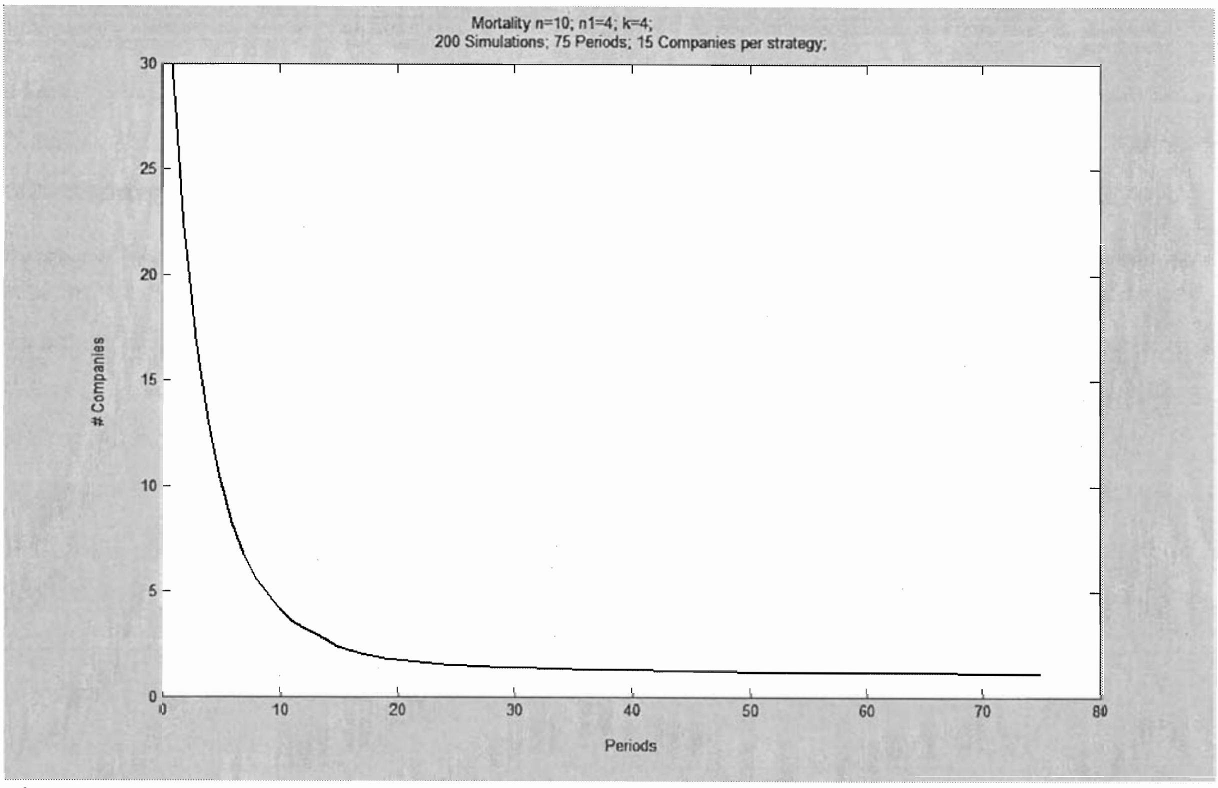


Figure 2a

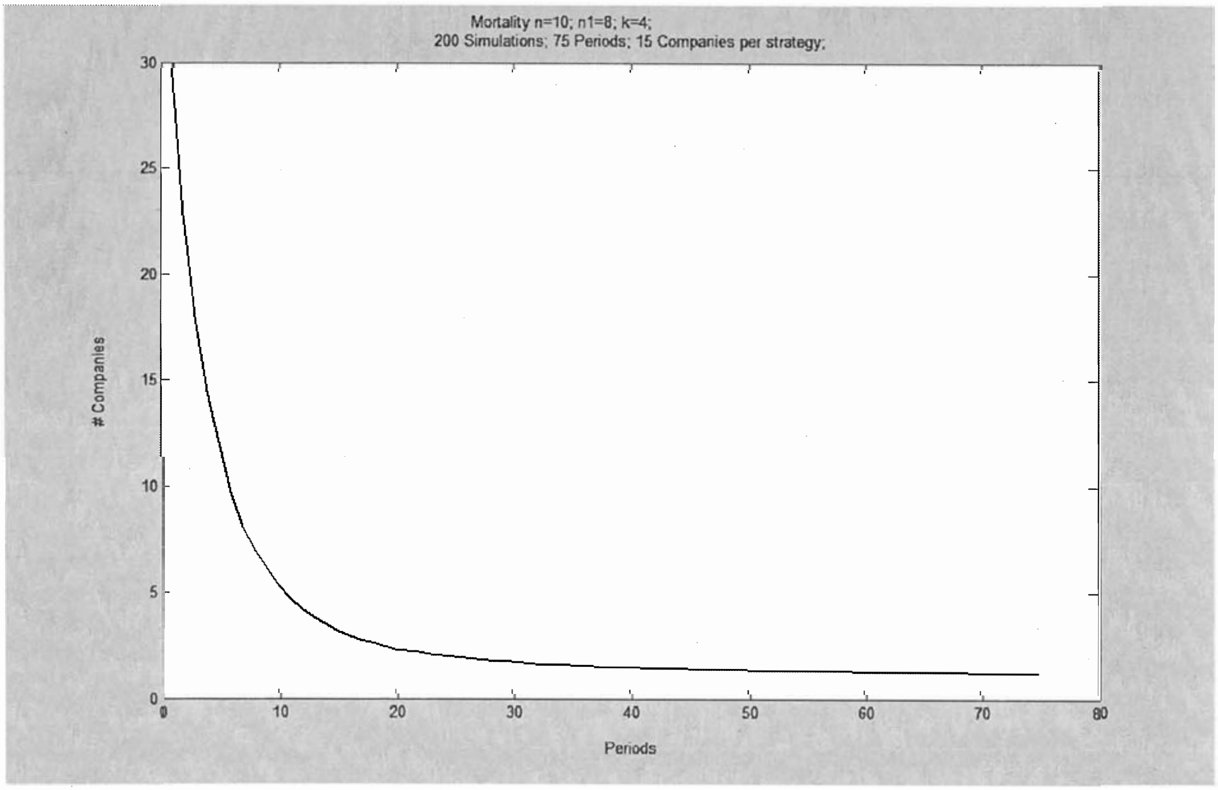


Figure 2b

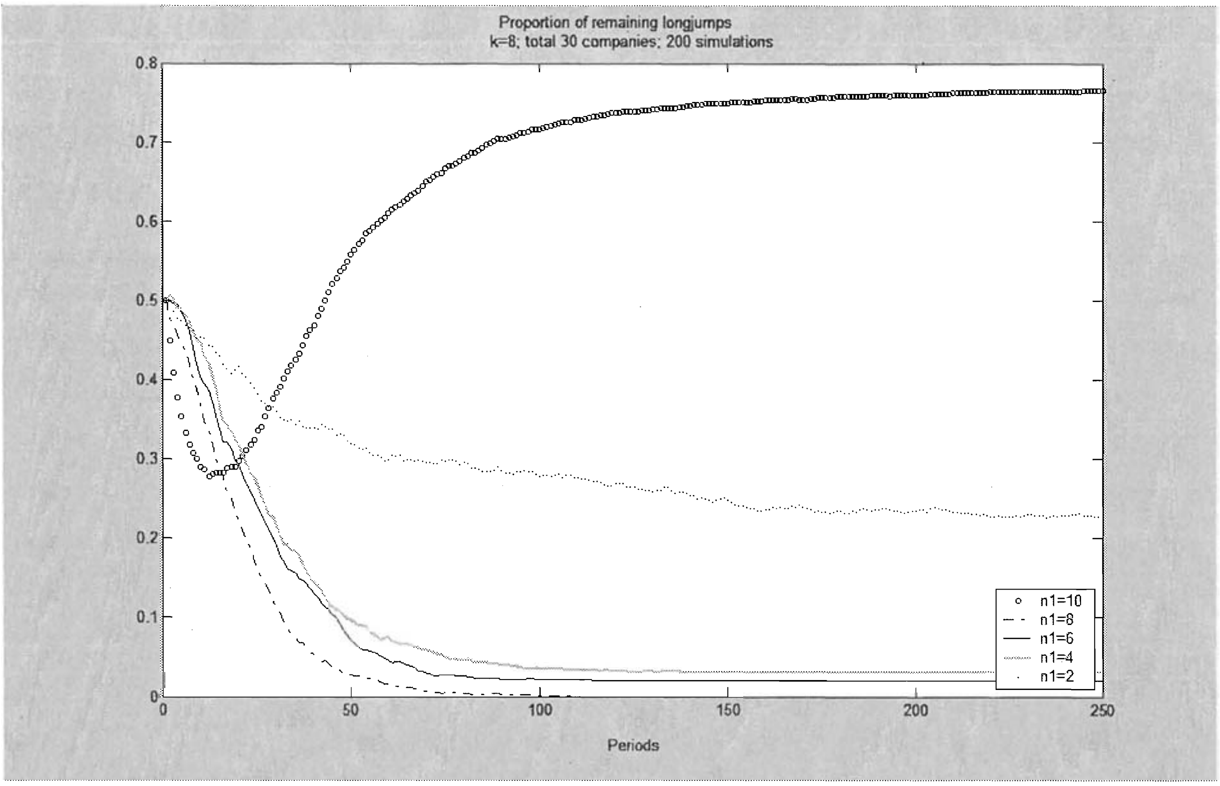


Figure 3a

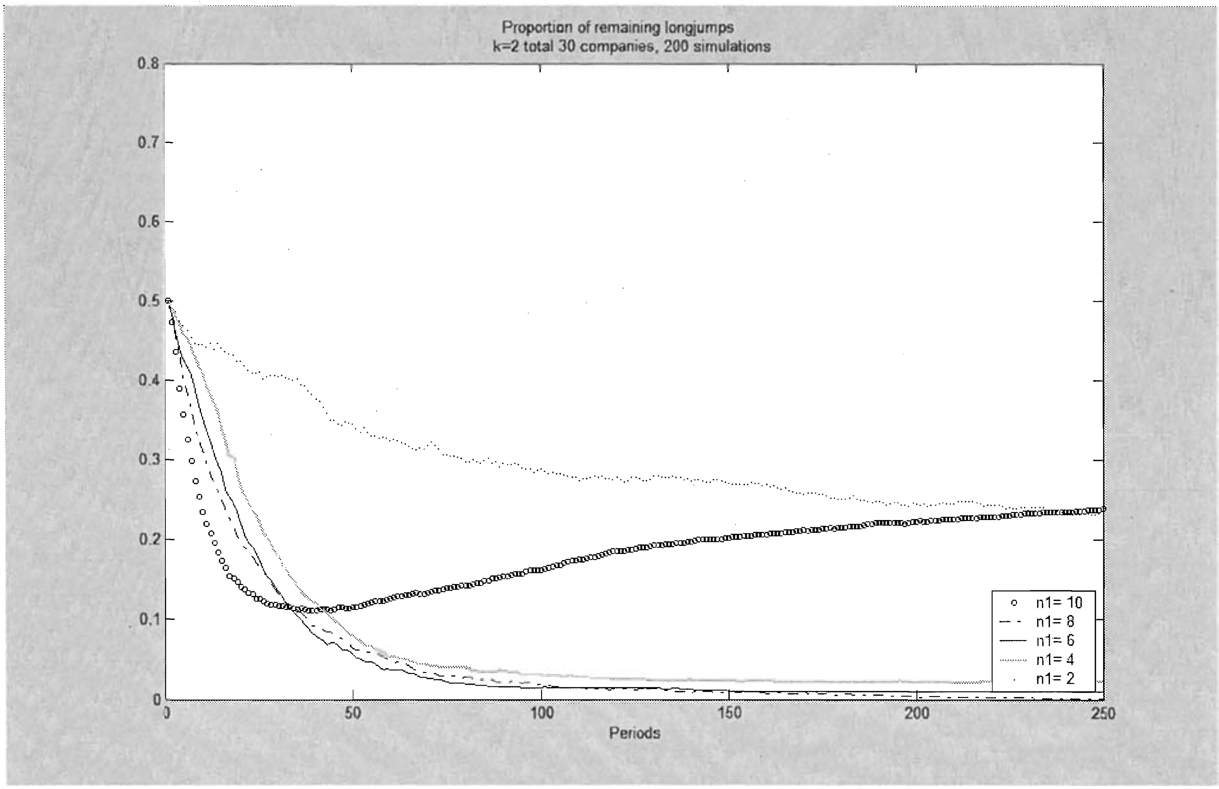


Figure 3b