INFORMATION, LEARNING AND DECISION-MAKING:
APPLICATIONS TO VENTURE CAPITAL FINANCE
AND STRATEGIC MANAGEMENT

by

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This thesis comprises three essays dealing with information and learning in business decision-making.

The first essay presents a theory explaining the existence of dedicated financial intermediaries (i.e., venture capitalists) who serve the entrepreneurial sector. Building on the well-established idea that informational asymmetries are central in entrepreneurial financing, the main hypothesis is that venture capitalists exist precisely because they develop special expertise in reducing information-based market failures through careful selection, monitoring, and other means. The primary contribution of this chapter lies in linking the theoretical structure to detailed evidence on venture capital investment in Canada. Specifically, the theory suggests four empirical predictions. It is argued that the evidence is consistent with these predictions and therefore with the central hypothesis.

In the second essay, two agents, an entrepreneur and a venture capitalist, engage in repeated, ultimatum-style bargaining about a two-dimensional financial contract. They base their offers on simple heuristics, which are processed by a genetic algorithm. The algorithm captures some fundamental principles of human learning. A simulation experiment reveals that with incomplete information, disagreement and delays in
bargaining are observed more frequently than under complete information. This can be explained by the sensitivity of agents’ learning to information. It is also found that the agent in the weak bargaining position might benefit from incomplete information.

The third essay explores a range of hypotheses that might explain differential intra-industry firm performance. A behavioral model is developed in which simple rules guide firms on whether to adapt internally and/or imitate others in order to effect organizational change. This dynamic, multi-period model, in which firms simultaneously compete, is simulated under assumptions which correspond to the hypotheses about differential firm performance. Results reveal that stochastic managerial choice and organizational inertia are plausible sources of differential firm performance. Experiential learning, in and of itself, has only limited influence on heterogeneous firm performance. Interestingly, imitation may be an undesirable strategy for underperforming firms either because it is aimed at a “moving target” or because the targeted market niche is already crowded.
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INTRODUCTION

The thesis contains three essays dealing with information and learning in business decision-making. The first essay focuses on the decision of a venture capitalist concerning whether to supply an entrepreneurial firm with financing. In order to address this issue, standard agency theory is used, which implicitly acknowledges pre-contractual and post-contractual learning by economic agents but does not explicitly model the learning process. By contrast, the second essay explicitly introduces inductive learning using a genetic algorithm. It investigates how bargaining over a multidimensional contract unfolds in the presence of incremental learning and asymmetric information. The third essay looks at managerial decisions concerning whether and how to effect organizational change. The model presented in the essay captures organizational learning and allows for examination of the phenomenon of differential firm performance. Different hypotheses about why firms perform differently are assessed.

The first essay, "Why do venture capitalists exist? Theory and Canadian evidence," seeks to develop a theoretical rationale for the existence of the venture capital industry. Why have a set of specialized firms that focus on financing the entrepreneurial sector? The basic hypothesis is that informational asymmetries are key to understanding the existence of the venture capital industry. A principal-agent model is developed and tailored to the venture capital context. Under the assumption that economic agents are perfectly rational, implications are derived from the model and tested for consistency with data on Canadian venture capital investment.

The essay makes both theoretical and empirical contributions to the literature on venture capital finance.
First, it presents a theoretical model based on the traditional framework of information economics which offers a rationale for the existence of venture capital firms. The model suggests that venture capitalists can cope better with moral hazard and adverse selection than other investors because they possess superior skills in screening and monitoring investee companies. In addition, they render value-added services to investee companies, which is shown to attenuate problems that may arise from asymmetry of information. The model predicts that venture capitalists may be expected to focus on industries where information asymmetries are important; that venture capitalists prefer to invest in firms that have some track record of performance; that venture capitalists tend to favor later stage over early stage investments; that venture capital backed firms which are sold through initial public offerings are among those which perform well; and that there is a negative relationship between the extent of venture capital ownership and the performance of entrepreneurial firms. Using empirical techniques ranging from simple descriptive statistics to regression analysis, we find that data on Canadian venture capital investment are largely consistent with these predictions.

The second essay, “A genetic algorithm approach to repeated bargaining with asymmetric information,” examines the effects of learning in bilateral bargaining under different information structures. It shares with the preceding chapter an interest in exploring asymmetric distribution of information as a potential source of market (in this case, bargaining) failures. It also casts the research question in terms of financial contracting in the venture capital context: Why would asymmetric information be a problem when a venture capitalist and an entrepreneur negotiate a financial deal? How is the agents’ ability to learn affected by incomplete information?

The multidimensional, multi-period bargaining model presented in this essay has applicability beyond the area of financial contracting between entrepreneurs and venture capitalists; its focus is broader than that of the model developed earlier. The essay also weakens some of the strong rationality assumptions made in
chapter one. Agents are represented as collections of simple decision rules. Their experiential learning is modeled by a genetic algorithm, which may produce new rules in every period. The evolutionary model thus delineates some of the cognitive processes that are hidden in the 'black box’ of a decision maker’s mind. Different information structures are directly incorporated into the model, which is analyzed via computer simulation.

I find that even under complete information about each other’s preferences and expectations, agents sometimes fail to reach an agreement within a given time limit. Under incomplete information, one can observe longer delays, more failures to agree, a larger variety of failure types (which, for example, refers to who breaks off negotiations), and a bigger variance of outcomes. Interestingly, results also show that incomplete information may have beneficial distributional consequences for the person who is in the weak bargaining position. Put differently, incomplete information may prevent the agent who is in a superior position from exploiting his bargaining power. This is consistent with evidence from experiments with human subjects. The results of the second essay broadly suggest that inefficient bargaining under incomplete information can be explained within the framework of boundedly rational decision making and learning. The paper thus complements game theoretic treatments of the subject which assume perfect rationality and offer a signaling rationale for inefficient outcomes. This is its primary contribution.

The third essay, “Differential firm performance in a behavioral model of organizational change,” seeks to improve our understanding of why, contrary to predictions derived from many neoclassical models, firms within the same industry perform differently. It assesses various hypotheses that might explain heterogeneous intra-industry firm performance through simulation of a model in which firms make decisions on whether and how to enact organizational change. The paper contributes to the strategy field in at least three distinct ways. First, it provides a formal and rigorous link between some prominent explanations for
heterogeneous firm performance and well-established empirical facts. Second, it suggests a simple formalization of the notion of dynamic capabilities. Third, it combines the resource-based view of the firm with behavioral decision theory.

The third essay shares a number of characteristics with its predecessor: it relies on the representation of economic agents (in this case, firms instead of individuals) as bundles of decision rules; it views learning as an essential feature of the decision making process; it utilizes computer simulation in order to gain insight into an analytically complex model; and it incorporates crucial hypotheses as assumptions into the simulation model. In addition, it focuses on a dynamic setting without exogenous shocks and considers incremental and radical forms of experimentation by agents, namely ‘adaptation’ and ‘imitation’ (compared with ‘mutation’ and ‘crossover’ in chapter two). Thus, the essay has strong methodological links with chapter two. However, agents learn to a lesser extent from history (i.e., feedback), which is an appropriate assumption in the context of organizational change. Forecasting of future performance largely replaces assessment of past results in determining which actions firms should take.

Chapter three yields a number of interesting results. Stochastic managerial choice and organizational inertia are found to be plausible explanations for differential firm performance. However, in the long run, no single firm or group of firms dominate an industry, which is consistent with empirical facts. Firms either converge, or take turns in leading their industry. Against widely held beliefs among strategy researchers, organizational learning may have only very limited influence on heterogeneous firm performance. In the simulations, path dependencies leading to differential performance can only be observed under special conditions. It is also revealed that imitation, though sometimes providing a viable means for undermining the competitive advantage enjoyed by a rival firm, may be an inefficient strategy for two reasons. It is usually aimed at a “moving target,” and the targeted niche may already be crowded.
In summary, the first and the second chapter look at similar topics using different methodological lenses, whereas chapters two and three use similar methodologies to address related but distinct questions in business decision making. Despite these similarities, each essay stands on its own as an analysis of a pertinent issue in either entrepreneurship theory or strategy.
CHAPTER 1

WHY DO VENTURE CAPITAL FIRMS EXIST?
THEORY AND CANADIAN EVIDENCE

1.1 INTRODUCTION

In both Canada and the United States, venture capital finance is a significant form of financial intermediation. There is no strict regulatory definition of the venture capital industry, unlike commercial banking or insurance but, generally speaking, venture capital firms provide privately held "entrepreneurial" firms with equity, debt, or hybrid forms of financing, often in conjunction with managerial expertise. In Canada these firms are playing an increasingly important role. As reported in Macdonald & Associates (1996), between the end of 1991 and the end of 1995, the amount of capital under management by Canadian venture capital firms grew from C$3.2 billion (or about $3.8 billion in 1995 dollars) to C$6 billion, implying an annualized real growth rate of about 12% per year. The rate of new investment by venture capital firms grew even more rapidly, rising from C$290 million in 1991 (or C$306 million 1995 dollars) to C$669 million in 1995, which corresponds to real growth of more than 20% per year.

Despite its growing importance, the venture capital industry has received much less academic scrutiny than
other parts of the financial sector.¹ This applies both to theory and to empirical investigation. At the theoretical level, perhaps the most fundamental question to ask about the venture capital industry is why it exists at all. Why have a set of specialized firms that focus on financing the entrepreneurial sector? Even if there were no dedicated venture capital firms, a combination of commercial banks, investment banks, private investors, and stock exchanges providing the necessary intermediation could still be imagined. In fact, among entrepreneurial firms, most finance is provided by banks and private investors (including family members), and many young entrepreneurial firms “go public” on stock exchanges without first seeking venture capital finance. In seeking to understand venture capital finance, it therefore seems important to ask what exactly is the niche filled by venture capital firms.

The primary objective of this paper is to present a theory explaining the existence of the venture capital industry and to investigate the consistency of this theory with empirical observations. Our basic hypothesis is that informational asymmetries are the key to understanding the venture capital industry. Previous papers have focussed on the importance of asymmetric information in venture capital markets, and several authors have suggested that a central distinction between venture capitalists and other financial intermediaries is that venture capitalists operate in situations where asymmetric information is particularly significant. In this paper we provide a simple formal model that distinguishes venture capitalists from other potential investors on the basis of their ability to deal with informational asymmetries. This model is also used to draw inferences about how venture capital financing would be expected to work. These predictions are then compared with the actual pattern of venture capital investment in Canada. This link between theory and

¹The venture capital industry is more difficult to study than other financial industries such as banking, insurance, stock markets, etc. Little of the relevant information is in the public domain, since the firms financed by venture capitalists are privately held and therefore do not have the same public reporting requirements as publicly traded firms. Also, regulatory scrutiny of the industry is modest compared to other financial services, so relatively little information arises from regulatory activities. Finally, there are no organized exchanges for venture capital investments, so no information derives from that source.
empirical evidence is the main contribution of the paper.

There are two major forms of informational asymmetry. One type, sometimes referred to as “hidden information,” occurs when one party to a transaction knows relevant information that is not known to the other party. For example, an entrepreneur developing a new product may have a much better idea about whether the product will actually work than does the venture capitalist who may finance the venture. The problem arises because the informed party typically has an incentive to misrepresent the information. The entrepreneur, for example, may have an incentive to overstate the likelihood of successful product development. Furthermore, the market may become crowded with “low quality” projects, precisely because it is hard for investors to distinguish between good quality and poor quality projects. This phenomenon is called adverse selection. Potential investors understand that adverse selection exists and may therefore be wary of funding such entrepreneurial endeavours.

The other type of informational asymmetry is often described as “hidden action.” In this situation one party to a transaction cannot observe relevant actions taken by the other party (or at least cannot legally verify these actions). For example, an investor in an entrepreneurial firm might not be able to observe whether the entrepreneur is working hard and making sensible decisions, or whether the entrepreneur is planning to “take the money and run.” This problem leads to what is called “moral hazard.” The informed party then has an incentive to act out of self interest, even if such actions impose high costs on the other party.

Both adverse selection and moral hazard may arise in any investment environment, but they seem

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2A local financial advisor summed up a typical reaction: “You can meet 10 entrepreneurs at a party and each one will tell such a good story that you will want to invest your life savings. Remember, however, that you will lose money on at least 7 out of the 10. My policy is never to invest in entrepreneurial ventures.”
particularly acute in entrepreneurial finance. With large established firms, investments are made safer by the use of existing assets as collateral, and by the development of reputation. Collateral and reputation effects can mitigate the negative effects of both adverse selection and moral hazard. Because entrepreneurial firms lack assets to provide as collateral, and because they lack the "track record" necessary to establish their reputation, the effects of informational market failures are more severe in entrepreneurial finance than in financing established firms.

Our central hypothesis is that venture capitalists emerge because they develop specialized abilities in selecting and monitoring entrepreneurial projects. In other words, venture capitalists are financial intermediaries with a comparative advantage in working in environments where informational asymmetries are important. This is their niche.³

The next section of our paper provides a brief review of relevant literature, followed by a section that sets out a formal model of venture capital finance and derives associated empirical predictions. The fourth section describes the data set obtained from Macdonald & Associates, and the fifth section compares the theoretical predictions with the data. The final section contains concluding remarks.

1.2 LITERATURE REVIEW

Akerlof (1970) is normally taken as the starting point of the formal analysis of informational asymmetry. Akerlof describes a situation where sellers of used cars have private information about the quality of their cars, but buyers cannot discern quality differences before purchase. In this setting, low quality cars or

³This analysis focuses on the venture capitalist’s role as a buyer of entrepreneurial assets. Venture capitalists must also be good at selling these assets. That is, they must also exit effectively from their investments.
“lemons” dominate the market, thus the market “selects” adversely. Akerlof showed that this adverse selection is inefficient in that potentially efficient (i.e., Pareto-improving) trades will not take place.

Adverse selection problems can arise in many circumstances. For example, in insurance markets, buyers may know their true risk better than insurance companies (as in Pauly (1974)), and in labour markets, workers may be more aware of their abilities than potential employers are (as in Spence (1973)). Spence points out that one natural market response to adverse selection is “signalling,” where an informed party (usually the seller of the high quality item) provides some signal of high quality. Thus, for example, product warranties may be signals of high quality. Rothschild and Stiglitz (1976) emphasize the role of screening, under which the uninformed party offers a contract or set of contracts that cause informed parties to self-select into different groups.

Hidden action (and moral hazard) was first discussed in insurance markets, where insured parties can take actions that either decrease or increase the risk of hazard. For example, after purchasing auto insurance, the insured party can either drive safely or dangerously. Early influential work on moral hazard includes Arrow (1973) and Pauly (1974), who showed that moral hazard causes market failure. Moral hazard problems are particularly important in many situations where one party acts as an agent for another party, such as when a client hires a lawyer, or the seller of a house hires a sales agent. In these situations, the “principal” cannot perfectly observe the effort (or other actions) of the agent. Jensen and Meckling (1976) argue that agency relationships are the key to understanding the modern firm. Thus, for example, the managers of the firm can be viewed as the agents of the owners, who might in turn be viewed as the agents of other investors in the firm.

Adverse selection and moral hazard are often viewed as crucial determinants of venture capital financing.
Sahlman (1990), for example, postulates that contracting practices in the venture capital industry reflect informational asymmetries between venture capitalists and entrepreneurs, and argues that the lack of operational history aggravates the adverse selection problem. MacIntosh (1994) also asserts the basic idea that informational asymmetries are fundamental in the venture capital sector, and this point is also emphasized in Amit, Glosten and Muller (1993). Various other papers implicitly recognize the importance of informational issues. For example, MacMillan, Zemann, and Narashima (1987) provide a valuable discussion of how venture capitalists screen new projects.

Chan (1983) highlights the role of venture capitalists in reducing the adverse selection problem in the market for entrepreneurial capital. He shows that an adverse selection result derives from the absence of any informed venture capitalists in the sense that only inferior projects are offered to investors. However, the introduction of informed investors may overcome this problem, leading to a Pareto-preferred solution. Amit, Glosten and Muller (1990) present an agency model in which investors are uncertain about the entrepreneur's type when submitting investment "bids." The authors relate the venture capital financing decision to the entrepreneur's skill level and predict which entrepreneurs will decide to enter into an agreement with venture capitalists.

Sahlman (1990) notes that staged investment, which creates an option to abandon the project, is an important means for venture capitalists to minimize agency costs\(^4\). The role of staged investment as a monitoring device is also examined by Gompers (1995). In addition, the active involvement of venture capitalists in the operation of their investee companies might mitigate the moral hazard problem. The empirical significance of the role of venture capitalists as monitors is supported by Barry et. al. (1990) and by Lerner (1995). In

\(^4\)Admati and Pfleiderer (1994) and Hellman (1994) provide formal models of staged finance in the venture capital context.
addition, Lerner (1994) suggests the use of syndication (i.e., coordinated investment by two or more venture capitalists) as a method of reducing problems caused by informational asymmetries. Two other useful papers that describe actions that venture capitalists can take to reduce problems arising from informational asymmetries include Tyebjee and Bruno (1984) and Fried and Hisrich (1994).

Chan, Siegel and Thakor (1990) seek to explain various “rules of thumb” in venture capital contracting practices as a response to informational asymmetries and, in a related paper, Hirao (1993) assumes that the entrepreneur’s unobservable actions affect the venture capitalist’s learning process, and uses this context to study the effects of different contracts. A more general overview of research challenges in the venture capital area is given by Low and MacMillan (1988).

Despite a number of empirical and descriptive studies on venture capital practices and activities, including some of those already mentioned and also MacMillan, Siegel and Narashima (1985), Bygrave and Timmons (1992), and Gompers and Lerner (1994), among others, empirical work on venture capital finance is still relatively modest in scope compared to the analysis of other financial intermediaries. Our paper seeks to add to this literature. Specifically, we provide a formal model that uses asymmetric information to explain the existence of venture capitalists, then compare the predictions of this theoretical structure with evidence on venture capital finance in Canada.

1.3 A THEORY OF VENTURE CAPITAL FINANCE

An entrepreneur has a potential project and seeks potential investors. To keep the analysis simple we assume that the project requires fixed financial input I from an investor. The expected cash flow from the project, net of production costs, is denoted R (for “net operating revenue”). This expected net operating revenue
depends in part on the effort, e, provided by the entrepreneur and it depends in part on the underlying project quality, q. In addition, the outcome depends on a random variable, u, with expected value 0. The realized net cash flow is therefore

\[ R(e,q) + u \]  

(1.1)

where the expected operating revenue is \( R(e,q) \). We assume that entrepreneurs and investors are risk-neutral expected value maximizers. We therefore ignore u and work with \( R \). Variable u plays one important role, however. Given unobservable random uncertainty, as represented by u, it is not possible for an investor who knows project quality q to infer effort e from the cash flow realization.

If e cannot be observed by the investor, then it is a hidden action and gives rise to a moral hazard (or "agency") problem. If q is known to the entrepreneur, but not to the investor, then it is hidden or private information and gives rise to potential adverse selection. The presence of exogenous uncertainty as represented by random variable u does not in itself cause market failure. \( R \) is taken to be increasing in e and q. We also assume that there are decreasing marginal returns to effort. The effort effects can be written formally as

\[ R_e > 0, \quad R_{ee} < 0 \]  

(1.2)

where subscripts denote (partial) derivatives.

Let the share of the proceeds that go to the investor (possibly a venture capital firm) be denoted \( \alpha \). The expected return \( V \) to the investor is

13
\[ V = \alpha R(e,q) - I \]  

(1.3)

The expected return to the entrepreneurial firm, denoted \( \pi \) (for "profit"), is its share of the proceeds, net of the costs of effort \( e \).

\[ \pi = (1-\alpha)R(e,q) - e \]  

(1.4)

Variable \( e \) is normalized so that providing \( e \) units of effort imposes cost \( e \) on the entrepreneurial firm.

1.3.1 Moral Hazard

To demonstrate the moral hazard problem, assume initially that \( q \) is known to both parties. A profit maximizing entrepreneur will maximize (1.4) with respect to \( e \), leading to the following first order condition:

\[ \pi_e = (1-\alpha)R_e - 1 = 0 \text{ or } R_e = 1/(1-\alpha) \]  

(1.5)

The second order condition for a maximum is \((1-\alpha) R_{ee} < 0\). Noting that the factor \((1-\alpha)\) is presumed to be strictly positive and using (1.2), this second order condition must hold.

The efficient or "first-best" level of effort is determined by maximizing the sum of (1.3) and (1.4) with respect to \( e \). This sum, denoted \( S \), is

\[ S = R(e,q) - I - e. \]  

(1.6)

Maximizing (1.6) with respect to \( e \) yields the following first order condition
It follows from (1.5), (1.7), and (1.2) that the entrepreneur will choose less than the efficient level of effort as long as \( a \) is strictly positive. This is the moral hazard problem. It is illustrated in Figure A1 in Appendix 1. It follows from the corresponding algebra and from Figure A1 that effort is declining in \( a \).

\[
de/d\alpha < 0
\]  

(1.8)

It is possible that the moral hazard problem might render the project infeasible. The investment is attractive to the investor only if the return equals or exceeds the alternative value that can be obtained by investing \( I \) elsewhere. Let this required return or opportunity cost be denoted \( r \). Then feasibility requires

\[
(1+r)I \leq \alpha R(e(\alpha),q)
\]  

(1.9)

The problem is that there may be no value of \( a \) that allows (1.9) to be satisfied. If the expected return to the investor is too low, this suggests raising \( a \), but then \( e \) will fall (from (1.8)), reflecting the idea that the entrepreneur will provide less effort as his stake in the firm falls.

Feasibility for the entrepreneur requires that the expected profit given by (1.4) exceed the return from the entrepreneur’s best alternative, which can be normalized to equal 0. It is possible that effort level \( e^* \) would in principle allow feasibility for both investor and entrepreneur, but that the actual effort relationship, \( e(\alpha) \) would not allow the project to be financed. Thus the moral hazard problem may cause the market to fail.

We now introduce the idea that investors can monitor the entrepreneur and, at some cost, induce the
entrepreneur to provide additional effort. Denote the monitoring cost \( m \). The expected return to the investor is therefore

\[
V = aR(e(a,m),q) - 1 - m
\]  

(1.10)

If the responsiveness of \( e \) to \( m \) is low, then the investor will not bother to monitor, as the cost will exceed the benefit. Some investments may be worthwhile, without monitoring, in spite of the moral hazard problem, but many projects will be abandoned. If \( e \) is highly responsive to monitoring, then the investor will undertake monitoring and will elicit an effort level closer to “first-best” level \( e^* \). Projects that are not financed by other investors will be feasible for investors who are good at monitoring (i.e., those for whom the responsiveness of \( e \) to \( m \) is high).

It is also possible that the investor provides valuable services, \( s \), to investee companies. These services (e.g., providing strategic and operational advice, helping in fundraising, adding reputation etc.) are observable by the entrepreneur. Ignoring monitoring for the moment and normalizing the cost of providing \( s \) to $1 per unit, the expected return to the investor is now

\[
V = aR(e(a),q,s) - 1 - s
\]  

(1.11)

We can think of the effect of \( s>0 \) on the operating revenues \( R \) in the following way. Services \( s \) can either produce a direct (positive) effect on \( R \) through \( R_e>0 \) (case 1) or it can have an indirect (positive) effect on \( R \) through enhancing the marginal productivity of the entrepreneur’s effort, or \( R_{es}>0 \) (case 2). When both effects are present, \( R_e>0 \) and \( R_{es}>0 \), we have case 3. Figure 1.1 illustrates these different cases and compares them with the benchmark case where \( s=0 \).
Case 1 is defined as the case in which the investor's provision of s does not affect the entrepreneur's productivity of effort, $R_e$, but raises revenues directly. Let us assume that this effect is additive. For each effort level $e$ expanded by the entrepreneur, the provision of $s > 0$ by the investor will increase the venture's revenues by $\Delta R$. This is expressed in Figure 1.1 as a parallel upward shift of the graph of $R(e)$ from the benchmark case to case 1. With respect to the moral hazard problem this means that, relative to the benchmark case, $R_e$ and thus the entrepreneur's incentive constraint (1.5) remain unchanged in case 1. Therefore our basic analysis for $s=0$ still holds (see equations (1.1)-(1.9) and Appendix 1.1). In other words, the moral hazard problems in the benchmark case and in case 1 are identical.

In cases 2 and 3, however, the provision of $s$ improves the productivity of $e$, and $R_e$ is consequently shifted upward. This results in steeper curves for cases 2 and 3 in Figure 1.1. The entrepreneur's incentive constraint (1.5) is affected by this change, and therefore a new analysis of the moral hazard problem is required. Let
us denote the case where $s = 0$ with superscript 0 and cases 2 or 3 where $s = k > 0$ with superscript $s$. “First-best” effort levels are denoted $e^*$, “second-best” effort levels $e'$. The new situation is depicted in Figure 1.2.

**FIGURE 1.2:** First- and second-best effort levels in base case ($s=0$) and under $R_e>0$

Figure 1.2 is based on the above distinction between different possibilities how $s$ can affect $R$, and it also draws on the previous discussion of the standard moral hazard problem (without monitoring or services rendered). It allows us to conclude that the moral hazard problem persists for $s > 0$ even if $R_e>0$. In this case, the “second-best” effort level $e'$ is still smaller than the “first-best” effort $e^*$. However, relative to the base case scenario, the entrepreneur is now be willing to put forth more effort ($e'>e^*$).

Thus the provision of $s$ might contribute to the realization of projects which otherwise would have been
abandoned, because they did not fulfill the investor's original feasibility constraint \( (1.9) \). Considering \( s \), the investor's feasibility constraint now becomes

\[
(1+r) I + s \leq aR(e(\alpha), q, s) \quad (1.12)
\]

If \( s \) is not prohibitively high, then it might relax this constraint through its direct and indirect positive effect on \( R \). Thus investors who are skilled at providing value-creating services to their portfolio companies will undertake certain projects which other, less skilled investors will shun.

There is ample evidence that venture capitalists provide valuable services to their portfolio companies. Gorman and Sahlman (1989) compiled a list of such services from a survey of venture capital investors. The five highest ranked and most frequently used activities they found can either be interpreted as directly enhancing investee revenues (e.g., introduction to potential customers and suppliers, and help to obtain additional financing) or as enhancing the entrepreneur's productivity of effort and thus indirectly boosting investee revenues (e.g., strategic planning, management recruitment, and operational planning).

We now turn to the case in which both monitoring and services are considered. The effects of \( s \) on \( R \) might be important enough to render projects feasible which were infeasible even with optimal monitoring. In fact, it seems natural to assume that a combination of monitoring and the provision of services constitutes a powerful tool in the hands of specialized investors to reduce moral hazard problems. Note, for example, that the entrepreneur's "second-best" effort provided in the case where \( s > 0 \) and \( m > 0 \) might be higher than the "first-best" effort in the benchmark case where \( s = 0 \) and \( m = 0 \). (Refer to Figure 1.2 and recall that if \( e \) is sufficiently responsive to \( m \), \( e^* \) might get fairly close to \( e^{**} \) under an optimal monitoring regime.)
Another point worth emphasizing is that providing services to entrepreneurs might make it easier and thus cheaper for investors to monitor them. Denoting $M(m|s)$ as the monitoring costs at a given level of $s$, it is very likely, for example, that $M(m|s>0) < M(m|s=0) = m$. Thus, the return to the investor given monitoring and services is

$$ V = aR(e(\alpha,m),q,s) - I - s - M(m|s) $$ \hspace{1cm} (1.13)

We note that investors who are good at monitoring and at providing valuable services to their portfolio companies are likely to invest in firms with more severe moral hazard problems, as their feasibility constraint is more likely to be fulfilled.

### 1.3.2 Adverse Selection

A similar pattern emerges when adverse selection is considered. Assume that the venture capitalist chooses the optimal amount of services rendered and the optimal amount of monitoring effort, giving rise to associated values of $e$ and $s$ for any given $\alpha$. Quality level $q$ is now unobservable to the investor. Suppose that the range of $q$ is such that the average quality project does not yield enough expected returns (for any value of $\alpha$) to allow both (1.13) and (1.4) to be positive. Thus the average project is not worth funding. Formally, we can write the investor’s expected return as

$$ EV = \int_{\alpha}[aR(e(\alpha,m(\alpha)),q,s(\alpha)) - I - s(\alpha) - M(m(\alpha)|s(\alpha))]f(q)dq < 0 $$ \hspace{1cm} (1.14)

where $f(q)$ is the probability density function for project quality. In order to simplify this expression we subsume the terms that do not bear directly on the analysis of the hidden information problem into investor’s costs $C$. With
\[ C = I + s(\alpha) + M(m(\alpha)|s(\alpha)) \]  

Inequality (1.14) reduces to

\[ EV = \int_q [\alpha R(q) - C] f(q) dq < 0 \]  

Inequality (1.16) says that the expected value across all projects is negative. However, some of the individual projects (those in the upper end of the quality distribution) may be very valuable. Suppose, for example, that the top 40% of projects could generate a positive net profit. Unfortunately, the entire market will normally fail in this situation, as it will typically not be worthwhile for investors to provide financing, even though many individual projects are worthwhile.

Now suppose that an investor can acquire information about the quality of an individual project by spending d before making the actual investment I. Parameter d can be interpreted as the cost of “due diligence”. This cost determines the probability, p(d), with which an investor can establish whether the quality of a certain project exceeds a threshold level of quality. We denote this threshold level of quality as q°. Let us implicitly define q° as follows:

\[ V = \alpha R(q) - C = 0 \quad \text{for } q=q^° \]
\[ V > 0 \quad \text{for } q>q^° \]
\[ V < 0 \quad \text{for } q<q^° \]  

The “detection function” p(d) is assumed to have the following properties:
Let us restate the assumptions concerning the sequence of events in the above model. Investment in an entrepreneurial firm is a one period, multi-stage process as illustrated in Figure 1.3.

In the first stage, the investor incurs an up-front cost of $d$ in order to assess the quality of a potential investment. With probability $p(d)$ the investor will become informed about $q$ and will therefore find out whether $q > q^0$ or $q < q^0$. Only in the former case an investment will be made. With probability $(1-p(d))$, however, the investor will remain uninformed about $q$ and, due to (1.16), refrain from investing. Stage 3, in which the entrepreneur displays effort and is monitored and supported by the investor, and stage 4, in which the benefits from the investment are reaped and distributed, occur only if in stage 1 $q$ is found to be
greater than \( q^0 \).

The expected net return to the investor can therefore be expressed as

\[
EV = p(d) \int_{q^0}^{q} (\alpha R(q) - C)f(q) dq - d \quad (1.19)
\]

Feasibility now requires that

\[
(1 + d) I \leq EV \quad (1.20)
\]

It follows immediately from (1.17), (1.18) and (1.20) that investors who are good at doing due diligence in the sense that low values of \( d \) yield a given value of \( p \) are likely to engage in due diligence, select high quality projects (ie., projects with positive expected return), and make investments.\(^5\) These are the investors that become venture capitalists. (For further formal analysis of the advise selection case, see Appendix 2).

We should emphasize that we assume that the efforts undertaken by the venture capitalist are not subject to free riding. That is, another investor cannot simply observe the venture capitalist and then underbid the venture capitalist who has undertaken diligence. Typically venture capitalists are able to keep the results of diligence and monitoring confidential until after financial contracts have been signed. Free riding does occur but, given the informational asymmetries in the venture capital sector, it seems plausible to abstract from

\(^5\)We acknowledge that the structure of the venture capital investment process as depicted in Figure 1.4 is a simplification. Venture capitalists make investments even if they are not completely certain that \( q^0 \) and therefore they may earn negative returns on individual investments. However, taking this fact into account does not change the analysis except to add some additional algebra. (Note that in our model expected returns to venture capital investments are positive, but actual returns can be negative if \( u < 0 \).)
free riding here.

1.3.3 Implications

The above formulation provides the simplest configuration that reflects the idea that venture capitalists are those investors who become skilled at selecting good projects in environments with hidden information and who are good at monitoring and advising entrepreneurs who might otherwise be vulnerable to moral hazard problems. The implications of this modelling framework are outlined below.

1. Venture capitalists will operate in environments where their relative efficiency in selecting and monitoring investments and in providing value-enhancing services gives them a comparative advantage over other investors. For example, as we have seen in the “hidden action” case, it may take effective monitoring m and specific services s to make a project attractive for an investor. In the “hidden information” case, on the other hand, market failure can be avoided if the probability of detecting whether a project is worth supporting is high enough for sufficiently low due diligence costs. This suggests strong industry effects in venture capital investments. We would expect venture capitalists to be prominent in industries where informational concerns are important, such as biotechnology, computer software, etc., rather than in “routine” start-ups such as restaurants, retail outlets, etc. The latter are risky, in the sense that random variable u has high variance, but they are situations that are relatively easy to monitor by conventional financial intermediaries, whereas the former draw much of their value from idiosyncratic knowledge that is much harder to assess. In principle, deep knowledge of traditional industries, such as retailing, is not less advantageous than deep knowledge of high-tech industries, but there is some evidence that such wisdom is harder to obtain for knowledge-based industries where informational asymmetries are therefore likely to be higher. (See, for example, Industry Canada (1994) on the particular difficulties and challenges that investors and lenders face with regard to the assessment of knowledge-based small- and medium sized enterprises.)
2. Within the class of projects where venture capitalists have an advantage, venture capitalists will still prefer projects where selection, monitoring and service costs are relatively low or, in other words, where the costs of informational asymmetry are less severe. In the presence of moral hazard, investors would prefer projects for which e is more responsive to m, and/or for which R and/or R_e are more responsive to s. In the presence of adverse selection, projects with a highly responsive p(d) would be favoured over those where the detection of quality is more difficult and thus more costly. Thus, within a given industry where venture capitalists would be expected to focus, we would expect venture capitalists to favour firms with some track record over pure start-ups. To clarify the distinction between point 1 and point 2, note that point 1 states that if we look across investors, we will see that venture capitalists will be more concentrated in areas characterized by significant informational asymmetry. Point 2 says that if we look across investment opportunities, venture capitalists will still favour those situations that provide better information (as will all other investors). Thus venture capitalists perceive informational asymmetries as costly, but they perceive them as less costly to deal with than do other investors.

3. If informational asymmetries are important, then the ability of the venture capitalist to “exit” may be significantly affected. Ideally, the venture capitalists might wish to sell off their share in the venture after it “goes public” on a stock exchange. If, however, these investments are made in situations where informational asymmetries are important, it may be difficult to sell shares in a public market where most investors are relatively uninformed. Public investors probably have a less responsive function p(d) and therefore (1.19) could be negative for them. This concern invokes two natural reactions: One is that many “exits” would take place through sales to informed investors, such as other firms in the same industry as the venture or to the venture’s own management or owners. These informed investors probably have similar, if not better detection functions p(d) than the venture capitalist. A second reaction is that venture capitalists might try to acquire reputations for only presenting good quality ventures in public offerings. (However,
this is an argument drawing on a multi-period scenario and would therefore require an extension of our model). Therefore, we might expect that the exits that occur in initial public offerings would be drawn from the better-performing ventures.⁶

4. The model implies that \( \frac{dR}{de} (= R_e) > 0 \) and \( \frac{de}{d\alpha} < 0 \). Together these two properties imply \( \frac{dR}{d\alpha} < 0 \). Other things equal, we can expect entrepreneurial firms in which venture capitalists own a large share to generate lower net returns. This would be due to the moral hazard problem. Higher values of \( \alpha \) reduce the incentives of the entrepreneur to provide effort. Nonetheless, it still might be optimal in a given situation for the venture capitalist to take on a high ownership share, as this might be the only way of getting sufficient financial capital into the firm. However, we would still expect a negative correlation between the venture capital ownership share and firm performance.

We note, however, that the model also suggests a negative relationship between \( R \) and \( \alpha \) for another reason. Specifically, the selection constraint for investors is that \( \alpha R \geq (1+r)I \) or \( R \geq (1+r)I/\alpha \). If the venture capital market were very competitive so that investors earned no rents, then this selection constraint would hold with equality and there would be an exact negative relationship between expected net operating revenues and \( \alpha \), whether or not moral hazard was present. Even if venture capitalists earn some expected rents, this selection constraint will still rule out combinations of low \( \alpha \) and low \( R \), which will tend to induce a negative correlation between \( R \) and \( \alpha \). The basic logic is that, for a given investment \( I \), investors will need to be compensated by a large ownership share \( \alpha \) if the expected net operating revenues are relatively low.

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⁶Empirical work by Megginson and Weiss (1991) and Gompers (1996) is consistent with the idea that the reputation of venture capitalists is very important at the IPO stage.
1.4 THE DATA SET

The data used for this study were collected by Macdonald & Associates Ltd. and made available to us on a confidential and anonymous basis. In addition, no individual firm-specific information is reported or discussed in our analysis. The data are derived from two surveys. The first survey, referred to as the "investment survey," began as an annual survey in 1991 and became quarterly in 1994. It asks just over 100 Canadian venture capital firms to identify their investees and to provide some information about each investment and divestiture. Investees are recorded in the database and follow-up information is requested in subsequent surveys. The investment survey asks about the amount and the stage of each investment and also seeks information about the venture capitalist's ultimate divestiture of its holdings in each investee.

This survey, which covers the period from 1991 through the first quarter of 1996, seeks to obtain comprehensive information from all Canadian venture capital providers. In an effort to get full information about the investee firms, the survey is sent to venture capital companies (as just noted) and to other investors who have investments in the venture-backed investees. However, some relevant venture capital providers may have been overlooked in the survey, and some surveyed venture capitalists may not report all of their investments. Nonetheless, Macdonald & Associates Ltd. estimate that the investment survey identifies 90% to 95% of the underlying population of Canadian firms supported by Canadian venture capitalists.

The second survey, referred to as the "economic impact" survey, began in 1993 and is conducted annually. It seeks additional information about the investees identified in the investment survey. Thus economic

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7This "exit" information, which is obtained on a regular basis from the investment survey, was complemented in November 1995 by an additional survey addressed to venture capital providers who had previously reported on divestitures.
impact information is sought about each investee that received an investment in or after 1991. Retrospective information is also requested. Suppose, for example, that an investee received an investment in 1991. The venture capitalist making the investment would have received a 1993 economic impact questionnaire asking for information about this investee going back as far as 1987. In many cases not much retrospective information can be provided, but the database contains economic information on a reasonable number of investees going back as far as 1987. The date of the investee’s original startup (which in some cases is well before 1987) is also reported.

The response rate for the economic impact survey over its three year life has varied between 56% and 74% (i.e., information has been received on 56% to 74% percent of the targeted investee firms). If the investment survey identifies 90 to 95 percent of the relevant underlying population, then the effective sample coverage is between 50% (.9 times 56%) and 70% of the underlying population. The economic impact survey collects balance sheet and income statement information on the investees (including revenues and taxes paid). It also collects information on the structure and amount of their employment, and on the nature of their industry.

A typical investee enters the data set when it receives its first investment from a venture capitalist. It may receive investments from additional venture capitalists as well. Subsequent rounds of investment may also occur. Eventually, an investee leaves the sample. This occurs when all venture capitalists have either written off (in the case of failure) or “cashed in” their holdings in the investee. Thus, the data set contains a series of “life histories” for venture capital-backed firms.

A “record” refers to information for one particular investee firm for one particular year. There are 387 investee firms in the data available from the economic impact survey, but information on about 18 of these firms is significantly incomplete. The remaining 369 firms provide 1298 reasonably complete records, and
therefore have an average of about 3.5 records each. The investment survey data includes information on 1086 Canadian investees. For some purposes, complete matched records are necessary\(^8\), but much interesting and relevant information is available from just the economic impact data (1298 records on 369 companies) or just the investment data (2017 records on 1086 companies).

These data sets target Canadian investees supported by the Canadian venture capital industry. A Canadian entrepreneurial company that received support exclusively from venture capitalists based in the US or Asia and had no support from Canadian venture capitalists would not be in our data set. This set of firms is probably fairly small, but there is no data available on its magnitude. It seems unlikely that this omission introduces much systematic bias over most subjects of interest in the data. Despite some possible selection bias in the economic impact data, the data set as a whole remains an important and unique data source.

1.5 INVESTMENT PRACTICES OF CANADIAN VENTURE CAPITALISTS

We now present some empirical evidence that addresses the predictions of the theoretical framework outlined in section 1.3. Some of this data, together with other empirical information on the Canadian venture capital industry is provided by Amit, Brander and Zott (1997). Before considering the implications of informational asymmetries, we provide a general characterization of important financial variables in the data, as shown in Table 1.1. All relevant table entries are in thousands of 1995 Canadian dollars.

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\(^8\) Matching the two data bases, we obtain 408 complete records on 302 investee companies. These numbers are low primarily because there are only 339 investee companies with records in both databases and because, for each investee, matches occur only in years when investments were undertaken.
TABLE 1.1: Summary financial data: 1987-94 (in real $1995)

<table>
<thead>
<tr>
<th></th>
<th>Mean ($000s)</th>
<th>Median ($000s)</th>
<th>Standard deviation</th>
<th>No. of records</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total assets</td>
<td>22928</td>
<td>5540</td>
<td>70707</td>
<td>1277</td>
</tr>
<tr>
<td>Total equity</td>
<td>8777</td>
<td>1893</td>
<td>25254</td>
<td>1274</td>
</tr>
<tr>
<td>VC-share of equity (%)</td>
<td>34</td>
<td>30</td>
<td>30</td>
<td>1218</td>
</tr>
<tr>
<td>Retained earnings</td>
<td>848</td>
<td>154</td>
<td>10098</td>
<td>1127</td>
</tr>
<tr>
<td>Total fixed assets</td>
<td>10745</td>
<td>1996</td>
<td>52353</td>
<td>1257</td>
</tr>
<tr>
<td>Long-term debt</td>
<td>6729</td>
<td>1056</td>
<td>28122</td>
<td>1157</td>
</tr>
<tr>
<td>Revenue</td>
<td>23657</td>
<td>6177</td>
<td>56077</td>
<td>1290</td>
</tr>
<tr>
<td>Investments in property, plant and equipment</td>
<td>1954</td>
<td>222</td>
<td>8180</td>
<td>1161</td>
</tr>
<tr>
<td>R&amp;D expenditures</td>
<td>837</td>
<td>79</td>
<td>2098</td>
<td>1067</td>
</tr>
<tr>
<td>Taxes paid</td>
<td>461</td>
<td>25</td>
<td>1315</td>
<td>1027</td>
</tr>
<tr>
<td>Number of Canadian employees</td>
<td>159</td>
<td>50</td>
<td>301</td>
<td>1293</td>
</tr>
</tbody>
</table>

Source: Macdonald & Associates Ltd. Economic Impact Database

As this table implies, the size of investee companies varies substantially, with a few large firms that make the average values much larger than the median values. The median investee has about 50 Canadian employees and has annual revenues on the order of C$6 million. A typical ownership share for the venture capitalist is approximately 30%.

The data in Table 1.1 also imply that firms in the data set spend, on average, about 3.5% of their revenues on R&D. This is about the same as the overall ratio of R&D spending to revenues for the Canadian economy as a whole. We should note, however, that these rather moderate R&D expenses may be due to different
accounting standards that prevail in small and relatively young companies in contrast to large and established firms. Revenues per Canadian employee are $148,800, and the average long term debt to equity ratio is a conservative 0.77. (The long term debt to equity ratios derived from Canadian COMPSTAT data is estimated to be 1.75 for companies of all sizes, and 0.90 for companies with annual sales less than $100 million.) The low debt-equity ratio may reflect the limited borrowing capacity of entrepreneurial firms. We note also that the average investee is profitable enough to pay nontrivial amounts of tax.

We now consider the implications of the information-based model described in Section 1.3. One of the implications was that venture capital would be focused on industries where the importance of monitoring and due diligence expertise is particularly great. Table 1.2 presents information about the industry breakdown of the investee companies, and compares these investment shares with the shares of these industries in total output (as measured by Canadian gross domestic product (GDP)).
TABLE 1.2: Industry classification

<table>
<thead>
<tr>
<th>Industry Classification</th>
<th>Early stage investment* (number of investees)</th>
<th>Total investment* (number of investees)</th>
<th>% of early investment</th>
<th>% of total investment</th>
<th>% of total output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biotechnology</td>
<td>95.4 (43)</td>
<td>121.5 (51)</td>
<td>17</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>Communications</td>
<td>83.7 (32)</td>
<td>225.1 (63)</td>
<td>15</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>Manufacturing and industrial equipment</td>
<td>78.7 (82)</td>
<td>461.6 (261)</td>
<td>13</td>
<td>21</td>
<td>24</td>
</tr>
<tr>
<td>Computer (hardware and software)</td>
<td>70.0 (100)</td>
<td>314.4 (182)</td>
<td>12</td>
<td>14</td>
<td>3</td>
</tr>
<tr>
<td>Miscellaneous</td>
<td>67.1 (58)</td>
<td>314.7 (178)</td>
<td>12</td>
<td>15</td>
<td>34</td>
</tr>
<tr>
<td>Medical/health</td>
<td>58.4 (34)</td>
<td>176.1 (59)</td>
<td>10</td>
<td>8</td>
<td>3</td>
</tr>
<tr>
<td>Energy/environmental technology</td>
<td>57.4 (33)</td>
<td>134.6 (68)</td>
<td>10</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>Consumer related</td>
<td>31.7 (27)</td>
<td>296.3 (109)</td>
<td>6</td>
<td>14</td>
<td>26</td>
</tr>
<tr>
<td>Electrical components and instruments</td>
<td>25.0 (42)</td>
<td>125 (89)</td>
<td>4</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>Total:</td>
<td>567.2** (451)</td>
<td>2169.3 (1060)</td>
<td>99**</td>
<td>100</td>
<td>101**</td>
</tr>
</tbody>
</table>

* In C$ mill.  ** Due to rounding
Sources: Macdonald & Associates Ltd. Investment Database. Output shares are based on estimates from Statistics Canada “Gross Domestic Product by Industry”, 1996, cat. no. 15-001-XPB.

As can be seen from Table 1.2, venture capital is much more heavily represented in biomedical areas, computers, and communications than would be implied by overall output shares of these industries in the economy as a whole. Venture capital has a slightly smaller share of manufacturing and industrial equipment than the economy as a whole, and a much lower share of “consumer related” and “miscellaneous” industries.
The main components of these categories are the retail sector and various services. This picture is even more pronounced when only early stage venture capital investments are considered. It seems very plausible that the industries where venture capitalists concentrate the most are those where informational asymmetries are most severe. It is of course possible that venture capitalists invest relatively heavily in high-tech industries for reasons unrelated to information. For example, the high-tech sector may simply have a disproportionately large number of new investment opportunities. More specifically, it is a growth sector and any growth sector will appear to have high levels of new investment from most financial intermediaries, including venture capitalists. Even so, venture capitalists have a heavier relative investment in high-tech industries than other financial intermediaries, and informational reasons offer a plausible explanation for this. Thus Table 1.2 is consistent with our theoretical expectations.

The second major implication of the information-based theory developed in Section 1.3 is that within the sectors where venture capitalists operate, they still prefer to invest in firms where the adverse selection and moral hazard problems are least severe. The following information is consistent with this expectation. First, Table 1.3 shows the age structure of the investee firms.
As shown on Table 1.3, quite a few investee companies are surprisingly old. Fully 12% of the 379 companies for whom information on age is available were founded prior to 1974. Since the data set is limited to firms that received at least one infusion of venture capital in 1991 or later, some firms obtain venture capital financing long after being founded. (We note, however, that these firms might have obtained earlier venture capital infusions. Our data suggests that many recorded investments are indeed follow-up investments.)

Furthermore, this information suggests that it takes longer than commonly perceived, and perhaps more venture capital than originally anticipated, to bring some investee firms to the stage at which exit is feasible. A company may be founded well before it obtains its first venture capital investment. These data raise the possibility that venture capital focuses on expansion of existing small companies rather than on the start-up phase. Tables 1.4 and 1.5 provide more information on this point.
### TABLE 1.4: Number of investments by stage and year

<table>
<thead>
<tr>
<th></th>
<th>Early stages</th>
<th></th>
<th>Later stages</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SE</td>
<td>ST</td>
<td>ES</td>
<td>EX</td>
<td>AC</td>
<td>TU</td>
<td>WC</td>
<td>OT</td>
<td>Count</td>
<td></td>
</tr>
<tr>
<td>1991</td>
<td>3</td>
<td>100</td>
<td>0</td>
<td>85</td>
<td>12</td>
<td>22</td>
<td>0</td>
<td>36</td>
<td>258</td>
<td></td>
</tr>
<tr>
<td>1992</td>
<td>15</td>
<td>111</td>
<td>0</td>
<td>65</td>
<td>23</td>
<td>41</td>
<td>2</td>
<td>50</td>
<td>307</td>
<td></td>
</tr>
<tr>
<td>1993</td>
<td>5</td>
<td>116</td>
<td>0</td>
<td>125</td>
<td>18</td>
<td>23</td>
<td>25</td>
<td>37</td>
<td>349</td>
<td></td>
</tr>
<tr>
<td>1994</td>
<td>3</td>
<td>128</td>
<td>11</td>
<td>206</td>
<td>12</td>
<td>23</td>
<td>0</td>
<td>15</td>
<td>398</td>
<td></td>
</tr>
<tr>
<td>1995</td>
<td>8</td>
<td>130</td>
<td>112</td>
<td>241</td>
<td>11</td>
<td>21</td>
<td>2</td>
<td>44</td>
<td>569</td>
<td></td>
</tr>
<tr>
<td>1996(Q1)</td>
<td>5</td>
<td>42</td>
<td>12</td>
<td>54</td>
<td>3</td>
<td>11</td>
<td>0</td>
<td>9</td>
<td>136</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>39</td>
<td>627</td>
<td>135</td>
<td>776</td>
<td>79</td>
<td>141</td>
<td>29</td>
<td>191</td>
<td>2017</td>
<td></td>
</tr>
</tbody>
</table>

Key: SE = seed, ST = start-up, ES = other early stage investments, EX = expansion, AC = acquisition, TU = turnaround, WC = working capital, and OT = other.

Source: Macdonald & Associates Ltd. Investment Database

### TABLE 1.5: Average size of investment by stage and year (in C$000's)

<table>
<thead>
<tr>
<th></th>
<th>Early stages</th>
<th></th>
<th>Later stages</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SE</td>
<td>ST</td>
<td>ES</td>
<td>EX</td>
<td>AC</td>
<td>TU</td>
<td>WC</td>
<td>OT</td>
<td>Total</td>
<td></td>
</tr>
<tr>
<td>1991</td>
<td>489</td>
<td>678</td>
<td>0</td>
<td>1165</td>
<td>2003</td>
<td>1424</td>
<td>--</td>
<td>1374</td>
<td>1058</td>
<td></td>
</tr>
<tr>
<td>1992</td>
<td>900</td>
<td>617</td>
<td>0</td>
<td>1104</td>
<td>1283</td>
<td>628</td>
<td>480</td>
<td>1480</td>
<td>925</td>
<td></td>
</tr>
<tr>
<td>1993</td>
<td>836</td>
<td>1101</td>
<td>0</td>
<td>1714</td>
<td>1665</td>
<td>1620</td>
<td>362</td>
<td>1662</td>
<td>1394</td>
<td></td>
</tr>
<tr>
<td>1994</td>
<td>425</td>
<td>677</td>
<td>854</td>
<td>1227</td>
<td>2338</td>
<td>1521</td>
<td>--</td>
<td>2391</td>
<td>1128</td>
<td></td>
</tr>
<tr>
<td>1995</td>
<td>414</td>
<td>688</td>
<td>1005</td>
<td>1300</td>
<td>2341</td>
<td>436</td>
<td>1378</td>
<td>1564</td>
<td>1098</td>
<td></td>
</tr>
<tr>
<td>1996(Q1)</td>
<td>101</td>
<td>1034</td>
<td>847</td>
<td>1297</td>
<td>2260</td>
<td>1601</td>
<td>--</td>
<td>890</td>
<td>1151</td>
<td></td>
</tr>
<tr>
<td>1991-96</td>
<td>621</td>
<td>771</td>
<td>977</td>
<td>1316</td>
<td>1824</td>
<td>1107</td>
<td>378</td>
<td>1559</td>
<td>1127</td>
<td></td>
</tr>
</tbody>
</table>

Source: Macdonald & Associates Ltd. Investment Database
Table 1.4 shows how many investments correspond to each stage in the entrepreneurial firm's life. It is based on investment records of investee companies that are in the Investment Database and includes investments made between 1991 and the first quarter of 1996. A given investee may obtain financing from multiple venture capitalists, and may also receive multiple rounds of investment from a given venture capitalist. Each investment, which may include debt, equity, or both, is recorded separately. We observe that a full 60% of the investments made over the period covered by our sample are late stage investments. Combining the fact that early stage investments are both smaller (from Table 1.5) and less numerous (Table 1.4) than late stage investments, we can infer that the venture capital industry seems to focus more on growth and development of firms than on start-up activity. Tables 1.3 to 1.5 together show that venture capitalists focus on firms with a long enough track record to provide significant information about the underlying quality of the venture. Pure start-up activity, where adverse selection and moral hazard problems are most severe, is less significant than later stage investment.

**FIGURE 1.4:** Average debt and equity by investment stage 1991-1996(Q1)
Figure 1.4 depicts the relative importance of debt and equity in an average or representative investment by stage. There are, for example, 39 seed investments in total. The total equity in these 39 investments is $21.89 million, giving an average of $561,000, while the total debt is $2.34 million, resulting in an average of only $60,000 (note that most seed investments have no debt). Figure 1.4 shows that equity is relatively more important at the early stages, and debt becomes more significant later, although equity remains more important in absolute terms for every stage except working capital.

**FIGURE 1.5: Distribution of venture capital exits (percentage of exits)**

- **Writeoff**: 17%
- **Acquisition**: 10%
- **Secondary**: 13%
- **Other**: 7%
- **IPO**: 16%
- **Company Buyout**: 37%

The third major implication of our information-based approach is that we might expect exit to be dominated by "insider" activity rather than by public offerings. Figure 1.5 shows the pattern of exits in the data and indicates that only about 16% of exits occur following initial public offerings (IPOs). About 10% are third party acquisitions, often by a firm in the same industry as the venture. The largest category of exit is company buyouts, in which the venture capitalist's holding is sold to officers or managers of the investee. Fully 37%
of exits are in this category. Secondary purchases are purchases of the venture capitalist's holding by a third party in a private transaction that is not an overall acquisition. The "other" category consists of exits for which the exit mode was not identified, but we believe that most of these are company buyouts. Approximately 17% of exits were in the "write-off" category. If informational asymmetries are important, it is not surprising that IPOs account for only a small share of exits while company buyouts are much more important. We wish to note, however, that the small share of IPOs may also partly reflect a minimum scale necessary to sustain a public market in a stock.

Our theoretical framework also suggests that returns would differ by exit vehicle and that, in particular, IPOs would have high returns precisely because venture capitalists seek to reduce the adverse selection problem confronted by buyers of IPOs by only "going public" with relatively strong investee firms.
**TABLE 1.6: Estimated real annual returns by exit type**

<table>
<thead>
<tr>
<th>Exit Type</th>
<th>Mean of individual real annual returns*</th>
<th>Standard deviation of individual returns</th>
<th>No. of observations</th>
<th>Real annual return of sum of investments**</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPO</td>
<td>43%</td>
<td>62%</td>
<td>26</td>
<td>26%</td>
</tr>
<tr>
<td>Acquisition</td>
<td>36%</td>
<td>61%</td>
<td>16</td>
<td>9</td>
</tr>
<tr>
<td>Secondary purchase</td>
<td>23%</td>
<td>41%</td>
<td>11</td>
<td>29%</td>
</tr>
<tr>
<td>Company buyout</td>
<td>2%</td>
<td>15%</td>
<td>37</td>
<td>0%</td>
</tr>
<tr>
<td>Writeoff</td>
<td>100% loss over holding period</td>
<td>-</td>
<td>24</td>
<td>100% loss over holding period</td>
</tr>
<tr>
<td>Other</td>
<td>2%</td>
<td>18%</td>
<td>7</td>
<td>13%</td>
</tr>
</tbody>
</table>

* Individual annual returns are calculated as:

\[
\text{(Proceeds from investment / cost of investment)} \times (1 / \text{holding period}) - 1
\]

** This number is calculated as:

\[
\text{(Sum of proceeds from investment / sum of costs of investment)} \times (1 / \text{average holding period}) - 1
\]

Source: Macdonald & Associates Ltd. Investment Database

These returns shown in Table 1.6 are consistent with our expectations. Write-offs of course represent a 100% loss over the holding period. Among the other forms of exit, IPOs are relatively profitable. Secondary purchases (i.e., secondary sales from the exiting venture capitalist’s point of view) are similarly profitable in aggregate, although with only 11 observations it is difficult to regard the return to secondary purchases as highly meaningful. In any case, the high return to IPOs is consistent with our expectations.

The final prediction of our model is that the venture capitalist’s ownership share should be negatively associated with the firm’s performance. This derives both from moral hazard and from the venture capitalist’s participation constraint that expected returns should at least equal the return from alternative investments. In
addition, it is possible that a negative correlation between a venture capitalist’s ownership share and a measure of firm performance could arise from dilution in a multi-period process (i.e., the possibility that low performance leads to high α). Unfortunately, we do not have adequate data (such as data on a venture capitalist’s ownership share in the start-up phase) to correct for dilution.

It is difficult to measure firm performance directly, but revenues per unit asset and taxes paid should both be good measures of performance. Table 1.7 reports the results arising from regressing these measures of firm performance on the venture capital ownership share, correcting for age of the firm.

TABLE 1.7: Effect of venture capital share on performance (Tobit regressions)

<table>
<thead>
<tr>
<th>Dependent variable.</th>
<th>Expl. variable</th>
<th>Coefficient</th>
<th>Standard error</th>
<th>t-statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>TaxesPaid</td>
<td>VCshare</td>
<td>-10.59</td>
<td>1.95</td>
<td>-5.44</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>log(Age)</td>
<td>454</td>
<td>61</td>
<td>7.44</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>Const.</td>
<td>-696</td>
<td>155</td>
<td>-4.50</td>
<td>.000</td>
</tr>
<tr>
<td>TaxesPaid/Assets</td>
<td>VCshare</td>
<td>-28.27</td>
<td>5.94</td>
<td>-4.76</td>
<td>.000</td>
</tr>
<tr>
<td>(x10000)</td>
<td>log(Age)</td>
<td>488</td>
<td>187</td>
<td>2.61</td>
<td>.009</td>
</tr>
<tr>
<td></td>
<td>Const.</td>
<td>-578</td>
<td>474</td>
<td>-1.22</td>
<td>.223</td>
</tr>
<tr>
<td>Revenues/Assets</td>
<td>VCshare</td>
<td>-46</td>
<td>20</td>
<td>-2.30</td>
<td>.021</td>
</tr>
<tr>
<td>(x1000)</td>
<td>log(Age)</td>
<td>-386</td>
<td>649</td>
<td>-0.60</td>
<td>.55</td>
</tr>
<tr>
<td></td>
<td>Const.</td>
<td>8958</td>
<td>1604</td>
<td>5.59</td>
<td>.000</td>
</tr>
</tbody>
</table>

Source: Macdonald & Associates Ltd. Economic Impact Database

As can be seen from these regressions, there is a statistically strong negative relationship between the venture capitalist’s ownership share and these measures of firm performance. Ideally we would like to use profit as
a measure of success, but profit is not available in the data. However, profit is closely related to taxes paid, so taxes should normally be a good proxy for profit. We acknowledge, however, that for emerging growth companies taxes paid may be a poor predictor of their value creation potential. Note that taxes are truncated from below at 0. (Firms do not pay negative taxes no matter how poor their performance.) Accordingly the estimation is done using Tobit estimation rather than ordinary least squares. The basic finding is that there is a strong negative relationship between whatever measure of performance we use and the share of the venture owned by the venture capitalist. This could be the result of moral hazard or it could be the result of the venture capitalist's self-selection constraint. It is also possible that ventures for which $\alpha$ is high pay out more earnings to the venture capitalist and therefore have lower future earnings. However, normalizing for asset size should mitigate this concern.

We emphasize that the amount of variation explained by the venture capital share is low. Thus, while the coefficient on the venture capital share is significant, variations in this share are, at most, a minor determinant of performance. It is also important that these results not be interpreted as suggesting that venture capital investment should be viewed as a negative influence, or that other sources of finance are better than venture capital. Venture capital investments could be an important positive influence on every firm in the data set, and could be the best source of financial capital available, and we would still expect to observe a negative correlation between venture capital ownership and performance. What the negative correlation tells us is that the best performing companies tend to be those in which the venture capital ownership share is not too high. However, if financial requirements are high and the owner's sources are meagre, then a substantial venture capital share might well be the best option, even if there is an associated moral hazard problem, as the alternative might be outright failure of the company.
1.6 CONCLUDING REMARKS

The theoretical framework we offer focuses on informational issues. Specifically, we view asymmetric information as the central feature of venture capital investment. Both major forms of asymmetric information, "hidden information" (leading to adverse selection) and "hidden action" (leading to moral hazard) are included in our analysis. While the model abstracts from some important elements of the venture investment process (such as bargaining, syndication, etc.), we believe that the informational issues are perhaps the most central issues to focus on at this stage.

We have shown that this information-based approach is consistent with the data on Canadian venture capital investments. Moral hazard and adverse selection create a market failure in entrepreneurial financing, which might lead many worthwhile projects to be unfunded or underfunded. The more skilled the venture capitalist is in reducing these sources of market failure, the more effectively this sector will function. Venture capitalists exist because they are better at this function than unspecialized investors. However, venture capitalists cannot eliminate adverse selection and moral hazard. Furthermore, these problems are more acute for younger firms, and most acute for start-ups. This explains why venture capitalists focus on later stage entrepreneurial firms. Later stage firms have a track record that provides information to the venture capitalist, and they have enough assets to reduce the problem associated with limited collateral under limited liability. By virtue of their expertise, venture capitalists are better at dealing with informational problems than are other investors (on average), but this advantage shows up most in later stage entrepreneurial firms rather than at the start-up stage.

This theoretical structure is also consistent with the pattern of exit. If asymmetric information is important, and remains important even at the exit stage, then outside public investors will not be in the best position to
evaluate the assets of the entrepreneurial firm, and insiders will be in a better situation to buy out the venture capitalist's position. These insiders might be management or officers of the investee, or they might be other firms in a related business. Thus it is not surprising that IPOs account for only a modest fraction of exit. In addition, our model predicts a negative relationship between the extent of venture capital ownership and firm performance. This relationship is found in the data.

There are several natural extensions to the line of reasoning presented in the paper. One complicating factor is the possibility that a venture capitalist's cost of monitoring an entrepreneur might vary with the venture capitalist's ownership share. It is sometimes suggested that it is easier for the venture capital firm to monitor if it has a larger ownership share. In our model, this would suggest that $m$ would exogenously depend on $\alpha$. Furthermore, we recognize that many aspects of venture capital activity have not been captured in our analysis. In particular, we abstract from staged investment, which is a common feature in venture capital finance and which can serve to ameliorate problems caused by asymmetric information. It would be interesting to extend our model to a multi-period analysis.

The challenge we and other researchers face is to develop theoretical structures that can be subject to empirical investigation. Ideally such theories should also provide normative implications for practice. Our paper is a small, but hopefully useful step in this direction.
CHAPTER 2

A GENETIC ALGORITHM APPROACH TO REPEATED BARGAINING WITH ASYMMETRIC INFORMATION

2.1 INTRODUCTION

Designing contracts when agents hold private information is not easy. Agency theory maintains that the non-disclosure of private information can cause market failures and result in inefficient contracts. Such problems are pervasive in domains where the relevant economic agents have access to different information, in financial markets for emerging companies, for example. With their lack of a track record and collateral, emerging firms often find it difficult to secure adequate financing, especially during the early-seed and start-up stages of their existence. Given the significance of the entrepreneurial sector for the economy as a whole, it is important to understand how private information affects financial contracting.

Learning about the information held by another party to a transaction is a natural way to bridge information gaps in contracting. This chapter postulates that agents, although endowed with only limited reasoning abilities, are capable of such learning. During the sometimes lengthy bargaining process that precedes most contracts of agreement, agents gradually discover more about the characteristics of the game they are playing. Empirical evidence seems to support this view. Roth and Erev (1995: p.164) state that “no one can look widely at experimental data without noticing that experience matters.” This chapter explores just how
experience matters in the bargaining process. More specifically, it asks the following questions: 1) Can learning agents overcome bargaining failures such as delays and failures to agree? 2) Are such failures observed only under conditions of asymmetric information?¹ and 3) How can bargaining inefficiencies be explained?

Game-theoretic models of bargaining under private information (see Kennan and Wilson (1993) for an excellent review) often use a signaling rationale to explain inefficient bargaining. This rationale relies on the assumption that it is only through the signals generated by costly but credible actions that the problems of asymmetric information can be overcome. These actions (such as delays in the negotiation process) then credibly convey private information. For example, during labor disputes, firms that cannot afford to pay high wages might have to endure a strike in order to prove their assertion.

This explanation of bargaining failures can be challenged on at least two grounds. First, human beings often lack the enormous rationality requirements imposed by game-theoretic models (Conlisk, 1996). It is not clear that ordinary people can perform the sophisticated analyses required to solve complicated signaling games. Second, Kennan and Wilson (1993:p.43) contend that "bargaining is substantially a process of communication." Adopting this view, however, requires acknowledging that there are many possibilities for exchanging information in negotiations. Agents send and receive a variety of informal messages from which they are able to draw inferences and thus learn. Bargaining thus involves learning; and this process should be modeled explicitly.

¹In this chapter, the terms ‘private information’ and ‘asymmetric information’ are used synonymously. They refer to the following settings. First, agents may possess different information about the value of a relevant parameter or the specification of a function (‘differential information’). Second, an agent may be informed about the value of a parameter whereas another agent is not (‘incomplete information’). ‘Differential information’ and ‘incomplete information’ are considered here to be distinct forms of asymmetric (or private) information.
This chapter develops an agent-based bargaining model that builds on the principle of learning through stochastic adaptation. Agents make decisions based on rules that are continually assessed for their potential to achieve a mutually beneficial agreement. Rules that prove less useful are discarded, while promising rules are retained and experimented with. A genetic algorithm (Holland, 1975; Goldberg, 1989; Mitchell, 1996) is used to model these dynamic stochastic processes. The algorithm produces rules that adapt well to their environment.

Under the premise of adaptive learning, an intuitive explanation for bargaining failures, such as delays and failures to agree, presents itself. This chapter develops the hypothesis that with the introduction of private information, learning of crucial determinants of the game (such as the preferences of other players) becomes more difficult and adaptation is hampered. It thus either takes a longer time for agents to reach a settlement than it would if agents had perfect information, or, due to misunderstandings and mistakes, agents may manouevre themselves into entrenched positions from which it is impossible to negotiate a successful deal.

The genetic algorithm model embodies the principle of inductive reasoning (Holland, Holyoak, Nisbett and Thagard, 1986; Arthur, 1994), allows for mistakes, and presupposes that agents have only limited cognitive abilities. It also implies that trial-and-error experimentation is a central feature of learning. The model has been demonstrated to approximate human-learning processes fairly well (Arthur, 1993), and even outperforms other heuristic learning models (Arifovic, 1994).

In the economics and management literature, promising applications of genetic algorithms can be found in areas such as game theory, with its explorations of the prisoner’s dilemma (Axelrod, 1987), coordination games (Bullard and Duffy, 1996; Arifovic and Eaton, 1995), signaling games (Arifovic and Eaton, 1996), rational expectations models (Routledge, 1994), models of economic growth (Arifovic, Bullard and Duffy,
and technological change (Birchenhall, 1995), and models of strategic management (Bruderer, 1993). This list is not exhaustive, but it does give a sampling of the broad range of issues that can be addressed with genetic algorithms. However, the potential for applying evolutionary techniques to economic problems has not been fully exploited.

Bargaining theory has been largely neglected as a fruitful field of application of models using genetic techniques.\(^2\) Dworman, Kimbrough and Laing (1995) is a laudable exception, drawing on genetic programming techniques to discover optimal negotiation policies in three-player coalition games. The authors find that in a highly complex but information-poor environment, artificial agents (i.e., computer models of economic agents) are able to evolve behavior that accords well with solutions prescribed by cooperative game theory.

The modeling approach employed by Dworman et al. (1995) grants a high degree of flexibility to players in choosing a coalition partner and in devising complex strategies. However, the assumed tournament structure of their model prescribes that each strategy of a player play a fixed number of games against randomly chosen opponents. This is a stark simplification of real-world bargaining. The model developed in this chapter therefore assumes that agents apply their most useful strategies with a higher probability (and thus more often) than less successful ones. Erev and Roth (1997) regard this principle, which they call “The Law of Effect,” as a robust property of human learning. Furthermore, the model extends the research question posed by Dworman et al. (1995) by introducing asymmetric information among the players. The

\(^2\)There is, however, a large body of theoretical and experimental literature on bargaining. It is not possible to give a satisfactory overview here. Useful discussions of theoretical models of bargaining situations with private information include, for example, Binmore and Dasgupta (1987), Harsanyi (1987), Osborne and Rubinstein (1990), and Kennan and Wilson (1993). Bargaining experiments involving asymmetric information are reviewed in Kuon (1994) and Kagel and Roth (1995). For recent computational studies on learning and bargaining, see Roth and Erev (1995) and Erev and Roth (1997).
goal of this chapter is to discover whether agents are able to identify optimal contracts even under conditions of asymmetric information.

To ease exposition and provide ample illustration of the model, this study considers the context of venture-capital finance, for which both the application of the genetic algorithm method and the focus on bargaining dynamics are novel. Many theoretic papers on venture-capital finance adopt a principal-agent framework for exploring contracting problems that involve informational distortions (e.g., Amit, Brander and Zott, 1998). Since the model presented in this chapter is deals explicitly with private information, it offers a supplementary perspective to previous research. It also offers a new method for analyzing complicated situations that are not readily amenable to traditional analytical tools (e.g., situations involving more than two agents and/or multiple moral hazard and adverse selection relationships in a dynamic context).

The main contributions of this chapter are as follows. First, by presenting a genetic algorithm model of bargaining and by performing computational experiments, it offers a learning-based behavioral explanation of inefficient financial contracts. Second, it presents a new approach to modeling bargaining dynamics that links several to-date disparate but relevant literatures. To the best of my knowledge, genetic algorithm learning has not yet been considered for analyzing informational problems in bargaining. Nor has much of the venture capital literature dealt with the implications of bargaining under private information. By knitting these concepts together, the model gains descriptive appeal.

2.2 THE MODEL

2.2.1 Two dimensions, two agents and their repeated two-stage game

Consider two risk-neutral agents who negotiate the design of a financial contract for a start-up project. The
contract stipulates how the parties will divide an exogenously determined up-front investment \( I^u \) and how they will split the subsequent proceeds from the project.

To facilitate the exposition of the model, the contracting problem is anchored in the context of venture-capital finance. Let one of the agents be an entrepreneur (E) who has a potential project in mind. E is able to provide some monetary resources for the project, thereby incurring opportunity costs, but to launch the project she needs the participation of a venture capitalist (VC). The involvement of a highly reputed and experienced venture capitalist is sometimes the precondition for other crucial players, such as banks, lawyers, clients, and suppliers, to support an entrepreneurial project. The venture capitalist has valuable resources at his disposition and seeks to make a profitable investment. Alternative investment opportunities are reflected in his opportunity costs. The consent of both agents is needed in order to initiate the venture.

The situation depicted here is a bilateral monopoly in which a single investor confronts a single investee. If the parties come to an agreement during bargaining, the project will be pursued, and gains from trade (if there are any) can be realized. If the negotiations fail, on the other hand, the venture will never take off. Since it is assumed that there are no alternative buyers or sellers of the ‘good’ (i.e., the entrepreneurial project), each party possesses bargaining power.\(^3\)

\(^3\)In the context of venture capital finance, a bilateral monopoly may arise as follows. An entrepreneur usually has a unique business idea. Since unique ideas are rare, the investor cannot easily turn to a third party who seeks money for a similarly profitable project. As a result, there may be ‘too much money chasing too few deals’. This gives the entrepreneur some bargaining power. On the other hand, the venture capitalist knows that if he refuses to support the project, other financiers might follow suit (they would probably want to free ride on the investor’s costly due diligence efforts). The entrepreneur’s reputation might be ruined. This in turn gives the venture capitalist some monopoly power over the supply of external resources. (Of course, if he accepts, others might want to free ride as well. However, the model assumes that contracts cannot be renegotiated.)
The financial contract to be negotiated is a vector (I, s) where I denotes the venture capitalist's initial investment and s denotes his share of the future net operating revenues. It follows that the entrepreneur's financial input is I-s-I and her profit share is 1-s. The model thus takes into account an input and an output variable. Although this representation simplifies reality, it captures the most essential features of financial contracts.

The bargaining process is modeled as a repeated two-stage game. In the first stage, the venture capitalist receives a signal from the environment about the quality of the project and makes an offer. In the second stage, the entrepreneur, after observing her own signal and VC's offer, makes a decision. If certain criteria are met and an agreement is forged, VC invests I and E contributes I-s-I. The venture is launched, and a period of production ensues in which the start-up firm produces, markets, and sells its products or services. At the end of this period, net operating revenues are realized and distributed according to the agreed-upon distribution plan. The company is liquidated, yielding a liquidation value of zero. Figure 2.1 illustrates this simple structure.

**FIGURE 2.1:** Bargaining and the investment process

- **Period 1: Bargaining round**
  - Goal: Agree on contract (I, s)
  - Stage 1: VC receives signal and determines offer (I, s)
  - Stage 2: E receives signal and VC's offer and accepts or rejects

- **Period 2: Production**
  - Agreement
  - VC invests I
  - E invests I-s-I
  - Venture is started
  - Net operating revenues R are realized and distributed according to s
  - Firm is liquidated
Note that the analysis focuses on the repeated two-stage bargaining process, which occurs in the first period. Nonetheless, assumptions about period two are important because agents form expectations, most notable about revenues, during period one about the results of period two. Thus the bargaining outcome partially hinges on the structure of the production phase.

2.2.2 Information asymmetry, bounded rationality and heuristics

Let q be an index for project quality. Low values of q indicate low levels of quality, high values of q indicate high quality. Agents do not know the true value of q; they face a pre-contract information problem. The venture’s true expected net operating revenues, R=R(q), which are a function of q, are thus ‘hidden’ from both the entrepreneur and the venture capitalist. However, both agents receive signals about q from their environment (e.g., from competitors, clients, market researchers, etc.). The venture capitalist receives signal x, and the entrepreneur receives signal y. The signals, which may differ, are drawn from the same interval as q, in other words, x, y and q have a common support. It is furthermore assumed that direct communication of privately observed signals is not credible.

Differential information (i.e., differences between the true quality q, signal x, and signal y) is just one type of asymmetric information that the model accommodates. It can also represent situations in which information is incomplete, i.e., when agents know only their own preferences and expectations, but not those of others. Under incomplete information, agents cannot tell whether in a certain bargaining round the other party made a mistake (or a bluff) or was telling the truth. This uncertainty may result in contractual inefficiencies since agreements that could make at least one of the agents better off might be delayed or even precluded. In this chapter, the exact effects of incomplete information on the efficiency of the bargaining outcome are investigated with a simulation experiment. The analysis of differential information is left for future research.
In dealing with asymmetric information, economic agents are often assumed to be ‘perfectly rational.’ For example, they are considered endowed with the ability to both look into the future and employ backward induction. Their cognitive and computational skills are assumed limitless. Perfectly rational agents are thus able to collect complete information on the objectives, preferences, beliefs, actions, and constraints of other players that they need in order to derive the optimal solutions to sophisticated schemes. While this approach has led to insightful normative results, its descriptive validity is questionable. Neelin, Sonnenschein, and Spiegel (1988), for example, use an experiment to show that people do not apply backward induction when they play repeated bargaining games.

In the present model, economic agents are assumed to follow decision-making heuristics that take the simple form of rules that specify the actions to be taken if certain preconditions are fulfilled. This does not imply that decision makers are irrational. Given their limited calculating and reasoning abilities, the use of heuristics may be a sensible way of handling decision problems. This is especially true if the rules of thumb are refined over time in a learning process. Following Simon (1955), such behavior can be labeled ‘boundedly rational.’

The general syntax of a rule is

\[ IF \ <condition(s)> \ THEN \ <action(s)> \]

A venture capitalist, for example, acts according to the heuristic

\[ IF \ <condition(s)> \ THEN \ <action(s)> \]

\[ 4The \ terms \ ‘rules \ of \ thumb,’ \ ‘rules,’ \ ‘heuristics,’ \ and \ ‘classifiers’ \ are \ used \ interchangeably \ in \ this \ study. \]
Whenever VC receives a signal $x$ about the quality of the proposed venture, he makes a contract offer to $E$ specifying the amount he is willing to invest and the share of profits that he expects in return for his investment.

Consider next the entrepreneur's rules. Denote $(I^b, s^b)$ as a benchmark contract that the entrepreneur has in mind. Any received offers will be compared with this benchmark. Upon observing signal $y$ and contract offer $(I, s)$, $E$ has two choices: accept or reject. More specifically, she follows either the rule

$$\text{IF observe signal } y \text{ and the venture capitalist offers } (I,s) \text{ with } I \geq I^b \text{ and } s < s^b \text{ THEN } \text{accept}$$

or the rule

$$\text{IF observe signal } y \text{ and the venture capitalist offers } (I,s) \text{ with } I < I^b \text{ and } s > s^b \text{ THEN } \text{reject}.$$
The above rules imply an extensive-form game similar to two-person repeated ultimatum bargaining. In ultimatum bargaining (see, for example, Gueth, Schmittberger and Schwarze, 1982), one of the agents (the ‘offerer’) is usually given the opportunity to make some money, conditional on offering part of it to a second player (the ‘respondent’). Gains can only be realized if both players consent to the proposed split of the “pie,” otherwise the opportunity expires. Since the respondent can signal only acceptance or rejection, and cannot make a counter offer (as would be possible in standard sequential bargaining games; for example, see Rubinstein, 1982), the offerer imposes an ultimatum on his counterpart: ‘take it, or leave it.’ If, however, the respondent decides to leave the bargaining table, the offerer will gain nothing at all.

The use of ultimatum bargaining as an analogy for the heuristic bargaining model presented in this chapter is now obvious. The venture capitalist makes all the offers, thereby imposing the ultimatums, while the entrepreneur is consigned to the role of nodding or shaking her head. The latter has bargaining power in the sense that if she walks away from the deal no one will realize any gains. However, in contrast to standard treatments of the ultimatum game, the “cake” that is to be distributed between the parties is not shrinking. (This does not mean, however, that time pressures are absent from the model. In fact, as will become clear later, agents behave “as if” they were under pressure to reach a deal.)

2.2.3 A more informal protocol for bargaining

In the bargaining literature, players are usually assumed to abide by strict protocols. The associated negotiation process is formal and structured, which makes it amenable to microeconomic and game-theoretic analyzes. Kreps (1990) considers the need for such precise protocols to be one of the fundamental problems of game theory. Indeed, casual observation suggests that trial-and-error methods of bargaining may not be uncommon in practice. At least at an early stage in the bargaining process, negotiators try out different proposals, and revise them if necessary. These proposals can be quite informal and can serve as a vehicle
for the exchange of a multitude of messages, whether the parties are aware of these exchanges or not. There are numerous occasions, such as presentations, interviews, meetings, lunches, telephone talks, factory visits, and product demonstrations, during which the two negotiating parties more or less openly tell each other what they think of the potential deal. This allows them to learn, that is, to make inferences about previously unknown or partially known aspects of the game. To analyze bargaining one must therefore consider the communication process as a whole, rather than as simply a formal process of offer and response, which constitutes only a small fraction of the bargaining process.

In practice, exchanged messages may take various forms - direct or indirect verbal or written statements, body language signs, etc. It is assumed here that E can always interpret VC’s offer \((I,s)\), and VC can always translate E’s intention into a response of ‘accept’ or ‘reject.’ Furthermore, both actors share a common understanding of how to interpret messages.

This conceptualization of a negotiation process departs from standard bargaining models in that it recognizes the importance of informal messages. It accommodates responses from E that are only tentative. An ‘accept’ response from E does not necessarily mean (as is commonly assumed in the literature) that the negotiation is finished and that players have reached a final agreement. Instead, such a response from E should be interpreted as: “we are on the right track, so let’s work towards an agreement.” Likewise, a response of “reject” does not necessarily imply that E wants to quit. Rather, it reflects E’s attitude that: “I do not like this offer, but feel free to make me another one.” Upon acceptance or rejection of the offerer’s initial proposal, the game is thus usually repeated and agents enter into another round of bargaining. The intuition behind this is as follows. Players learn inductively through trial and error. They therefore need opportunities to try out different options and take the resulting feedback into account when making up their minds. For example, a VC might suggest a contract that is unfavorable to himself, but E’s response allows him to learn more about
her preferences. If the negotiation were to come to an end immediately after E accepted, it would signal that the VC should not have made such an offer in the first place. Under these circumstances, experimentation would not take place and learning would be stifled. E’s answers should rather be considered more or less non-committal so that both parties can learn.

How, then, does the negotiation process terminate if responses are considered non-committal? Either the allotted time for bargaining runs out, or agents gain a firm opinion about their preferred move, given the previous rounds of bargaining. Firm opinions will manifest themselves in homogeneous sets of heuristics, that is, in sets containing mainly identical rules. In this case, the system reaches a steady state (which is formally defined in section 2.4). In order to fully comprehend this termination criterion, it is helpful to have a better understanding of the ways in which agents apply, evaluate, and process their rules.

2.2.4 Entrepreneurs and venture capitalists as stochastic adaptive learners

2.2.4.1 Representation of rules

The venture capitalist’s heuristics are modeled as bit strings (‘chromosomes’) of length 11. Each of these eleven bits can assume a value of either 0 or 1, that is, the representation of rules is binary. Chromosomes are subdivided into subsections (‘genes’). The first three bits on a chromosome encode the signal the VC receives from the environment. These positions on the chromosome are thus called ‘signal genes.’ They constitute the “if <condition>” element of the VC’s rules. The next four bits represent the suggested investment plan, I, and can therefore be termed ‘investment genes.’ The final four bits encode the proposed sharing plan, s, and are thus referred to as ‘share genes.’ The investment gene and the share gene together represent the action prescribed by the VC’s rules. Figure 2.2 illustrates this schema.

———

5Both agents are given a certain time to come to an agreement. They do not know this time limit, so bargaining is effectively modeled as an infinitely repeated game.
This representation scheme allows for $2^3=8$ different signals, $2^4=16$ different values of I and $2^4=16$ different values of s, or a total of $n_{\text{max}}=8*16*16=2,048$ rules. The total number of rules could be made arbitrarily large by using a finer grid, that is, by using longer genes and thus longer chromosomes. A signal gene of length 7, for example, would accommodate encoding $2^7=128$ signals and, given that the lengths of the investment and share genes do not change, would enable the representation of $128*16*16=32,768$ rules. The relatively short length of the chromosomes in the present model specification has the advantages of simplicity and computational convenience without sacrificing generalizability. For a detailed description of how to code signals and messages and how to decode genes, see Appendix 2.1.

The entrepreneur’s rules are represented as chromosomes of length 12. The conditional element of the chromosome consists of three genes, namely, a signal gene (3 bits), an investment gene (4 bits), and a share gene (4 bits). The action element (i.e., E’s response) is encoded by one bit. This representation scheme (which is illustrated in Figure 2.3) allows for the consideration of $m_{\text{max}}=4096$ rules. This number is determined by the number and length of E’s genes and can be made arbitrarily large in the same sense as described above for VC. Again, for the interpretation of E’s representation scheme, see Appendix 2.1.
2.2.4.2 How rules are matched and evaluated: Learning by experience

The bargaining process is organized chronologically by two types of time measures: generations and iterations. An iteration $i \in \{1, 2, \ldots, i_{\text{max}}\}$ is equivalent to an exchange of messages; it corresponds to a bargaining round. A generation $g \in \{1, 2, \ldots, g_{\text{max}}\}$ is a longer time period consisting of $i_{\text{max}}$ iterations. In other words, there are $i_{\text{max}}$ bargaining rounds within a given generation. The simulation of the bargaining process will be carried out for $g_{\text{max}}$ generations, at most. Thus a maximum of $g_{\text{max}} \times i_{\text{max}}$ bargaining rounds will take place.

VC has $n$ heuristics, E has $m$ heuristics. Each rule is associated with a fitness value, $f$, indicating how useful, on average, the rule is for finding an agreeable financial contract (i.e., one that yields a nonnegative expected utility to both agents). At the beginning of the simulation, all fitness values are set equal to a neutral benchmark value $f^0$. Agents start bargaining in a state of complete inexperience. Their rules are completely undifferentiated in terms of fitness evaluation.

An iteration starts with VC observing a private signal $x$. If the venture capitalist has exactly one rule that recognizes $x$, he will offer the contract specified by this rule. If none of his rules matches $x$, VC creates a new
rule for this signal that prescribes a random action (i.e., a contract offer). The new rule replaces the least successful of VC’s heuristics (i.e., the one with the lowest fitness value). If there are several candidates for replacement, one will be chosen randomly. This procedure guarantees that the total number of VC’s rules remains unchanged. If, on the other hand, more than one rule recognizes x, the heuristic to be used will be chosen by an ‘internal’ auction. Each matched rule ‘submits’ a bid equal to its fitness. The chances of winning the auction are proportional to the magnitude of the bid. This probabilistic method ensures that, on average, a rule with a relatively high fitness value will be chosen. According to the selected rule, the venture capitalist sends a message (I,s) to the entrepreneur.

The entrepreneur simultaneously receives (I,s) and privately observes signal y. She then searches for an appropriate rule to determine her response. Her search results in the construction of a choice set containing classifiers that match both (I,s) and y. If the set is empty, E creates a new rule with a random answer. If the set contains more than one rule, E holds a stochastic auction similar to the one described above for VC.

Once the entrepreneur has formulated her reply and sent it to VC, bargaining in this particular round is completed, and both agents assess the outcome. To understand how this assessment, which eventually leads to an updating of fitness values, is carried out, some additional notation is needed.

Denote $C^V(I)$ as the venture capitalist’s opportunity cost of capital and $R^V(x)$ as his expectation of the venture’s net expected operating revenues. Analogously, $C^E(I^u-I)$ and $R^E(y)$ are the entrepreneur’s opportunity costs and her expectations of the project’s net revenues. Note that both agents base their expectations of the venture’s prospects on their privately observed signals. They assume that the true quality type of the project, $q$, equals the most recently observed signal. The model thus assumes highly simplistic beliefs of the agents regarding $q$. 

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Since VC and E are risk-neutral, their utility functions can be written as

\[ U^V(I, s|x) = s \cdot R^V(x) - C^V(I) \text{ for VC,} \]  
\[ U^E(I, s|y) = (1 - s) \cdot R^E(y) - C^E(I^E - I) \text{ for E.} \]  

In each bargaining round, the venture capitalist calculates \( U^v \); the entrepreneur computes \( U^E \). (Note that such calculations require much less sophisticated knowledge and information processing capabilities than other optimization schemes.) The values of these variables are then used to evaluate the performance and to update the fitness of the rules employed by the agents.

The motto behind the fitness updating process is: “Reward successful rules, punish unsuccessful ones.” If information on preferences is incomplete, no player can tell whether or not a certain offer is acceptable to the other agent. Provided E accepts a proposal, VC rewards the rule he used if it yields \( U^v \geq 0 \). In that case, \( (U^v + f^b) > f^b \) is added to the rule’s total sum of payoffs received in a generation. (Recall that \( f^b \) is a neutral benchmark value.) A new average fitness value is thus calculated. By the same token, VC punishes heuristics that, if accepted, yield \( U^v < 0 \). The total payoff of this rule is also increased by \( (U^v + f^b) \), which, in this case, is smaller than \( f^b \).

Due to incomplete information, when E rejects an offer VC cannot tell whether or not the rejection is the result of a mistake. In this scenario, the VC’s best strategy is to assume that his offer is not attractive to E, that is, that the offer will generate an expected loss for the entrepreneur. This assessment will be correct on average. Rules with contract offers that elicit a negative response from E are punished. They are unlikely to lead to an agreement.
The entrepreneur, on the other hand, rewards rules that either accept good offers \( (U^E > 0) \) or that reject bad ones \( (U^E < 0) \). By contrast, rules that reject good offers or accept bad ones are punished. The entrepreneur’s decision criteria about whether to reward or punish are similar to the venture capitalist’s. Appendix 2.2 explains precisely how fitness values are calculated on the basis of expected payoffs for both agents.

The updating of fitness values represents learning by experience, which is closely related to reinforcement learning (for a simple model that incorporates reinforcement learning, see Erev and Roth, 1997). Updated fitness values serve to differentiate between rules, and highly fit rules (i.e., positively reinforced rules) will be employed more often, on average, than will be the poorly fit rules (i.e., negatively reinforced rules). Relative differences in the fitness values of an agent’s rules matter in another respect. In the long run, classifiers with higher fitness values will proliferate, whereas classifiers with lower fitness values will be replaced. This mechanism is modeled by a genetic algorithm described in the next section.

### 2.2.4.3 The genetic algorithm: Learning by experimentation

At no point in the bargaining process are agents guaranteed that their presently available rules are the best. Indeed, given that the agents’ rule sets are smaller than the total number of rules \( (n << n_{\text{max}} \) and \( m << m_{\text{max}} \)), agents consider only a relatively small number of alternatives. It therefore behooves both the venture capitalist and the entrepreneur to look for new and better heuristics in the course of their negotiations.

This quest for improvement is modeled for each agent by a genetic algorithm. In its simplest form, it can be described in terms of three genetic operators: reproduction, mutation, and crossover. Reproduction denotes the process of copying rules from one generation to the next. Usually, heuristics with a higher fitness level receive more copies than do the less fit ones, which might not get reproduced at all. (It may be, however, that strong rules are periodically abandoned and weak ones retained in the agents’ repertoires. This can be
interpreted as a sampling error.) This system of reproduction ensures that when searching for better rules, agents look for rules with a proven record of excellence.

Mutation is a form of experimentation that involves small changes. When rules are copied, single bit positions are randomly inverted (albeit with a low probability). Consequently, mutated rules must be translated anew. For example, there is a big difference between the binary numbers ‘1001’ (in decimal notation: 9) and ‘0001’ (decimal: 1) although only one bit position is changed.

A more radical source of experimentation is crossover, which denotes a structured but random exchange of genetic material between pairs of chromosomes. This is a major source of variation in the model and, together with mutation, provides an effective mechanism for identifying highly fit rules. Mutation and crossover thus model learning by experimentation. For more details on the genetic operators, see Appendix 2.3.

By evolving according to the above mechanisms, the agents’ rule sets adapt to each other. This is because the usefulness of a player’s heuristics depends to a large extent on the exact form of the other player’s rules (as well as on the signal received from the environment). The expected payoff to VC’s rules hinges largely on E’s answers, and E’s share of the pie relies, of course, on VC’s contract offer. A system with mutually adapting sets of rules is called ‘co-evolutionary.’

It is clear that the model, especially its genetic algorithm component, implies bounded rationality (Simon, 1955). The cognitive and computational requirements imposed on the artificial agents are relatively moderate. In addition, agents behave myopically by entertaining only very simple beliefs about the future. In addition, agents are allowed to make mistakes. These are probably reasonable assumptions. Furthermore,
agents make decisions on the basis of the results from past actions. Choices that yielded high expected payoffs in the past are more likely to be repeated in the future. This is an example of reinforcement learning typical of animal and human learning behavior (Roth and Erev, 1995; Erev and Roth, 1997). Third, genetic algorithm learning is inductive since it relies on examples of useful rules to find better ones. Inductive reasoning, in turn, is an essential mode of the human brain for solving complex, multidimensional problems (e.g., Arthur, 1994). Finally, the stochastic nature of the genetic algorithm (see Appendix 2.4) allows for the consideration of trial-and-error methods of experimentation, which are common among economic agents (Nelson, 1994).

It must be acknowledged that a genetic algorithm model cannot capture all facets of human learning. Human learning is probably “more purposive and directed than probabilistic” (Chwelos and MacCrimmon, 1997) and at hinges at least partially on deductive reasoning (Arthur, 1994). It remains an important task for future research to determine how well genetic algorithm learning describes human behavior.

2.3 INFORMATION STRUCTURES AND EXPERIMENTAL DESIGN

2.3.1 Information structures

Information influences the way we learn. It is generally the case that the more deeply we understand a situation, the better are our judgements about its implications, and the more we learn from it. The model therefore assumes that the quality of information and the accuracy of learning are positively correlated. That is, the higher the quality of the information available to the agents, the more accurate their updating of the fitness values of rules becomes. The central hypothesis of the simulation experiment is that adaptation through learning will be adversely affected by the presence of private information. The presence of private information also implies a higher fraction of bargaining failures in the form of delays, or even cancellations.
of negotiations, than would occur under perfect information.

The presence of private information is a factor in real-world bargaining. In their review of the experimental literature on bargaining under asymmetric information, Kennan and Wilson (1993:pp.93-94) state that “all ... [reviewed] experiments can be interpreted, in effect, as involving bargaining with private information, as evidently most players did not know the preferences of the opposing bargainer... This situation is aggravated by the difficulty of establishing common knowledge among the subjects as to the nature of the game being played.”

The model presented above incorporates asymmetric information in several ways. First, it posits that players do not know the exact specification of other players’ rules. This lack of knowledge is never mitigated during the negotiation process. Second, if the agents receive different signals about project quality, they will possess different information about a crucial model parameter. Such differing perceptions may lead to inefficient distortions of the bargaining process. And third, negotiators might possess private information in the sense that they know only their own preferences and expectations, and not those of others.

The following sections present with simulations of the model and concentrate on the implications of incomplete information. For this purpose, the bargaining model is analyzed under two informational structures: incomplete information (case 1) and complete information (case 2). The results are then compared. To abstract from the problems arising from the possession of different information, the signals to the agents will be kept identical. Table 2.1 summarizes the two cases.
2.3.2 Fitness updating under incomplete information

Recall that fitness values serve to differentiate 'good' rules, which foster a profitable agreement, from 'bad' rules, which preclude a deal or lead to an expected loss. The venture capitalist's updating policy in the case of incomplete information is therefore to reward rules that yield a nonnegative expected utility and that are accepted by E. VC takes acceptance of an offer as a sign that an agreement based on the offered contract can be reached. Although this is a reasonable assumption on the part of VC, he may still be wrong on occasion. The possibility of making a mistake about the other person's preferences and expectations is the most important consequence of incomplete information.

On the other hand, if a contract offer implies an expected loss for VC, or if it is rejected by E, the relevant rule is punished. Table 2.2 shows the modifications to the total sum of expected payoffs under different rules in generation g up to iteration i. The new fitness value of that rule is then calculated as a new average expected payoff (as described in Appendix 2.2).
TABLE 2.2: VC's fitness updating scheme under incomplete information

<table>
<thead>
<tr>
<th></th>
<th>E accepts</th>
<th>E rejects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected utility gain for VC ($U^v &gt; 0$)</td>
<td>$(f^b + U^v) \geq f^b$</td>
<td>$(f^b - U^v) \leq f^b$</td>
</tr>
<tr>
<td>Expected utility loss for VC ($U^v &lt; 0$)</td>
<td>$(f^b + U^v) &lt; f^b$</td>
<td>$(f^b + U^v) &lt; f^b$</td>
</tr>
</tbody>
</table>

Similarly, the entrepreneur rewards rules that accept profitable contract offers or that reject unprofitable ones. She punishes heuristics that suggest the acceptance of unprofitable contracts or that recommend the rejection of profitable offers. Table 2.3 shows the terms that are added to the total sum of expected payoffs of a rule under different scenarios.

TABLE 2.3: E’s fitness updating scheme under incomplete information

<table>
<thead>
<tr>
<th></th>
<th>E accepts</th>
<th>E rejects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected utility gain for E ($U^E \geq 0$)</td>
<td>$(f^b + U^E) \geq f^b$</td>
<td>$(f^b - U^E) \leq f^b$</td>
</tr>
<tr>
<td>Expected utility loss for E ($U^E &lt; 0$)</td>
<td>$(f^b + U^E) &lt; f^b$</td>
<td>$(f^b - U^E) &gt; f^b$</td>
</tr>
</tbody>
</table>

At the end of every generation, the fitness values of rules whose conditions have not been matched during the previous $i_{max}$ bargaining rounds are diminished. Such rules, which are never activated during bargaining, are deemed not useful. Both agents update to incorporate this kind of information.
2.3.3 Fitness updating under complete information

Under complete information, the venture capitalist knows the entrepreneur's preferences and expectations and can thus detect mistakes made by E. This is impossible under incomplete information. In updating the fitness value of a rule under complete information, the venture capitalist does not need E’s (possibly mistaken) reply to his contract offer, but takes her true expected utility into account. This is fitness updating policy is more accurate than the updating policy under incomplete information since E’s expected utility is a better indicator of whether or not she likes a particular contract than is her response to a contract offer, which might be inconsistent with her true preferences. The venture capitalist’s scheme for retaining and discarding rules under complete information is depicted in Table 2.4.

<table>
<thead>
<tr>
<th></th>
<th>Expected utility gain for E (U_E^E ≥ 0)</th>
<th>Expected utility loss for E (U_E^E &lt; 0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected utility gain for VC (U^V ≥ 0)</td>
<td>(f^b + U^V) ≥ f^b</td>
<td>(f^b + U^b) &lt; f^b</td>
</tr>
<tr>
<td>Expected utility loss for VC (U^V &lt; 0)</td>
<td>(f^b + U^V) &lt; f^b</td>
<td>min { (f^b + U^V), (f^b + U^b) } &lt; f^b</td>
</tr>
</tbody>
</table>

Under this scenario, the entrepreneur is also in a position to recognize mistakes made by VC. She can find out whether the venture capitalist has made an offer that is not profitable for himself. However, the entrepreneur does not benefit much from this additional knowledge because the quality of her reply to VC’s offer does not depend on VC’s expected profit or loss; it depends only on her own profit or loss. (By contrast, the quality of VC’s contract offer depends on whether the offer is acceptable for both players). The entrepreneur’s fitness updating scheme under complete information is therefore identical to the one under
incomplete information (see Table 2.3). There is one advantage to the entrepreneur when information is complete. Suppose VC makes a mistake by offering a contract that would result in an expected loss for himself. Suppose further that E accepts this offer, as it is a good one for her. Recognizing that VC has made a mistake, the entrepreneur can determine if the rule she employed is likely to accept only offers that are completely unacceptable for VC. If so, the entrepreneur will punish the rule because it will never lead to an agreement.

Finally, it should be noted that by punishing rules that endorse contract offers that the entrepreneur either cannot or does not accept, the venture capitalist acts “as if” he is under pressure to reach a deal. Similarly, by punishing rules that reject acceptable offers, the entrepreneur acts “as if” she bends to time pressures. Even though the costs of delays are not modeled explicitly, agents in the model view delays as problematic.

### 2.3.4 Experimental Design

The experiment abstracts from differential information and focuses exclusively on a comparison of complete and incomplete information. Both players receive the same signal of the project’s quality:

\[ x = y = 5. \]  

(2.3)

The agents are risk neutral, and their opportunity costs are

\[ C^v(I) = I \]  

(2.4)

\[ C^e(I^c-I) = I^c-I \]  

(2.5)

where
(Note that the superscript \( v \) indicates the venture capitalist, \( E \) the entrepreneur.) VC and E's projections of the venture's expected net operating revenues are, respectively:

\[
R^v(x) = \left(\frac{I^v}{3}\right) x - 5
\]

\[
R^E(y) = \left(\frac{I^E}{3}\right) y - 5.
\]

Together with utility functions (2.1) and (2.2), these simple linear forms (which were chosen for convenience) define the economic model that characterizes the agents. They imply that there exist many individually rational contracts, that is, contracts that yield nonnegative expected utility to both agents. The conditions for individual rationality are

\[
U^v(I, s|x=5) \geq 0 \iff s \geq \frac{3}{4}I
\]

\[
U^E(I, s|y=5) > 0 \iff s < \frac{19}{4} + \frac{3}{4}I.
\]

For example, contracts \((I=3, s=4/15), (I=9, s=10/15), \text{or} (I=14, s=11/15)\) all satisfy inequalities (2.9) and (2.10) and thus constitute potential bargaining outcomes. The problem for the bargaining agents is which of the multiple possible equilibria they should agree on.

The most important parameters of the genetic algorithm are shown in Table 2.5. Other constants (as well as the entire Delphi 2.0 source code) are available from the author upon request.
TABLE 2.5: Important parameters of the genetic algorithm

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f^b$ (initial fitness of E's and VC's rules)*</td>
<td>30</td>
</tr>
<tr>
<td>$g_{\text{max}}$ (maximum number of generations)</td>
<td>250</td>
</tr>
<tr>
<td>$l_{\text{max}}$ (maximum number of iterations per generation)</td>
<td>100</td>
</tr>
<tr>
<td>$n$ (number of VC's rules)</td>
<td>20</td>
</tr>
<tr>
<td>$m$ (number of E's rules)</td>
<td>20</td>
</tr>
<tr>
<td>$p_c$ (probability of crossover)</td>
<td>0.6</td>
</tr>
<tr>
<td>$p_m$ (probability of mutation)</td>
<td>0.01</td>
</tr>
</tbody>
</table>

* $f^b=30$ is a 'neutral' benchmark value. Any fitness value above 30 signifies an expected utility gain, any value below 30 expresses an expected utility loss for the respective actor. The value of $f^b$ was chosen to be greater than zero because the genetic algorithm cannot process negative fitness values.

The simulations are based on a six-cell experimental design consisting of a Cartesian product of the two cases of incomplete and complete information and three initial random seeds. An initial random seed determines the specification of the agents' initial rules. The same initial random seed always leads to the design of the same starting rules. After the initialization of starting rules, different sequences of random numbers are generated and used in each simulation. The experimental setup thus allows for a comparison of the effects of two different information structures on three distinct sets of original rules. In each cell, 100 separate simulation runs were conducted. Thus 600 simulations were run in total.

Detailed data sets were recorded for the first 20 runs in each cell. For the remaining 80 runs, only the bargaining outcome was recorded. A detailed data set keeps track of each player's rules and their various attributes (such as parents, crossover location, fitness, etc.) as well as important population statistics (e.g., average, maximum, minimum fitness of rules, number of mutations and crossovers, most frequently offered
contract, its profitability, etc.) in every generation. Thus, a detailed data set of a simulation run may consist of up to \(250 \times 2 \times [20 + 1] = 10,500\) individual data records.

2.4 SIMULATION RESULTS: PRESENTATION AND DISCUSSION

The maximum number of generations, \(g_{\text{max}}\), is set equal to 250. If no agreement is reached within this time frame, negotiations are considered unsuccessful. Agents stop bargaining before the allotted time limit when the system consisting of the two rule populations reaches a steady state. This happens when the following three conditions are fulfilled for three consecutive generations:

(C1) At least 80\% of the venture capitalist's offers made in a generation \(g\) are identical.

(C2) The entrepreneur's answers in generation \(g\) to the venture capitalist's most frequently offered contract are identical. They must be either all "accept" or all "reject".

(C3) If \(E\) rejects \(VC\)'s most frequently offered contract, there must be no contract proposed to her yielding an expected utility gain.

It should be noted that these operational criteria for defining a steady state equilibrium take into account the highly interactive character of the simulation model. Both sets of classifiers (E's and VC's) must co-evolve towards a high degree of homogeneity in order for conditions (C1)-(C3) to be concurrently fulfilled.

With this definition of a bargaining outcome in mind, it can be seen from Table 2.6 that on average steady states are reached much faster under complete than under incomplete information.
TABLE 2.6: Average length* of a bargaining game (in brackets: standard deviation)

<table>
<thead>
<tr>
<th></th>
<th>Initial seed 1</th>
<th>Initial seed 2</th>
<th>Initial seed 3</th>
<th>All initial seeds</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Complete information</strong></td>
<td>85 (73)</td>
<td>103 (87)</td>
<td>106 (85)</td>
<td>98 (82)</td>
</tr>
<tr>
<td><strong>Incomplete information</strong></td>
<td>164 (84)</td>
<td>169 (80)</td>
<td>162 (85)</td>
<td>165 (83)</td>
</tr>
</tbody>
</table>

*In generations. Recall that each generation has 100 iterations. If no equilibrium was obtained until generation 250, game length was set equal to 251.

On average, a game under incomplete information is up to twice as long as a game with the same initial conditions under complete information. This is because the updating of fitness values is much more precise and involves much fewer mistakes if players are endowed with knowledge of the other person's signals, preferences and expectations. Therefore convergence to a steady state is faster under complete information.

However, even if the game reaches a steady state, an agreement is not necessarily forged. For example, if the proposed deal yields a negative expected utility for the entrepreneur, the latter might reject it, and rightfully so. Alternatively, if the proposed deal prescribes unfavorable conditions for the venture capitalist, he should walk away from it. Table 2.7 summarizes the possible equilibrium outcomes of the game.
### Table 2.7: Possible bargaining outcomes in equilibrium

<table>
<thead>
<tr>
<th>VC’s expected utility ($U^v$)</th>
<th>E’s expected utility ($U^e$)</th>
<th>E’s answer</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\geq 0$</td>
<td>$\geq 0$</td>
<td>“accept”</td>
<td>Type I: Mutual agreement</td>
</tr>
<tr>
<td>$\geq 0$</td>
<td>$&lt; 0$</td>
<td>“reject”</td>
<td>Type II: E breaks off the negotiations</td>
</tr>
<tr>
<td>$&lt; 0$</td>
<td>$&lt; 0$</td>
<td>“reject”</td>
<td>Type III: Both VC and E quit</td>
</tr>
<tr>
<td>$&lt; 0$</td>
<td>$\geq 0$</td>
<td>“accept”</td>
<td>Type IV: VC breaks off the negotiations</td>
</tr>
</tbody>
</table>

The definition of a steady state requires co-evolutionary adaptation of both agents’ rule populations. Table 2.7 shows that with this definition, unilateral cancellations of negotiations are possible. The interpretation of a unilateral break-off is that E quits only after VC has demonstrated a high degree of stubbornness by repeatedly refusing to make a better offer (outcome type II). On the other hand, VC walks away from the deal only after he has become discouraged by his own inability to find a better offer and by E’s apparent satisfaction (outcome type IV). These behavioral interpretations of the model are not unreasonable.

It is evident from the analysis of the simulation experiment with respect to the distribution of outcome types that bargaining under complete information leads to a successful result more often than under incomplete information (see Figure 2.4).
FIGURE 2.4: Distribution of outcome types (in per cent)

<table>
<thead>
<tr>
<th>Initial seed 1</th>
<th>Initial seed 2</th>
<th>Initial seed 3</th>
<th>All initial seeds</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Complete information</strong></td>
<td><strong>Complete information</strong></td>
<td><strong>Complete information</strong></td>
<td><strong>Complete information</strong></td>
</tr>
<tr>
<td>TEL=8</td>
<td>TEL=21</td>
<td>TEL=20</td>
<td>TEL=16</td>
</tr>
<tr>
<td>AGR=92</td>
<td>AGR=79</td>
<td>AGR=80</td>
<td>AGR=84</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Incomplete information</strong></th>
<th><strong>Incomplete information</strong></th>
<th><strong>Incomplete information</strong></th>
<th><strong>Incomplete information</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>VQ=6</td>
<td>VQ=2</td>
<td>VQ=5</td>
<td>VQ/EQ=6</td>
</tr>
<tr>
<td>TEL=31</td>
<td>TEL=40</td>
<td>TEL=38</td>
<td>TEL=36</td>
</tr>
<tr>
<td>AGR=63</td>
<td>AGR=57</td>
<td>AGR=57</td>
<td>AGR=59</td>
</tr>
</tbody>
</table>

AGR = agreement (type I), VQ = venture capitalist quits (type IV), EQ = entrepreneur quits (type II), TEL = time elapsed (no agreement reached within set time limit). In the six leftmost cells the percentage value corresponds to the absolute number, because 100 experiments were conducted for each of these cells.

Note that there are bargaining failures even with complete information. Such failures, however, are due entirely to elapsed bargaining time and never to one of the disagreement equilibria of Table 2.7 (types II-IV).

Under incomplete information, in contrast, the model generates almost the full spectrum of disagreement outcomes. Only type III outcomes are never observed. This is because the experiment is specified as a constant positive sum game. (Note that $U^V + U^E = 5$, which can be derived from inserting equations (2.3), (2.6), (2.7) and (2.8) into (2.1) and (2.2)). In other words, at least one of the agents will always benefit from a deal.

Besides suggesting that inefficient bargaining outcomes are more frequent under incomplete information than they are under complete information, Figure 2.4 also indicate that different initial rule sets affect the final result. For example, the first initial random seed and its associated set of initial rules seem to lead to
more agreements than do the other two.

A closer look at the distributions of agreement outcomes for two of the three different initial seeds in Figures 2.5 and 2.6 reinforces the conjecture that initial conditions may influence final results. Under complete information, for example, initial random seed 1 often results in outcomes favoring a rather low equity contribution by the venture capitalist (see Figure 2.5), whereas seed 2 advocates more medium to high venture capital investments in the complete information case (see Figure 2.6).

**FIGURE 2.5:** Frequency of agreement outcomes for first random seed
Figures 2.5 and 2.6 also facilitate a comparison of outcome patterns between the two basic information structures. First, under complete information, the algorithm seems more prone to produce certain points of gravity (e.g., points (0,3), (2,5), (3,6) in Figure 2.5) towards which contract offers evolve. In contrast, the picture for the incomplete information case is more scattered. Here, outcomes are more evenly distributed throughout the core, which is the region between the lines representing individual rationality constraints (2.9) and (2.10). Second, most contracts under incomplete information yield a higher utility for VC than for E, one nonetheless observes some outcomes from which E would benefit more than VC. Such results occur less
frequently when information is complete. The results shown in Table 2.8, which reports how the agents tend to split total expected utility $U^V + U^E = 5$ when they reach an agreement, supports this finding.

### TABLE 2.8: Mean (standard deviation) of expected utility in case of agreement

<table>
<thead>
<tr>
<th></th>
<th>Initial seed 1</th>
<th>Initial seed 2</th>
<th>Initial seed 3</th>
<th>All initial seeds</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Complete information</strong></td>
<td>VC: 4.25 (0.65)</td>
<td>VC: 4.08 (0.75)</td>
<td>VC: 4.06 (0.75)</td>
<td>VC: 4.14 (0.72)</td>
</tr>
<tr>
<td></td>
<td>E: 0.75 (0.65)</td>
<td>E: 0.92 (0.75)</td>
<td>E: 0.94 (0.75)</td>
<td>E: 0.86 (0.72)</td>
</tr>
<tr>
<td><strong>Incomplete information</strong></td>
<td>VC: 3.26 (1.37)</td>
<td>VC: 2.97 (1.42)</td>
<td>VC: 3.19 (1.45)</td>
<td>VC: 3.13 (1.43)</td>
</tr>
<tr>
<td></td>
<td>E: 1.74 (1.37)</td>
<td>E: 2.03 (1.42)</td>
<td>E: 1.81 (1.45)</td>
<td>E: 1.87 (1.43)</td>
</tr>
</tbody>
</table>

Table 2.8 shows that the utility gap between the venture capitalist and the entrepreneur is in the range 3.1-3.5 in the case of complete information, but shrinks to a value between 0.9 and 1.5 under incomplete information. (Note, however, that the standard deviation under incomplete information is almost double the standard deviation under complete information). While incomplete information creates a bargaining environment that is more prone to inefficiencies in terms of disagreements and longer bargaining durations, it also fosters a more equal distribution of outcomes. The venture capitalist’s considerable bargaining power, which stems from his being the first mover in every bargaining round, is weakened under incomplete information by his lack of knowledge about E’s preferences and about her appraisal of the venture’s expected profitability. Thus, hiding information from the venture capitalist protects the entrepreneur from being exploited. However, this protection policy comes at the cost of a higher risk of failure. This is a delicate tradeoff for the entrepreneur.

In summary, the major experimental findings of this chapter are that relative to a complete information
scenario, incomplete information leads to delays (cf Table 2.6), a greater variety of disagreement outcomes (cf Figure 2.4), and, on average, a larger share of the pie for the entrepreneur (cf Table 2.8). A sensitivity analysis carried out for different parameters of the genetic algorithm (i.e., mutation and crossover probabilities, game length) confirmed that these results are reasonably stable.

These results can be compared with benchmark solutions obtained from game theoretic models. To do this, the Nash solution for co-operative bargaining games is derived.6 Nash (1950, 1953) postulated that any agreement point (commonly known as the Nash bargaining solution) of a game will satisfy a set of four axioms. He showed that these axioms together imply that the agreement points of the game are defined by a unique solution that maximizes the so-called Nash product, which, for the problem here, takes the form

\[ \pi = U^V \cdot U^E. \]  

(2.11)

The maximization of (2.11) is carried out with respect to the variables \( s \) and \( I \) and is subject to the constraints:

\[ 0 \leq s \leq 1, \quad 0 \leq I \leq I^a \]  

(2.12)

and

\[ U^V \geq 0, \quad U^E \geq 0. \]  

(2.13)

Substituting (2.3) - (2.8) into (2.1) and (2.2), we can rewrite (2.11) as

---

6Note that these calculations assume that \((I,s) \in \mathbb{R}^2\), whereas in the simulations \(I\) and \(s\) are integers.
\[ \pi = (20s - I^v)(5 - 20s + I). \]  
\[ (2.14) \]

An optimal solution will be denoted as \((I^o, s^o)\). The first-order condition for (2.14) is

\[ s^o = 1/8 + 1/20 I^o. \]  
\[ (2.15) \]

Since any vector \((I^o, s^o)\) defined by (2.15) and (2.12) is an agreement point of the game, the Nash optimization program predicts multiple equilibria. (For a graphical illustration of the Nash solution, see line N in figures 2.5 and 2.6.) Each contract \((I^o, s^o)\) yields \(U^v = 20s^o - I^v = 20(1/8 + 1/20 I^o) - I^v = 2.5\) to the venture capitalist and \(U^e=2.5\) to the entrepreneur. In other words, the Nash bargaining solution prescribes an equal split of the pie (which is to be expected since the game is symmetric). Of course, these calculations presuppose that information is always complete, they therefore yield an only imperfect benchmark for the agents in the model. Nonetheless, it is interesting to note that the outcome points produced in the experiment with incomplete information would lie closer to the line defining the Nash bargaining solution than would the outcome points generated under complete information.

2.5 CONCLUSIONS

This chapter develops a rationale for inefficient bargaining under incomplete information that is different from the ones advocated by standard game theory. The sensitivity of learning and adaptation to information structures is shown to be a possible reason for delays and failures to reach an agreement. The less information economic agents possess, the more difficult is the correct interpretation of messages, and the more inaccurate are their actions based on these messages. The model also yields the (perhaps surprising) result that the respondent in the repeated bargaining game may actually benefit from incomplete information.
The entrepreneur can expect a larger share of the pie, on average, when crucial information is hidden from both actors than when both actors are fully informed. Although her average expected utility is still less than that of the venture capitalist, the latter can no longer fully exploit his powerful position of being the first mover in each bargaining round. This is consistent with data from experiments with human subjects that concludes “incomplete information increases the bargaining power of the weak player and decreases the bargaining power of the strong player” (Kuon, 1994: p.268).

The observed tendency of moving toward a more equal split of the pie under incomplete information could be of relevance to the debate about whether people are ‘fair’ when playing ultimatum games. According to the data generated by this model, the noble trait of fairness is perhaps not so much an intention as a consequence of adaptive learning under incomplete information. This bold interpretation must be considered with caution, however, since it is not clear that the same results as those reported here would be obtained with different model structures, especially ones in which the agents are not symmetric.

It can be stated with some certainty, however, that the model presented in this chapter constitutes a novel, descriptive approach to bargaining. It links the concepts of multidimensional contracts, asymmetry of information, bounded rationality, and inductive learning in a first step toward modeling free flow bargaining. By taking informal communication processes into account, it considerably widens the scope for incorporating relevant bargaining actions. Future research in this direction could extend this type of modeling to offer-counteroffer processes, and, finally, to free, uninhibited message flows.

The model distinguishes between learning by experience (reinforcement learning) and learning by experimentation. Learning is defined here as finding a contract that satisfies both parties, that is, one that lies in the core of the game. It does not, however, refer to the task of discerning the true quality, q, of the project,
which could eventually mitigate the problems associated with adverse selection (see the seminal article of Akerlof, 1970). To introduce this type of learning, the model structure would have to altered such that a venture capitalist (or an entrepreneur) could become adept at inferring the true type of the proposed venture from signals by engaging in a series of repeated bargaining games. Such a skilled agent would then start a new bargaining game with initial rules shaped by previous negotiations. Normative questions such as how inexperienced entrepreneurs should bargain with experienced venture capitalists could subsequently be examined.

The model could be extended by incorporating time discounting, more sophisticated beliefs, asymmetric agents, asymmetric signals, more complicated contracts, and post-contract actions, for example. As such, a number of significant theoretical issues could be addressed. On the experimental side, it would be interesting to compare data from experiments with human subjects with the results from computer simulations in order to determine how well the genetic algorithm model captures human learning. Are there parameters and other elements of the model that could help it align more accurately with actual human behavior? Can the model explain experimental data more convincingly than can other learning models? Ultimately, the hope is that the present approach can be built upon and extended to provide normative guidance to practitioners as to how to surmount barriers to efficient and effective bargaining.
CHAPTER 3

DIFFERENTIAL FIRM PERFORMANCE
IN A BEHAVIORAL MODEL
OF ORGANIZATIONAL CHANGE

3.1 INTRODUCTION

A satisfactory answer to the question "Why are firms different?" continues to elude researchers in strategic management despite two decades of empirical and theoretical research aimed at finding one (Rumelt, Schendel, and Teece, 1994). A closely related, yet more focused question is: "Why do firms perform differently?" These questions have captured the academic community's interest because differences among competing firms should be obvious, and yet conventional economic theory cannot account for them. In a competitive equilibrium, any differences between firms should be eliminated by competition.

On the empirical side, Schmalensee (1985) approached the conundrum of heterogeneous firm performance by disaggregating business-unit profits into components capturing industry effects, corporate-parent effects, and market share effects. His seminal work confirmed the importance of industry effects and triggered a debate on the relative influence of industry and business on firm performance. By extending Schmalensee's approach, Rumelt (1991) and McGahan and Porter (for example, 1997a) were able to show that business effects are "about twice as important as industry effects to performance" (McGahan, 1998: p.24).
This chapter examines theoretically why and under what circumstances firms in the same industry differ in performance in a dynamic setting without exogenous shocks. It abstracts from industry effects and other non-firm related effects that the empirical literature has taken into account. Its predominant concern is the effects of business-specific characteristics on firm profitability. The chapter develops a behavioral model of a firm in which simple rules guide firms on whether to adapt internally to a changing environment and whether or not to imitate others in order to effect organizational change. Through simulation of the model, in which firms compete simultaneously, the analysis considers various conditions that are thought to give rise to the emergence of sustainable competitive advantage.

Although there is no shortage of theoretical approaches to explain the sources of differential profitability, this chapter contrasts four influential but competing hypotheses regarding the nature of such differences that have been put forward in the literature. These hypotheses include 1) limits on the strategy of imitation of best practice through, for example, causal ambiguity (Lippman and Rumelt, 1982); 2) organizational inertia or, reversing the argument, first-mover advantages (see, for example, Lieberman and Montgomery, 1988); 3) learning from experience (Arrow, 1961); and 4) managerial choice behavior (see, for example, Rumelt, Schendel and Teece, 1994: p.43 and p.225). The objective of this chapter is to assess which (sets of) explanations are likely to be the most important. The chapter takes on this challenge by incorporating the above hypotheses as assumptions into a model of firm behavior and then systematically adding and dropping assumptions and simulating the respective model specifications to appraise the validity of different sets of assumptions in generating heterogeneous firm performance.

The results indicate that managerial choice and organizational inertia are plausible sources of differential firm performance. Experiential learning regarding organizational change, on the other hand, leads to diverging firm performance only under certain conditions. The importance often attributed to this argument
in the literature should therefore be critically reviewed. The chapter confirms that from the viewpoint of underperforming firms, a situation in which such firms lack possibilities for imitation is unattractive because it perpetuates performance differences. However, and perhaps quite surprisingly, the opportunity to imitate others does not necessarily present underachieving firms with a viable strategy for better performance. Firms that utilize an imitation strategy shoot at “moving targets,” and they aim at market niches which might already be occupied. The model thus cautions against the use of imitation for effecting organizational change.

The main intention of this study is to integrate four important conceptual approaches to differential firm performance in one rigorous and formal model and to establish a link with empirical findings. The chapter makes two additional contributions to the strategy field. First, it suggests a simple formalization of the notion of dynamic capabilities. Second, it formally combines the resource-based view of the firm with behavioral decision theory.

In modeling firm behavior, the chapter draws on the notion of dynamic capabilities introduced by Teece, Pisano and Shuen (1997). The authors define a dynamic capability as the “ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments” (p.516). Put differently, a dynamic capability enables a company to create new products and processes and respond to changing market circumstances. It is usually embedded in complex organizational processes. Since these processes aim at changing aspects of the organization, one could say that dynamic capabilities are conceptually related to the construct of “change rules” in the present model, which are the rules that characterize firms in the model. In fact, a change rule can be interpreted as a codified dynamic capability. This is a simplification of a rich and complex concept, but it may be viewed as a step towards a more encompassing model of dynamic capabilities.
The literature on dynamic capabilities is relatively sparse. Teece, Pisano and Shuen's (1997) seminal work views dynamic capabilities as unique to a firm because they are shaped by the firm's asset positions and by its evolutionary paths. This uniqueness accounts for heterogeneous wealth creation and capture by firms. The present study takes a slightly different position in that the model presented here is not evolutionary. Rules remain fixed throughout the life of a firm, only their evaluation changes. Each firm uses the same set of rules, which are initially associated with identical evaluations. One important goal of the analysis is to see whether uniqueness emerges endogenously, i.e. whether some firms prefer to use different subsets of rules than others, and what the performance implications of this are.

In another important contribution to the literature on dynamic capabilities, Helfat (1997) provides an empirical investigation of the dynamic R&D capabilities in the U.S. petroleum industry. In particular, she investigates the role of complementary assets in the context of changing market conditions. Her findings suggest that complementarities have a positive effect on the development and/or deployment of dynamic capabilities. Despite this important empirical contribution and the conceptual approach described above, no attempt has been made to develop a rigorous formal model of dynamic capabilities to explore their alleged impact on creating and sustaining competitive advantage. This chapter provides a starting point for such an endeavor.

The model presented in this chapter merges the resource-based view of the firm with behavioral decision theory, as suggested by Amit and Shoemaker (1993). The resource-based view of the firm argues that heterogeneous bundles of resources and capabilities within firms may account for differences between firms, and ultimately for heterogeneous firm performance. Important early contributions to this literature, which have drawn inspiration from the work of Penrose (1959), include Wernerfelt (1984), Barney (1986), and Conner (1991). In an attempt to make the theory more dynamic, Dierickx and Cool (1989: p.1504)
acknowledge that "critical resources are accumulated rather than acquired". They make an important
distinction between flow variables, which can be altered instantaneously, and stock variables, which need
time to develop and are therefore candidate sources of competitive advantage. Barney (1991) and Peteraf
(1993) identify and examine the conditions under which firm resources (especially capabilities and other
organizational processes) contribute to sustained competitive advantage. Both authors argue within a rational
equilibrium framework, which does not easily accommodate uncertainty, complexity, and conflict, which,
according to Amit and Shoemaker (1993), constrain organizational decision making. It seems appropriate
to use behavioral models of decision making, since firms choose, develop, allocate and deploy resources
and capabilities in a dynamic context. In doing this, the present study follows a rich tradition of research
established by Cyert and March (1963) and Nelson and Winter (1982).

There is also a long tradition of using computer simulation to investigate issues related to organizational
change. Objectives have ranged from understanding or describing how individual organizations learn (e.g.,
Levinthal and March, 1981; Sastry, 1997) to examining how populations of organizations evolve (e.g., Lant
and Mezias, 1990). In contrast to these earlier studies, this chapter does not focus on a single firm, nor does
it adopt a population perspective. Instead, it looks into the 'black boxes' of the decision-making of a limited
number of individual firms within an industry and attempts to understand the relative performances of these
firms. It thus combines the two perspectives.

Lant and Mezias (1990) investigate the effectiveness of several exogenously given change strategies
(adaptation, imitation, and inertia) when firms are faced with a fundamental restructuring of their
environment. As in the present study, the authors take firm performance to be the dependent variable of their
simulation analysis. However, the present study diverges from Lant and Mezias (1990) in several important
aspects. First, it is not confined to a population view. Second, in the model developed here, firms may
endogenously choose their change strategy (i.e., dynamic capability). Third, the environment of a firm is stable, with the exception of the possibly fluctuating decisions of rivals. Finally, firm performance is endogenously assigned.

There are several advantages to using computer simulation as research method. First, it allows researchers to model highly complicated and complex interactions between firms. As Lant and Mezias (1990: p.151) state, "A computer simulation can take a complex set of assumptions, simulate a set of organizational processes, and represent the implications of these processes for organizational outcomes." Second, it traces and highlights the unfolding of longitudinal processes and their implications over long time horizons. This is important for the examination of sustainability. Third, whereas longitudinal empirical data represent only one trajectory of events emanating from a given set of initial conditions, computer simulation can generate many such trajectories based on the same set of conditions (Mezias and Eisner, 1997: p.268). This allows one to develop a better general understanding of the underlying processes involved in firm performance than is possible with longitudinal data. A fourth advantage of using simulation methodology is that it can easily accommodate bounded rationality (Simon, 1955). Decision makers often use heuristics when making managerial choices and they sometimes make mistakes (Kahneman, Slovic and Tversky, 1982). These factors can be accommodated in a simulation model.

The computer simulation in this study complements the theory development. Sastry (1997) provides an excellent example of how computer simulations can support theory development. She formalizes a verbal theory of punctuated change and discovers gaps in the theory through the use of simulations. She is then able to suggest additional assumptions that complete the theory. This study uses a different approach. By simulating the dynamic interaction between firms, the model assesses the validity of various (sets of) hypotheses for the emergence of differential firm performance.
There are two important caveats to be noted about the approach used in this study. First, the results of a computer simulation run are likely to be sensitive to numerous explicit and implicit assumptions. Second, the programming itself influences the outcomes. There could be glitches in the source code or its logic might be erroneous. To minimize these effects, the chapter reports the results of sensitivity checks, describes the program flow, and includes a flow chart of the algorithm. The source code is available upon request. It is written in Delphi 2.0, which is a graphical programming interface that uses a form of Turbo Pascal as programming language.

3.2 A BEHAVIORAL MODEL OF THE FIRM

In neoclassical economic theory, firms are often represented as production functions, whereas in game theory they are usually described in terms of their strategy space. The model developed here views firms as bundles of capabilities that are managed dynamically for the purpose of earning profits. More specifically, a firm is viewed as a set comprising the following three elements: a vector of decision variables; a collection of change rules; and a probability distribution over these heuristics. This model is consistent with resource-based theory, behavioral decision theory, and Teece, Pisano and Shuen's (1997) notion of dynamic capabilities.

3.2.1 Vector of decision variables

The decision variables in the model are output quantity, product innovation rate, and process innovation rate. The choice of output quantity has repercussions for all firms in the industry because the price of the products offered is partially determined by an inverse linear demand function common to the industry. By setting a certain pace of product innovations, a company can differentiate its products from those of its competitors and demand a higher price; by choosing an appropriate pace of process innovations, it can lower its
production costs. (For a more detailed description of these variables and for other formal aspects of the model, refer to the section “The Formal Model” below.) These decisions affect the day-to-day operations of a firm, which can be called “routines” (Nelson and Winter, 1982), when they are regular and predictable. The vector of decision variables can therefore be interpreted as representing the current business practices of a firm. In a sense, it reflects the resources and capabilities of a firm, upon which its business practices rely.

### 3.2.2 Collection of change rules

The bundle of change rules represents a company’s body of wisdom about how to modify its business practices. Firms use rules partly because they lack the comprehensive and sophisticated information processing and computation capabilities required to derive an analytical solution to complex inter-temporal optimization problems. Alternatively, firms may simply not possess all the information necessary to find this solution. Levinthal and March (1993: p.103) highlight the importance of a behavioral approach to strategy when they state that “strategic management is the art of dealing intelligently with the three grand problems of decision making: 1. The problem of ignorance. 2. The problem of conflict. 3. The problem of ambiguity.” The use of heuristics is one reasonable way to deal with these issues.

A change rule is a recipe for how a firm should enact organizational change - whether it should favor adaptation or imitation, and to which decision variables it should apply any of these strategies. A rule might stipulate, for example: “Adaptively increase output quantity, keep the product innovation rate at its current level, and copy the industry leader’s process innovation pace.” Adaptation and imitation have been chosen here as the components of basic change operations because they constitute fundamental possibilities for organizational improvement: gaining first-hand experience through adaptive experimentation versus acquiring second-hand experience through mimicry (for a discussion of the circumstances under which imitation is preferred to learning through first-hand experience, see Dutton and Freedman (1985)). Levinthal
(1981) and Sastry (1997) consider only the possibility of adaptation, whereas Lant and Mezias (1990) also incorporate imitation into their model of organizational change. The present study builds on the latter approach and extends its scope by rendering the choice between adaptation and imitation endogenous to the model.

A change rule could be interpreted as a formal representation of what Teece, Pisano and Shuen (1997: p.515) call a "dynamic capability," whereby "the term 'dynamic' refers to the capacity to renew competencies so as to achieve congruence with the changing business environment...the term 'capability' emphasizes the key role of strategic management in appropriately adapting, integrating, and reconfiguring internal and external organizational skills, resources and functional competencies." The analogy between heuristics for organizational change and dynamic capabilities is as follows. Since firms in the model may change their decision variables at any time, the environment in which they operate is inherently dynamic. The desire to make profits forces firms to continually try to achieve congruence, that is, search for the best possible fit with their changing environment. In other words, firms seek to set the values of their decision variables such that they maximize profits given the decisions made by other firms. Since decision variables may be seen as reflecting a firm's competencies in routine business operations, any change thereof requires specific skills and capabilities. For example, the product innovation rate could describe a company's regular R&D activities. To modify them, a firm might have to reorganize internally, develop new knowledge networks, or reallocate critical resources. The successful application of a change rule requires that the firm is indeed capable of carrying out these steps (albeit possibly at some cost). The concept of change rules thus rests on the assumption that the firm has all the necessary skills for implementing organizational change. In this broad sense, it can be viewed as a codified dynamic capability.

Change heuristics are technically represented in the model as strings of length three, drawn from the set \{0,
1, 2, 3. “0” encodes the action “retain value,” “1” represents “imitate industry leader’s value,” “2” represents “adaptively adjust value downward,” and “3” represents “adaptively adjust value upward.” The first element in a string tells a firm how to set the value of the quantity variable, the second refers to the product innovation rate, and the third element defines an action with respect to the process innovation rate. For example, rule “120” calls for imitating the product quantity of the industry leader, lowering the rate of product innovations by a certain margin, and retaining the speed with which process innovations are realized. Note that the decision variables in the model are flow variables; they can thus be adjusted instantaneously. With three decision variables and four possible actions, there are a total of 64 rules per firm for organizational change per firm.

3.2.3 Probability distribution over rules

Each decision rule is subject to an evaluation of its usefulness which involves the calculation of a so-called fitness value. From this fitness value the probability that the rule will be selected for determining how to go about changing current business practices is derived. In general, the higher a rule’s fitness, the greater is its likelihood of selection. The derived probability distribution over change rules constitutes the third and last element of a behavioral model of the firm.

3.3 THE SIMULATION ALGORITHM

The algorithm presented below was inspired by Arthur (1991). At the beginning of every period, each firm must choose the values of its decision variables. This decision is split into two distinct parts. First, a firm (always) searches for an appropriate change rule according to certain selection criteria (for example, firms could look for rules that promise to increase performance). Once a candidate rule has been determined, the firm must decide whether or not to implement the suggested changes. This implementation decision
constitutes the second part of the firm's overall decision problem.

Once these issues are settled, firms compete: they simultaneously announce their chosen output quantities and innovation rates. A firm's payoff is contingent on the decisions made by all firms in the industry (mainly through the inverse demand function - see the formal model). At the end of a period, firms receive information about other firms' choices and take this information into account when reevaluating the usefulness of their change rules. They then enter into a new round of search, possible organizational change, competition in the marketplace, and reappraisal of rules. At the end of the last period, the simulation terminates. Figure 3.1 illustrates this flow of activities.
FIGURE 3.1: Flow of the algorithm from the point of view of a firm

START

Initialize all variables and parameters

Select a change rule

Randomly decide whether to change

YES

Implement new values

NO

Simultaneously compete with other firms

Assess profits and observe other firms' choices

Calculate new fitness values

Update beliefs and cost structure

NO

Last Period?

YES

END
3.3.1 The costs of organizational change

Organizational change is defined as the modification of the value of at least one decision variable. A modification usually bears some costs. For example, when imitating a corporate competitor, a firm needs to gather information about what its rival is doing and how the action is done. Channels for acquiring this information include consultants, trade shows, publications, and networks of clients, suppliers and other professionals. Other sources of change costs include sunk investments in skills and work relationships under the old system and the costs of mistrust between individuals within a firm (see Ichniowski et al., 1997).

The structure of a firm’s change costs is defined by several parameters. Recall that there are three decision variables and two basic actions per variable, namely adaptation and imitation. The cost of applying a specific action to a specific decision variable is given by a distinct parameter. This implies $2 \times 3 = 6$ change cost parameters. In addition, the more variables are simultaneously changed, the more disruptive, and thus the more expensive, organizational change becomes. The model therefore includes parameters describing the costs of undertaking simultaneous changes. All firms have the same initial cost structure.

Learning by doing reduces change costs. Each time a firm implements a specific type of organizational change, the involved cost parameters decrease by a fixed margin. In time, firms learn to cope more effectively and efficiently with the disruption and stress caused by certain modes of change. Put differently, “the higher the level of accumulated experience with reorientation, the less organizational competence is destroyed in subsequent reorientations” (Sastry, 1997: p.262). It may thus become more attractive to a firm to implement the same kind of change in the future.
3.3.2 Beliefs, updating of decision rules, and organizational learning

Firms maintain beliefs about the effectiveness of their decision rules. These beliefs are expressed as a probability distribution over the set of rules. Probabilities are derived at the end of each period by considering the potential future performance implications of each rule under the simplifying assumption that other firms maintain their current decisions. Fitness values are calculated as the expected net present values of changes in performance resulting from organizational change, minus the respective change costs. Under deterministic rule selection, firms assign a probability of 1 to the rule with the highest fitness and a probability of 0 to all others. Under stochastic selection, fitness values are linearly translated into probabilities. The higher the fitness, the heavier the probability weight.

It should be emphasized that the calculation of fitness values, and hence firms’ beliefs, do not take history fully into account (with the exception of possibly decreasing change costs through learning by doing). Fitness values are based on an anticipation of the future rather than on an interpretations of the past. This structure is based on the logic that, especially when organizations change, experience is often a poor teacher (see Levinthal and March, 1997). Despite its low emphasis on experience, the model can be considered a learning model based on the definition that “an entity learns if through its processing of information, the range of its potential behaviors is changed” (Huber, 1991: p.89). A firm in the model acquires knowledge, and thus learns, by observing (and then possibly imitating) other organizations and by searching for information about the firm’s performance and its environment. This process may cause changes in behavior, that is, changes to the values of decision variables.
HYPOTHESES FOR SUSTAINED HETEROGENEOUS FIRM PERFORMANCE

One of the simplest and most fundamental explanations of heterogeneous firm performance is that firms perform differently because the behavior of managers differs: "Firms faced with the same situation may act differently due to differences in beliefs, differences in aspirations, or differences in the administrative processes producing decisions ... Similarly, firms (or their managers) may fail to adopt best practice because they do not perceive it, [or] because they do not like it" (Rumelt, Schendel and Teece, 1994: p.226). The unsystematic aspects of differing managerial choice can be modeled as a random process. For example, firms may select change rules randomly on the basis of their probability distributions over rules. As a consequence, they are likely to consider different actions for effecting organizational change. Different actions may imply different performances. This chain of arguments suggests the following hypothesis:

**Hypothesis 1:** Firms exhibit differential performance because they are likely to select different change rules in every period.

Another way of phrasing Hypothesis 1 is to say that differences among firms may arise from not only intention, but also stochastically. (Hypothesis 1 does not address the systematic biases of some managers.)

It is widely believed that in many industries firms gain proficiency simply through the repetitive use of activities. As a result of such 'learning by doing,' the costs of carrying out these activities are reduced (Arrow (1961) provides one of the first analyses of this phenomenon). Learning-based approaches to sustainable competitive advantage build on this argument by proposing that firms may differ in efficiency because of differences in their histories (differences in their histories of production, for example). Lieberman (1987) shows that in most industries, learning is rapidly diffused through competing firms. This may not be
the case, however, when the notion of learning by doing is applied to activities that are more difficult to copy or substitute than, say, production processes. Activities related to organizational change may exemplify such a case; learning how to change a specific organization is usually proprietary. Spence (1981) demonstrates that under this condition, learning-based cost advantages can bestow a sustainable advantage on a firm. This idea is transformed into the following hypothesis:

**Hypothesis 2:** Firms exhibit sustainable differential performance because change costs can be reduced through learning by doing. As a result, they embark on different trajectories of organizational change.

In contrast to the previous hypothesis, this hypothesis is reconcilable with the concept of competitive equilibrium because it posits that firm-specific efficiencies are related to an intangible asset (experience) that cannot be easily purchased or competed away.

Reaping the advantages of being a first mover is another argument that is sometimes offered in response to the question of why some firms perform better than others within the same industry. So-called first-mover advantages enable firms to either establish (possibly long-lasting) powerful positions in an industry (through technological leadership, preemption of strategically valuable assets, or the creation of consumer switching costs (Lieberman and Montgomery, 1988)), or earn (relatively short-lived) Schumpeterian rents. In both cases the key to securing a competitive advantage is being one step ahead of the competition.

The flip side of this argument is the contention that many organizations possess some degree of inertia (how else could anybody move ‘first’?). “As long as the organization does not change..., inertia builds up over time through ongoing social and structural processes” (Sastry, 1997: p.247). The model captures this reluctance to change by separating the choice of a change rule from the decision whether to implement it. In any given
period, each firm selects a most-favored rule, but then realizes the suggested changes only with a certain probability. This allows for the possibility that some firms will act whereas others remain inert and allows stochastic factors to influence the relative performance of firms. This reasoning is captured in the following hypothesis

**Hypothesis 3**: Firms exhibit differential performance when organizational change is uncertain (and thus at times asynchronous).

Another popular explanation among strategy scholars for sustainable competitive advantage is imperfect imitability of resources and capabilities. Barney (1991) and Peteraf (1993) view this as one of the crucial conditions for sustainability. The argument originates with Lippman and Rumelt (1982), who assert that the reasons for important differences in efficiency between firms are usually not well understood, not even by the managers of the more profitable firms themselves. They refer to this phenomenon as “causal ambiguity,” which naturally limits emulation of best practice within an industry. Mechanisms that further “isolate” (Rumelt, 1984) firms from imitation by rivals are found in unique historical conditions, social complexity, and patent rights. These arguments are captured in the following hypothesis:

**Hypothesis 4**: Firms exhibit differential performance when they have limited opportunities to imitate each other.

The simulation model presented in this chapter distinguishes among these four fundamental and often-cited hypotheses for the emergence of sustainable competitive advantage (see, for example, Rumelt, Schendel and Teece, 1994: p.225 ff). It also explores their validity in a highly dynamic context through computer simulation. The model can be fine-tuned to reflect any subset of the hypotheses. More specifically, hypotheses are built as corresponding assumptions into the model.
3.5 THE FORMAL MODEL

Assume there are n firms competing with a differentiated product in a market. In each of p periods each firm has to make decisions about how much to produce, how many product innovations to pursue, and how many process innovations to implement. Formally, these decision variables are denoted $q_{jt}$, which is the output quantity of firm j in period t, $r_{jt}$, which is the rate of product innovations of j in t, and $i_{jt}$, which is j’s rate of process innovations in period t. According to Milgrom and Roberts (1995), these three decision variables are among the major determinants of firm performance in modern manufacturing. Arguably, this is also true for a wider range of industries. Innovation rates are crucial determinants of success in the pharmaceutical and semiconductor industries, for example. Product innovations in particular serve to improve products and thus enable firms to demand higher prices. Process innovations, on the other hand, are generally aimed at reducing production costs. However, both product and process innovations can influence firm profits in a variety of ways.

Consider, for example, process innovations. Business processes have recently been the focus of managers and management consultants in many companies, giving rise to movements such as Total Quality Management, Business Process Redesign (or Re-engineering), Time-based Competition, and Downsizing, to name a few (see also Keen and Knapp, 1995). It is generally acknowledged that an enhanced awareness of the importance of processes has helped some firms make significant cost savings. Total production costs in the model, denoted by $C_{jt}$, are inversely related to accumulated process innovations. If $v$ denotes variable production costs (which are assumed to be constant across time and firms), we have the following:

$$C_{jt}(q_{jt}, i_{jt}) = q_{jt} \cdot v \cdot (1 + 3/\Sigma i_{jt}) \quad (3.1)$$
Note that total production costs in equation (3.1) are determined by total output multiplied by variable costs. However, variable production costs decrease with accumulated process innovations over time. For \( t \to \infty \) the term \( \Sigma i_{jt} \) will likely grow quite large, in which case total production costs are likely to approach \( q_{jt} \cdot v \) asymptotically.

The costs of process innovations of firm \( j \) at time \( t \), \( I_{jt} \), must also be taken into account. These costs are sometimes referred to as the "process paradox." For a characterization of this paradox, consider a report on re-engineering projects that finds that "in all too many companies, re-engineering has been not only a great success but also a great failure. After months, even years of careful redesign, these companies achieve dramatic improvements in individual processes only to watch overall results decline" (Hall, Rosenthal and Wade, 1993). In other words, process innovations may entail significant costs, which sometimes outweigh the benefits. Changes made at one point of the production process to improve workflow or coordination of activities, for example, might increase workload at other points. The associated costs are thus:

\[
I_{jt} = i_{jt}^2
\]

For product innovations, there is a similar trade off between benefits and costs. On the upside, a large number of product innovations are likely to result in a tighter fit of a company's product line with market needs. They thus enable the company to charge a higher price, because customers have a higher willingness to pay. On the downside, intensifying R&D efforts and thus increasing the rate of product innovations is costly. If \( \epsilon \) denotes the aggregate exogenous price of all input factors (such as technology or human capital) that facilitate product innovations, the total costs of product innovations, \( R_{jt} \), can be written as a function of \( \epsilon \) and \( r_{jt} \). In the model, this function takes the simple quadratic form:
The higher the exogenous price level and the higher the rate of product innovations, the more expensive will be the realization of the desired number of product improvements.

Theoretical research has established that Cournot competition can often be modeled as a two-stage game in which firms set capacity levels in stage one and prices in stage two (for a summary of these results, see Tirole, 1988). So even when firms in reality are price-setters, there are circumstances under which it is reasonable to model them as quantity-setters. This supports the approach taken in the present model, in which the inverse demand function is partially specified as

\[ p_t(q_t) = (n^* K - \sum q_i) \]  

(3.4)

where \( K \) is a constant and \( p_t \) is the price of an undifferentiated product. A lower aggregate quantity translates linearly into a higher price, and vice versa.

Besides the indirect influence a firm exerts on price through its quantity decision, it can also directly affect price through its choice of product innovation rate, which differentiates the company's product from those of its rivals. If a firm is more innovative than its competitors it may demand a higher price; if it is less innovative than the average player in the industry, it must accept a lower price. This relationship is captured by the fully specified inverse demand function

\[ p_{jt}(q_{jt}, r_{jt}) = (n^* K - \sum q_i) \times \left\{ r_{jt} / [(1/n) \times \sum r_{jt}] \right\} \]  

(3.5)
$P_{jt}$ is the final price of a differentiated product. The multiplier \( \{r_{jt}/ [(1/n) \times \sum r_{i,j}] \} \) is greater than 1 if a firm’s rate of product innovations at time $t$ is greater than the average rate in the industry. Other firms co-determine the price firm $j$ may ask for its products through their aggregated quantity and product innovation rate decisions. Each firm’s profit thus depends on the combined choices of all other firms. (Note that the model ignores the total stock of product innovations and thus applies predominantly to markets where being current is important, i.e., to so-called “fashion markets”.) Firm $j$’s revenues, $M_{jt}(q_{jt}, r_{jt})$, can be written as

$$M_{jt}(q_{jt}, r_{jt}) = q_{jt} \times P_{jt}(q_{jt}, r_{jt}) \quad (3.6)$$

The essence of the formal model is that firms compete in each period on quantity (through product quantity, $q_{jt}$), on quality (through the rate of product innovations, $r_{jt}$), and on production costs (through the rate of process innovations, $i_{jt}$). The model thus diverges somewhat from pure Cournot competition. It acknowledges a variety of competitive moves that involve distinct trade offs between benefits and costs. A higher output quantity, for example, tends to increase revenues through a higher sales volume, but it also depresses revenues through a lower price. These trade offs are captured by the profit function of firm $j$, $\pi_{jt}$, which describes a company’s profits before any change costs:

$$\pi_{jt} = M_{jt} - C_{jt} - R_{jt} - I_{jt} \quad (3.7)$$

Inserting equations (3.1)-(3.6) into (3.7), profit (before change costs) can also be written as

$$\pi_{jt} = q_{jt} (nK - \sum q_{i,k}) \times \{r_{jt}/ [(1/n) \times \sum r_{i,j}] \} - q_{jt} \times (1 + 3/\sum i_{jt}) - \epsilon^2 r_{jt}^2 - i_{jt}^2 \quad (3.7')$$

This is the objective function (before change costs) to be maximized by firm $j$ for period $t$. It is difficult to
compute an analytic solution to the optimization problem posed by (3.7') for all firms at all dates. For this purpose, one would have to solve a game with n*p*3 decision variables (three variables per firm per period). It is relatively easy, however, to determine an asymptotic solution to (3.7') based on a period-by-period optimization approach (see Appendix 3.1). The asymptotic solution does not solve the full dynamic maximization problem.

3.6 SIMULATING THE MODEL

The model makes four major assumptions which refer to the four hypotheses for differential firm performance developed earlier. The first assumption refers to the mode by which a firm selects a change rule. There are two basic possibilities. On the one hand, the firm may choose the rule that is most likely to increase future earnings (in other words, the one with the highest fitness value). This is the case of deterministic selection (A1). On the other hand, a firm may choose its heuristic stochastically. Rules with higher fitness values have a higher chance of being selected, but rules with lower fitness are not precluded from selection. This is the case of stochastic selection (B1), which corresponds to Hypothesis 1, because under B1 firms are likely to select different rules in each period.

The second assumption concerns the costs of change. These costs may be either zero (A2) or positive but decreasing as a function of experience (B2). B2 thus expresses Hypothesis 2. The costs of change decrease by a fixed percentage each time a certain type of change is implemented. Suppose, for example, that in a given period a firm adapts its output quantity and imitates its rival's product innovation rate. The firm will consequently gain experience implementing these types of changes. Their future costs will therefore be lower.
The third assumption refers to the probability that a selected rule is executed. Although rules provide recipes for organizational change, they may not always be utilized. The simulation contrasts the case in which organizational change is enacted with certainty (A3) with the case in which the probability of change is smaller than unity (B3), which corresponds to Hypothesis 3.

The last of the major assumptions concerns the possibility of imitation. For purposes of exposition, the simulation focuses on two extreme cases: one in which imitation is fully possible (A4) and one in which it is impossible (B4). The latter embodies Hypothesis 4. This view of imitation as either perfectly doable or not doable at all abstracts from the numerous possible intermediate situations. For example, although isolation mechanisms erected by a firm often limit the ability of rivals to mimic, imitation can never be fully precluded. There are many sources for information leaks; their number is probably on the rise because of the growing importance of information processing in today’s business environment.

**TABLE 3.1: Major assumptions made in the model**

<table>
<thead>
<tr>
<th>Assumption 1: How a rule is selected</th>
<th>A1: Rules are selected deterministically</th>
<th>B1: Rules are selected randomly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assumption 2: The costs of change</td>
<td>A2: Change costs are zero</td>
<td>B2: Change costs are positive but decrease through learning by doing</td>
</tr>
<tr>
<td>Assumption 3: Implementation of rules</td>
<td>A3: Rules are always implemented</td>
<td>B3: Rules are implemented with p&lt;1</td>
</tr>
<tr>
<td>Assumption 4: Possibility to imitate others</td>
<td>A4: Imitation is fully possible</td>
<td>B4: Imitation is impossible</td>
</tr>
</tbody>
</table>

Table 3.1 summarizes the variations on the four major model assumptions. The “B” alternative of each
assumption is more likely to foster the emergence of heterogeneous firm performance than is the “A” alternative. B-cases correspond to the hypotheses that were formulated earlier: B1 embodies Hypothesis 1, etc. If the hypotheses are valid, then moving from an A-formulation of an assumption to the respective B-formulation should increase the likelihood of observing sustainable competitive advantage.

In the strategy literature, competitive advantage is often measured by the amount by which an incumbent outperforms the average firm in its industry. A similar approach is used here. When only two firms are considered, for example, competitive advantage in a certain period is defined as the amount by which the industry leader outperforms its rival. Sustainability, on the other hand, can be defined as “the tendency of abnormally high or low profits to continue in subsequent periods” (McGahan and Porter, 1997b: p.2). It is conceptualized in this paper as the average number of periods that industry leadership lasts. For example, if a simulation runs for 200 periods (as is the case for most of the simulations reported) and industry leadership changes 9 times, sustainability is 20. The higher this number, the more sustainable are performance differences.

For simplicity, the model considers an industry with only two firms. All simulations were run in a stable environment which is called “equilibrium setting.” That is, exogenous parameters such as input prices were held constant and there were no demand shocks. In addition, neither the firms’ profit functions nor the other model components specifying or influencing firm behavior were changed during the simulations. Only decision variables and (if applicable) cost parameters were subject to endogenous change. According to the formula derived in Appendix 3.1, the asymptotic solution is $q_* = 3, r_* = 3^{1/2}, i_* = 0$, which yields an asymptotic profit of 6 per firm (see also Appendix 3.2, which contains further characterization of the simulation experiments).
The following sections describe, analyze, and interpret the results of the simulation experiments.

3.6.1 Assumption set (A1, A2, B3, A4): Uncertain implementation of organizational change

This is one of the simplest scenarios (in terms of the number of B-assumptions made) that yields differential firm performance, at least in the early stages of the simulation. Under A1, a firm selects the rule with the highest nonnegative fitness in each period. If the chosen rule has a positive fitness value, it suggests organizational change and promises to increase performance under the condition that the vector of decision variables of the other firm remains constant throughout.

In the example shown below, organizational change occurs in each firm in one out of three periods on average. Uncertainty implies that a firm might change even when the other firm randomly decides not to implement any organizational change. The changing firm may then gain an advantage (or lessen a disadvantage) because it is likely to improve its performance whereas its rival's profits stagnate or even decrease. A firm actively pursuing organizational change can thus take over or defend an industry leadership position. In Figure 3.2, firm 2 manages to command an early lead and is able to stay ahead of its competitor for most of the early stages of the simulation. The sustainability of its lead is thus quite high, at least initially. Eventually, however, the two firms' profits converge.
The explanation of heterogeneous firm performance in this case is simple. When initial values of decision variables constitute a disequilibrium, uncertainty and thus asynchronicity of organizational change caused by organizational inertia or "first moves" may cause firms to engage in a race with lags and leads toward the asymptotic equilibrium. Figure 3.3, which depicts the trajectories of firms' decision variables over time, supports this interpretation. In many periods during the first half of the simulation, firm 2 outperforms firm 1 in terms of output quantity and product innovation rate. Naturally, one would like to know why firm 1 is unable to catch up with its rival? Are not adaptation and imitation excellent strategies for achieving this goal? It should be noted that frequent adaptation is actually limited by assumption B3 (uncertainty of change). Imitation, on the other hand, is an imperfect strategy because it aims at a moving target. An imitating firm is able to copy only the business model that the industry leader had in place in the previous period. In the meantime, the leader may already have made further beneficial changes.
This simple case is interesting for two reasons. First, it shows that Hypothesis 3 may explain differential firm performance. Second, it has an interesting economic implication. Suppose that equilibrium conditions in an economy change through a sudden shift in the industry environment. For example, input prices may unexpectedly shoot up or demand surges. In such a case, firms suddenly find themselves in disequilibrium and must search for new optimal levels of their decision variables. If this happens often in an industry (as it does in the turbulent environment of high technology), one can expect pronounced differentiation between firms. Each environmental shock is likely to jolt firms into a race towards a new optimum. Note that the above results are sensitive to the choice of initial values for decision variables. In particular, the reported findings only obtain if firms start competing in disequilibrium.
If, in addition, the possibility of imitation is precluded (as in the case where A1, A2, B3, and B4 simultaneously hold), one gets qualitatively comparable, yet stronger results. In this case, firms that underperform possess one less means of catching up with the leader. The lack of the ability to imitate slows convergence of firms’ decisions and performances, while widening performance gaps and making them more sustainable (for an illustration, see Figure 3.4). It should be emphasized that while the deterrence of imitation may be important for explaining the sustainability of a firm’s competitive advantage, it cannot account for its emergence. To *generate* performance differences between firms, there must be a source of genuine differentiation. Barriers to imitation do not cause differences between firms but can serve to sustain them once they are present.

**FIGURE 3.4:** Firm performance when frequency of change is 1/3 and imitation is not allowed

![Graph showing firm performance](image)

**FIGURE 3.5:** Performances (before change costs) differ consistently with high change costs

![Graph showing performance differences](image)

**FIGURE 3.6:** In the presence of high change costs, firms implement different values asymptotically

![Graph showing decision variables](image)
If one also allows for positive change costs and assumes B2 instead of A2, lasting performance differences may ensue, as is shown in Figures 3.5 and 3.6. The figures depict an example of a model with the assumption set (A1, B2, B3, B4) in which all change cost parameters are set equal to 2 and the discount rate of learning is assumed to be only 1%.

The depicted situation is that of a purely adaptive race between two firms in which change costs and slow learning distort firms’ incentives to strive for asymptotically optimal values. For example, if a firm implements a higher than optimal output quantity (such as firm 2 does after period 80), it may have no incentives to subsequently lower. The fitness values of rules that recommend the implementation of a lower quantity are likely to be negative because relatively high change costs that outweigh any benefits of change. Similarly, an underperforming company may lack incentives to raise its output quantity or product innovation rate because the costs of these measures are prohibitive. As a result, firms may get “stuck” with decisions that are suboptimal in the long run. This result is consistent with empirical findings by Ichniowski et al. (1997) who observe that certain innovative business practices are not adopted in existing firms even though they promise productivity gains. The authors state that “However, recently opened lines at ‘greenfield’ sites, as well as older lines that had been closed but were opened with new owners and workers, are adopting innovative work practices” (p.308). They suggest that “nonpecuniary barriers to change beyond the direct costs of the work practices” -in other words, change costs- might explain seemingly suboptimal decisions made by existing firms.

3.6.2 Assumption set (A1, B2, B3, A4): Uncertain and costly implementation of change

This particular set of assumptions is the only one that may yield endogenous specialization in change strategies. In the example shown below, one firm specializes in adaptation, the other pursues a hybrid strategy of imitation and adaptation.
The experimental setting of the investigated example is as follows. Firms incur moderate change costs (all cost parameters are set equal to 2) and learn quickly (i.e., discount change costs by 20%). The probability with which they implement change is one third. The case illustrates how firms differentiate their internal change cost structures (see Figure 3.7, which shows the evolution of the cost parameters for adaptive and imitative changes of the process innovation rate for each firm). One firm (in this particular case, firm 2) becomes an a skilled adaptor while largely ignoring the possibility of imitation. (The company may as well be indifferent to the strategy of imitation because it would not want to mimic an underperforming competitor. ) The other firm (here, firm 1) pursues a more hybrid strategy in which it also emphasizes imitation. In this way, it is able occasionally to catch up with its strongly performing.

![Figure 3.7: Evolution of cost parameters for changing process innovation rate during first hundred periods](image)

The purely adaptive strategy favored by firm 2 outperforms the hybrid strategy adopted by firm 1 (see Figure 3.8). Through initial luck and the self-reinforcing effect of cheaper adaptation, firm 2 manages to quickly
build a strong position in its industry in terms of high output quantity and favorable innovation rates. Firm 1 imitates its rival quite effectively on a number of occasions, but must eventually recognize that imitation becomes more and more unattractive (this observation derives from additional data that was collected during the simulation). This result is somewhat counterintuitive: If the champion in the industry does things correctly, why does it not pay to imitate its behavior? It should be kept in mind, however, that mimicking a rival's high output level is likely to contribute to overproduction in the industry, and will thus probably lead to falling prices. In addition, imitating high R&D efforts may lead to better products and thus higher prices, but if the imitating firm must also incur the high R&D expense. As a result, firm 1 finds itself stuck between its imitative and adaptive strategies. When imitation loses its appeal, the firm must pay the price for having failed to sufficiently hone its adaptive skills. The latter become too expensive to exert. By contrast, firm 2, the astute adaptor, manages to hold on to its competitive advantage.

These results are robust to changes in initial values. However, they are sensitive to the size of adaptive changes. With a smaller step size, the same results obtain but to a lesser degree. In addition, with a high probability of change or with different random seeds, these results may not obtain at all. It is important that one firm have a random series of quick adaptive changes towards the beginning of the simulation while the other firm does not, else cost structures do not differentiate sufficiently.

One of the lessons from this case is that the assertion that firms perform differently because of path dependencies (Hypothesis 2) is only partially correct. With B2, heterogeneous performance only obtains if
B3 also holds. Further simulations, for example of the case (A1, B2, A3, A4), confirm that learning, in and of itself, does not cause differential firm performance. Learning can only reinforce pre-existing differences; it cannot cause firms to engage in different activities in the first place.

It may be of interest to check whether any subset of Hypotheses 1 to 4 is really necessary to generate heterogeneous firm performance. For this purpose, consider the deterministic base case, (A1, A2, A3, A4), in which both firms obviously always make identical choices. This guarantees that their performances indeed remain completely symmetrical throughout the simulation (see Figure 3.9). In addition, the values of firms’ decision variables rapidly converge toward the asymptotic solution (see Figure 3.10).

Recall that when evaluating the fitness of a rule, firms calculate the estimated net present value of the incremental change in performance that would ensue from an application of the rule. By contrast, the asymptotic solution (see Appendix 3.1) is not derived from a full net present value (NPV) maximization.
encompassing the entire simulation run. Yet, firms’ decision variables in many cases still converge towards this asymptotic solution, even though their evolution is guided by computations of NPV. This is because change costs are either zero to begin with or they asymptotically approach zero in the long run (because of experiential learning). The calculation of a rule’s fitness value (see 3.3.2) thus simplifies to: 

\[(\text{Expected future per-period performance} - \text{Present performance})/\text{Discount factor}\].

Maximizing this term is equivalent to maximizing future performance because ‘present performance’ is a constant. It is also equivalent to the approach to calculate the asymptotically optimal solution. The two approaches (period-by-period maximization and maximization based on calculating NPV) are asymptotically equivalent.

### 3.6.3 Assumption set (B1, A2, A3, A4): Random selection of change rules

A random selection of rules introduces noise into the simulation and fosters differentiation and prevents convergence of firm performances (see Figure 3.11). The major finding here is that Hypothesis 1 may go a long way in explaining the origin of differentiation processes. Starting at low initial values, firms’ decision variables gradually approach the asymptotically optimal solution, albeit in an erratic manner. Output quantity and product innovation rates then oscillate in narrow bands around their equilibrium levels, whereas the process innovation rate has a tendency to slowly but steadily drop towards zero (see Figure 3.12).

The movement of decision variables around their asymptotic equilibrium levels occurs mostly because each firm periodically makes random moves that harm itself while directly benefitting its opponent. For example, if a firm with a high output stance accidentally lowers the number of goods produced, the other firm benefits from a higher price and, at the same time, may have a chance to profitably increase its own output. On average, firms will exploit the opportunities arising from the mistakes of others.
Figure 3.11 shows that over the long run there is no dominant firm in the industry. The competitive advantage enjoyed momentarily by an industry leader is neither large nor sustainable. Firms take quick turns in assuming industry leadership. This result is consistent with the empirical findings of McGahan and Porter (1998) and McGahan (1998) who report that business effects on firm profitability are less stable than industry effects. In the present model, it is primarily the homogenizing effect of imitation that prevents firms’ performances from drifting widely apart.

It is important to consider how plausible it is that competitive advantage arises from mistakes. The finding is consistent with the idea that decision making in firms is hampered by “uncertainty about the economic, industry, regulatory social and technological environments, competitors’ behavior and customers’ preferences; complexity concerning the interrelated causes that shape the firm’s environments, the competitive interactions ensuing from differing perceptions about these environments; and by intra-organizational conflicts among those who make managerial decisions and those affected by them” (Amit and Shoemaker, 1993: p.33). In short, managerial decision making is not perfect. This lack of perfection is partly
captured in the model by the stochastic rule selection, which can be interpreted as reflecting the basic uncertainty or conflict within the organization about which rule is best to use. (Note that the model does not take structural or systematic differences between managers' decision making processes into account. Incorporating these would probably bias the simulation strongly towards producing differential firm performance.)

The results reported above are sensitive to the assumed size of adaptive modifications. The smaller this step size, the less severe are the negative consequences of mistakes, and the more quickly imitation realigns firm performances.

Further simulations reveal that in the presence of stochastic selection of rules, other hypotheses for differential firm performance become less important. For example, the results are only modestly affected by change costs or by slow learning about how to implement organizational change (see Hypothesis 2). To be precise, one should distinguish here between cost effects and learning effects here. On the one hand, there are no learning effects because, first, even if differential learning from experience took place, firms (by assumption B1) would not pay much attention to it. Second, differential learning is largely precluded by the random choice of rules. Random differences in the use of adaptation versus imitation are not sufficient to generate distinct, self-reinforcing patterns of learning. On the other hand, there could be minor cost effects on sustainability. Very high change costs in conjunction with a slow learning speed may present firms with incentives to implement only a few changes at a time. This tends to increase sustainability. Under assumption B1, Hypothesis 2 is thus largely irrelevant for explaining the creation and only slightly relevant for explaining the sustainability of competitive advantage.

Hypothesis 3 also loses much of its explanatory appeal when Hypothesis 1 concurrently holds. One source
of randomness in the model suffices to sow the seeds of heterogeneity, whether it be random selection (Hypothesis 1) or random implementation (Hypothesis 3). Hypothesis 1 is more powerful than Hypothesis 3 in that it injects noise into the dynamic system more often and more consistently (i.e., in all periods). However, under asynchronous implementation of change, average sustainability is higher. The less often companies change, the smaller are their chances of altering the status quo.

With regards to the importance of Hypothesis 4, it should be clear from previous discussions that heterogeneous firm performance does not originate in a lack of imitation, it can only be sustained by it. It thus comes as no surprise that under stochastic rule selection the average sustainability and the average size of competitive advantage are bigger without imitation.

Given these results, it is hardly surprising that all four hypotheses combined may yield differentiation patterns that are impressive, both in terms of the size and the sustainability of competitive advantage. In the case (B1, B2, B3, B4), heterogeneous firm performance can be pronounced and stable. For an illustration, see Figure 3.13, which shows an example with stochastic rule selection where imitation is precluded, the probability of change is 2/3, and all cost parameters are set equal to 2 and discounted by 20% whenever the respective changes are made.
FIGURE 3.13: Differential firm performance before change costs in the (B1, B2, B3, B4) case

For a comprehensive summary of simulation results in tabular form, see Appendix 3.3.

3.7 CONCLUSIONS

This paper constitutes the first effort in the strategy field to link the notion of dynamic capabilities with behavioral decision theory in order to reflect on the empirical observation of performance differences between firms within the same industry. It presents a formal model of intra-industry competition that is rooted in the concept of rule-based firm behavior. Simulation of the model allowed for an assessment of different hypotheses about differential firm performance. It also highlighted the need to distinguish among the causes for differentiation, the sustainability of competitive advantage, and for the magnitude of competitive advantage.
In the first set of simulations, firms chose rules deterministically. They consistently applied only their best available heuristic in any given period. In this case, the necessary condition for differentiation is organizational inertia or asynchronous change (Hypothesis 3). The possible sequentiality of implementation decisions resulting from this condition creates the opportunity for firms to react to each other's decisions. As a result, given suboptimal initial values for decision variables, firms make different decisions, implement different kinds of organizational change, and perform differently. However, their decisions and performances converge to the asymptotically optimal solution in the long run. That is, their long-term behavior is quite rational.

An interesting finding is that imitation is not always a desirable option, even if it does not entail any costs. The industry leader may suffer when others imitate because its position is challenged, and the challenger may suffer because mimicking the high output quantity or the high innovation rates of the leader increases its direct costs of production and innovation while also contributing to price deterioration. In other words, imitation is often not viable because it implies moving into a crowded niche. Hermalin (1994) presents a similar result for the domain of executive compensation. He finds that the best response to other firms providing strong incentives for managers can be to provide weak incentives, and vice versa. The equilibria in his model exhibit heterogeneity in incentives due to the nonconvexities inherent in the underlying agency problem between firms and their managers.

The introduction of change costs and their reduction through learning by doing (Hypothesis 2) were found to have only a negligible effect on simulation results. In extreme cases, change costs might prevent firms from implementing the asymptotically optimal solution. However, learning by itself was found to neither trigger nor sustain heterogeneous firm performance. Learning might produce a differentiating effect on firms' cost structures only when found in conjunction with organizational inertia. In this case, preferences
for certain types of organizational change (such as adaptation or a hybrid strategy of imitation and adaptation) emerged endogenously. This is an improvement over Lant and Mezias (1990) who assume exogenous preferences. It may also be worth noting that in the model here a firm that adopted a hybrid strategy was sometimes “stuck in the middle” (Porter (1985: pp.16-17) introduced this expression in the context of generic strategies). Due to its lack of specialization and the costs of change, such a firm underperformed its rivals over extended periods of time.

Firms may also make choices in a more liberal manner by selecting rules randomly (Hypothesis 1). The noise introduced into the model in this ‘stochastic scenario’ proved sufficient to cause heterogeneous firm performance. Noise also prevented firms’ costs structures from differentiating significantly. Contrast this result with the following quote from Levinthal and March (1993: p.102): “Organizations engage in activities at which they are competent with greater frequency than they engage in activities in which they are less competent...These distinctive competencies invite utilization which furthers their additional development...The result is that distinctive competence is accentuated, and organizations become specialized to niches in which their competencies yield immediate advantage.” The model presented in this chapter shows that this conclusion cannot be applied without further qualification to activities that are related to organizational change. There are conditions under which the ability to learn is not paramount to explaining the emergence of diverging patterns of firm performance.

An important question remains open at this point. Are the effects identified in this paper of a first- or second-order? This chapter did not examine all possible hypotheses for the emergence of differential firm performance, so it is not possible to speak about other important sources of differentiation between firms. Notably, as many strategy researchers contend, managers may decisively affect the relative performances of their firms by making strategic long-term decisions. The model in this chapter seems to de-emphasize the
role of executive leadership and instead stresses that success has an important stochastic element. It does not refute the positive view of managers; it rather complements it.

Empirical confirmation of these simulated results will be a challenge. In reality, some basic assumptions under which firm behavior is examined in the computer simulation model (such as the use and content of heuristics) cannot be rigorously controlled. The operationalization of independent variables (i.e., the four fundamental hypotheses or their corresponding B-assumptions) will not be easy. One might be able to find proxy variables for the likelihood with which companies realize organizational change, for the ease of imitation within an industry, and for the magnitude of change costs and the importance of learning effects. However, to determine whether a firm makes decisions in a more stochastic or rather deterministic way will require some ingenuity. Nonetheless, some implications from the model, such as the limitations of imitation strategies, might be amenable to empirical investigation.

The fundamental question of how organizations learn, (whether they employ and process rules, for example) is an interesting and promising avenue for future research, both on the empirical and on the theoretical side. Huber (1991: p.107) concedes that “there is little in the way of substantiated theory concerning organizational learning and there is considerable need and opportunity to fill in the many gaps.” Field studies need to be conducted to determine to what extent organizational change is based on routines, which forms these routines take, how they are processed, stored, and interpreted. “Do experimenting organizations or close approximations exist? What are the enabling conditions? ...These questions beg to be answered” (Huber, 1991: p.94).

Extensions of the computer simulation model developed in this chapter could provide a useful theoretical framework within which empirical research can be conducted. For example, the following research questions
could be pursued: How do external shocks affect the results? What performance patterns can be observed in industries with more than two firms? Can the model be calibrated to actual empirical evidence? Under what circumstances do we find asymmetries between winners or losers, as described by McGahan and Porter (1997b)? These questions are all of a descriptive nature. At the end of the day, it would be interesting to draw normative implications from the model. In particular, it would be helpful for firms to know how they should behave in order to achieve a more sustainable competitive advantage and what they could do to avoid underperforming their rivals for too long.
BIBLIOGRAPHY

CHAPTER I


**CHAPTER II**


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**CHAPTER III**


APPENDIX 1.1: Illustration of the Basic Moral Hazard Problem

Figure A1.1 shows the marginal cost of effort (a horizontal line) and the marginal expected benefit of effort (given by $R_e$). The efficient amount of effort occurs where marginal benefit equals marginal cost, and is denoted $e^*$ in the diagram. The marginal benefit perceived by the entrepreneur is only $(1-\alpha)R_e$, which is strictly below $R_e$. It follows that the amount of effort actually chosen, denoted $e'$, is less than the efficient amount. The basic problem is that the entrepreneur cannot precommit to provide effort level $e^*$. Once financing is obtained and share $\alpha$ of the firm has been sold to the investor, the entrepreneur will only provide effort level $e'$. If the investor and the entrepreneur could contract over $e$, then they could agree that $e^*$ would be provided, but this is impossible under the assumption that $e$ cannot be observed (or at least legally verified) by the investor.

FIGURE A1.1: Moral hazard

![Diagram showing the relationship between marginal return $R_e$, entrepreneurial effort $e$, and $e^*$]
APPENDIX 1.2: Formal Analysis of the Adverse Selection Problem

From (1.18) we derive the first-order condition

\[ EV_d = p'(d) \int_0^\infty (\alpha R(q) - C) f(q) dq - 1 = 0 \]  

(1.21)

where F is the cumulative distribution of q. Let

\[ K = \int_0^\infty (\alpha R(q) - C) f(q) dq \]  

(1.22)

Then (1.21) simplifies to

\[ p'(d) = \frac{1}{K} \]  

(1.23)

To derive the second-order condition, \( EV_d \) is differentiated with respect to d, yielding

\[ EV_{dd} = p''(d) \int_{q^*}^\infty (\alpha R(q) - C) f(q) dq \]

\[ = p''(d) K \]  

(1.24)

It follows from (1.17) and (1.18) that (1.24) is strictly negative, which is the precondition for (1.23) to yield a maximum.
(1.23) has interesting implications. Suppose that R(q) is such that there are many worthwhile projects and a few projects that have very low negative expected returns. q° is therefore low. Specifically, assume that K is relatively large, resulting in a rather low value of p(d), which in turn implies a relatively large optimal value of d (if a solution to (1.23) exists at all). Thus, with such a constellation of parameters, it pays to invest high d in due diligence. On the other hand, if R(q) is such that K is relatively small (which may happen if there are only few attractive projects and many ‘lemons’, i.e. if q° is high), this will result in a relatively small optimal value of d (depending, of course, on the shape of p(d)).

In order to illustrate the point that an investor with a highly responsive detection function p(d) (say, investor h with a detection function p(d^h)) is more likely to invest in projects with high asymmetry of information than an investor with a less responsive p(d) (say, investor l with a detection function p(d^l)), let us consider the following case. Assume that q° is high and K is small, resulting, according to (1.23), in a large p'(d). This is fairly realistic, as the pattern of returns of venture capitalists is usually skewed with most investments generating either disappointing or negative returns and only a few becoming ‘stars’.

It may happen that investor h finds it worthwhile to spend d^h>0 (which is the value of d^h that satisfies 1.23) and go ahead with projects q°q°, while investor l finds that the optimal value of d^l is d^l=0 and thus refrains from investing. (Of course, even if d^h>0, the investor’s feasibility constraint (1.20) has to hold before investment I is made.) These points are illustrated in Figure A1.2.

Note that for some values of K, both d^h and d^l can be positive in our example. Then it pays even for investor l to do due diligence. Again, it also depends on constraint (1.20) whether either investor l or h or both find the investment attractive.
FIGURE A1.2: Optimal due diligence for different detection functions $p(d)$

$p(d')$ - "more responsive"

slope = $1/K$

$p(d^h)$ - "less responsive"

$d^* = 0$

$d^h > 0$
APPENDIX 2.1: Coding and Decoding of Rules

The venture capitalist

The venture capitalist’s signal gene takes on a binary value from the set \{'000', '001', ..., '111'\}, which can be mapped into a decimal number. Let the common support of q, x and y be defined as \{1, 2, ..., 8\}. This means that the lowest possible quality or signal value is 1 and the highest is 8. According to the principle of “concentrated, mapped, fixed-point coding” (see Goldberg, 1989: p.82 ff.), decoding a binary value involves two steps. First, the binary code is decoded as an unsigned integer (step one). For example, signal code ‘011’ corresponds to $0*2^2+1*2^1+1*2^0=3$. In step two, the decoded unsigned integer is linearly mapped to a specified interval \([\min(\text{variable}), \max(\text{variable})]\). The lower and upper boundary of this interval are given by the lowest and highest value, respectively, that the variable in question can take. For signals x and y, for example, we have \(\min(\text{signal})=1\) and \(\max(\text{signal})=8\), as defined by their support. Therefore, code ‘000’ is decoded as 0 in step one and then mapped to \(\min(\text{signal})=1\) in step two. Code ‘111’ is decoded as 7 in step one and then mapped to \(\max(\text{signal})=8\) in step two. Other codes map linearly in between \(\min(\text{signal})\) and \(\max(\text{signal})\). For example, ‘011’ maps to signal value 4.

The decoding of the venture capitalist’s investment gene and of the share gene is analogous. The most important differences are that for the investment gene \(\min(I)=0\) and \(\max(I)=I^u\), and for the share gene \(\min(s)=0\) and \(\max(s)=1\). The length of these substrings is 4, which permits us to distinguish among 16 individual values. Each increment of 1 in the binary representation of the genes corresponds to an increment of \(1/15*I^u\) for I, or to an increment of \(1/15\) for s, respectively, in decimal notation. For example, investment gene code ‘0100’ is decoded as 4 in step one and then translated to \(4/15*I^u\). Similarly, share gene code ‘1001’ means that VC claims \(9/15\) of operating profits for himself.
A final example for VC, consider rule code ‘100.1011.1010’ (the decimal points have been added to enable
easier recognition of the different genes). It corresponds to the classifier “IF <observe signal 5> THEN
<offer the contract (I=11/15*P, s=10/15)>”.

Note that the decoding instructions imply that variables assume discrete values. It would be easy to change
the interpretation of codes towards viewing them as intervals rather than single values. Thus, investment
code ‘0001’ could represent a range [1/15*I, 2/15*P) of investment plans. However, this would complicate
the analysis without adding much insight. (It is not very intuitive either.) Also note that reversing the
decoding procedure is a recipe for encoding decimal values.

The entrepreneur

The mapping of the binary values of the entrepreneur’s investment and share genes into decimal numbers
(and vice versa) is analogous to the two step procedure described above for the venture capitalist. The action
part of E’s heuristics is modeled by a single bit. ‘1’ represents the answer ‘accept’, ‘0’ means ‘reject’. To
give a complete example for E, consider rule code ‘010.0101.1010.1’. It corresponds to the heuristic “IF
<observe signal 3 and the venture capitalist offers (I,s) with I≥5/15*P, s≤12/15> THEN <accept>”.

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APPENDIX 2.2: Calculation of Fitness

Two parameters are tracked for each rule to characterize its fitness. The first of these parameters is \( p_{gi}^k \), which is equal to 1 plus the total number of times rule \( k \) has participated in bargaining rounds in generation \( g \) up to iteration \( i \). The second one is \( r_{gi}^k \), the total sum of expected payoffs rule \( k \) has collected in generation \( g \) up to iteration \( i \). The current fitness \( f_{gi}^k \) of rule \( k \) is then calculated as its average performance in generation \( g \) up to iteration \( i \): \( f_{gi}^k = \frac{r_{gi}^k}{p_{gi}^k} \) for all \( k \).

At the beginning of the first generation \((g=1)\), \( r_{i,1}^k \) and \( p_{i,1}^k \) are initialized as follows: \( r_{i,1}^k = f_k \), and \( p_{i,1}^k = 1 \) for all \( k \). At the beginning \((i=1)\) of a generation \( g \) with \( g > 1 \), \( r_{g,1}^k \) is set equal to \( f_{g-1,\text{max}}^k \) (the most recent fitness value which characterized rule \( k \) in the previous generation \( g-1 \)) and \( p_{g,1}^k \) is set equal to 1 for all \( k \).

At the beginning of iteration \( i \) where \( i > 1 \), \( p_{g,i}^k = p_{g,i-1}^k \) and \( r_{g,i}^k = r_{g,i-1}^k \) for all \( k \) and all \( g \). If a rule \( k' \) participates in bargaining in any iteration \( i \), \( r_{g,i}^{k'} \) is augmented by the expected payoff resulting from the bargaining outcome, and \( p_{g,i}^{k'} \) is increased by 1. Subsequently, a new fitness values \( f_{g,i}^{k'} \) is computed.
APPENDIX 2.3: The Genetic Algorithm

The genetic algorithm consists of three operators: reproduction, crossover and mutation. In the model presented in this paper, these operators are applied at the end of each generation $g < g_{max}$ (after bargaining round $i_{max}$) to the venture capitalist’s and to the entrepreneur’s chromosomes (i.e., rules) separately. In fact, in the computer program there are two identical genetic algorithms working separately and independently on the agents’ populations of chromosomes.

Reproduction makes copies of individual chromosomes. The probability that a chromosome $k'$ of generation $g-1$ will obtain a copy is equal to its relative fitness $f_{g-1,imax}^k / (\sum_k f_{g-1,imax}^k)$. In total, n copies are made of the venture capitalist’s strings and m copies are made of the entrepreneur’s strings. The choice of a chromosome for reproduction is made through sampling with replacement. It can be described as the spin of a biased roulette wheel. Each chromosome is allocated a slot whose size is equal to its relative fitness. The number of spins of the wheel is equal to the number of chromosomes in a population. The copied strings enter into an agent-specific mating pool where they undergo the genetic manipulations of crossover and mutation.

For crossover, first a pair of chromosomes (the ‘parents’) is selected with equal probability from the mating pool through sampling without replacement. Then, secondly, with probability $p_c$, the following operations are performed. An integer number $s$ is selected at random from $[1, \text{length of chromosome} - 1]$. The chosen strings are split into parts at position $s$, and two new chromosomes (the ‘children’) are formed by the parents through swapping parts. An example for length of chromosome=11 and $s=4$ is given below:
Parent 1: (1 0 1 | 0 0 1 0 0 0)
Parent 2: (0 1 1 0 | 1 1 0 1 0 1 1)

The resulting chromosomes are

Child 1: (1 0 1 1 1 0 1 0 1 1)
Child 2: (0 1 1 0 0 0 1 0 0 0)

Children replace their parents.

The strings in the mating pool, whether crossed over or not, are finally subject to mutation. With probability $p_m$, mutation randomly alters the value of a certain bit position within a string. '0' becomes '1' and vice versa. Each position has the same likelihood of being switched. In the actual implementation of the algorithm, the application of the mutation operator is combined with the application of the crossover operator.

After crossover and mutation, the fitness value of any chromosome in the mating pool is set equal to the one of its (in terms of a bitwise comparison) most similar parent. If there is an identical rule already present in the current population, a child will be given the fitness value of such an identical rule instead. In order to avoid premature convergence of the genetic algorithm and also in order to facilitate the distinction between similar fitness values at later stages of the run, a scaling procedure like the one suggested by Goldberg, 1989 is used with a scaling factor of 2. Consequently, before the application of the genetic algorithm, fitness values are calibrated (i.e., scaled fitness values are calculated) such that the maximum fitness of all rules in a set is twice as big as their average fitness. The genetic procedures described above are based on scaled fitness. However, surviving offspring carry their regular fitness (and not the scaled one) into the next
generation. Note that the use of such a scaling procedure does not qualitatively change the results reported here.
APPENDIX 2.4: Stochastic Elements of the Model and the Prerequisites of Adaptation

The genetic algorithm model incorporates the following stochastic elements and processes:

- Specification of initial rules
- Specification of the condition parts of entirely new rules which are generated during bargaining if there are no matching rules in a set
- Choice of rules through auctions held to determine which one of several matched rules participates in a certain bargaining round
- Selection of rules for reproduction
- Selection of bits for mutation
- Choice of rules and chromosome parts for crossover
- Others

Despite its stochastic character, the system, however, does not entirely lack direction. Adaptation ensures that the agents' rules evolve towards solutions with the highest possible payoff in terms of expected utility. An adaptive learning outcome is achieved because multiple classifiers are considered which perform differently; agents are able to calculate the expected utility payoff of their heuristics; relatively weak rules are abandoned and relatively strong ones are replicated; and new rules are constantly injected into the system via mutation and crossover.
APPENDIX 3.1: Asymptotic Solution

Assuming that $t \to \infty$, the first simplification one can make is to get rid of the term $3/\sum_{i,j}t_{ij}$, which, for large $t$, is likely to become negligible. Asymptotically, the optimal solution for $i_{ji}$ is obviously zero. Furthermore, firms are initially symmetric, so one can expect a symmetric solution for $r_{ji}$. Simplifying (3.7') along these lines yields

$$\pi_{ji} = q_{ji}(nK - \sum q_{k}) - q_{ji}v - \epsilon^2 r_{ji}^2$$

which is to be maximized with respect to $q_{ji}$. The first order condition for $q_{ji}$ is

$$\frac{\partial \pi_{ji}}{\partial q_{ji}} = (nK - v) - 2q_{ji} - \sum q_{k} = 0$$

Solving (3.8) for $q_{ji}$, one obtains

$$q_{ji} = nK - \frac{n}{n+1}(nK - v)$$

where $q_{ji}$ denotes an optimal asymptotic value for the quantity decision variable if the second order conditions for a maximum hold. Plugging $q_{ji}$ back into (3.7') and again setting $i_{ji}=0$ yields yet another expression for asymptotic profit, namely

$$\pi_{ji} = \alpha (r_{ji} / \sum r_{ik}) - q_{ji}v - \epsilon^2 r_{ji}^2$$

where
\[ \alpha = \frac{n}{(n+1)^2}(nK-v)(K+v) \]  

(3.11)

Taking the derivative of (3.10) with respect to \( r_{jm} \) yields the first order condition for \( r_{jm} \):

\[ \frac{\partial \pi_{jm}}{\partial r_{jm}} = \alpha \left[ \frac{(\sum r_{jm})-(\sum r_{jm})^2}{(\sum r_{jm})^2} \right] - 2e^2 r_{jm} = 0 \]  

(3.12)

Solving (3.12) for \( r_{jm} \) one obtains

\[ r_{jm}^* = \frac{[\alpha(n-1)/2]^{1/2}}{(ne)} \]  

(3.13)

\( r_{jm}^* \) denotes the optimal asymptotic value for the product innovation rate provided that the second order conditions for a maximum hold. These second order conditions stipulate that \( \frac{\partial^2 \pi_{jm}}{\partial q_{jm}^2} < 0 \), \( \frac{\partial^2 \pi_{jm}}{\partial r_{jm}^2} < 0 \) and that the determinant of the Hessian matrix of \( \pi_{jm} \) with respect to \( q_{jm} \) and \( r_{jm} \) be positive. It may be assumed that this system of inequalities holds for some combinations of the parameters \( n, K, v \) and \( e \).
APPENDIX 3.2: Characteristics of Simulation Runs

Simulations are based on a replicable series of random numbers. At the beginning of each run the seed of the random number generator is set equal to 3. Other important parameters which remain constant throughout all simulations are reported in Table A3.1 below.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\epsilon$</td>
<td>1</td>
<td>Input prices are constant at 1</td>
</tr>
<tr>
<td>$K$</td>
<td>5</td>
<td>The fact that this parameter of the inverse demand function remains constant ensures that there are no demand shocks</td>
</tr>
<tr>
<td>$n$</td>
<td>2</td>
<td>There are exactly two firms in the industry</td>
</tr>
<tr>
<td>$\nu$</td>
<td>3</td>
<td>Variable production costs are constant at 3</td>
</tr>
</tbody>
</table>

These parameters can be used to derive the asymptotic solution to the firms’ dynamic optimization problem. Asymptotically, a rational firm would implement $q^*_n=3$, $r^*_n=3^{1/2}$, $i^*_n=0$. These values yield an asymptotic profit of 6. In addition, firms usually use a step size of 5% when adaptively adjusting any of their decision variables upward or downward. This step size does not seem unreasonable if a period represents, for example, a quarter of a year. Under this interpretation, most simulation experiments would cover a span of 50 years, because they are run for 200 periods. In general, however, the question how a simulation period maps to real time can (in conjunction with the assumed step size) be answered quite flexibly. Initial values in most cases are $q=1$, $r=1$, $i=1$. In other words, firms do not start competing in asymptotic equilibrium. Costs of change usually drop by 20% as a result of ‘learning by applying change rules’.
APPENDIX 3.3: Summary of Simulation Results

TABLE A3.2: Summary of simulation results

<table>
<thead>
<tr>
<th>Assumption Set</th>
<th>Heterogeneous Performance</th>
<th>Convergence</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>(A1, A2, A3, A4)</td>
<td>No</td>
<td>Yes</td>
<td>-</td>
</tr>
<tr>
<td>(A1, A2, A3, B4)</td>
<td>No</td>
<td>Yes</td>
<td>Same as (A1, A2, A3, A4)</td>
</tr>
<tr>
<td>(A1, B2, A3, A4)</td>
<td>No</td>
<td>Yes, but not necessarily to asymptotic solution</td>
<td>Learning has no effects on differentiation; firms may get stuck at suboptimal values (cost effect)</td>
</tr>
<tr>
<td>(A1, B2, A3, B4)</td>
<td>No</td>
<td>Yes, but not necessarily to asymptotic solution</td>
<td>Same as (A1, B2, A3, A4)</td>
</tr>
<tr>
<td>(A1, A2, B3, A4)</td>
<td>Yes</td>
<td>Yes</td>
<td>Race towards asymptotic solution</td>
</tr>
<tr>
<td>(A1, A2, B3, B4)</td>
<td>Yes</td>
<td>Yes</td>
<td>Similar to (A1, A2, B3, A4); higher sustainability because of lack of imitation</td>
</tr>
<tr>
<td>(A1, B2, B3, B4)</td>
<td>Yes</td>
<td>Firms converge, but not necessarily to the same values</td>
<td>Similar to (A1, A2, B3, B4); lasting differences as a result of cost effect possible</td>
</tr>
<tr>
<td>(A1, B2, B3, A4)</td>
<td>Yes</td>
<td>Firms converge, but not necessarily to the same values</td>
<td>Endogenous differentiation of change cost structures possible; lasting differences as a result of (differential) costs possible</td>
</tr>
<tr>
<td>(B1, A2, A3, A4)</td>
<td>Yes</td>
<td>No</td>
<td>Regression to the mean: Firms take turns in outperforming each other; mistakes important</td>
</tr>
<tr>
<td>(B1, B2, A3, A4)</td>
<td>Yes</td>
<td>No</td>
<td>Similar to (B1, A2, A3, A4)</td>
</tr>
<tr>
<td>(B1, A2, B3, A4)</td>
<td>Yes</td>
<td>No</td>
<td>Similar to (B1, A2, A3, A4)</td>
</tr>
<tr>
<td>(B1, B2, B3, A4)</td>
<td>Yes</td>
<td>No</td>
<td>Similar to (B1, A2, A3, A4)</td>
</tr>
<tr>
<td>Assumption Set</td>
<td>Heterogeneous Performance</td>
<td>Convergence</td>
<td>Remarks</td>
</tr>
<tr>
<td>---------------</td>
<td>--------------------------</td>
<td>-------------</td>
<td>--------------------------------</td>
</tr>
<tr>
<td>(B1, B2, B3, B4)</td>
<td>Yes</td>
<td>No</td>
<td>High sustainability through lack of imitation</td>
</tr>
<tr>
<td>(B1, A2, A3, B4)</td>
<td>Yes</td>
<td>No</td>
<td>Similar to (B1, B2, B3, B4)</td>
</tr>
<tr>
<td>(B1, B2, A3, B4)</td>
<td>Yes</td>
<td>No</td>
<td>Similar to (B1, B2, B3, B4)</td>
</tr>
<tr>
<td>(B1, A2, B3, B4)</td>
<td>Yes</td>
<td>No</td>
<td>Similar to (B1, B2, B3, B4)</td>
</tr>
</tbody>
</table>