

JYVÄSKYLÄ UNIVERSITY SCHOOL OF BUSINESS AND ECONOMICS

**EXPLORATION AND EXPLOITATION:  
ORGANIZATION'S AGE AND THE NATURE OF ITS  
INNOVATIVE BEHAVIOR**

Master's thesis  
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<p>Abstract</p> <p>This study examines the relationship of an organization's age and its innovative activity. The innovative activity of an organization is discussed and examined through the concepts of exploration and exploitation, basing on the previous literature on organizational ambidexterity. Three hypotheses on the relationship of aging and the innovative behavior of an organization are formed based on the ambidexterity literature and the theories of the effect of aging on an organization. These hypotheses are tested with logistic regression analyses on a patent data set covering the modern biotechnology industry in Finland between 1973–2008. The results of the analyses show that age has a weak but significant effect on the nature of an organization's innovative behavior.</p> <p>There are relatively few previous studies that empirically investigate the effect of aging on an organization's explorative and exploitative actions and the existing studies have provided contradictory and inconsistent results. This study aims to add clarity on the phenomenon and provide additional empirical evidence on it in order to better understand the effect of aging on innovative activity. The study contributes both to the aging literature by providing evidence on the effects of aging on innovative activity and the ambidexterity literature by providing empirical information on the relationship of exploration and exploitation on the firm level. Interesting questions for future research, such as the role of financing in predicting the nature of an organization's innovative behavior, also arise from the results of the study.</p>	
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## CONTENTS

1 INTRODUCTION.....	7
2 THEORETICAL BACKGROUND.....	9
2.1 Exploration, exploitation, and organizational ambidexterity.....	9
2.1.1 The relationship of exploration and exploitation.....	10
2.1.2 Organizational ambidexterity.....	11
2.2 Aging.....	13
2.2.1 Liabilities of newness, adolescence, and obsolescence.....	14
2.2.2 Aging and innovation.....	16
2.3 Previous studies on the relationship of exploration/exploitation and aging.....	18
2.3.1 The findings of individual papers.....	18
2.3.2 Conclusion from the previous studies.....	21
3 HYPOTHESES.....	23
3.1 Firm age and exploitation.....	23
3.2 Firm age and exploration.....	23
3.3 Firm age and its overall innovative behavior.....	24
4 EMPIRICAL SETTING.....	25
4.1 Biotechnology and the biotechnology industry.....	25
4.2 The modern biotechnology industry in Finland.....	26
5 METHODOLOGY.....	29
5.1 Data and sample.....	29
5.2 Variables and measures.....	31
5.2.1 Dependent variables.....	31
5.2.2 Independent variable.....	32
5.2.3 Control variables.....	32
5.3 Econometric method.....	34
5.3.1 Descriptive statistics.....	34
5.3.2 Correlations.....	34
5.3.3 Logistic regression analysis.....	35
6 RESULTS.....	37
6.1 Descriptive statistics.....	37
6.2 The relationship of explorative and exploitative innovative actions.....	40
6.2.1 Correlations.....	40
6.2.2 Logistic regression.....	43
6.3 Overall innovative actions.....	45
6.3.1 Correlations.....	46
6.3.2 Logistic regression.....	48
7 DISCUSSION AND IMPLICATIONS.....	51
7.1 Summary and conclusions.....	51

7.2 Contribution, limitations and future directions.....55  
REFERENCES.....57

# 1 INTRODUCTION

Active research on the field of organizational ambidexterity and the two elements behind it, exploration and exploitation, was initiated in 1991 when J. G. March published his pioneering article about the trade off between these two different types of actions that are both vital for a firm's success and survival (Raisch & Birkinshaw 2008). In this groundbreaking article, March (1991) did not only present the trade-off between explorative and exploitative actions that compete over the same scarce resources, but also pointed out that it is important for an organization to pursue both types of actions. After the publication of March's (1991) paper, the balance of explorative and exploitative actions, ambidexterity, has gained a lot of attention, and in addition to the organizational learning literature (that March's 1991 article among others represents), the topic has also been studied from various other viewpoints. In addition of concentrating on exploration and exploitation and their relationship, the previous literature on organizational ambidexterity has covered areas such as the antecedents and performance outcomes of organizational ambidexterity as well as the impact of environmental factors and other moderators. (Raisch & Birkinshaw, 2008.) Previous studies have examined ambidexterity on individual, team, and organizational levels and more recently also on the level of networks. Majority of the previous work, however, has been conducted on the organizational level (Stadler *et al.*, 2014). Despite the vast amount of studies conducted on exploration, exploitation, and organizational ambidexterity, the scholars in the field still struggle to find consensus on such basic issues as what exactly is exploitation (Gupta *et al.* 2006). Many of the areas of this research still require further clarification (Raisch & Birkinshaw 2008).

In addition to exploration, exploitation, and organizational ambidexterity, the other area of interest in this thesis is aging. The effects of aging on an organization have been widely studied and different theories on the relationship of firm age and risk of failure have been presented (see for example Henderson 1999). From these studies, it seems evident that the relationship of firm age and survival is complex and still today the scholars are striving to

clarify the nature of the relationship as well as the mechanisms behind it. To make the subject even more complicated, the relationship seems to depend on industry and environmental conditions. (See for example Le Mens *et al.* 2014.)

To bind together the aging and organizational ambidexterity literature, the thesis concentrates on the relationship of innovation and age. Tushman and Anderson (1986) and Sørensen and Stuart (2000), among others, have addressed the nature of the innovative activity of an organization. Basing on their work, it seems to be so that older organizations favor their existing areas of expertise in their innovative actions as younger organizations are more likely to go beyond their existing innovative domains. However, as became evident when reviewing the empirical studies conducted on this relationship, the results of empirical studies vary significantly. One of the major goals of this study is to provide some clarity on these more or less contradictory results among previous empirical studies on the relationship of the nature of innovative actions and the age of an organization.

Following the logic of Sørensen and Stuart (2000), this thesis aims to clarify the effects of aging on an organization's innovative behavior. As Sørensen and Stuart (2000: 83) note, the innovative behavior of an organization is always bound to the industrial context and so affected, for example, by the stage of the life cycle of the industry. However, the purpose of the study is to investigate the effect of pure aging on the organizational level innovative behavior, regardless of this industry or environmental context and to show how the effect of organization's own features, in this case age, affect its innovative behavior. To study this relationship, three hypothesis are formed based on previous literature of exploration, exploitation, and aging. The hypotheses are tested with statistical analyses on a patent data covering the modern biotechnology firms in Finland between 1973–2008 in order to answer the question of how aging affects the nature of an organization's innovative activity. Based on the results, the relationship of exploitative and explorative innovative actions and an organizations age is further discussed. The study aims not only to provide clarity on the somewhat contradictory results of the previous literature on the effects of aging on a firms innovative behavior, but also to contribute to the firm level studies of organizational ambidexterity by providing empirical evidence on the phenomenon from the modern Finnish biotechnology industry.



## **2 THEORETICAL BACKGROUND**

This section starts by defining the key concepts of the thesis, exploration, exploitation and organizational ambidexterity and by discussing the relationship of exploration and exploitation as well as the key features related to organizational ambidexterity. After this, the focus moves on to aging and the relationship of aging and innovation. Finally, the results of previous studies on the specific topic of the effect of aging on explorative/exploitative innovative actions are addressed and reviewed.

### **2.1 Exploration, exploitation, and organizational ambidexterity**

Exploration is a term referring to the act of searching new knowledge and/or resources and aiming to find new ways of action. March (1991: 71) defined that "terms such as search, variation, risk taking, experimentation, play, flexibility, discovery, [and] innovation" describe actions that fall in the category of exploration.

Exploitation, in turn, refers to the use of existing knowledge and resources and basing actions on these existing resources. According to March (1991: 71) "such things as refinement, choice, production, efficiency, selection, implementation, [and] execution" describe actions that fall in the category of exploitation.

The term organizational ambidexterity refers to an organization's ability to successfully pursue simultaneously both explorative and exploitative actions and to find a balance between these two different types of actions. Raisch and Birkinshaw (2008: 375) define organizational ambidexterity as "an organization's ability to be aligned and efficient in its management of today's business demands while simultaneously being adaptive to changes in the environment".

### 2.1.1 The relationship of exploration and exploitation

The above presented short definitions make a distinction between new and existing knowledge when determining if an action is explorative or exploitative. The division between exploitation and exploration is not always so straightforward, however, as the previous literature on the subject lacks a consensus on what exactly falls in the category of exploitation. As mentioned above, March (1991) linked the word innovation to exploration. This is widely accepted in the later literature, too. However, as it seems that there is no question about the words innovation and learning being part of the definition of exploration, there is no consensus on whether these two words can be linked to exploitation also (Gupta *et al.* 2006). As He and Wong (2004), among many others, treat exploitation and exploration as different types of approaches to learning and innovation, other scholars, such as Rosenkopf and Nerkar (2001), claim that these terms refer to exploration alone. For example, when it comes to innovations, He and Wong (2004) state that explorative innovations aim at reaching for new fields of products or markets and exploitative innovations aim at improvements among the existing ones. On the other hand, Rosenkopf and Nerkar (2001) see that all actions that relate to innovation are explorative and exploitation includes solely the use of existing knowledge and is not associated with any degree of learning. Yet, as Gupta *et al.* (2006: 694) conclude based on Yelle's (1979) work, "[e]ven when an organization is attempting to do nothing more than replicate past actions, it accumulates experience and goes down the learning curve, albeit in an incremental manner". So, it would seem that it makes most sense to make the division between exploration and exploitation based on the degree of learning and innovation and not on whether or not they exist at all. (Gupta *et al.* 2006.)

March (1991) first presented the idea of there being a trade-off between exploration and exploitation, two different learning processes that compete over the same scarce resources. He also claimed that for organizations to survive and become successful, they should pursue both exploration and exploitation. (March 1991.) This is important since an organization that becomes involved with solely exploration will not be successful as the profits of this explorative action are never collected through exploitation. On the other hand, an organization that becomes involved with solely exploitation becomes stuck with its existing knowledge which will also threaten its long-term survival. (Levinthal & March 1993: 105.)

Gupta *et al.* (2006) have pointed out that the relationship of exploration and exploitation is not straight forward. They showed that these two ways of action can be mutually exclusive, but they can also be orthogonal depending on the scarcity of resources and the level of analysis. If the resources are scarce, it is likely that exploration and exploitation are mutually exclusive, but if the constraints of scarcity are absent, they can be seen as orthogonal. The level of analysis also affects the mutual exclusiveness/orthogonality as due to the different types of learning, resources, and routines required for exploration and exploitation, it is easier for a group or an organization to pursue both as it is for an individual. (Gupta *et al.* 2006.) Also March (1991) discussed these cognitive

restrictions of an individual. For this reason, on an individual level it is likely to require a punctuated equilibrium (temporal changes between explorative and exploitative periods) to be able to achieve both exploration and exploitation, but on organizational or subsystem level, it is also possible to pursue both exploration and exploitation simultaneously (ambidexterity) (Gupta *et al.* 2006).

Gupta *et al.* (2006: 699) present the idea that it might not be necessary or even beneficial for an organization to pursue both exploration and exploitation on certain circumstances as the balance between these two (organizational ambidexterity) can be achieved on a broader system level (and is then not required on the level of an individual organization). Also March (1991: 72) recognized that part of the challenge of balancing exploration and exploitation arises from the various system levels: "the individual level, the organizational level, and the social system level."

### 2.1.2 Organizational ambidexterity

There seems to be a wide consensus on the importance of ambidexterity for the success of an organization (Raisch & Birkinshaw 2008; Gibson & Birkinshaw 2004). There are several studies supporting this thought of ambidexterity being important for an organization (Turner *et al.* 2013: 318). He and Wong (2004) have shown that an ambidextrous innovation strategy positively affects sales growth rate. Kristal *et al.* (2010) have revealed the positive effect of an ambidextrous supply chain strategy on a firm's profit level and market share. Morgan and Berthon (2008) found that an ambidextrous innovation strategy enhances the business performance of a firm. Also Lubatkin *et al.* (2006) have shown that there is a positive link between ambidextrous orientation and relative performance. There are also other examples of the positive outcomes of ambidexterity in various industry contexts (Turner *et al.* 2013: 318). However, also studies supporting the idea of Gupta *et al.* (2006) for an solely explorative or exploitative strategy being the best in some cases do exist. In their 2005 study, Ebben and Johnson showed that for a small firm it is more beneficial to follow either a flexibility or an efficiency strategy than to try to combine them both. This is a good example of ambidexterity not automatically leading to success even though it often does so. For this reason, the benefits of ambidexterity or lack of them should be carefully considered in each particular situation instead of automatically assuming that there are some. (Turner *et al.* 2013: 318.)

The elements of organizational ambidexterity have been studied in various fields of study. These include "organizational learning, technological innovation, organizational adaptation, strategic management, and organizational design" (Raisch & Birkinshaw 2008: 377). Depending on the field of study, these elements (exploration and exploitation) have been described through different concepts. For example, as Levinthal (1997) discusses local search and long-jump, Dewar and Dutton (1986) deal with radical and incremental innovation, and Burgelman (1991) considers induced and autonomous strategic processes. (Raisch & Birkinshaw 2008.)

An organization can achieve ambidexterity through different mechanisms.

In previous studies, four mechanisms are commonly presented for achieving ambidexterity. These are structural, behavioral (or contextual), systematic, and temporal approaches. (Stadler *et al.* 2014: 175.) In the structural solution for achieving ambidexterity, individual business units pursue either exploration or exploitation, but as these units are structurally interdependent, this results into an overall ambidexterity (Simsek *et al.* 2009: 868; Stadler *et al.* 2014: 177). The behavioral solution suggests that exploration and exploitation are pursued simultaneously within the same business unit (Gibson & Birkinshaw 2004: 211). In the systematic solution, there is no balance of exploration and exploitation on the organizational level, but the ambidexterity is achieved on a broader social system level as one organization concentrates on exploration and another one on exploitation (Gupta *et al.* 2006). The temporal solution presents exploration and exploitation as a cyclical process where periods of exploration and exploitation follow each other (Simsek *et al.* 2009: 882). Gupta *et al.* (2006) referred to the temporal solution (punctuated equilibrium) not as an ambidexterity, but as an option for ambidexterity when aiming to achieve a balance between exploration and exploitation, due to the lack of simultaneity in pursuing both types activities in this solution.

When it comes to the modes of action in achieving ambidexterity, Stettner and Lavie (2014) have pointed out the tendency of previous literature to focus on one specific mode of action. They, instead, suggest that an organization should pursue ambidexterity by balancing exploration and exploitation across different modes of action, instead of within each mode separately, to gain enhanced performance. By balancing across modes they mean, that a firm can, for example, exploit on an internal organization level, but explore on an alliance level, so combining these two actions in different modes (exploiting internally, but exploring externally). Trying to balance each mode individually leads to weakened performance since “a firm that pursues both exploration and exploitation cannot follow persistent patterns of behavior that are essential for effective use of its routines” (p. 1906) and by finding the balance across the modes this can be avoided. By balancing across modes, the structural separation of exploration and exploitation that promotes ambidexterity is easily achieved. (Stettner & Lavie 2014.)

Most of the research on organizational ambidexterity has been done on an organization or business unit level, but also subunit, and individual levels have been studied (Raisch & Birkinshaw 2008; Stadler *et al.* 2014). As Raisch and Birkinshaw (2008: 397) state, the tension of exploration and exploitation is usually structurally resolved at one step down. This means that on a business unit level, an organization can achieve ambidexterity through subunits: one focusing on exploitation and another one on exploration. A subunit can achieve ambidexterity by having two teams with different focus and, finally, a team can achieve ambidexterity by dividing the different roles of exploration and exploitation to individuals. (Raisch *et al.* 2009: 687.) From the contextual approach point of view this way of resolving the tension of exploration and exploitation on a lower organizational level can be understood through an example provided by Gibson and Birkinshaw (2004) who showed that at a business unit level ambidexterity can be achieved through employees who, in

favorable environment, can act both exploratively and exploitatively (Gibson & Birkinshaw 2004; Raisch *et al.* 2009: 687). On an individual level, it is often considered that individuals are only focused on exploration or exploitation (Raisch *et al.* 2009: 687). However, Smith and Tushman (2005) among some others, have noted that it is necessary for some members of the top management team to be able to both explore and exploit (Smith & Tushman 2005; Raisch *et al.* 2009: 687). Yet, it is difficult for an individual to conduct these both types of actions (Gupta *et al.* 2006:696). Stadler *et al.* (2014), among others, have recently pointed out the importance of networks. They state that future research should pay closer attention to networks in order to provide a better understanding, for example, on how the balance of exploration and exploitation is affected by network ties and how networks can facilitate the different mechanisms that can be used to achieve ambidexterity. This deeper understanding of networks and their effects to exploration and exploitation could help in the implementation of the solutions for achieving ambidexterity provided by the previous literature. (Stadler *et al.* 2014.)

The effect of environmental factors on organizational ambidexterity has also been studied (Raisch & Birkinshaw 2008). Shifts in the competitive landscape of an organization shape its behavior on organizing explorative and exploitative actions and the firm level actions are so adjusted to the environment (Siggelkow & Levinthal 2003; Lewin *et al.* 1999). In addition to the environmental factors, there are also other factors that affect the ambidexterity of an organization. These include factors such as market orientation of the firm, resource endowment, and the scope of the firm. (Raisch & Birkinshaw 2008: 395).

To conclude, organizational ambidexterity is a widely studied and extremely complex multidisciplinary subject. There is a vast amount of studies on ambidexterity, its antecedents and its effects on performance outcomes as well as the environmental and other factors affecting it. Yet, the field of research is still somewhat disconnected and there are areas that need further clarification. As Raisch and Birkinshaw (2008: 376) note, “organizational ambidexterity is still in the process of developing into a new research paradigm in organizational theory”, but it is not there quite yet. (Raisch & Birkinshaw 2008.)

## 2.2 Aging

Aging is a process that involves and affects all organizations. The organizational theory literature on the age related effects on an organization appears to be contradictory and inconsistent. The authors on the field seem to be lacking an agreement on whether aging leads to positive effects for an organization or if the resulting effects are negative. (Hannan 1998.) The liability of aging (performance declining as a function of age) has been studied and shown by, for example, Barnett (1990), Barron *et al.* (1994), and Ranger-Moore (1997) who have provided evidence of the phenomenon from such industries as the telephone industry, credit unions, and life insurance companies. However, as Hannan (1998) has pointed out, even when there is an agreement on the

outcome of performance declining with age, the organizational ecology literature lacks consensus on the mechanisms through which the effects of aging occur. There is no common understanding on how aging affects the internal processes of an organization or its environmental fit (Sørensen & Stuart, 2000: 81). In addition, the liability of aging is not the only existing view of the effects of aging as some scholars claim that a liability of newness exists instead (Hannan 1998). The rest of this chapter first introduces the different views on the relationship of an organization's age and risk of failure and then discusses how aging affects the innovative activity of an organization.

### 2.2.1 Liabilities of newness, adolescence, and obsolescence

Organizational ecology literature has traditionally dealt with age dependence of organizations by studying their failure rates. The views of different authors about this relationships between firm age and failure, however, differ and this has led to three distinct views of the age dependence: liability of newness, liability of adolescence, and liability of obsolescence. (Henderson 1999: 281.)

Liability of newness as a term was first used by Stinchcombe (1965) already in the 1960's. He claimed that new organizations face problems that cause them to fail more often than older organizations. These four problems specific to new organizations are: having to learn new roles, having to invent and define new roles, having "to rely on social relations among strangers" (p. 149), and having to create a new customer base. This means that in new organizations, especially in new types of organizations, employees need to learn their roles without the help of existing employees (as there are no), and some roles even need to be invented. This can cause confusion among the people of the organization until the roles are defined and standardized and the responsibilities clearly divided. When it comes to relying "on social relations among strangers", it is simply a question of having to trust that strangers will do their job well which is not an issue in older organizations where the relationships of trust have had time to develop. Also, having to create the customer base from scratch can be difficult especially if potential customers have strong ties to older established organizations and are not willing to change their product or service provider without a well-grounded reason. (Stinchcombe 1965: 148-150.)

Liability of newness has been associated with liability of smallness since many new organizations are small in size, but Freeman *et al.* (1983: 705) have shown that these two, in fact, are two separate phenomena. They have also provided evidence for the existence of liability of newness, and shown that the time taken for its effect to wear off depends on the population of organizations. (Freeman *et al.* 1983.) Hannan and Freeman (1984) claim that liability of newness could be explained with increasing reproducibility. With reproducibility they mean that the structure of the organization is not changing radically, but is reproduced instead: it has "very nearly the same structure today that it had yesterday" (Hannan & Freeman 1984: 154). The reproducibility of structure is a prerequisite for the organization to achieve reliability and accountability and these two features increase the likelihood of the organization

to survive. Another explanation could also be legitimacy that tends to be lower for new organizations. (Hannan & Freeman 1984.)

The liability of newness, however, has been shown not to apply in all populations and Fichman and Levinthal (1988) have shown in their study of auditor–client relationships, that there is a “honeymoon period” in the beginning of the relationship. By this they mean that the risk of the relationship to end is not highest in the very beginning, but instead it increases during the first years being highest few years after the beginning until it starts to decrease again. (Levinthal & Fichman 1988.) Describing this same phenomenon, Brüderl and Schüssler (1990) have introduced the concept of liability of adolescence. The liability of adolescence logic states that there is an inverted U-shaped relationship between an organization's age and the risk of failure. This is due to all organizations having some resources in the beginning and these initial resources help them through the very beginning, moving the highest risk of failure to the adolescence of the organizational life-cycle. Another reason for the highest risk of failure being not in the very beginning of an organization's life but some years later is that the key individuals in the organization are not likely to abandon the organization until enough information of the organization's performance is available to make the judgment of whether the organization is successful or not. In order to have this information, there needs to be a phase of monitoring the performance in the beginning and the decision of possible failure can not be made before it. (Brüderl & Schüssler 1990.)

In addition to liabilities of newness and adolescence, there is a third view of the relationship of an organization's age and risk of failure, the liability of obsolescence. According to this view the risk of failure increases as the organization ages. This is due to growing difficulties of matching the changing environments. (Barron *et al.* 1994: 387.) Le Mens *et al.* (2014: 1–2) name changes in the preferences of the key audience (customers, employees etc.) of the organization as the most significant environmental drift in this context. In addition of the mismatch with external forces, the difficulties faced as the organization ages can be also due to growing inefficiency inside the organization, as Barron *et al.* (1994: 387) note, but in this case, the liability is not of obsolescence but of senescence.

Henderson (1999) claims that the differing views of the three different age related liabilities described above arise from the differing strategies of individual firms. According to him, the age dependency pattern depends on the strategy of a firm and this causes differences in the experienced age related liabilities inside and between populations. This means that multiple types of age dependencies can be identified in one population and the liabilities of newness, adolescence, and obsolescence are actually complementing and not excluding each other. (Henderson 1999.) The current view on this relationship of aging and risk of failure is in line with Henderson's (1999) view in the sense that it is not seen as straight forward and universally shared, but the pattern is actually dependent on the industry and environment conditions (see for example Le Mens *et al.* 2014).

### 2.2.2 Aging and innovation

The term innovation refers to “the initiation, adoption and implementation of new ideas or activity in an organizational setting” (Pierce & Delbecq 1977: 27). This chapter concentrates on the relationship on aging and innovation in an organization. The discussion is based on the ideas of Tushman and Anderson (1986) about radical and incremental innovation and their initiators and the ideas of Sørensen and Stuart (2000) about the effects of aging on innovation. Tushman and Anderson (1986) focus on the effects of innovation on the evolution of industry environments and organizations within them over time. Sørensen and Stuart (2000) discuss how aging affects the innovative activities of an organization with the emphasis on the individual organization and not the industry level.

An organization's innovative behavior tends to change from radical to incremental with time. The underlying reason for this is the competition over a dominant design of a product (requiring radical innovation) eventually changing to a price competition that requires enhancement of the production (incremental innovation). At the same time the scale of production tends to increase. (Abernathy & Utterback 1978.) The process, however, can not be infinitely improved and the evolution of a technological system can be interrupted by a technological breakthrough that introduces new technology and opens the competition over a dominant design again (Tushman & Anderson 1986: 440-441).

The major breakthrough in technology described here can be classified either as “competence-destroying” (involving radical innovation) or “competence-enhancing” (involving incremental innovation), depending on its relationship with the competencies of the incumbent firms in the industry. If the breakthrough is competence-enhancing, the existing firms are able to use their existing skills and knowledge to exploit it, but if it is competence-destroying, then the existing skills and knowledge that they have are not useful in exploiting the new technology. As the competence-enhancing technological breakthroughs build on the ground of existing knowledge and technology in the industry, it is the existing incumbent firms that are usually responsible of this kind of breakthroughs. On the other hand, the competence-destroying breakthroughs are most often initiated by new entrants in the industry. (Tushman & Anderson 1986.) However, it is noteworthy that Tushman and Anderson (1986) have not investigated the effect of actual firm age, but instead they have distinguished between new entrants and incumbents in the industry (Sørensen & Stuart 2000: 83). As competence-destroying technological breakthroughs are relatively rare (Tushman and Anderson (1986) found only eight of them for three different industries in 190 years in total), competence-enhancing breakthroughs are more common (Tushman & Anderson 1986).

The idea of technological evolution being shaped by competence-enhancing and competence-destroying discontinuities is also supported by the theories of liabilities of newness and aging. As the competence-enhancing breakthrough is initiated by existing organization and builds on its existing knowledge and skills, it widens the gap between incumbents and new entrants



in the benefit of existing firms (liability of newness). On the other hand, the competence-destroying breakthrough is often initiated by a new entrant and does not rely on the existing knowledge and skills in the industry. As this changes the industry environment by altering the competitive situation, it benefits the new entrant firms as the older ones might find it hard to adapt to the new environment (liability of aging). (Tushman & Anderson 1986: 460-461.)

Sørensen and Stuart (2000) have explained the changes in the innovative behavior of an organization through the concepts of organizational competence and environmental fit. With organizational competence they describe an organization's internal ability to produce innovations and with environmental fit they describe how well the innovations fit to the external demand. (Sørensen and Stuart 2000: 83-84.) Even though aging may create some disadvantages to the organizational competence (such as internal inefficiency due to the growing bureaucratization (Barron *et al.* 1994: 387)), the overall effects of aging on organizational competence are positive. This is due to the gained efficiency and knowledge. As the liability of newness logic suggests, the gained experience and strengthened relationships created over time strengthen the organizational efficiency (Stinchcombe 1965; Sørensen and Stuart 2000: 84). The gained knowledge also reinforces an organization's capability to produce new innovations (Cohen & Levinthal 1990) which indicates that the organizational competence grows as a function of age. (Sørensen & Stuart 2000.)

In addition to the organizational competence, the second important concept in Sørensen and Stuart's (2000) discussion is the environmental fit. The liability of obsolescence logic suggests that as organizations age, they might not be able to fully adjust themselves to the changing environmental demands (Barron *et al.* 1994). As the structural inertia in an organization increases with age (Hannan & Freeman 1984), it can not easily adjust the adopted routines to changing environments. This decreases the environmental fit further isolating the organization from its environment. (Sørensen & Stuart 2000.)

As the absorptive capacity of an organization is cumulative and path-dependent, falling behind in the technological development of a quickly changing technological field easily leads to the organization not being able to absorb and utilize the information on that field later on as it is missing the critical information in between (Cohen & Levinthal 1990; Sørensen & Stuart 2000: 87). Even if an organization would have the required absorptive capacity, the cost of change is likely to keep it within its existing competencies, especially in the industries where creating new competencies through innovations requires large investments. This will lead the organizations to eventually end up with obsolete technological competencies as they fall behind in a changing environment. (Abernathy & Utterback 1978: 41; Sørensen & Stuart 2000: 87.)

These ideas about the organizational competence and environmental fit lead to the conclusion that as organizations gain competence as they age, the gap to their environment grows at the same time if the environment changes. This causes older firms to prefer their existing area of expertise over new areas in their innovative behavior. This behavior is also reinforced if the innovations in the existing innovative areas of the organization turn out successful. Comparably, younger organizations that are not as set to their existing routines

than their older counterparts, are more likely to search for innovation in areas further away from their existing competencies. (Sørensen & Stuart 2000: 87–88.)

To conclude the discussion of aging and innovation here, it seems that old organizations are likely to stay within the areas of their existing competencies and use them as the basis of their innovative behavior. Younger organizations, on the other hand, are not as bound to their existing knowledge and are so more likely to search for new innovative domains. (Sørensen & Stuart 2000.)

## **2.3 Previous studies on the relationship of exploration/exploitation and aging**

This section presents the results of previous empirical studies conducted on the relationship of an organization's age and its explorative and/or exploitative behavior. Exploration and exploitation and the effect of aging on an organization's behavior are both widely studied subjects. Many exploration and exploitation related quantitative studies also recognize the relationship to firm age using it as a control variable (see for example Rothaermel and Deeds 2004). However, as many of those studies rely on conclusions made based on previous literature, there are relatively few studies conducted aiming to investigate and clarify this specific relationship of these two topics (explorative/exploitative behavior and firm age) and to test those conclusion. 10 articles dealing with this specific subject were identified and are presented here. The key findings of each article are first presented and then followed by conclusions that combine the work together.

Several searches in the Web of Science database were made by using different combinations of the key words “exploration”, “exploitation”, “innovation” “age”, “aging”, and “firm age”. From the resulted lists of articles the ones presented here were selected based on the topics of the papers. In those cases where it was difficult to say whether or not the article deals with the age-behavior relationship of interest here based on the topic only, the article was further studied to make the evaluation. As the Sørensen and Stuart's study from 2000 was identified as the pioneering work on this topic, the list of articles citing their paper was also gone through in a similar manner to ensure that all relevant studies are found.

### **2.3.1 The findings of individual papers**

The 10 studies presented in this chapter are summarized below in Table 1. In the key findings column only the key findings directly related to the topic of the relationship of aging and explorative/exploitative behavior are listed.

TABLE 1 Summary of the studies concerning firm age and explorative/exploitative behavior.

Author	Year	Research topic	Studied industries	Key findings
Sørensen and Stuart	2000	The relationship of organizational aging and innovation processes.	Semiconductor, biotechnology.	1. Innovative activity increases with age. 2. The nature of the innovations of older firms is more likely to be incremental than radical. 3. Older firms fall behind in technological development.
Huergo and Jaumandreu	2004	Innovative activity as a function of firm age.	Manufacturing firms in several industries.	Probability of producing innovations is on average stable, but varies between industries.
Dunlap–Hinkler <i>et al.</i>	2010	Predicting the likelihood of a breakthrough innovation based on previous innovative actions.	Global pharmaceutical industry.	No correlation between firm age and explorative activity.
Withers <i>et al.</i>	2011	Innovation capabilities and the level of innovation.	SMEs in multiple industries.	The nature of the age dependency of the level of innovation activity is dependent on the level of innovative capabilities.
Coad and Guenther	2013	The relationship of firm age and diversification pattern.	German machine tool industry.	Both explorative and exploitative actions related to product diversification decrease with aging.
Voss and Voss	2013	The performance outcomes of explorative/ exploitative product and market strategies.	The US nonprofit professional theaters.	1. Organizational ambidexterity negatively correlates with firm age in both product and market domains. 2. Firm age has a negative correlation with exploration in product domain and with exploitation in market domain.
Chen	2014	Balance of inertia (exploitation) and adaptability (exploration) over time.	Nonprofit organizations in the US.	The balance between exploration and exploitation as a function of firm age is nonlinear.
Xie and O'Neill	2014	Product diversification patterns.	Generic pharmaceuticals in the US.	There is an U-shaped relationship between firm-age and exploitative product-market entries.
Choi and Phan	2014	The effect of firm age and unfavorable environment on the balance of explorative and exploitative behavior in new product development.	Korean technology-based manufacturing SMEs.	There is a negative relationship between firm age and relative explorative orientation in new product development.
Shi and Zhu	2014	The relationship of firm age and political connection with innovation outputs.	Chinese IT and pharmaceutical industries.	A positive link between firm age and the amount of innovative outputs.

Sørensen and Stuart (2000) do not use the terms exploration and exploitation in their work directly, but as their work on the effect of aging on organizational innovation is highly related to this topic, their work was included here. They have conducted a study on the industries of semiconductor and biotechnology to find out how aging affects innovative behavior of an organization. According to their results the innovative activity of a firm increases as the firm ages, but for older organizations the innovations are more likely to be incremental of nature. They also found that older firms fell behind in technological development which was shown by investigating their patent citations: older firms cited on average older technology in their patents. (Sørensen and Stuart 2000.)

Huergo and Jaumandreu (2004) also studied the likelihood of an organization to produce innovation as a function of the organization's age. Like in the case of Sørensen and Stuart (2000), this paper does not discuss exploration and exploitation directly, but as the innovative activity it studies is closely related, the study was included. The results of Huergo and Jaumandreu (2004) from the Spanish manufacturing sector show that on average, there is not a significant difference in the probability of innovation as organizations age, but they also found that this tendency varies significantly between industries.

The main focus of the study of Dunlap–Hinkler *et al.* (2010) was on the effect of an organization's innovative history on its likelihood of producing a breakthrough innovation. However, as they got also interesting results regarding firm age and exploration that are also, according to their own notion, in contradiction with the ones of Sørensen and Stuart (2000), the study was included here. Dunlap–Hinkler *et al.* (2010) studied the global pharmaceutical industry and their findings regarding firm age and explorative activity showed no correlation between firm age and explorative activity.

Withers *et al.* (2011) have studied the relationship of innovation capabilities and innovative activity of a firm and the moderating effect of firm age on it. In their study of small and medium-sized enterprises they found that older firms produce more innovations if innovation capabilities (such as opportunity recognition) are on a high level, but if the innovation capabilities are low, younger firms are more likely to produce more innovations.

In their product diversification pattern study on machine tool manufacturers in post-war Germany, Coad and Guenther (2013) found that as firms age, their product diversification rates decrease. They also came to the conclusion that diversification happens in waves (product diversification followed by a period of no diversification). Coad and Guenther (2013) distinguished between explorative product diversification (new product variation) and exploitative product diversification (product in a new submarket), but found that the rate of both types of actions decreases as a firm ages. Their results indicate that both exploration and exploitation in relation to product diversification decrease with aging.

The main focus of the study of Voss and Voss (2013) was on the link of firm performance and its explorativity/exploitativity in both product and market strategies, but as they also provided some interesting results on the relationship of ambidexterity and firm age, their work was also included here.

They studied the US nonprofit professional theaters and found that on both product and market domains the correlation with firm age and organizational ambidexterity was negative. Although it is not directly reported by Voss and Voss (2013), the correlation table (p. 1466) they have provided indicates that when it comes to exploration and exploitation separately, there is a significant negative correlation between firm age and product exploration as well as between firm age and market exploitation. The correlations between firm age and market exploration and product exploitation were insignificant.

Chen (2014) has provided results about the age dependency from the nonprofit sector. He uses the terms inertia and adaption as synonyms for exploitation and exploration and has developed a model that suggests that the balance of inertia and adaption (exploitation and exploration) has a wave shaped relationship with an organization's age. Accordingly, the relationship of firm age and innovative behavior is non-linear.

Xie and O'Neill (2014) have investigated the product diversification patterns of the US generic drug enterprises. They found an U-shaped relationship between firm-age and likelihood of exploitative product-market entries. According to them, young firms are more unlikely to use exploitative market entries as old firms are more likely to use them in their product-market diversification.

Choi and Phan (2014) studied the effect of firm age and unfavorable environment on the balance of explorative and exploitative behavior in the context of new product development. The data for the study was from Korean technology-based manufacturing SMEs. Regarding the firm age and behavior relationship, they found that firm age has a negative effect on the relative explorative orientation in new product development.

Shi and Zhu (2014) conducted a research on Chinese IT and pharmaceutical firms in order to clarify the relationship of firm age and political connection with the innovation outputs of the organization. According to their results, aging is positively linked to the amount of an organization's innovative outputs.

In addition to these 10 studies, there is a vast amount of studies contributing to the understanding of the relationship of firm age and organizational behavior, innovation etc., but in order to keep the amount of studies here reasonable, the studies that were not clearly focusing on aging and exploration/exploitation (or innovative activity directly related to them) were left out.

### **2.3.2 Conclusion from the previous studies**

To conclude the 10 studies introduced above, the common insights as well as contradictory results about the firm age and exploration or exploitation and overall innovative actions are listed here.

When it comes to the overall innovative activity, two of the studies seem to find an increase in the overall activity as an organization ages (Sørensen and Stuart 2000; Shi and Zhu 2014). Also Withers *et al.* (2011) claim that this is the case, but only when the level of innovation capabilities of the organization are

high. Contradictory, one study found aging to lead to a decrease in overall innovative activities (Coad and Guenther 2013) and also Withers *et al.* (2011) state that this is the case when the level of innovation capabilities of the organization are low. Huergo and Jaumandreu (2004) found no relationship between firm age and overall innovative activity on general, but they stated that this depends on the industry in question.

Regarding exploration alone, Sørensen and Stuart (2000) found that young organizations are usually the ones responsible of explorative actions. Coad and Guenther (2013) found that explorative actions (as well as exploitative ones) decrease with age and also Choi and Phan (2014) found a negative link between firm age and relative explorative activity. Voss and Voss (2013) found a negative link between exploration and firm age only in product domain (not in market domain) and Dunlap-Hinkler *et al.* (2010) found no correlation between exploration and firm age.

Regarding exploitation, Sørensen and Stuart (2000) found exploitation to increase with age. Coad and Guenther (2013) found that exploitative actions (and also explorative ones) decrease with age and Voss and Voss (2013) found a negative link between exploitation and firm age in product domain, but not in market domain. Xie and O'Neill (2014) concluded that there is an U-shaped relationship between firm age and exploitative activity.

Another interesting notion from these studies, is the approach to the idea of linearity of the age-behavior relationship. As most of the studies treat the relationship of firm age and innovative activity as linear, Chen (2014) claims that the relationship, in fact, is wave shaped. Coad and Guenther (2013), too, found this wave shaped relationship between innovative activity and firm age. Also, as mentioned, the relationship of firm age and exploitation is U-shaped according to Xie and O'Neill (2014).

Based on these results, it seems that the relationship of exploration/exploitation and firm age is not clear. The empirical evidence regarding the effect of age on innovative activity seems to be widely contradictory.

## 3 HYPOTHESES

In this section, three hypotheses on the effect of firm age on its explorative and/or exploitative behavior are formed based on the literature presented in previous sections.

### 3.1 Firm age and exploitation

Growing structural inertia isolates an aging organization from its environment as it is harder for the organization to adapt to the changes in the environment (Hannan & Freeman 1984; Sørensen & Stuart 2000). Once the organization has fallen behind in technological development in a changing environment, it is hard for it to utilize the information on this technological field anymore due to the cumulative and path-dependent nature of absorptive capacity (Cohen & Levinthal 1990; Sørensen & Stuart 2000: 87). As the gap between the organization and its environment grows, it leads to the organization to rely on its existing capabilities on a growing manner and when the use of existing area of expertise in innovation turns out to be successful due to gained efficiency, this behavior is further reinforced (Sørensen & Stuart 2000: 87-88). Also, with time the nature of an organization's innovative behavior tends to change from radical to incremental (Abernathy & Utterback 1978).

As relying on existing knowledge and capabilities in innovation creation as well as incremental innovation are both associated with exploitation, it can be assumed that the exploitative behavior of a firm increases with age. This implies that an organization's age is positively related to the rate of its exploitative innovative behavior and leads to hypothesis 1:

*Hypothesis 1: The likelihood of the nature of an organization's innovative action to be exploitative increases with age.*

### 3.2 Firm age and exploration

Unlike their older counterparts, young organizations are not suffering from decreased environmental fit caused by growing inertia and enhanced competence. Young organizations also are not as bound to their existing competencies as the older ones. Accordingly, a young organization can more easily move beyond its existing areas of competence to adapt the environmental changes it faces. (Hannan & Freeman 1984; Sørensen & Stuart 2000.) Young organization's are more likely to search for new innovative domains (Sørensen & Stuart 2000). Also, as noted by Tushman and Anderson (1986), it is the new entrants of an industry (usually young organizations) that most often initiate competence-destroying breakthroughs.

As moving to new innovative domains beyond the existing ones as well as breakthrough innovations are both associated with exploration, it can be assumed that the exploitative behavior of a firm is highest among young organizations. This implies that an organization's age is negatively related to the rate of its explorative innovative behavior and leads to hypothesis 2:

*Hypothesis 2: The likelihood of the nature of an organization's innovative action to be explorative decreases with age.*

### 3.3 Firm age and its overall innovative behavior

Older organizations usually have larger knowledge base which provides better basis for creating new innovations due to the innovative activity being of cumulative nature (Sørensen & Stuart 2000; Cohen & Levinthal 1990). Also the fact that older organizations have higher level of organizational competence, provides them with better prerequisite to produce new innovations (Sørensen & Stuart 2000). In addition, the number of competence-enhancing breakthrough innovations tends to be greater than the amount of competence-destroying innovation and it is the incumbent firms (older organizations) that are most often responsible of the competence-enhancing innovations (Tushman & Anderson 1986). Following this logic, it can be assumed that the overall rate of producing new innovations is higher for older organizations than for the younger ones. This means that an organization's age is positively related to the rate of its overall innovative activity and leads to hypothesis 3:

*Hypothesis 3: The likelihood of an organization to produce an innovative action increases with age.*



## 4 EMPIRICAL SETTING

The empirical setting of the study is the modern biotechnology industry in Finland between 1973–2008. This section first defines biotechnology and discusses the modern biotechnology industry generally. Then, the specific features of the industry in Finland, and the major changes it has faced since the birth of the industry are introduced.

### 4.1 Biotechnology and the biotechnology industry

OECD (2005: 9) defines biotechnology broadly as “[t]he application of science and technology to living organisms, as well as parts, products and models thereof, to alter living or non-living materials for the production of knowledge, goods and services.” Biotechnology includes several different techniques and applications in several different sectors of industry. (OECD 2005: 6, 9.) Examples of the fields that use biotechnology are such as agrobiotech, pharmaceuticals, diagnostics, and bioenergy, among others (Mattsson 2008: 85).

The modern biotechnology industry is considered to be born in 1973 when the recombinant DNA technology was invented by Herbert Boyer and Stanley Cohen. The other important invention for the early modern biotechnology followed shortly after when Milstein and Kohler first used the hybridoma technology to produce monoclonal antibodies in 1975. These two inventions laid the ground for modern biotechnology by providing effective tools for modifying micro-organisms. (Stuart *et al.* 1999: 322.)

Biotechnology, however, has longer history than just the modern era as the first actual biotechnology products, such as ethanol and citric acid, that were manufactured by fermentation, were introduced already in the 19th century. In the 20th century, the biotechnology industry further evolved and new types of products were introduced during the era of “classic biotechnology”, covering three decades before the beginning of the modern era (from 1940s until the beginning of the modern era in 1970s). During this period, began the manufacturing of products such as antibiotics and enzymes. (Ruutu

1990: 199.) Also, already during the classic period, in the 1950s, Watson and Crick first discovered the structure of DNA, which enabled the groundbreaking innovations that started the era of modern biotechnology almost 20 years later. (Mattsson 2008: 74.)

Generally, entering the biotechnology business requires a large scale of resources. As biotechnology is based on different areas of biology, physics, chemistry, and technology, expertise in various fields is required. In addition, entering the industry requires sufficient financial resources as the product development takes time and the strict legislation on areas such as pharmaceuticals and food increases costs. Due to the capital and knowledge intensive nature of the industry, different strategic alliances are common in the biotechnology sector. (Ruutu 1990.)

## 4.2 The modern biotechnology industry in Finland

Already in the classic era of biotechnology, a Finnish biochemist A. I. Virtanen received the 1945 Nobel Prize in Chemistry for his invention of an improved fodder preservation method (patented in 1932). As this remarkable invention implies, the biotechnology research in Finland was already going on strong at the time the modern biotechnology industry was born in the 1970s (Ruutu 1990, 199; Mattsson 2008: 75–77).

In the beginning of the modern era, both *de novo* and *de alio* type of entrants slowly entered the industry. At the time, the *de novo* entrants were mainly diagnostic firms as the *de alio* entrants were firms with previous experience from pharmaceuticals, chemicals, food and animal feed, and such. However, also other sub-fields of the biotechnology started to attract new entrants, especially after the 1970s. The gradual inflow of new entrants characterized the industry until the late 1980s, but after 1989 the industry started to grow rapidly until the beginning of the 21st century after which the growth slowed down again. Although the industry has attracted both *de novo* and *de alio* entrants, the majority (approximately 90 %) of them has been of *de novo* type. (Mattsson 2008: 75–76.)

The changes in the growth rate of the industry can be explained through the changes in the industrial environment. Already in the end of the 1970s, the industry benefited from important developments in the available technology and the founding of the European Federation of Biotechnology. On the national level, an annual networking event, *Biotieteiden päivät*, was introduced at this time also. (Mattsson 2008: 80.) Ten years later, at the end of 1980s, the Finnish government introduced a national biotechnology program (1988). This program led to the creation of six regional centers of excellence that have advanced the biotechnology research and the co-operation between universities and the industry. Also a set of other major public programs for both funding and developing the biotechnology sector, were launched at the time. (Mattsson 2008: 77–78; Schienstock & Tulkki 2001; Enari 1988; Nybergh 1988; Viikari 1988.)

The most important sources of funding in the industry have been the Finnish Innovation Fund (SITRA), the Finnish Funding Agency for Technology and Innovation (TEKES), and the Finnish Academy which are all public

institutions. Also the venture capital investments that were still rare in Finland in the 1980s started to grow and be available in the 1990s and reached their highpoint in 2000. (Mattsson 2008; Schienstock & Tulkki 2001; Enari 1986; FVCA 2006.) As the inter-organizational collaboration as well as collaboration with research institutes and access to sufficient funding have proved to be important factors for succeeding in the biotechnology industry (Oliver 2001; Powell *et al.* 2005; Schienstock and Tulkki 2001), the centers of intelligence and the available funding were important growth stimulators for the industry from the 1980s onwards. Yet, despite the favorable political environment and increasing funding, only 1.2 % of the Finnish GDP came from biotechnology in 2000 (Academy of Finland 2002: 26; Mattsson 2008: 77).

Even though the industry was growing, it did not meet the high expectations set by the environment and was out-shadowed by the blooming information and telecommunication sector. This led to decreased funding from the public sector and also the venture capital investments were declining. At the same time, in the beginning of the 21st century, the national biotechnology program came to its end and the world economy faced a downturn. (Mattsson 2008: 78–81; Schienstock & Tulkki 2001; FVCA 2006.) This decline in both funding and the public image of the industry then led to the declining growth rate of the industry after the year 2000.

The other important events that the biotechnology industry has faced are the recession in Finland in the 1990s and Finland becoming a member of the European Union in 1995. The Finnish economy faced a serious recession in the beginning of 1990s when the GDP growth was negative for three subsequent years (Official Statistics of Finland 2013). In 1995, the membership of the European Union caused the regulatory environment to change affecting also the biotechnology industry (Mattsson 2008: 81).



## 5 METHODOLOGY

This section introduces the biotechnology actor data set that was used for constructing the sample and data for this research. The data constructed for this research and the variables used in the analyses are also introduced. Lastly, the econometric method chosen for the analyses is presented. The main method applied in the research was logistic regression analysis, but also some descriptive statistics and correlation analysis are briefly discussed as they were used to describe the data and to support the logistic regression analysis and its results.

### 5.1 Data and sample

To investigate the relationship of firm age and the nature of its innovative behavior, an existing dataset on the modern Finnish biotechnology industry was used. This dataset consists of the whole population of the actors in the modern Finnish biotechnology industry from its beginning in 1973 until the year 2008. The whole population covered in the data set was identified by analyzing several biotechnology firm listings as well as biotechnology related articles published in *Kemia-Kemi* and *Kauppalähti*. *Kemia-Kemi* is the most important industry journal in the Finnish chemical industry focusing not only on chemistry but also biochemistry and so covering the biotechnology sector. *Kauppalähti* is the most widely circulated Finnish newspaper focusing on general commerce. In addition, all the patents that fell into patent classes considered as biotechnology patent classes and that were granted in Finland after the year 1970 were screened. For this, Esp@cenet patent database was utilized. For each biotechnology actor identified, basic information (such as founding date and, if different, date of entering the industry as well as exit date for the firms that had left the industry) was listed. After identifying the population, the data was verified by presenting the names of the identified actors to six biotechnology industry experts and the firms that were not familiar to any of the experts were removed from the data. In the firm identification step

and selecting the patent classes that are biotechnology related, OECD's definition (OECD 2004) of biotechnology and the related patent classes was used. A more specific description of identifying and verifying the population and can be found in Mattsson 2008. (Mattsson 2008: 94–101.) In addition to the for-profit organization's specifying in biotechnology activities (dedicated biotechnology firms, DBFs) used in Mattsson's (2008) study, the whole dataset also includes other actors in the biotechnology industry: companies with biotechnology activities (CWBA), research institutes, biotechnology incubators, public financiers, private investors, other service firms, and non-biotechnology actors.

As mentioned, in order to identify the biotechnology actors, a collection of biotechnology patents granted in Finland was gathered. This patent data set was used in constructing the sample used in this research. The original set of patent data included 1292 patents for 216 different organizations. As this data contained both non-profit and for-profit organizations as well as some non-biotechnology actors (firms that have patented in a biotechnology patent class, but are not actual biotechnology firms), some exclusions were made in order to get a more homogeneous sample and to rule out the non-biotechnology actors. For the sample used here, only the firms that were dedicated biotechnology firms, DBFs (focusing on biotechnology activities only), or companies with biotechnology activities, CWBAs (companies that have biotechnology and other activities), were included. These two types of firms (DBFs and CWBAs) formed majority of the original data. By including only DBFs and CWBAs a more homogeneous sample with only for-profit organizations that actually use biotechnology in their operations was obtained. So, the sample in this research included all the DBF and CWBA firms that had applied patents in biotechnology patent classes during 1973–2008. In the case of 43 patents that had more than one applicant (1–3 applicants were listed for each patent), the patent was first listed to each of the firms individually before removing the lines that did not have a CWBA or DBF as an applicant.

After excluding the non-DBF/CWBA firms, some individual patents were removed from the original data. As the birth of modern biotechnology industry is considered to be the year 1973 (Stuart *et al.* 1999: 322), 6 patents that were applied before 1973 were excluded from the final data. The original data also included some patents applied in 2009, but in order to have only full years included, the end of data collection was set to the end of 2008. As the patents in the original data were documented for the firm to which the patent was granted and the delay between applying and granting the patent in some cases was several years, it happened in several occasions that the patent was applied before the firm was founded. In these cases, the patent was moved from the firm it was documented for to its predecessor (the real applicant), if the predecessor could be identified. For example, the company called Finnish Immunotechnology exited the industry in 2001, but the operations continued with a new name, FIT Biotech. As FIT Biotech entered the industry in 2001, but had two patents that were applied before this (these two patents were applied in 1999 and 2000, and granted in 2001 and 2006), the patents were moved from FIT Biotech to its predecessor, Finnish Immunotechnology. However, in 5 cases

it was unclear who the applicant (predecessor firm) actually was and these 5 patents were excluded from the data as they could not be associated with any of the firms with certainty. One patent was also excluded as it did not have international patent classification. International patent classification was used in classifying the patents as explorative or exploitative as is explained later. After these exclusions, the final data used in this research included 1121 patents for 151 different organizations. This set of patents was used in the analysis focusing on the hypotheses 1 and 2. To investigate hypothesis 3, the data set was modified so that also the years within the observation period during which an organization had existed but not applied for a patent were included and each year for each firm was only included once. In this modified data (referred as the second data set later on) there were altogether 1862 years for the 151 organization.

The use of patent data has both advantages and disadvantages. When patents are discussed as an indicator of technological activities, there are some shortcomings. These shortcomings include differences in patenting behavior between and within industries and differences in the value of patents (Levin *et al.* 1987; Gambardella *et al.* 2008). However, the use of patents as an indicator of technological activities has also great advantages. These advantages include the clarity of ownership and specific information provided on the patented technology. Patent data is also easily accessible and objective. (Hall *et al.* 2005; Griliches 1990.) Among the indicators of technological activities, patent data is able to provide most detailed information (Griliches 1990). As said, patenting behavior varies between industries making the relevance of using patents as indicators of technological change also varying between industries. However, in the context of this study, patent data can be considered as a valid indicator since, as Levin *et al.* (1987: 786) have noted, in biotechnology industry the protection of intellectual property is intense (Levin *et al.* 1987: 786; Belderbos *et al.* 2010: 874).

## 5.2 Variables and measures

### 5.2.1 Dependent variables

In regression analysis, the dependent variable is the variable the behavior of which is attempted to explain with the other variables (Metsämuuronen 2005: 658). Two different dependent variables were used in this study. Both of these variables are dichotomous (they get only two values: 0 and 1). The first variable was called "Type of action" and it classified each patent either as exploitative (0) or explorative (1). The classification to explorative and exploitative actions was conducted based on patent classes. The International Patent Classification system (IPC) was used as the IPC class(es) was available for most of the patents (one patent did not have an IPC patent class as was mentioned before). The IPC system divides patents first into sections and then further to classes, subclasses, groups, and subgroups (Patentti- ja rekisterihallitus 2005: 27). The subclass-level was the level of interest in this research. A patent was classified as

explorative if the applicant organization did not have applied patents in the same patent class in the past five years. The explorativity of a patent class also remained for the following three years after it turned explorative. The patents that did not fall in the explorative class were classified as exploitative. The same procedure has been used previously by Belderbos *et al.* (2010). The idea behind this classification is that patenting in a previously unfamiliar patent class indicates explorative behavior as staying in the familiar technology areas can be considered exploitative. The five year time frame used in the classification is based on the idea that if an organization does not closely follow the changes of a specific technology field, it easily falls behind as the technology evolves and is not able to exploit its knowledge in the field anymore (Cohen & Levinthal 1990; Sørensen & Stuart 2000: 87). The three year duration of the explorativity of a certain patent class, on the other hand, builds on the idea that an organization does not master a technology field right after entering it, but it remains new for a while. (Belderbos *et al.* 2010: 875.) The application year of the patent was the year of interest in this study (instead of the year the patent was granted) to ensure that the year would represent the exact time of the related innovative activity as accurately as possible. The Type of action variable was used as the dependent variable when testing the hypotheses 1 and 2.

The other dependent variable in the study was called “Patenting activity”. This variable was created in order to be able to assess the innovative activity of an organization overall. The variable simply indicates whether a firm has filed a patent (coded as 1) or has not (coded as 0) at a specific year. This variable was used as a part of the second data set (that included also the years during which no patents had been applied) as the dependent variable when testing hypothesis 3.

### 5.2.2 Independent variable

An independent variable is the predicting variable of interest that is used to explain the variation of the dependent variable (Metsämuuronen 2005: 658). The independent variable of the research was the age of an organization at the year of applying a patent (in the second data set also at the years patents had not been filed). This variable was called “Age” and it was calculated by subtracting the founding year of the organization from the year it had filed a patent (and in the second set of data also from the year it had not filed a patent).

### 5.2.3 Control variables

In regression analysis, a control variable is a variable that is added to the regression model as a predictor since it is known to have or potentially has an effect on the dependent variable. Control variables are added in the model in order to be able to differentiate the effect of the independent variable from the effects of the control variables. (Ketokivi 2009: 111.) As explained in the theoretical background chapter, environmental factors have been shown to affect the ambidexterity (and so the nature) of an innovation (see Raisch and Birkinshaw 2008 for examples). To control the environmental factors that might



effect the dependent variables, eight control variables were used in this research. These variables were called "GDP", "Recession", "P1", "P2", "P3", "P4", "Density", and "Financing".

To control the changes of the economic environment over the observation period, the variable GDP was included in the analysis. This variable presents the yearly values of the Finnish GDP at market prices (with the reference year 2010) that were derived from Statistic Finland (Official Statistics of Finland 2013). To further control the possible effects of the recession that the Finnish economy faced in the early 1990's, a dummy variable called "Recession" was created. The variable was coded as 1 for the recession years 1991–1993 (indicated by negative growth in the Finnish GDP) and 0 for all the other years.

To further control the effects of changes in the Finnish biotechnology industry specifically, a set of dummy variables (P1, P2, P3, and P4) was created to indicate the period during which a patent was applied (or was not applied in the second dataset). Mattsson (2008) divided the industry into four distinct periods separated by the major changes in the industry environment. First of these periods began from 1978 and presented the early stage of the modern biotechnology industry with moderate entries of both *de novo* and *de alio* firms. The second period was from the year 1988 onwards indicating a period of growing legitimation and funding after governmental efforts to support the industry. The third period starts from the year 1995 when the industry faced major regulatory changes as Finland joined the European Union. The fourth period started from 2000 after which the industry environment changed to less favorable due to decreased funding and public image of the industry and the downturn of the world economy at the beginning of the new millennium. The same four periods were used here with the exception that the years 1973–1977 were added to the first period in the P1 variable. These years were not covered by Mattsson's (2008) study as the observation period in his study started from 1978. Another option would have been to create a fifth dummy variable for these early years (1973–1977), but as there were only 3 patents applied between 1973–1977, there would not have been enough observations in this group to construct a separate variable.

In order to control the effects of competition in the industry, a control variable "Density" was used. This variable indicates the level of competition that was measured as the number of the biotechnology firms at the industry each year. The number of firms was calculated as the cumulative sum of the difference between the number of entries and exits for each year. The information of the entries and exits in the industry was taken from the original set of biotechnology data that was used in constructing the sample (and most of the data) for this research.

Previous research has shown that equity financing has a positive effect on innovation and patenting rates (see for example Kortum and Lerner 2000). The effect of equity financing was controlled with a control variable "Financing". This was a dummy variable indicating whether or not a firm had received private equity funding during the past three years. The financing information was taken from the original biotechnology dataset and a dummy variable was used as the exact amount received was not known in many cases. To take into

account the possibility of the effects of the received funding to have an effect for a period longer than only the following year, the three year time-frame was applied.

## 5.3 Econometric method

The main method in this research for analyzing the data was logistic regression analysis. However, also correlations and descriptive statistics were utilized to support the results of the logistic regression analyses and to introduce the data.

### 5.3.1 Descriptive statistics

Descriptive statistics offer several ways to describe and summarize data so that it is easy to see what the data actually consists of. These include, for example, frequencies, averages, percentiles, and statistical dispersions. Frequencies indicate the amount of each value in the dataset. Quartiles are percentiles that divide the data into four groups that each present one fourth of the data. The 25th percentile (or the lower/first quartile) shows the point below which the lowest 25 % of the values are, the 50th percentile (or the second quartile) shows the 50 % point and the 75th quartile (or the upper/third quartile) shows the 75 % point. Averages include mean, median, and mode. Mean is the sum of all values divided by the number of them. Mode indicates the value that has the highest frequency, and median indicates the middle value when the data is arranged from lowest to highest (or highest to lowest). Median is the same as the 50th percentile. Standard deviation is the indicator of statistical dispersion used in this study. Standard deviation is an indicator for how far from the mean the values of a variable are dispersed. (Metsämuuronen 2005: 319–329.)

In addition to these, the minimum and maximum values are used in this thesis. These figures simply indicate the smallest (minimum) and the largest (maximum) values in the data.

### 5.3.2 Correlations

Correlation is an indicator of a statistical dependence between two variables. If two variables correlate, a change of the value of one of the variables means that also the value of the other variable changes. The measure of the statistical significance of the correlation is p-value. A p-value smaller than the set significance level means that a statistically significant correlation exists. The significance level of the analysis indicates the risk of making a false conclusion of a correlation existing when it actually does not exist. In human sciences the risk level of 0.05 (5 %) is often sufficient. In addition to the statistical significance, the other point of interest in interpreting the results of a correlation analysis, is the correlation coefficient. The values of a correlation coefficient vary between -1 and 1. A negative coefficient indicates that when the value of one variable increases, the value of the other variable decreases and a positive coefficient indicates that the values of both of the variables either increase or decrease together. The correlation coefficient also shows how strong the

correlation between two variables is. Roughly, a correlation coefficient between 0.80 and 1.00 indicates very strong correlation and a correlation coefficient of 0.60–0.80 indicates strong correlation. For a moderate correlation, the coefficient is between 0.40 and 0.60 and if the value of the coefficient is lower than 0.40, the correlation is weak. In interpreting the results of correlation analysis, it is useful to draw figures to visually examine the relationships of each pair of variables. This is due to possible anomalies that can cause distortions in the correlation coefficients. For example, if the correlation between two variables is curvilinear (this is the case if, for example, the values of one variable first increase and then decrease as the values of the other variable increase), it is not detected when calculating the correlations, but the existing dependency can be easily detected visually from a figure. (Metsämuuronen 2005: 339, 345–346, 350, 397–398, 415.)

To test the correlations of the variables of the dataset in this research, two-tailed Spearman's rank order correlation coefficient (Spearman's Rho) was selected as the most appropriate method. Instead of the absolute values of the variables, Spearman's rank order correlation coefficient is calculated with ranked values. The rank order method does not require the variables to be continuous and so it can be used also for variables measured at an ordinal scale. The two-tailed test implies that there is no assumption of the direction of the correlations and they are tested to both directions. (Metsämuuronen 2005: 341–342, 412–413.)

### 5.3.3 Logistic regression analysis

Regression analysis is a statistical analysis tool that can be used when there is a need to evaluate the effect of changes in one variable on another variable. It also allows the estimation of the effect of several predictors (independent or control variables) on a dependent variable simultaneously. In regression analysis, the effect of each predicting variable on the dependent variable is estimated and it can be used to identify the significant predictors of the dependent variable. (Metsämuuronen 2005: 658.)

Logistic regression analysis is a special form of regression analysis that is suitable for situations where the dependent variable is dichotomous (as is the case in this research). It can be used either to find out which combination of the predicting variables can explain the dependent variable best or if all the variables are known to be important predictors, logistic regression can be used in investigating how important each of them is in explaining the dependent variable. The variables can so also be compared to see which of them are more important predictors than the others. (Metsämuuronen 2005: 687–688.)

The assumptions in logistic regression analysis are not as strict as in the more traditional linear regression analysis. In logistic regression, the predicting variables do not need to be normally distributed and the relationship of the dependent and independent variables does not need to be linear (as is required in linear regression analysis). However, in logistic regression an assumption of a linear relationship between the predicting variables and the logistic transformation of the dependent variable does exist. Also multicollinearity is an important issue in logistic regression analysis. If the correlations between the

predicting variables are too high (there is multicollinearity), a variable that is not actually a significant predictor of the dependent variable can appear in the model as a significant predictor due to its high correlation with another predicting variable that actually is a significant predictor. On the other hand, if the correlations are too weak, a proper model can not be built. (Metsämuuronen 2005: 688–689.)

In logistic regression analysis, as well as in linear regression analysis, a regression model is built. This model includes significant predictors (independent and control variables) and a constant term that together can be used in predicting which value the dependent variable gets. The better the model is, the higher is the reliability of the prediction. As in the correlation analysis, in logistic regression analysis also, the statistical significance of the whole model and the individual predicting variables and the constant term is assessed through p-values. These p-values are calculated from the Wald test statistics, the results of Wald test that indicate the goodness of a variable as a predictor. For a significant predictor, the p-value is  $\leq 0.005$ . In addition to the p-value, each of the predictors also gets a regression coefficient in the analysis. This coefficient indicates the strength and direction of the relationship of the predictor and dependent variable. (Metsämuuronen 2005: 690–692.)

In analyzing the goodness of the overall logistic regression model, a classification table is often used. This table shows the predicted and actual observations in each group and shows the percentage of the observations that was predicted correctly. However, there are more reliable ways of assessing the goodness of the model by examining the difference of the predicted and actual values mathematically. One of these measures is the Nagelkerke's  $R^2$  value that indicates the portion of the variance of the dependent variable that can be explained through the model (coefficient of determination). (Metsämuuronen 2005: 694–696, 702–703, 705.) There is no absolute definition for what is a good coefficient of determination since it depends on how complicated the phenomenon that the model aims to explain is. For a complex phenomenon, the model rarely gets a coefficient of determination over 20 %. (Ketokivi 2009: 103.)

Another measure used in this research for the goodness of fit of the model is the Hosmer and Lemeshow test. For a good model the resulting significance (the p-value of the chi-squared test) of the test is  $> 0.005$ . For the Hosmer and Lemeshow test a cut value between 0 and 1 (usually 0.5) is set and this value is the threshold that defines which group the predicted values are placed (0 or 1 when the dependent variable is dichotomous). Despite analyzing the goodness of the model through different test statistics, a visual inspection of the residuals of the logistic regression analysis should also be done. Residuals are calculated as the difference between the expected and observed values and a non-normal distribution of the residuals indicates that there might be some troubles with the model. (Metsämuuronen 2005: 697–698, 704, 707–708.)

## 6 RESULTS

This section presents the results of the study on the relationship of a firm's age and the nature of its innovative behavior conducted in this thesis. The data used in the study is first introduced through descriptive statistics. Then, the correlations and results of logistic regression are presented first for the analysis of the relationship of explorative and exploitative innovative actions and then for the analysis of overall innovative actions. All the descriptive statistics and statistical tests were conducted with the IBM SPSS Statistics (version 22) statistical analysis program.

### 6.1 Descriptive statistics

When the division of the sample firms to DBFs (dedicated biotechnology firms) and CWBAs (companies with biotechnology activities) was explored, it was found that out of the total of 151 firms 40 (26.5 %) were CWBAs and 111 (73.5 %) were DBFs. The amount of patents for these two types of firms showed that DBFs were responsible of 804 patents (71.7 %) (out of the total of 1121 patents) and CWBAs were responsible of 317 patents (28.3 %). The frequency table of the division of the patents between DBFs and CWBAs is presented in Table 2.

The division of the patents to explorative and exploitative ones showed that 889 (79.3 %) of the all 1121 patents were explorative and 232 (20.7 %) were exploitative ones. The frequencies of the explorative and exploitative patents and their division to DBFs and CWBAs is also presented in Table 2.

The average age of filing a patent for all the sample firms was 10.86 years as the mode and median were 2 and 6.00 years respectively. The same figures for filing an explorative patent were 10.04 (mean), 2 (mode), and 5.00 (median) years and for an exploitative patent 14.00 (mean), 6 (mode), and 9.00 (median). In Table 3, the means, medians, and modes as well as minimum and maximum ages and standard deviations are presented for all observations and for explorative and exploitative cases separately. Figure 1 shows the division of patents as the function of firm age for the whole sample.

TABLE 2 Frequency table of the division of the patents between DBFs and CWBAs.

	Explorative	Exploitative	Total
CWBA patents	233	84	317
DBF patents	656	148	804
Total	889	232	1121

TABLE 3 Descriptive statistics for the age at the time of filing for a patent for explorative, exploitative, and all patents.

	<i>N</i> *	Mean	Median	Mode	Min.	Max.	STD**
Explorative	889	10.04	5.00	2	0	111	17.157
Exploitative	232	14.00	9.00	6	4	89	16.071
All	1121	10.86	6.00	2	0	111	17.007

\* Number of observations

\*\* Standard deviation

TABLE 4 Descriptive statistics for the age at the time of filing for a patent for DBFs and CWBAs.

	<i>N</i> *	Mean	Median	Mode	Min.	Max.	STD**
DBF patents	804	5.55	5.00	2 and 3	0	22	4.509
CWBA patents	317	24.33	14.00	14	0	111	26.830

\* Number of observations

\*\* Standard deviation

TABLE 5 Quartiles of the filing years of patents.

Percentile	
25	1994
50	2001
75	2004

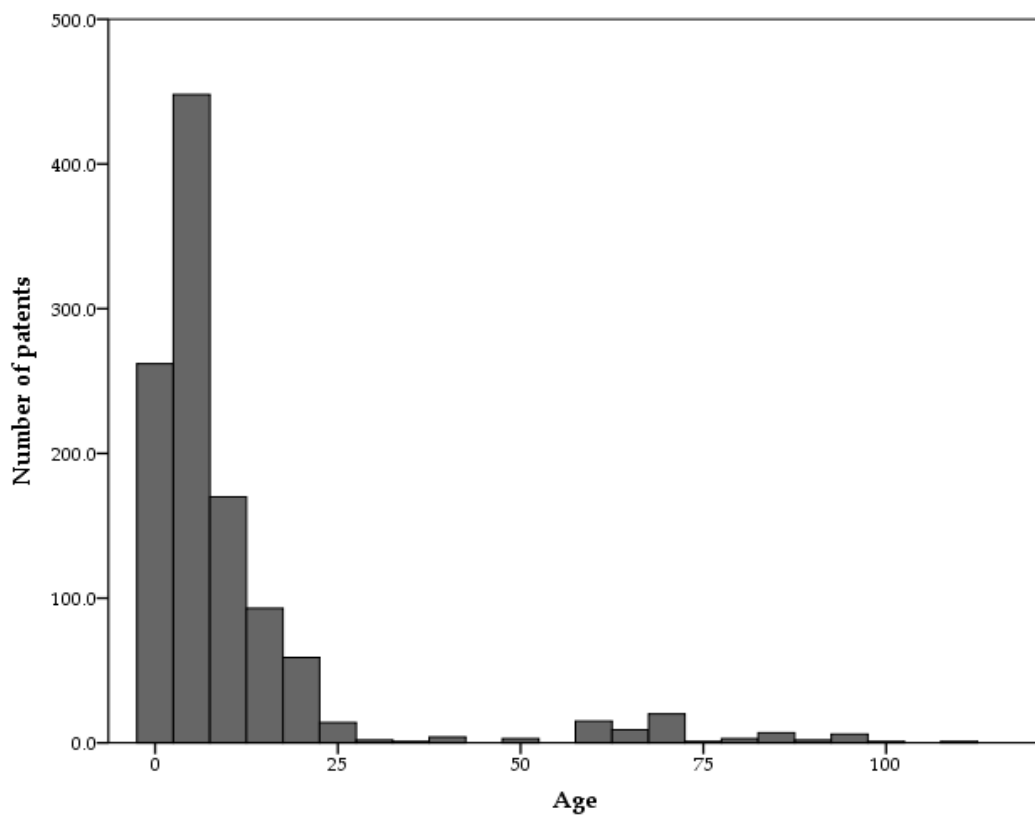


FIGURE 1 The division of patents as a function of firm age for the whole data.

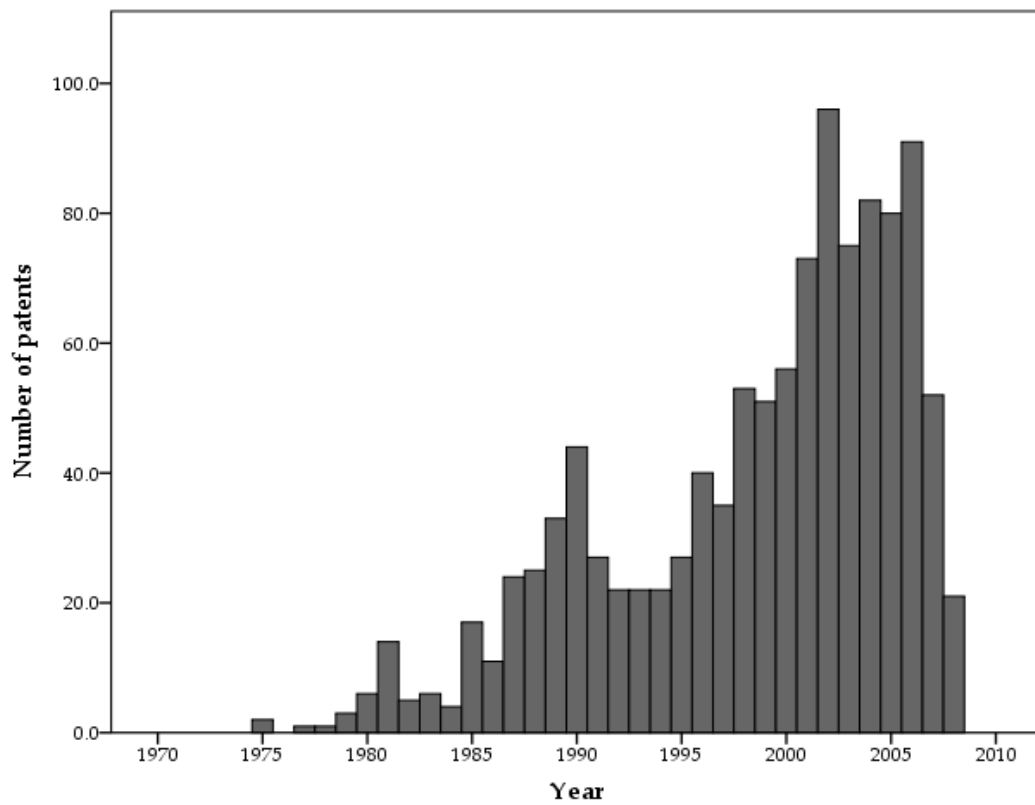


FIGURE 2 The number of patents filed in each year (whole data).

The average age was also calculated for the two different types of firms, DBFs and CWBAs, separately. For DBFs the average age of filing a patent was 5.55 years, the mode was 2 and 3 (the mode got two values) and the median was 5.00 years. For CWBAs these figures were 24.33 (mean), 14 (mode), and 14.00 (median) years. In addition to these figures, the minimum and maximum ages and standard deviations for the age at filing a patent for the DBFs and CWBAs are presented in Table 4.

To investigate the division of applied patents for different years within the observation period 1973–2008, a diagram of the number of filed patents for each year was drawn. This diagram is presented in Figure 2. The decline of patents applied in the last years of observation period (seen in Figure 2) is most likely due to the delay between filing and granting of the patent. As the delay can be several years and the patents are not listed in the patent databases before they are granted, not all of the patents filed during the last years have been visible in the patent database at the moment of data collection.

To further describe the division of patent application between years, quartiles were calculated. The lower quartile (25th percentile) was 1994, the median (50th percentile) was 2001, and the upper quartile (the 75th percentile) was 2004. The quartiles are also presented in Table 5.

These results indicate that majority (79.3 %) of the patents is explorative and majority of the firms included in the sample (71.7 %) present DBFs. The results also show that the average age of filing a patent is higher (14.00 years) in the exploitative cases compared to the 10.04 years of the explorative ones. The age of filing a patent varied between 0 and 111 years, the average (for both types of patents) being 10.86 years which is significantly closer to the minimum than the maximum end. The results also show that, in average, the DBF firms have applied patents younger than the CWBA firms (the average age for filing a patent was 5.55 years for DBFs and 24.33 years for CWBAs). The descriptives show that half of the patents were filed after 2001 and 25 % of them were filed during the last four years of the observation period (after 2004).

## **6.2 The relationship of explorative and exploitative innovative actions**

This section presents the results related to hypothesis 1 and 2. These hypotheses were studied by using a dataset with only the observed actions (only the years when patents were applied were included for each year). The Type of action variable with explorative actions coded as 1 and exploitative actions as 0 was used as the dependent variable.

### **6.2.1 Correlations**

The interdependence of the variables was first investigated by calculating Spearman's rank-order correlations for each pair of variables. The results of the correlation analysis are listed in Table 6. In order to find the possibly problematic relationships (anomalies), a visual inspection of the data was done by drawing scatter plots of each pair of continuous variables (Age, GDP, and



Density) and no such relationships were found. For the other variables (Type of action, Recession, Financing, P1, P2, P3, and P4), this visual inspection was not done since it would not have provided any relevant information due to the dichotomous nature of the variables.

The results of the Spearman's rank-order correlation analysis show that there is a significant correlation between all of the pairs of variables except for between the variables Age and Recession and Type of action and Recession as well as between the pairs P1 (period 1) and Type of action and P3 and Type of action. Also, the variables P3 and Type of action had significant correlation only on 0.05 level. However, with most pairs that showed significant correlation, the correlation was weak (below 0.40 or if negative, above -0.40). The only cases with moderate (0.40-0.60 or -0.40--0.60) correlation were related to the periodical variables. These cases were, P1 and GDP, P1 and Density, P2 and Recession, P2 and GDP, P2 and Density, P4 and Financing, P2 and P4, and P3 and P4. Correlation was strong (between 0.60-0.80 or -0.60--0.80) for the variable pairs GDP and Financing and Density and Financing. Very strong (above 0.80 or if negative, below -0.80) correlation was observed between the variable pairs Density and GDP, P4 and GDP, and P4 and Density.

When it comes to the direction of the correlation (negative or positive), it should be noted here that in the case of dichotomous variables (many of the variables used here are dichotomous) the coding of the variables affects the direction of the correlation. For example, the Financing variable here was coded as 1 for the cases where the firm had received a private equity investment during the previous three years and 0 for other cases, but it could have been done also the other way around (0 if the investment was received and 1 in other cases). Had the coding been done so that the zeros were ones and ones were zeros, all the correlation coefficients related to this variable would change direction (negative correlation would become positive and vice versa). This said, as most of the variables in this analysis are dichotomous, not too much attention should be paid to the direction of the correlations here.

For comparison, the same correlations were calculated for a dataset from which the CWBA firms were excluded. This was done in order to see if even more homogeneous data, including only the DBF firms (that have biotechnology as their core activity) would provide differing results. The results of this correlation analysis are presented in Table 6.

TABLE 6 Correlation matrices (using Spearman's Rhos) for the whole data (above) and the DBF-only data (below).

	1	2	3	4	5	6	7	8	9	10
(1) Age	1.000									
(2) Type of action	-0.316**	1.000								
(3) Recession	-0.019	-0.024	1.000							
(4) GDP	-0.138**	-0.111**	0.340**	1.000						
(5) Financing	-0.102**	-0.166**	0.211**	0.681**	1.000					
(6) Density	-0.152**	-0.119**	0.265**	0.987**	0.677**	1.000				
(7) P1	0.206**	0.043	0.079**	-0.481**	-0.245**	-0.481**	1.000			
(8) P2	0.128**	0.066*	-0.567**	-0.509**	-0.327**	-0.525**	-0.139**	1.000		
(9) P3	-0.119**	0.038	0.123**	-0.262**	-0.230**	-0.248**	-0.144**	-0.218**	1.000	
(10) P4	-0.120**	-0.104**	0.292**	0.861**	0.600**	0.863**	-0.340**	-0.516**	-0.534**	1.000
	1	2	3	4	5	6	7	8	9	10
(1) Age	1.000									
(2) Type of action	-0.336**	1.000								
(3) Recession	-0.055	-0.077*	1.000							
(4) GDP	0.207**	-0.243**	0.321**	1.000						
(5) Financing	0.197**	-0.305**	0.219**	0.625**	1.000					
(6) Density	0.198**	-0.243**	0.301**	0.996**	0.620**	1.000				
(7) P1	-0.114**	0.041	0.017	-0.150**	-0.096**	-0.150**	1.000			
(8) P2	0.031	0.133**	-0.648**	-0.472**	-0.338**	-0.477**	-0.026	1.000		
(9) P3	-0.183**	0.169**	0.094**	-0.525**	-0.317**	-0.524**	-0.041	-0.145**	1.000	
(10) P4	0.161**	-0.237**	0.318**	0.778**	0.504**	0.780**	-0.140**	-0.491**	-0.770**	1.000

\* Correlation is significant at the 0.05 level (2-tailed). \*\* Correlation is significant at the 0.01 level (2-tailed).

The Spearman's correlations for the dataset with DBFs only were in majority of the cases very similar to the ones for the whole data (there were no great differences in the strengths of the correlations). However, there were also some differences in the strength or direction of the correlations. The correlation between the variables Age and GDP remained weak, but the direction went from negative to positive. The same happened to the pair Age and Density. The previously (for the whole data) weak correlation that existed for the variables Age and P2 became insignificant. The correlation between Type of action and Recession became significant, but only on the 0.05 level. The correlations between the pairs Type of action and P2 and Type of action and P3 became significant (but weak) on the 0.01 level. The correlation between Recession and P1 became insignificant and the correlation between Recession and P2 went from moderate to strong. The correlation between P1 and GDP went from moderate to weak, the correlation between P3 and GDP went from weak to moderate, and the correlation between P4 and GDP went from very strong to strong. The correlation between P1 and Density was weak (previously moderate), the correlation between P3 and Density was moderate (previously weak), and the correlation between P4 and Density was strong (previously very strong). The correlations between P2 and P1 and P3 and P1 went from weak to insignificant. The correlation between P3 and P4 went from moderate to strong.

As was explained above, the direction of the correlation is not of too much interest with the dichotomous variables. For both analyses, the one with the whole data and the one with DBFs only, the results showed that a significant correlation (although a weak one) exists between firm age and the type of an innovative action.

### 6.2.2 Logistic regression

In order to further analyze the relationship between firm age and the nature of its innovative actions, a logistic regression analysis was performed. This analysis aimed to find a model that could predict whether an observation is explorative or exploitative. At first, the analysis was conducted for the whole data in one step including the independent (Age) and control variables (Recession, GDP, Financing, Density, P1, P2, P3), except for the P4, variable as predictors. The P4 variable was excluded due to redundancy as it is already defined through the P1, P2 and P3 variables and so is unnecessary for the analysis. The dependent variable was Type of action. This first model was statistically significant compared to a constant only model ( $p < 0.000$ ), but the coefficient of determination was poor: Nagelkerke's  $R^2$  of 0.079 indicated that only 7.9 % of the changes in the dependent variable could be predicted with this model. In the model, only the variables Age ( $p < 0.000$ ) and Financing ( $p < 0.000$ ) appeared to be statistically significant predictors ( $p < 0.05$ ). After the first analysis, a series of logistic regression analyses where each of the predicting variables were removed one by one from the model starting from the one with highest p value (least significant), Density, was performed. The three variables indicating the period of a patent application (P1, P2 and P3) were treated as one

in the sense that they were all either included or excluded in a model. This series of analysis confirmed the result of only Age and Financing being significant predictors since when all the other variables were removed from the model, Nagelkerke's  $R^2$  value was 0.070 indicating that the coefficient of determination was still very close to the one in the first model. With only the two variables left, two last models were tested: one with only Age as the predicting variable and one with only Financing as the predicting variable. With only Age as the predictor, the model was able to predict 1.2 % (Nagelkerke's  $R^2 = 0.012$ ) of the changes in the dependent variable and with only Financing as the predictor, the same figure was 4.2 % (Nagelkerke's  $R^2 = 0.042$ ). These results show that the two variables (Age and Financing), indeed, are the only significant predictors of the independent variable (removing them from the model clearly weakens the coefficient of determination), but even they are not very good predictors as the model overall predicts poorly whether the dependent variable gets the value 1 (explorative) or 0 (exploitative).

When the CWBA firms were excluded from the data, leaving only the observations of the DBF firms in the dataset, the ability of the model to explain the groups of the dependent variable increased significantly. With the DBFs only data, the first model with all the independent and control variables (except for P4) as the predictor, the Nagelkerke's  $R^2$  value of 0.261 indicated the model being able to predict 26.1 % of the changes in the dependent variable. In this first model the variables Age ( $p < 0.000$ ), Financing ( $p < 0.000$ ), Density ( $p = 0.046$ ), and P3 ( $p = 0.003$ ) appeared to be statistically significant predictors. From this initial model the predicting variables were, again, removed one by one, starting from the least significant (Recession), to see which variables actually are important predictors.

Even though the variables Density and P3 appeared to be significant in the first model, removing them did not affect the coefficient of determination that was still 23.4 % for a model with only the variables Age and Financing as predictors. As with the whole data, removing these last two predictors significantly weakened the model's ability to predict the dependent variable. For a model with only Age as the predictor, the coefficient of determination was 9.7 % and for a model with only Financing as the predictor it was 16.1 %. This indicates that these two variables are the vital predictors for the model, Financing being the most important one.

The best model found here to predict the Type of action was the one with Age and Financing as the predicting variables applied on the data including only the DBF firms. For this model, the Nagelkerke's  $R^2$  value was 0.234 indicating a 23.4 % ability to predict the dependent variable as mentioned above. The p-value of Hosmer and Lemeshow test for the model was  $< 0.000$  indicating that the model itself is not a good predictor for whether the Type of action variable gets the value 0 or 1. The reason for this can be seen in the classification table (Table 7). The table indicates that even though the model is 97 % correct predicting the explorative actions (coded 1), it is only 8.8 % correct for the exploitative actions. Also the non-normal distribution of standardized residuals, which was visually detected, indicates that the model has problems in predicting the groups of the dependent variable.

TABLE 7 Classification table of the dependent variable for the best model.\*

Type of action Observed	Predicted		Correct Percentage
	0	1	
0	13	135	8.8
1	20	636	97.0
Overall percentage			80.7

\* The cut value is 0.500

The correct classification of the exploitative actions (0) increases if the cut value is increased (it is 0.5 for the situation above). However, as this procedure decreases the correct classification of the exploitative actions at the same time, this will not enhance the model overall.

The regression coefficients and p-values for the predicting variables and the constant of the model are shown in Table 8. From the negative (-0.131) regression coefficient of the variable Age (in Table 8), it can be seen that as the age increases the value of the dependent variable decreases. Since the coding of the dependent variable (Type of action) was done so that an explorative action was 1 and an exploitative action was 0, this means that increasing age increases the likelihood of an action to be exploitative and decreasing age increases the likelihood of an action to be explorative. Further, it means that there is support for a firm's innovative behavior following the predictions in hypotheses 1 and 2 and these hypotheses can not be rejected. However, although the coefficient of determination for the model was sufficient (23.4 % of the variance of the dependent variable could be explained with the model), the problems of the model indicated by the Hosmer and Lemeshow test and the non-normal standardized residuals should be taken into account when interpreting the results. The results are further discussed in the conclusions section.

TABLE 8 The regression coefficients and significances of the predicting variables and the constant.

Variable	Regression coefficient	Significance
Age	-0.131	0.000
Financing	1.961	0.000
Constant	1.747	0.000

### 6.3 Overall innovative actions

To be able to study the overall innovative activity of a firm, the dataset was modified so, that all those years during which a firm had existed within the observation period (1973–2008) were included (also the years when no patents

were applied) and each year for each firm was only listed once. The Patenting activity variable, indicating whether or not the firm in question had applied a patent in a particular year, was used as the dependent variable. The dichotomous nature of the dependent variable enabled the use of logistic regression analysis also on this second dataset which was used to test hypothesis 3.

### 6.3.1 Correlations

With the second dataset, the interdependence of the variables was again investigated by calculating Spearman's rank-order correlations for each pair of variables. Table 9 lists the results of the correlation analysis. Each pair of continuous variables was checked for possible anomalies by drawing scatter plots and no anomalies were found. For the other variables this was not done since as with the first data, visual inspection of the dichotomous variables would not have provided any relevant information.

Also with this second dataset, it appears that there is a statistically significant correlation between most pairs of the variables. Only the variable pairs Age and Patenting activity, Age and GDP, Age and Financing, Age and Density, Age and P4, Patenting activity and Recession, Patenting activity and P2, and Patenting activity and P3 showed non-significant correlations. Correlation was very strong for the variable pairs GDP and Density, P4 and GDP, and P4 and Density. Recession and P2, GDP and P1, and Density and P1 showed strong correlation, and for the pairs GDP and Financing, GDP and P2, Density and Financing, Financing and P4, Density and P2, P1 and P4, P2 and P4, and P3 and P4 correlation was moderate. For the rest of the pairs, the correlations were weak. Again, the coding of the dichotomous variables affects the direction of the correlations and this should be acknowledged when drawing conclusions of the direction of the correlations.

For comparison, the same correlations were calculated also for a dataset from which the CWBA firms were excluded. The results of this second DBF-only data are presented in Table 9.

As with the first set of data, the correlations of the second dataset for the whole data and DBFs-only data were rather similar. There were some differences between the whole and partial data, though. For the DBFs-only data, the correlation between Age and GDP, Age and Financing, Age and Density, Age and P4, Patenting activity and Recession, and Patenting activity and P2 turned significant (for the whole data it was non-significant) although it remained weak. For the pair Recession and GDP, the correlation went from weak to moderate and for the pairs GDP and Financing, Density and Financing, and P3 and P4 from moderate to strong. The previously strong or moderate correlation of P1 and GDP, P1 and Density, and P1 and P4 was weak for the partial data. The correlation between the variables Recession and P1 was weak for both (whole and partial) data, but for the partial data it was only significant at the 0.05 level as for the whole data it was significant at the 0.01 level also.

TABLE 9 Correlation matrices for the second dataset (using Spearman's Rhos) using the whole data (above) and the DBF-only data (below).

	1	2	3	4	5	6	7	8	9	10
(1) Age	1.000									
(2) Patenting activity	-0.039	1.000								
(3) Recession	-0.065**	-0.019	1.000							
(4) GDP	0.035	0.100**	-0.310**	1.000						
(5) Financing	0.010	0.155**	-0.146**	0.563**	1.000					
(6) Density	0.015	0.107**	-0.231**	0.983**	0.564**	1.000				
(7) P1	0.126**	-0.110**	-0.137**	-0.628**	-0.234**	-0.647**	1.000			
(8) P2	-0.093**	-0.015	0.628**	-0.405**	-0.245**	-0.401**	-0.218**	1.000		
(9) P3	-0.072**	-0.013	-0.152**	-0.102**	-0.229**	-0.072**	-0.222**	-0.242**	1.000	
(10) P4	0.036	0.105**	-0.274**	0.862**	0.553**	0.862**	-0.400**	-0.436**	-0.442**	1.000

	1	2	3	4	5	6	7	8	9	10
(1) Age	1.000									
(2) Patenting activity	-0.024	1.000								
(3) Recession	-0.108**	-0.082**	1.000							
(4) GDP	0.382**	0.133**	-0.410**	1.000						
(5) Financing	0.275**	0.167**	-0.185**	0.618**	1.000					
(6) Density	0.388**	0.132**	-0.370**	0.989**	0.619**	1.000				
(7) P1	-0.184**	-0.091**	-0.059*	-0.341**	-0.146**	-0.342**	1.000			
(8) P2	-0.196**	-0.122**	0.660**	-0.562**	-0.296**	-0.575**	-0.089**	1.000		
(9) P3	-0.102**	-0.025	-0.150**	-0.361**	-0.338**	-0.351**	-0.107**	-0.228**	1.000	
(10) P4	0.304**	0.148**	-0.341**	0.855**	0.561**	0.856**	-0.243**	-0.517**	-0.622**	1.000

\* Correlation is significant at the 0.05 level (2-tailed). \*\* Correlation is significant at the 0.01 level (2-tailed).

Except for the pair Age and P1, the directions of the correlations were same for the partial data as they were for the whole data. Based on the correlation calculated with the second dataset, it appears that there would not be a dependency between a firm's age and patenting activity. However, it also appears that most of the other variables have a weak correlation with Patenting activity. These relationships were further investigate with a set of logistic regression analyses.

### 6.3.2 Logistic regression

Again, the relationship of Patenting activity and the independent and control variables was further investigated with logistic regression. First, a one step model with all the predictors (the independent and control variables), except for P4 due to redundancy, was tested for the whole data. The independent variable was Patenting activity and the model aimed to predict whether or not a company has applied a patent at as specific year. This first model tested was statistically significant ( $p < 0.000$ ) against a constant only model, but its coefficient of determination was only 4.1 % (Nagelkerke's  $R^2$  value for the model was 0.041), indicating that only a small fraction of the variance of the dependent variable could be predicted with this model. In this first model, the variables GDP ( $p = 0.031$ ) and Financing ( $p < 0.000$ ) were statistically significant ( $p < 0.05$ ) predictors of the independent variable.

After testing the first model with all the predictors in it, a series of analyses was conducted so that the predicting variables were removed one by one to see which of them are actually important in explaining the variance of the independent variable. Again, the three variables indicating the period (P1, P2, and P3) were treated as one and all of them were either included or excluded in a model. As the variable Age appeared to be least significant of the predicting variables with the  $p$ -value of 0.780 in the first model, it was the first to be removed. Age did not appear to be a significant predictor of the patenting activity as removing it from the predicting variables did not affect the coefficient of determination at all. After one by one removal of the variables, the last two variables left in the model were Financing and Density. The model with these two variables as the predictors still had a coefficient of determination of 3.7 % and the removal of the Density variable from the model only weakened this coefficient with 0.5 percentage points (from 3.7 % to 3.2 %). When the Density variable was left in the model and the Financing variable was removed from it, the coefficient of determination dropped to 2.3 %. These results indicate that, as the first model indicated, the Financing variable is the only one of the variables used here that is a significant predictor of the dependent variable, but even this variable is not a very good predictor as it alone only explains a very small fraction of the variance of the dependent variable.

The same procedure was applied with the DBF only-data to see if the models would fit better in this data as they did with the first dataset. This did improve the model's ability to predict the value of the dependent variable, but not as drastically as with the first set of data. The first model applied with all the independent and control variables (except for P4) had a coefficient of



determination of 8.1 %. In this model, it appeared that Age ( $p = 0.001$ ), GDP ( $p = 0.014$ ), Financing ( $p < 0.000$ ), and Density ( $p = 0.019$ ) are significant predictors in the model. In the following models the variables were again removed one by one, starting from the least significant (the period variables P1, P2, and P3) to test if all these variables actually are important predictors of the dependent variable.

The removal of the periodical variables P1, P2, P3 and the variable Recession did not affect the coefficient of determination at all. The rest of the variables were removed from the model one at a time and these variables, Age, GDP, Financing, and Density, weakened the coefficient of determination by 1.3, 0.9, 1.6, and 2.4 percentage points respectively. As all the four variables (Age, GDP, Financing, and Density) appeared to be significant predictors of the dependent variable, the model with these four predictors was selected as the best. This model had the Nagelkerke's  $R^2$  value of 0.081 indicating a 8.1 % ability to predict the dependent variable. Even though the coefficient of determination for the model is not very high, the p-value of Hosmer and Lemeshow test (0.201) indicates that the model itself is good for predicting the value of the dependent variable. However, from the classification table (Table 10), it can be seen that although the model successfully predicts the years when a firm has not applied for a patent (coded as 0) with a 96.8 % of them correctly predicted, it has trouble in predicting the years when a patent has been filed (coded as 1) with only 7.1 % of them predicted correctly. Also the visual inspection of the residuals that are not normally distributed indicates that there are some problems with the model which is not surprising taken into account the poor ability of the model to predict the years with applied patents correctly.

TABLE 10 Classification table of the dependent variable for the best model (second dataset).\*

Type of action			
Observed	Predicted		Correct Percentage
	0	1	
0	776	26	96.8
1	339	26	7.1
Overall percentage			68.7

\* The cut value is 0.500

Lowering the cut value increases the correct classification of the 0-coded years, but as the correct classification of the 1-coded years decreases at the same time, this will not improve the model overall.

The regression coefficients and p-values for the predicting variables and the constant of the model are shown in Table 11. It is noteworthy that the regression coefficient of the variable GDP is  $< 0.000$  which indicates that it actually is not explaining the variation in the dependent variable. As the correlation analysis showed a very strong correlation between the variables

GDP and Density, it could be so that there is a problem with multicollinearity and the GDP variable appears to be significant due to the high correlation with a significant variable, even though it is not significant.

The negative (-0.046) regression coefficient of the variable Age indicates that as the age of a firm increases, the value of the dependent variable decreases. Since the dependent variable is 0 for the years during which no patents were applied and 1 for the years a patent was applied, this means that as a firm ages, the likelihood of it applying for a patent decreases. This indicates that there is no support for the hypothesis 3 that suggested the relationship to be contrary. As with the first set of data, however, the limitations of the model should be noted when interpreting the results. This is further discussed in the conclusions section.

TABLE 11. The regression coefficients and significances of the predicting variables and the constant (second dataset).

Variable	Regression coefficient	Significance
Age	-0.046	0.001
GDP	0.000	0.006
Financing	-0.611	0.000
Density	0.016	0.000
Constant	-0.223	0.725

## 7 DISCUSSION AND IMPLICATIONS

In this section, the study is first summarized and conclusions arising from the results of the study are presented. The contribution of the study, its limitations, and the possible future directions of research on the topic are also discussed.

### 7.1 Summary and conclusions

The aim of this study was to empirically investigate the relationship between the age of an organization and the nature of its innovative activity in order to clarify the somewhat contradictory results of previous studies on the subject. More specifically, three hypotheses about the effect of aging on an organization's explorative, exploitative, and overall innovative activity were formed based on previous literature on exploration, exploitation, organizational ambidexterity, aging, and innovation. These hypotheses were then statistically tested with a set of biotechnology patent data covering the modern biotechnology industry in Finland from its birth in 1973 until the year 2008.

The differences observed between explorative and exploitative patents in the data indicated that, on average, explorative patents were applied younger than the exploitative ones. This makes sense as there needs to be exploration first in order to have something to exploit. The results of series of logistic regression analyses showed that aging has a positive effect on the likelihood of an organization's innovative action to be exploitative and a negative effect of its likelihood to be explorative. The relationship of aging and overall innovative activity of an organization seemed to be so, that the likelihood of an innovative action decreases with aging which was contradictory to what was hypothesized. The analyses also showed that in addition to aging, the variable Financing (indicating if an organization had recently received private equity financing) was a significant predictor of both the type and overall likelihood of an innovative action and also the variables GDP (the yearly GDP of Finland) and Density (the overall amount of biotechnology firms) were significant in predicting the overall likelihood of an innovative action. Though, it seems that

GDP is not really a significant predictor but only appears as one due to its very strong correlation with the Density variable. Yet, although these significant predictors were identified, the regression models resulting from the analyses were not very good predictors of the phenomenon overall. Even though the coefficient of determination clearly improved when only the dedicated biotechnology firms were included in the data (ruling out the companies with biotechnology activities), they were still only 23.4 % and 8.1 % respectively for the model predicting the type of an innovative action and the model predicting the overall innovative activity of an organization. The correlation analyses conducted for all the variables used in the study supported the results of the logistic regression analyses. Only the direction of the effect the Financing variable on the dependent variables was different in the regression and correlation analyses. Some significant relationships between the dependent variable and the predicting variables in the correlation analysis also appeared as insignificant in the logistic regression analysis. The differences between the results of correlation and regression analyses, however, are not uncommon as correlation analysis considers the relationship between two variables separately but regression analysis takes into account also the effect of the other variables included in the model on the relationship.

The results of the study indicate that age affects the the type of an innovative action of an organization and the overall likelihood of the organization to conduct an innovative action so, that as an organization ages, the likelihood of the innovative action to be explorative and the overall likelihood of an innovative action decreases and the likelihood of the innovative action to be exploitative increases. Yet, the effect of aging is not very strong and it alone is a poor predictor of the phenomenon. Overall, the variables used here are not explaining the phenomenon with a very high reliability, although the 23.4 % coefficient of determination gained from the first set of logistic regression analyses can be considered sufficient for a complex phenomenon (see Ketokivi 2009: 103). In order to be able to predict the dependent variables more reliably, especially the overall innovative activity of an organization for which only a 8.1 % coefficient of determination was obtained with the best model, more variables that are able to explain the variance of the dependent variables would need to be included.

The results are in line with the the thoughts of Abernathy and Utterback (1978), Tushman and Anderson (1986) and Sørensen and Stuart (2000) whose ideas were also the basis of the hypothesis formation in this study. Abernathy and Utterback (1978) claimed that an organization's innovative behavior changes from radical (explorative) to incremental (exploitative) over time. Tushman and Anderson (1986) concluded that new entrants are most often responsible of competence-destroying (explorative) innovation as the incumbent firms are the ones most often responsible of competence-enhancing innovations (exploitative) in an industry. Sørensen and Stuart (2000) discussed organizational competence and environmental fit that together cause older organizations to stay with their existing areas of expertise (exploitation) and young organizations to more often search for new areas (exploration) due to the increase in organizational competence and decrease in environmental fit in a

changing environment with time. All these ideas are in line with explorative innovative actions decreasing and exploitative innovative actions increasing with age as was shown here. However, unlike the ideas of Sørensen and Stuart (2000) and Tushman and Anderson (1986) suggest about the innovative activity increasing with age as was hypothesized here also, the results indicated that the likelihood of an innovative action actually decreases with age. Sørensen and Stuart (2000) suggested that the growing organizational competence leads to growing rate of innovations as an organization ages and Tushman and Anderson (1986) claimed that the competence-destroying innovations that are most often initiated by new entrant firms are rarer than the competence-enhancing innovations that are most often initiated by incumbent firms. The reason for this surprising result could be the nature of the biotechnology industry that causes a bias in the data. The industry is largely characterized by specialized firms small in size (Allansdottir *et al.* 2002) and due to the difficulties of reaching economic profitability and lack of resources, many small biotechnology companies have been short-lived as they have been sold to bigger companies at a young age (Ruutu 1990). As the data here consists solely of biotechnology organizations, this results to most of the organizations in the data being rather young. As there are more young than old organizations in the data, the result of young organizations being more likely to innovate than older ones could partly arise faultily from the fact that the relative portion of young organizations in the data is greater. Had the analysis been conducted with a data consisting of the CWBA (companies with biotechnology activities) firms only, the result would most probably have been different as the CWBA firms contain more old firms and the difference between the young and the old firms in the data would not have been as great. This was not done, however, as the purpose of the study was to focus on the biotechnology industry and as the CWBA firms tend to operate in several industries, their actions are not as bound to the biotechnology industry as they are for the firms that operate solely in this field. The closer investigation of this relationship of the age and overall innovative activity of an organization is an interesting topic for further research.

The previous empirical studies on the relationship of aging and the nature (explorative or exploitative) of an organization's actions are contradictory. The results of the previous studies are mostly in line with the results of the analyses conducted here. As was found here, Sørensen and Stuart (2000) found that young organizations are more likely to explore than their older counterparts and older organizations, on the other hand, are more exploitative of nature. Also Coad and Guenther (2013) as well as Choi and Phan (2014) found the explorative actions to decrease with age. Voss and Voss (2013) found this negative relationship in product domain only. The result of the likelihood of overall innovative activity declining with age is supported by the results of Coad and Guenther (2013) who found a similar relationship and the results of Withers *et al.* (2011) who found this negative relationship only when the level of innovation capabilities of the organization were low. However, there are also studies in which a relationship of the opposite direction has been found. Coad and Guenther (2013) found also the exploitative actions to decrease with age and Voss and Voss (2013) found that this is the situation in market domain.

Regarding the overall innovative activity, Sørensen and Stuart (2000) and Shi and Zhu (2014) found an increase in the innovative activity as an organization ages. Also Withers *et al.* (2011) found a similar relationship when the level of innovation capabilities of the organization were high. Few of the studies found also other features of the relationship of firm age and the nature of its behavior that are not in line with the results here. Dunlap-Hinkler *et al.* (2010) found that here is no correlation between firm age and exploration, Xie and O'Neill (2014) found an U-shaped relationship between firm age and exploitation, and Huergo and Jaumandreu (2004) found no relationship between the overall innovative activity and firm age on a general level, but they also mentioned that this depends on the industry in question. In addition, Chen (2014) and Coad and Guenther (2013) found the relationship of firm age and innovative activity to be wave shaped.

The main reason for the results differing from some of the results of previous studies can, again, be found in the nature of the biotechnology industry. As Huergo and Jaumandreu (2004) also note, the changes in innovative activity of an organization over time are industry dependent. As most of the previous studies have been conducted on different industries, some of them in settings very far from the biotechnology field in such industries as the non-profit professional theaters (Voss & Voss 2013), it is not surprising that the results are somewhat different from the ones in this study. If only the three previous studies that are conducted in the settings most similar to the one in here are considered, it is evident that the results actually are not so different. These three studies are Sørensen and Stuart's study from 2000 conducted on biotechnology (and semiconductor) industry, the study of Dunlap-Hinkler *et al.* from 2010 conducted on pharmaceutical industry, and the study of Shi and Zhu from 2014 conducted on pharmaceutical (and IT) industry. As mentioned, the results of Sørensen and Stuart (2000) on the nature of an organization's innovative behavior are similar to the ones here. However, regarding the overall innovative activity, the results differ from the ones of Sørensen and Stuart (2000) and Shi and Zhu (2014), but this is most likely due to the data of this study containing mostly young organizations as was discussed before. Another dissimilarity in the results is that, unlike here, Dunlap-Hinkler *et al.* (2010) found no correlation between firm age and explorative activity. They also claim that the previous results of Sørensen and Stuart (2000) about age affecting the innovative activity of an organization are caused by firm size (that usually correlates with firm age) and not age. This is most likely not the case, however, since the vast majority of the DBFs are small firms (Allansdottir *et al.* 2002: 37) and according to the results here, age seems to have a significant effect on the nature of innovative activity even when the data is limited to DBFs only. The differences are likely to occur due to other reasons. They could be due to the difference in the sample population as Dunlap-Hinkler *et al.* (2010) did not view the whole biotechnology industry but focused on pharmaceutical companies only. As the effect of age was significant, but not very strong here, it would make sense that it could turn insignificant in certain populations.

As mentioned, the ability of the logistic regression models to predict the value of the dependent variables increased when the data was limited to only

DBFs (compared to the data containing both DBFs and CWBAs). This is, first of all, due to the division of the patents as the function of firm age. As is shown by Figure 1, the frequencies of patents applied at each age are rather steady in the younger end, but very scattered in the older end with several ages at which no patents have been applied. When the CWBAs are excluded from the data, this scattered end is left out as the DBFs only have patents applied at ages 0–22 (see Table 4), which makes it easier to fit a model in the data. Another reason could be the increased homogeneity of the data as the CWBAs operating in other industries too are not as bound to the biotechnology industry as the DBFs that are focusing only on biotechnology.

The coefficients of determination that were 23.4 % and 8.1 % for the models predicting the nature of innovative activity and overall innovative activity. This means that the variables included in the models explain rather small portion of the variation of the dependent variables. As Age also was not the most significant predictor in the model, the conclusions made from the effect of age should be kept moderate. An organization's age does have a statistically significant effect on its innovative behavior, but this effect is not very strong.

## 7.2 Contribution, limitations and future directions

This study contributes to the firm level studies of organizational ambidexterity as well as to the previous studies of the effects of aging and an organization's innovative behavior. The study provides evidence of the effects of aging on innovative behavior in the context of the modern biotechnology industry in Finland.

The fact that the size of the organizations was not controlled in the study could be seen as a major limitation of the study as the effect of aging has been criticized to actually be caused by firm size (see Dunlap-Hinkler *et al.* 2010). As said, however, the DBF firms are generally small in size. According to Allansdottir *et al.* (2002: 37), 90 % of the European DBFs are small or micro sized firms. Even though the size was not directly controlled, the fact that age was a significant predictor of innovative behavior in a population containing only DBFs that are generally of similar size, it can be said that the effect of age is independent of the effect of size. The size was not directly controlled here due to the simple reason that the size information was not available for many of the organizations in the data.

Another point of possible criticism is the use of patent data as the measure of innovative behavior. As mentioned, patent data has been criticized due to the patenting behavior and the value of patents differing between industries (Levin *et al.* 1987; Gambardella *et al.* 2008). However, in the biotechnology industry, intellectual property is comprehensively protected with patents (Levin *et al.* 1987: 786) which make them a valid measure of the technological activities in this industry (Belderbos *et al.* 2010: 874).

A true limitation of this study is the somewhat artificial division of the patents to explorative and exploitative ones. As each organization was considered separately, the possibility of knowledge and experience moving

from one firm to another after, for example, a merger or an acquisition is ruled out. In reality, in many cases some or all the know-how of a predecessor firm is likely to move to the successor firm causing some of the actions categorized here as explorative ones to actually be exploitative of nature. Due to the practical limitations, this could not be considered, however. In most cases, there was no information available on to what extent (if at all) the knowledge or know-how of a firm was transferred to its successor (for example for an acquiring firm). As said, this leads to the division of the patents to be partially artificial. Yet, as the possible know-how inherited from a predecessor firm could not have been reliably measured here, the division of the patents to explorative and exploitative ones is as reliable as was possible to achieve.

The results of the study provide important information on the relationship of firm age and innovative behavior. The results, however, are not generalizable to other industries as they are and further research on the phenomenon is needed. The generalizability of the results is limited due to the effect of aging varying between industries as is indicated by the empirical studies conducted on the subject (see for example Huergo and Jaumandreu 2004). As Sørensen and Stuart (2000) discuss, it is not only the firm-level aging process, but also the evolutionary process on the industry level, that affects innovative behavior. In order to generalize the results, they need to be considered together with other empirical results from different industries and contexts.

In addition to the differences in the effect of age on innovative behavior between industries, another topic for future research to deal with is the question of what exactly are the causes that reliably explain an organization's innovative behavior. This topic has already gained interest and there are empirical studies on the topic (see for example Sørensen & Stuart, 2000; Dunlap-Hinkler *et al.*, 2010), but due to the complexity and context dependence of the phenomenon, further studies are needed in order to understand it and to make universal conclusions. As this research shows, firm age, received private equity financing, and the number of competitors in the industry are important predictors of the phenomenon in the biotechnology industry. Even though it is already shown that sufficient funding is important for succeeding in the biotechnology industry (Schienstock & Tulkki, 2001) and that equity financing has a positive effect on innovation rates (Kortum & Lerner, 2000), the role of financing in relation to the nature of the innovative behavior would be an interesting future avenue for research. Out of all the variables used in this study, the received private equity financing turned out to be the most important predictor of the nature of an organization's innovative behavior. Financing, however, was a dummy variable here, including only the information whether or not an organization had recently received private equity financing (due to the lack of information on the exact amount in many cases). To more thoroughly examine the effect of financing on an organization's innovative behavior, the role of both private and public financing should be further investigated.



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