An Empirical Multivariate Examination of the Performance Impact of Open and Collaborative Innovation Strategies

Von der Fakultät Konstruktions-, Produktions- und Fahrzeugtechnik
der Universität Stuttgart
zur Erlangung der Würde einer Doktor-Ingenieurin (Dr.-Ing.)
genehmigte Abhandlung

Vorgelegt von
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Geleitwort der Herausgeber

Über den Erfolg und das Bestehen von Unternehmen in einer marktwirtschaftlichen Ordnung entscheidet letztendlich der Absatzmarkt. Das bedeutet, möglichst frühzeitig absatzmarktorientierte Anforderungen sowie deren Veränderungen zu erkennen und darauf zu reagieren.

Neue Technologien und Werkstoffe ermöglichen neue Produkte und eröffnen neue Märkte. Die neuen Produktions- und Informationstechnologien verwandeln signifikant und nachhaltig unsere industrielle Arbeitswelt. Politische und gesellschaftliche Veränderungen signalisieren und begleiten dabei einen Wertewandel, der auch in unseren Industriebetrieben deutlichen Niederschlag findet.

Die Aufgaben des Produktionsmanagements sind vielfältiger und anspruchsvoller geworden. Die Integration des europäischen Marktes, die Globalisierung vieler Industrien, die zunehmende Innovationsgeschwindigkeit, die Entwicklung zur Freizeitgesellschaft und die übergreifenden ökologischen und sozialen Probleme, zu deren Lösung die Wirtschaft ihren Beitrag leisten muss, erfordern von den Führungskräften erweiterte Perspektiven und Antworten, die über den Fokus traditionellen Produktionsmanagements deutlich hinausgehen.

Neue Formen der Arbeitsorganisation im indirekten und direkten Bereich sind heute schon feste Bestandteile innovativer Unternehmen. Die Entkopplung der Arbeitszeit von der Betriebszeit, integrierte Planungsansätze sowie der Aufbau dezentraler Strukturen sind nur einige der Konzepte, welche die aktuellen Entwicklungsrichtungen kennzeichnen. Erfreulich ist der Trend, immer mehr den Menschen in den Mittelpunkt der Arbeitsgestaltung zu stellen - die traditionell eher technokratisch akzentuierten Ansätze weichen einer stärkeren Human- und Organisationsorientierung. Qualifizierungsprogramme, Training und andere Formen der Mitarbeiterentwicklung gewinnen als Differenzierungsmerkmal und als Zukunftsinvestition in *Human Resources* an strategischer Bedeutung.

Von wissenschaftlicher Seite muss dieses Bemühen durch die Entwicklung von Methoden und Vorgehensweisen zur systematischen Analyse und Verbesserung des Systems Produktionsbetrieb einschließlich der erforderlichen Dienstleistungsfunktionen unterstützt werden. Die Ingenieure sind hier gefordert, in enger Zusammenarbeit mit anderen Disziplinen, z. B. der Informatik, der Wirtschaftswissenschaften und der Arbeitswissenschaft, Lösungen zu erarbeiten, die den veränderten Randbedingungen Rechnung tragen.

Die von den Herausgebern langjährig geleiteten Institute, das

- Fraunhofer-Institut für Produktionstechnik und Automatisierung (IPA),
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- Institut für Arbeitswissenschaft und Technologiemanagement (IAT), Universität Stuttgart

arbeiten in grundlegender und angewandter Forschung intensiv an den oben aufgezeigten Entwicklungen mit. Die Ausstattung der Labors und die Qualifikation der Mitarbeiter haben bereits in der Vergangenheit zu Forschungsergebnissen geführt, die für die Praxis von großem Wert waren. Zur Umsetzung gewonnener Erkenntnisse wird die Schriftenreihe „IPA-IAO - Forschung und Praxis“ herausgegeben. Der vorliegende Band setzt diese Reihe fort. Eine Übersicht über bisher erschienene Titel wird am Schluss dieses Buches gegeben.

Dem Verfasser sei für die geleistete Arbeit gedankt, dem Jost Jetter Verlag für die Aufnahme dieser Schriftenreihe in seine Angebotspalette und der Druckerei für saubere und zügige Ausführung. Möge das Buch von der Fachwelt gut aufgenommen werden.

Engelbert Westkämper   Hans-Jörg Bullinger   Dieter Spath

Vorwort der Autorin

Innovationen waren und sind die Triebfedern unternehmerischer und gesellschaftlicher Entwicklungen. Die Veränderung der Innovationslandschaft stellt Unternehmen heutzutage vor die Herausforderung, ihre Innovationsmodelle neu zu gestalten. Während meines gesamten Dissertationsprojekts hat mich „Open Innovation“ als neues Innovationsmodell, das die Bedeutung von unternehmensexternen Innovationsquellen betont, und insbesondere das Zusammenspiel von Offenheit mit dem organisationsinternen Innovationspotential von Unternehmen motiviert und fasziniert.

Die vorliegende Arbeit wurde von der Fakultät Konstruktions-, Produktions- und Fahrzeugtechnik (Maschinenbau) der Universität Stuttgart als Dissertationsschrift genehmigt. Sie entstand während meiner Tätigkeit am Institut für Arbeitswissenschaft und Technologiemanagement IAT der Universität Stuttgart und dem Fraunhofer-Institut für Arbeitswirtschaft und Organisation IAO in Stuttgart.

Herrn Prof. Dr.-Ing. Dieter Spath gilt mein ganz besonderer Dank für die Annahme dieser Arbeit, die Übernahme des Hauptberichts und die wissenschaftliche Betreuung und Förderung am Institut. Er ermöglichte mir einen erfolgreichen Abschluss meiner Dissertation.

Herrn Prof. Dr.-Ing. Engelbert Westkämper möchte ich für die Mitwirkung an meinem Dissertationsverfahren und der Übernahme des Mitberichtes danken.

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Herrn Dr. Reinhard Büscher, Europäische Kommission, gebührt mein Dank für seine Zustimmung zur Nutzung der IMP^{3}rove Datenbank für die empirischen Untersuchungen. Ohne diese Zustimmung wäre diese Arbeit nicht möglich gewesen.

Meine Kollegen am Fraunhofer IAO und Projektmitarbeiter der Managementberatung A.T. Kearney haben in unterschiedlicher Weise zum Gelingen der Arbeit beigetragen. Larissa Scheiffele, Domagoj Caleta, Theodor Malcotsis, Yvonne Siwzcyk und allen IMP^{3}rove Teammitgliedern möchte ich hiermit ganz besonders danken.

Abschließend möchte ich mich ganz besonders bei meiner Familie bedanken. Ohne die Förderung meiner schulischen und akademischen Ausbildung und den persönlichen Rückhalt wäre diese Arbeit nicht möglich gewesen.

Meine Dissertation widme ich in Anerkennung meinen Eltern.

Stuttgart, im Februar 2011 Sabine Brunswicker

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List of Abbreviations

ANOVA	Analysis Of Variance
AIC	Akaike Information Criteria
BIC	Bayesian Information Criterion
CEO	Chief Executive Officer
CIS	Community Innovation Survey
DN	Deductive-Nomological
e.g.	exemplum gratiae
GDP	Gross Domestic Product
EO	Entrepreneurial Orientation
ERP	Enterprise Resource Planning
ICT	Information and Communication Technology
IT	Information Technology
IP	Intellectual Property
IPR	Intellectual Property Rights
ISO	International Standardization Organization
KIS	Knowledge Intensive Services
KMO	Kaiser-Meyer-Olkin
LR	Likelihood Ratio
ML	Maximum Likelihood
MSA	Measure of Sampling Adequacy
NIH	Not Invented Here
NPD	New Product Development
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squared
P&G	Procter & Gamble
PCA	Principle Component Analysis
POM	Proportional Odds Model
R&D	Research and Development
SD	Standard Deviation
SME	Small and Medium-sized Enterprises
SPSS	Statistical Package for Social Science
TCE	Transaction Cost Economics
TQM	Total Quality Management
VCR	Video Casette Recording
VIF	Variance Inflation Factor

1 Introduction

"No matter who you are, most of the smartest people work for someone else" (Joy's law)[1]

1.1 Motivation

Following the discourse of executives, management thinkers and policy makers over the last four decades there is no doubt about the relevance of innovation from an economic perspective. Innovation is crucial to create and sustain a firm's long-term competitive advantage (Drucker, 1985; Hamel, 2000; Nelson & Winter, 1977; Porter, 1996). However, the nature and landscape of innovation has changed (Chesbrough, 2003b; OECD/European Communities, 2005; Rothwell, 1993). A new division and mobility of labor, globalization, reduced product life-cycles, increased development costs, and the fast accessibility of information at low costs make it more difficult to reap the benefits from investments into innovation and challenge traditional models of innovation. The burgeoning literature on "open innovation" claims that firms have to *purposively* open their innovation activities, and to connect internal and external ideas to profit from innovation (Chesbrough, 2003a; Chesbrough, Vanhaverbeke & West, 2006). The cause of this claim towards a new paradigm of innovation has already been provided in the seminal work of the economist Friedrich Hayek in 1945, arguing that centralized models of planning are prone to failure due to their inability to aggregate distributed knowledge (Hayek, 1945). The explosion of information and knowledge in the recent years makes the problem of dispersedness of knowledge even more salient, and exacerbates the challenges for those engaging in innovation (Becker, 2001).

Since 2003, the discussion on open and collaborative innovation has been concentrated at the firm level. It has revitalized firms' interest to tap into external sources of innovation. Prominent case studies on large technology-oriented firms such as Procter & Gamble demonstrate that firms have (re)-discovered the value to be gained from external innovation sources (Dodgson, Gann & Salter, 2006; RTM, 2007). In 2006, Procter &Gamble's open innovation strategy "Connect & Develop" has contributed to an increase of the firm's R&D productivity by nearly 60 % and its innovation success rate by nearly 200 % (Huston & Sakkab, 2006).

Searching for new ideas, solutions and opportunities is a central part of the innovation process and requires firms to invest significant time, money and other resources. First empirical evidence on open innovation points out that external search strategies for new ideas alleviate the limitations when using purely internal knowledge during the innovation process (Lakhani, Jeppesen, Lohse & Panetta, 2006; Laursen & Salter, 2006). Firms can search "widely" and draw on a range of different sources to search for new ideas, such as customers, consumers

[1] attributed to the Sun Microsystems co-founder Bill Joy; cited in Lakhani & Panetta (2007)

(Brockhoff, 1998; von Hippel, 1986), universities (Fabrizio, 2006; Laursen & Salter, 2004) or suppliers (Dyer, Cho & Chu, 1998; Sako, 1996). As regularly overseen, external search for new ideas is not the only factor constituting of firms' openness. Firms may also draw more deeply on external innovation assets in co-development relationships or leverage long-term partnerships to successfully commercialize innovations (Granovetter, 1973; Norman & Ramirez, 1993; Vanhaverbeke & Cloodt, 2006).

The discussion on how firms can benefit from external sources of innovation does not diminish the need to understand how firms generate and manage innovations internally (Cohen & Levinthal, 1990; Dahlander, Frederiksen & Rullani, 2008). A firm's internal innovation assets and innovation routines remain crucial to capture the value from innovation even when firms divert their attention to external sources for innovation (Grant, 1996; Nelson & Winter, 1977). The presence of valuable external sources of ideas does not imply that they "flow" easily across firms' boundaries. As captured in the concept "absorptive capacity", firms need to be able to recognize them, access them, transform or assimilate them and turn them into value (Cohen & Levinthal, 1990). While internal organizational practices and capabilities for innovation may play a vital role in open innovation, either as enablers or hinderers, this is widely neglected (Todorova & Durisin, 2007). Indeed, systematic managerial practices for innovation such as the stage-gate processes, formalized systems for idea generation or project selection have gained high attention among researchers and practitioners over the last decades. However, most research completely abstracts from how organizational practices can influence the sourcing and absorption of external innovation (Bessant, von Stamm, Moeslein & Neyer, 2009; Cooper & Kleinschmidt, 1987; Drucker, 1985; Pavitt, 2002). Little is known whether or not organizational practices for innovation shape a firm's ability to create value from open and collaborative innovation.

1.2 Limitations of Existing Research and Problem Delineation

Open and collaborative innovation strategies constitute a research area that is of high relevance. First empirical research provides evidence that open styles of innovation are relevant in practice. Nevertheless, there is a range of limitations in existing research (Dahlander & Gann, 2007; Laursen & Salter, 2006).

1.2.1 Limitations of Existing Research

In existing research there are six areas of limitations that underline the motivation for this research and emphasize its scientific relevance. They provide the rationale for a more profound and scientific investigation and allow framing the problem area.

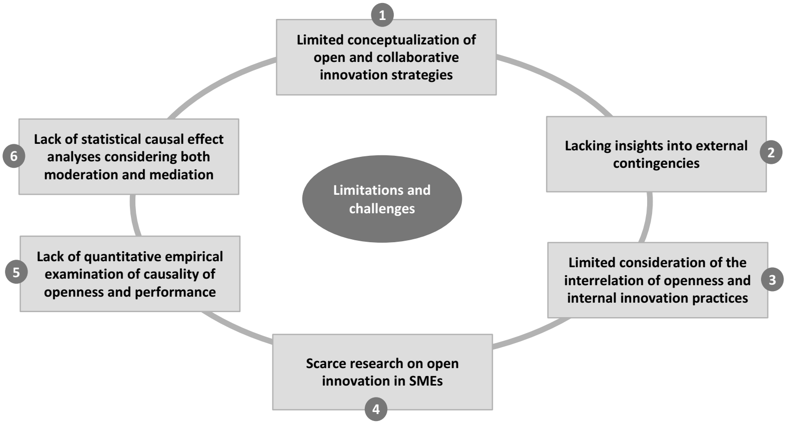

Figure 1: Overview on Limitations and Challenges of Existing Research

- *Limited conceptualization of open and collaborative innovation strategies:* In existing research openness is regularly treated as a binary variable. Highlighting the dichotomy between open and closed has limitations (see chapter 2.2). As demanded by other researchers, it is important to conceptualize openness in a sound manner (Dahlander & Gann, 2007).
- *Lacking insights into external contingencies of openness:* The current discourse suggests that open styles of innovation are a choice the firm can make. However, factors external to the organization such as the appropriability regime or the industry dynamic may restrict a firm's opportunity to capture the value from openness. So far, little effort has been taken to understand the constraints of external conditions (see chapter 2).
- *Insufficient consideration of the interrelation of openness and internal innovation practices*: Internal innovation routines and assets still matter even if firms engage in open styles of innovation. Internal semi-procedural innovation routines – in practice often called processes – have become important in firm-level innovation management (Bessant, 1999; see chapter 2.3). Although there is tremendous research on different types of internally oriented organizational innovation practices and capabilities, little is known whether and how they influence a firm's ability to capture the value from open innovation. Existing work on innovation routines and structures does not touch upon the "enabling" role. In addition, existing concepts of organizational innovation practices are fragmented and not linked to the concept of absorptive capacity (see chapter 3.3).
- *Scarce research on open innovation in small and medium-sized enterprises (SMEs):* Open innovation strategies are discussed in the context of large R&D intensive firms (Huston & Sakkab, 2006). However, good practices from large organizations cannot be transferred to SMEs directly (Edwards, Delbridge & Munday, 2005; Jenert, 2008; de Jong & Marsili,

2006; Spithoven, Clarysse & Knockaert, 2009). There is hardly any empirical evidence whether and how small and medium-sized enterprises (SMEs) benefit from purposively opening the innovation processes (van de Vrande, de Jong, Vanhaverbeke & de Rochemont, 2009; see chapter 2.2.2). In an open innovation research it is claimed that firms don't have to be big and powerful to hierarchically control all innovation activities; and thus, SMEs are an important topic of research (Chesbrough, 2006c; Lichtenthaler, 2008).

- *Lack of quantitative empirical examination of causality between open innovation and firm performance:* The relevance of open innovation is documented in case studies of large firms. Empirical evidence on the causal relationship between openness and a firm's innovation performance in financial terms is scarce. There is no quantitative empirical study that has investigated multivariate causal relationships between open innovation strategies and financial performance based on a large firm-level database of SMEs (see chapter 2.2.4). However, rigor quantitative statistical causal effect analyses and regression modelling considering the specifics of financial performance indicators are required to statistically infer causality (see chapter 2.2.4).
- *Lack of statistical causal effect analyses considering both moderation and mediation:* Understanding the causal effects of different open innovation strategies is crucial both in a theoretical and practical way. Causal moderation and causal mediation analyses are required to explain complex phenomena such as firm performance (see chapter 4). Only if so called moderating and mediating effects are considered in multivariate statistical modeling, it is possible to consider relevant contingencies and organizational enablers (or hinderers) of openness.

1.2.2 Problem Delineation

To overcome limitations of existing research, this research addresses causal relationships of open innovation strategies and a firm's innovation-based value creation considering external boundary conditions and internal innovation practices. As depicted in Figure 2 the overall research problem takes a "janus-faced" view towards openness. From a firm perspective, it integrates an "external" and an "internal" perspective towards open and collaborative innovation strategies and their effect on a firm's innovation performance and value creation.

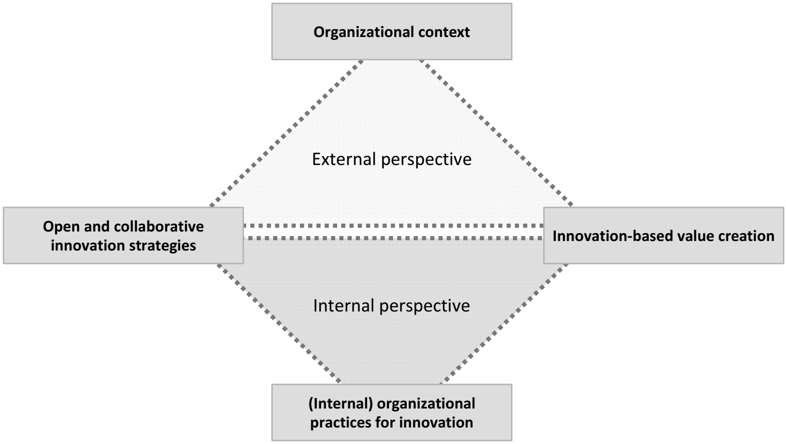

Figure 2: Dimensions of the Overarching Research Problem

1.3 Aim, Objectives and Research Questions

1.3.1 Aim and Objectives

The existing trend towards open and collaborative innovation strategies and first indications on their impact on a firm's innovation performance motivates this research. To shed light on the role of open innovation strategies and internal innovation routines in explaining firm performance, this research aims for the following:

> The overarching aim is to develop and empirically examine an integrated causal framework to statistically explain multivariate causal relationships of firm's open and collaborative innovation strategies and innovation-based value creation. This framework considers the interrelation with external boundary conditions and organizational practices for innovation.

This research takes an open system view of a firm's innovation systems and considers specifics of SMEs. A large database of 1,489 validated and up-to-date firm-level datasets provides the basis for the statistical estimation of multivariate causal effects and empirical explanation.
Due to the multilayered character of the overarching aim of this research, the following sub-goals guide the research activities:

- Conceptualizing open and collaborative innovation strategies based on the systematic review of existing empirical research and consideration of relevant theories

- Composing internal organizational practices for innovation based on the review of state-of-the art of empirical research and the consideration of relevant theories and constructs
- Developing an integrated conceptual framework describing the multivariate causal relationships between open and collaborative innovation strategies and innovation-based value creation considering both an external and internal factors as moderators and mediators; theoretically grounded directional hypotheses support the transformation into multivariate statistical regression models
- Empirically identifying components of organizational innovation practices and patterns of innovation search of SMEs
- Statistically modelling and empirically examining the multivariate causal relationships of open and collaborative innovation strategies and firm's innovation-based value creation
- Statistically modelling and empirically examining the moderating effects of organizational context on the relationship between openness and innovation-based value creation
- Statistically modelling and empirically examining the interplay of open and collaborative innovation strategies and organizational innovation practices in affecting a firm's innovation-based value creation

1.3.2 Research Questions

The following research questions guide the research activities:

a) How can different types of open and collaborative innovation strategies be conceptualized and measured?

b) What are components of (internal) organizational practices and routines for innovation and what are appropriate measurement constructs?

c) What is the role of different types of open and collaborative innovation strategies in explaining innovation-based value creation and how are they bounded by organizational context?

d) Do internal innovation routines and practices lay in the causal-pathway of openness and innovation-based value creation and explain how firms can benefit from openness?

1.3.3 Contributions

This research aims to make significant contributions both in a *theoretical* and *pragmatic* way. Results may significantly enhance existing literature on open and collaborative innovation. At the same time, they should enhance actions and decisions when engaging in more open styles of innovation and highlight limitations of openness as a strategic choice. Most importantly, this research does not abstract a firm's internal innovation activities from external innovation. Thus, results contribute to existing literature and theory on organizational innovation practices, and reveal the facilitating role of internal innovation to benefit from external idea sourcing. From a practical perspective, findings may help managers to better understand the interrelations between external and internal innovations. The most important contribution of this research will result from the *empirical investigation* of the role of different styles of openness and their interrelation with external boundary conditions and internal innovation in explaining innovation-based value creation. Quantitative multivariate causal effect analyses allow causality being inferred in a rigid, reliable and generalizable manner. After having presented the results, chapter 7 discusses contributions to theory and practice in more detail and critically evaluates them.

1.4 Scientific-Theoretic Position and Research Strategy

1.4.1 Scientific Objectives

This research initiative qualifies as *research of empirical science*; it builds upon observable "real" data that is gathered at the firm-level (Popper, Fleischmann, Fleischmann & Fleischmann, 1973). It also qualifies as applied research because theoretical knowledge is applied to support managerial activities and decisions and to *design* potential decision alternatives. This research addresses three scientific objectives (Schnell, Hill & Esser, 1993; Schweitzer, 1978):

- *Descriptive scientific objective:* The precise description of key "elements" (concepts, constructs, phenomena) is a fundamental objective of any scientific research.
- *Theoretical (explanatory) scientific objective:* Explanation of causal relationships is central to this research; it is empirically inferred (see chapter 1.4.2).
- *Pragmatic and instrumental scientific objective*: This research also aims to be of pragmatic value to real problems in innovation management.

As outlined in the following chapter, the integration of theoretical and pragmatic scientific principle is central to this research.

1.4.2 Scientific-theoretic Position and Statistical Causal Effect Examination

Popper's theory of *scientific explanation* encourages this research and also influences its research strategy (Popper et al., 1973). Scientific explanation implies the presupposition that science sometimes should provide explanations (rather than merely descriptions) and that the task of a model of scientific explanation is to characterize and structure such explanations. *Causation* and causal claims are central to scientific explanation. The Deductive-Nomological (DN) model has greatly influenced the discussion on *explanation* in scientific theory (Hempel, 1965; Popper et al., 1973). Following this model, the "explanandum" is logically derived from the "explanans". That is, the explanation should take the form of a sound deductive argument. In addition, the explanans must contain at least one law of nature which constitutes the

nomological[2] component of the model (Hempel, 1965). However, there are regularly particular conditions under which a specific law operates. In science such as biology, psychology and economics generalizations regularly fail to meet the criteria of lawfulness.
Most causal thinking in the social science is probabilistic rather than deterministic (de Vaus, 2001). In organizational and managerial science there are only hypotheses or assumptions ("tendencies") rather than deterministic rules and laws (as they exist in natural science). Thus, statistical "laws" and hypotheses provide the basis of statistical deduction, as proposed by the deductive-statistical explanation (Hempel, 1965; Popper et al., 1973). Behaviour of people and organizations is not determined but it is constrained. As a result, there are just probabilistic explanations (de Vaus, 2001). Following the idea of *statistical explanation* and the probabilistic nature of causation, this research integrates two major scientific objectives when investigation causal effect relationships (Schweitzer, 1978): A *theoretical scientific* and a *pragmatic scientific* objective (Figure 3).

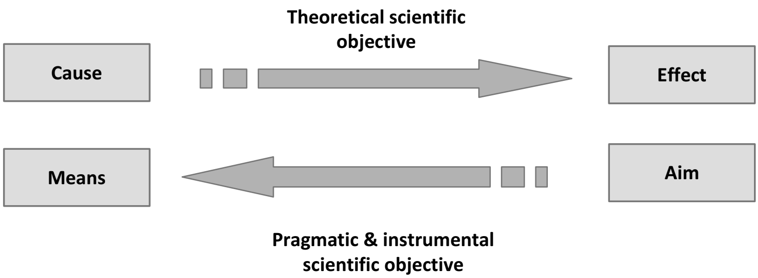

Figure 3: Interrelationship of Theoretical and Pragmatic Scientific Objectives

The theoretical scientific objective subsumes the *empirical examination* of a causal effect relationship. Here, a scientific gain is achieved as the causal proposition is examined empirically based on real data. A pragmatic scientific aim means that recommendations and decision guidelines are empirically grounded that allow the design of the "real" object – in this case the innovation management system (including innovation strategies and organizational structures/routines) - based on a "objective-means" relationship (Möller, 2006, Popper et al., 1973). Theoretical propositions are transformed into technologies (in this case managerial technologies), as the effect is turned into an objective and the cause is implemented as a "means" (see Figure 3).

1.4.3 Research Design and Research Process

Research design refers to the structure of an enquiry; its central role is to ensure that the evidence obtained enables to answer the research question as unambiguously as possible

[2] Nomological being a philosophical term of art which means "lawful"

(Munch & Verkuilen, 2005; de Vaus, 2001). It embodies the plan to implement the research question such as the strategies of inquiry and specific methods such as data collection and analysis (Creswell, 2009). “Explanation” and “causal effect” examination are perceived as the most valuable but also the most challenging scientific activities. In explanatory research the purpose is to develop and evaluate causal relationships. The probabilistic nature of causation, as opposed to deterministic causation, characterizes this research strategy and its research design. Explanatory research requires a more rigid research design and a more rigid research process than mere descriptive research (Schnell et al., 1993); especially if causal explanations are more complex. Simple correlation does not mean that one factor causes the other; and while one can observe correlation one cannot observe cause. One has to *infer* cause. One of the fundamental purposes of research design in explanatory research is to prevent invalid inferences. To do so, this research positions research design in a broader context and perceives research as an interactive process: Research design directly influences causal-inferences and contributions vis-à-vis theory and data (Munch & Verkuilen, 2005).

Experimental (or quasi-experimental), qualitative observational and *quantitative observational* research traditions represent distinct responses to methodological questions for the appropriate research design. *Experimental research design* has some undeniable strength. Indeed, experiments are the most powerful means of gaining control and establishing internal validity of causal claims (Munch & Verkuilen, 2005). It requires that some independent variable can be consciously manipulated and thus, it is very difficult to apply it to complex organizational problems (Creswell, 2009). *Qualitative observational research* that has been dominating existing research in open and collaborative innovation adopts an interpretive approach to data and usually lacks generalizability, accuracy and objectivity. It is usually not appropriate for statistical explanations of causal effects and causal inference. To investigate complex organizational and economic problems, methodological discussions consider a quantitative observational research design superior to qualitative research (Creswell, 2009). *Quantitative observational research* is an appropriate means for testing objective proposition and causal models by examining the relationships among measurable variables. Thus, this research follows a quantitative observational research design – a so called “natural and quasi-random” experiment (Wooldridge, 2002). Observational data from a large sample of firm-level data provide the basis for empirical examination of the causal relationships (1,489 datasets of European SMEs). Data and variables are collected in so called “ex-post facto” manner, in “natural” setting. They are not manipulated (Munch & Verkuilen, 2005; Schnell et al., 1993). A large scale benchmarking sample offers great potential to investigate causal processes at a European scale. A newly developed survey instrument was used to analyze innovation management in SMEs at a firm-level. It advances existing cross-national innovation surveys such as the Community Innovation Survey (CIS) that is used in existing empirical innovation studies (Laursen & Salter, 2006). Observations based on structured measurement instrument and analysis procedure ensure transparency and accountability due to the fact that the methods and procedures used can be made visible and accessible to other parties (Hakim, 2000).

Cross-sectional data provides the basis for *multivariate statistical estimation* of causal relationships that consider the notion of ceteris paribus: Holding all other relevant variables fixed are at the crux of establishing a causal relationship. Multivariate regression modelling offers means to make a claim about *multivariate causal relationships* with a high degree of precision and statistical rigor (Creswell, 2009; Munch & Verkuilen, 2005). In addition, it allows examining more complex relationships that go beyond uni-directional relationships of independent and dependent variables (see chapter 3).

There are distinct research activities that flow from this quantitative empirical research and allow implementing a quantitative observational research design (see Figure 4). All activities do not take place in a linear matter but are embedded in an interactive process.

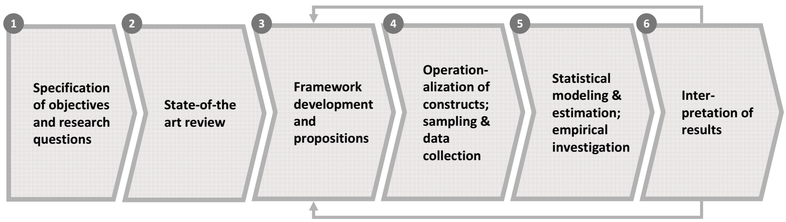

Figure 4: Major Research Activities

As a *starting point* of this research the overarching research questions are specified. They guide all activities of this quantitative empirical research. *Second*, research activities entail a structured review of the current state of empirical research; this is fundamental and reveals gaps in existing research; it also points out what theoretical perspectives should be considered. The *third* research activity deals with the development of conceptual framework that includes a set of propositions and quantitative, directional hypotheses making causal claims (Creswell, 2009). It is the backbone of solid causal effect analyses. Indeed, this research pays extensive attention to causal modelling before empirically investigating causal relationships. The framework provides the basis for regression modelling and probabilistic explanation of causal relationships based on empirical data. *Fourth*, the processes of operationalization of constructs and development of measures and sample are central research activities. They establish the fundamental connection between empirical observation and mathematical expression of quantitative relationships. The nature of measures and variables need to be considered in statistical modelling and regression analyses (see chapter 4).

Fifth, the empirical examination of the causal framework and statistical estimation of multivariate causal relationships represent the most critical research activities. Here, causality is inferred. It involves intensive learning and interpretation. *Finally,* results are reflected and conclusions are drawn in terms of their theoretical and practical implications.

1.5 Structure of the Thesis

The structure of the thesis reflects the major research activities:

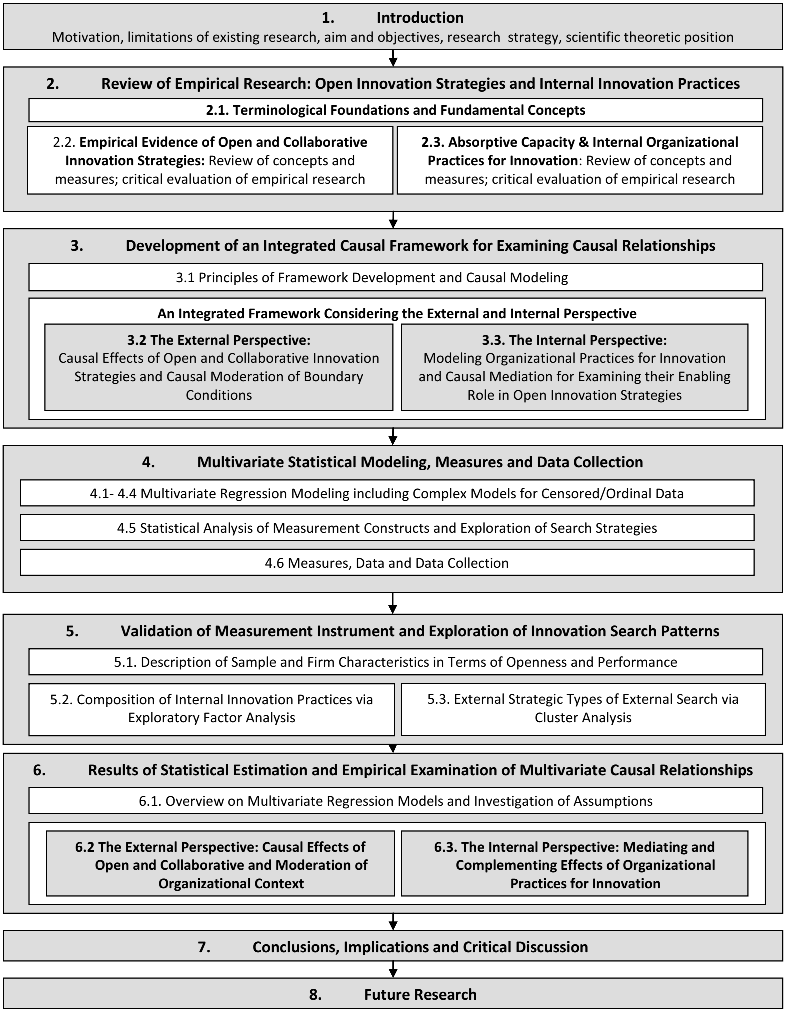

Figure 5: Structure of Thesis

2 Critical Review of Empirical Research: Open Innovation Strategies and Internal Innovation Practices

2.1 Terminological Foundations and Fundamental Concepts

"A rose is a rose is a rose. And a rose by any other name would smell just as sweet."[3]

The following chapters introduce fundamental terminologies and concepts of this research.

2.1.1 Innovation, Innovation System and Organizational Innovation Management: A Firm Level Perspective

2.1.1.1 Innovation

Nowadays, innovation is "instilled" in every dimension of social and economic life (Blättel-Mink, 2006; Fagerberg, Mowery D.C. & Nelson, 2005; Fagerberg & Verspagen, 2009). Despite its popularity, defining innovation remains contradicting (see review of definitions e.g. Garcia & Calantone, 2002).

Just like Schumpeter (1939) this research draws a sharp conceptual distinction between the invention and the innovation noting that any invention not carried out into practice is economically irrelevant (Schumpeter, 1912; Nelson, Winter & Sidney G., 1982). Invention is the discovery of new knowledge and problem solution potentials which is not exploited commercially. Innovation means *invention implemented* and *turned into economic value* (Schumpeter, 1912).

This research takes a *firm-level* and *holistic perspective* towards innovation that refers to something "new" at the firm level. Innovation is the output of the firm's innovation system and can be classified as (1) new "offerings" including new products or services, or (2) new processes, administration organizational forms and business models that change the way a firm creates and delivers its "offerings" (Tether & Tajar, 2008; Tidd, 2001; Pfeiffer, 1971). As shown in Figure 6, it is also differentiated between incremental and major innovations describing different degrees of novelty (Hauschildt & Salomo, 2007; Kopalle & Govindarajan, 2006; Tidd, 2001). Novelty refers to the firm level. Usually researchers refer to an incremental – radical dichotomy that defines the opposing points of a continuum (Tidd, 2001; O'Connor, 2008). Radical innovations transform existing industries but are extremely rare. Really new innovations that exhibit a discontinuity on either the market or the technical dimension at the

[3] Gertrude Stein & William Shakespeare; see also Shakespeare & Watts (2000)

micro (firm) level also create a significant performance difference and are more common. What is clear is that both radical and really new innovations share characteristics that incremental innovations do not: From a *firm perspective*, there is high uncertainty in multiple dimensions. In this research, they are treated together as “major innovations“(O'Connor, 2008).

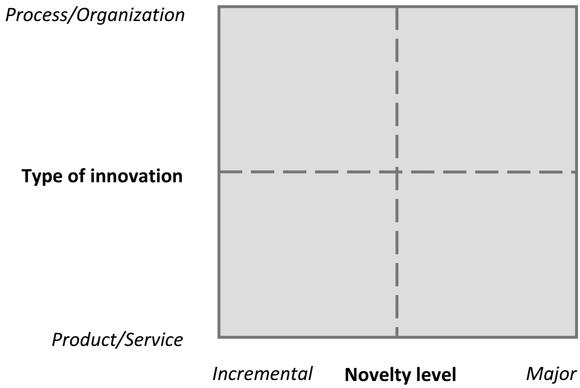

Figure 6: Types of Innovation (see also Spath & Warschat, 2008)

2.1.1.2 The Firm’s Innovation System: An Open System Perspective

From a firm perspective, innovation is the output of the firm’s innovation system and its interfaces with the environment (Figure 7).

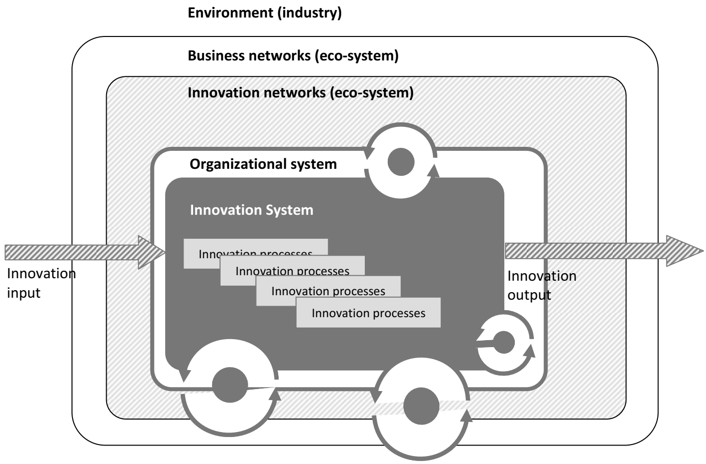

Figure 7: A Firm’s Innovation System Embedded in its Environmental Context

The firm's innovation system and its interfaces define the focus of managerial activities (Fuller & Moran, 2001; Hauschildt, 2004). It delineates the reference system and the scope of this research. Following the ideas of system theory, the firm's innovation system is defined as an *open system* having direct interfaces with other actors of its innovation networks, the organizational system, and the overall firm's eco-system (Allen, 2001; Bertalanffy, 2001; Capra, 1985).

2.1.1.3 Organizational Innovation Management

Just like *innovation,* the term *innovation management* is notoriously ambiguous and lacks a clear definition (Adams et al., 2006). In this research, innovation management is defined as the organization-wide management of innovation activities. It encapsulates the design of the *organizational innovation system* to successfully turn innovation input into output. In short, innovation management entails the dispositive constitution of various organizational innovation processes (Hauschildt, 2004; Nelson & Winter, 1977; Pfeiffer, 1980; Vahs & Burmester, 2005). Such a holistic definition contrasts a more narrow perspective where innovation management describes the management of individual innovation projects or initiatives (Balachandra & Frair, 1997; Cooper & Kleinschmidt, 1987; Goffin & Mitchell, 2005; p. 23). Innovation management can also be classified according to type of innovation addressed. While some managerial approaches deal with technological or product innovation (Chiesa, Coughlan & Voss Chris A., 1996; Cooper & Kleinschmidt, 1987), others concentrate on management of non-technological innovation such as organizational innovations (Adams et al., 2006; Goffin & Mitchell, 2005; Tidd, 2001; Westkämper & Dunker, 2004). This research covers both. In SMEs, innovation management is usually not strictly separated from operational management (Jenert, 2008). The term innovation management is often used interchangeable with R&D management, technology management or knowledge management; however each managerial concept addresses different managerial issues and questions (see discussions in Cetindamar, Phaal & Probert, 2009; Hauschildt, 2004; Specht, Beckmann & Amelingmeyer, 2002; Spath, Wagner, Aslanidis, Bannert, Rogowski & Ardilio, 2006; Vahs & Burmester, 2005).

Innovation routines – structures, processes, and decision rules, which allow for regular innovation activity – are central to innovation management (Bessant et al., 2009; Pavitt, 2002). Routines are generally defined as regular and predictable behavioural patterns *within* firms that are coping with a world of complexity and continuous change that precludes decisions and behaviour that maximize anything of importance (Nelson et al., 1982). Characteristics of organizational innovation routines will be discussed in more detail in chapter 3.3.2.

2.1.2 The Firm's Innovation Value Chain

The launch of an innovation represents the end of a myriad of activities and events, some of which can be identified as sequential, others as concurrent (Brown & Duguid, 2006; Rothwell, 1992; Rothwell, 1993). It also represents an important event in a firm's value creation activities as they may improve their performance when exploiting an innovation further. At an organizational level, innovation activities can be conceptualized as continuous problem solving and knowledge transformation activities that generate a regular flow of ideas that are turned into economic value (Nelson, 1962; Roper, Du & Love, 2008). The *innovation value chain* describes how innovation input is turned into value and considers different innovation processes in an interconnected way without imposing a linear and sequential order. As shown in Figure 8, an integrated framework of the innovation value chain comprises at least three distinct phases, which are interlinked and mutually dependent (Bullinger & Engel, 2006; Herstatt & Verworn, 2002; Rothwell, 1992; Rothwell, 1993; Rothwell, 1992; Westkämper & Alting, 2000):

(A) Opportunity scanning and idea management
(B) The development of an innovation
(C) Launch and continuous improvement

Considering the interactive and dynamic nature of innovation, these firm-specific innovation processes can be seen as a part of a broader dynamic in which innovation takes place (Nelson et al., 1982; Roper et al., 2008).

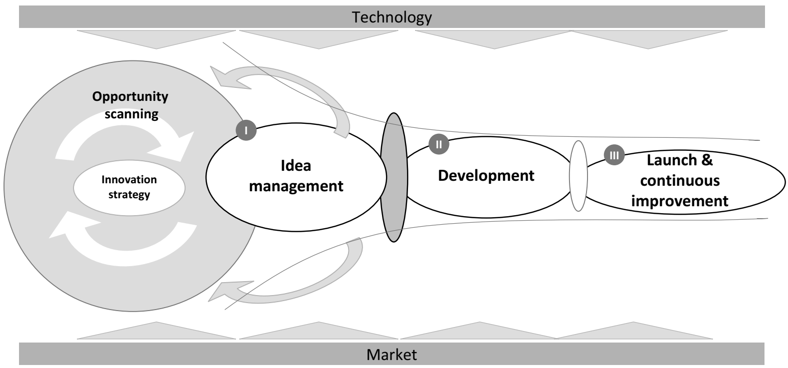

Figure 8: The Firm's Innovation Value Chain

2.1.3 Innovation Performance and Innovation-based Value Creation

The ultimate objective of innovation is to improve firm's economic performance and value creation (OECD/European Communities, 2005; Schumpeter, 1912). A firm's innovation performance describes a firm's output performance both at the innovation value chain and the innovation system level (Chiesa et al., 1996). It is multidimensional and cannot be measured with one single measure (Andrew, Haanaes, Michael, Sirkin & Taylor, 2008; Moore, 2005).

Throughout the innovation value chain, there are distinctive results and outcomes that describe a firm's innovation performance and innovation-based value creation. The successful introduction of an innovation describes a firm's performance in successfully transforming internal and external knowledge and turning it into an output that performs a market function (Roper et al., 2008). It offers the possibility to further exploit this innovation financially and create a higher income from innovation. However, when an innovation project actually succeeds in meeting its specific targets but fails to achieve competitive separation in the marketplace it impedes further value creation (Moore, 2005). At an innovation system level, a firm's innovation performance describes the financial impact of new offerings that create customer value – such as the share of income from new products and services (Andrew et al., 2008; OECD/European Communities, 2005). A fair amount of time passes between the successful introduction of an innovation and any noticeable success resulting from it (Aschoff, Doherr, Ebersberger & Peters, 2006).
Innovation-based value creation is also linked to firm growth (Khadjavi, 2005; Szerb & Ulbert, 2004) as firm growth captures a firm's value creation. Growth is multidimensional and can be defined along several dimensions such as total assets, employees, and revenues (Delmar, Davidsson & Gartner, 2003; Weinzimmer, Nystrom & Freeman, 1998). For example, prior research has shown that growth in income is not highly correlated with growth in employees (Weinzimmer et al., 1998) and that there are different types of dominant growth. Different types of growth represent different types of value creation processes. While employment growth describes a firm's knowledge accumulation, income growth represents a firm's performance in product-markets and financial value creation.

2.1.4 Small- and Medium-sized Enterprises (SMEs)

Small and medium-sized enterprises (SMEs) are the central focus of this empirical research. As the term suggests SMEs are profit-oriented organizations that are characterized by their smallness. Referring to the official definition of SMEs at a European level laid down in the Commission Recommendations 2003/361/EC, they employ less than 250 employees. In addition to the headcount ceiling, an enterprise qualifies as SME if it meets either the turnover ceiling of less than € 50 million or the annual balance sheet ceiling € 43 million (European Commission, 2003); but not necessarily both. Table 1 details the classification of SMEs:

Table 1: Classification of Small and Medium-sized Enterprises

Class	Number of employees (N; headcount)	Turnover (T, in million €)	Annual balance sheet (ABS in million €)
Medium-sized enterprises	$50 \leq N < 250$	$10 \leq T \leq 50$	$10 \leq ABS \leq 43$
Small enterprises	$10 \leq N < 50$	$2 \leq T \leq 10$	$2 \leq ABS \leq 10$
Micro enterprises	$N < 10$	$T \leq 2$	$ABS \leq 2$

While this definition is common in all European Member States, some countries have adapted the classification in national statistics and surveys. For example, in Germany the upper ceiling has been elevated to 500 employees both in official statistics and national innovation surveys (Aschoff et al., 2006).

There is a significant body of research literature on small businesses that refers to concepts and terms, such as *new venture*, *start-up*, *high-tech start-up, gazelle* or *entrepreneurial firms*. Most of these terms describe subgroups of SMEs such as enterprises with a specific strategic orientation or those SMEs that are not only small but also young (see appendix chapter 12.1 for detailed definitions). In this research, SMEs that are younger than two years are not taken into consideration; the founding process is a special managerial problem. It is widely reported that SMEs demonstrate specific organizational and managerial characteristics:

- An owner-manager, a group of partners or the members of a family dynasty regularly dominate most small businesses (Roper, 1999). In turn, these dominating people usually drive strategic directions and actions. In entrepreneurial firms, the individual – the entrepreneur – takes up the central role in a firm's strategic actions (see Wiklund & Shepherd, 2005; Wiklund, Patzelt & Shepherd, 2009).
- In addition, they are characterized by a lower degree of formalization of processes than large complex organizations, and rather flat organizational structures (Bessant, 1999; Brem, Kreusel & Neusser Christian, 2008). Indeed, many studies have shown that increases in size are directly related to increases in complexity measured by hierarchical levels, the number of administrative positions, and the ratio of administrators to other employees (Baldridge & Burnham, 1975). In turn, SMEs can demonstrate flexibility and fast decision making.
- Due to their smallness they have limited access to resources including materials, human and financial resources (Acs & Audretsch, 1987; Harryson & Kliknaite, 2006; Vossen, 1988; Wiklund & Shepherd, 2005). Their smallness does not allow them to exploit economies of scope and scale (as large firms can) and cannot easily diversify risk (Vossen, 1988). In addition, their smallness limits their market power and reputation as a business partner (van de Vrande et al., 2009). As a result, they often rely on inter-organizational partnerships, alliances and "personal" networks to get access to critical resources, new markets and legitimacy (Bae & Gargiulo, 2004; Baum, Calabrese & Silverman, 2000; Birley, 1985; Harryson & Kliknaite, 2006).
- SMEs usually show a high proximity to their customers and often rely on "niche-strategies" (Vossen, 1988).

2.2 Empirical Evidence of Open and Collaborative Innovation Strategies

The following chapters introduce the notion (or paradigm) of open innovation and present the results of a systematic review of existing empirical research on open and collaborative innovation.

2.2.1 The Notion of Open Innovation: A Firm-level Management Framework for Profiting from Innovation

2.2.1.1 Closed versus Open Innovation

From a firm's perspective, open and collaborative innovation models challenge the notion of "closed" innovation assumptions where all innovation activities are under the firm's control ensuring the appropriation of rents from innovation activities (Chesbrough, 2003c; Chesbrough, 2003b; Chesbrough, 2006d; Chesbrough, 2006c; Vanhaverbeke & Cloodt, 2006). Referring to Chesbrough (2006) "open innovation" can be defined as following (Chesbrough, 2006a; p.1):

> "Open Innovation is the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively. Open Innovation is a paradigm that assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, […]".

Traditionally large firms relied on internal R&D to create new products, and internal R&D labs were a strategic asset and presented a considerable entry barrier for rivals. They regularly favoured the *vertically integration* put forward by Chandler (1962) and exploited their R&D capabilities and internally controlled and owned complementary assets to outperform others (Chandler, 1962; Chesbrough, 2006c; Teece, 1986).
The traditional way organizations generated new ideas, developed and commercialized them - basically controlled the overall innovation process - has been labelled as "closed innovation model" (Figure 9). In the closed innovation model, research projects are launched from the internal knowledge base of the firm. Some of these projects are commercialized while others are stopped.

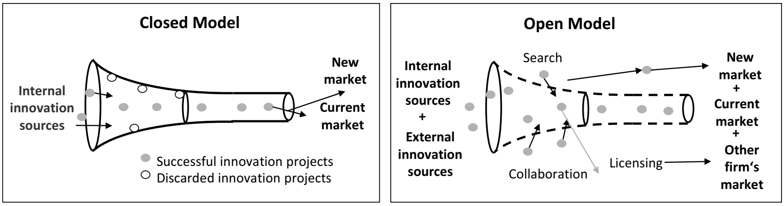

Figure 9: Open versus Closed Innovation Model

Chesbrough (2006) claims that AT&T Bell Laboratories stand as example of this model, with many notable research achievements but notoriously inward focused culture (Chesbrough, 2006c). The closed innovation model is usually accompanied with the Not Invented Here (NIH) syndrome. The open innovation model contrasts this traditional model (see Figure 9). In an open innovation model, projects can be launched from internal or external sources and new ideas can enter at various stages. Projects can also go to market in many ways, such as out-licensing or a spin-off venture in addition to traditional sales channels (Chesbrough, 2003b; Chesbrough, 2004).

In line with the open system perspective, the paradigm of open innovation shift stresses the porosity of the firm's boundaries. This new management model describes a cognitive framework for a firm's strategies to profit from innovation and to take advantage of *internal* and *external knowledge* (Chesbrough et al., 2006; Fredberg, Elmquist & Ollila, 2008; West, Vanhaverbeke & Chesbrough, 2006). In an open model of innovation, the negative perspective towards knowledge spillovers that was predominating the traditional innovation model has faded and the merits of acquiring and accessing *external knowledge* are acknowledged and strategically exploited (Chesbrough, 2003a; Grimpe & Sofka, 2009).

2.2.1.2 A Firm-level Framework and the Centrality of the Innovation-based Value Creation

The relevance of external knowledge has been acknowledged long before the burgeoning literature on open innovation in economic and innovation research (see critical discussion of Dahlander & Gann, 2007). Indeed, the economist Friedrich Hayek provided the cause of the problem already in 1945 arguing that centralized models of planning are prone to failure due to inability to aggregate distributed knowledge (Hayek, 1945). Unlike competing concepts, the open innovation concept is a firm-level management framework rather than an analysis of the interaction of various actors in the innovation system (Simard & West, 2006). In addition, it emphasizes that external knowledge plays an *equal role to internal knowledge* not just a supplemental one. A differentiating factor of the (new) innovation model is the centrality of the business model and its focus on *innovation-based value creation* (Chesbrough, 2006b; Chesbrough & Appleyard, 2007; Fredberg et al., 2008). One critical element of the business model is specifying two goals: first, it must create *value in its eco-system* (or value network) and second, it must allow the innovator to claim a sufficient portion of the value to sustain its position (Christensen, Olesen & Kjær, 2005; Chesbrough, 2006d). Thus, the ultimate goal of openness is not just to learn but to create and capture the value when innovating in an organizational boundary spanning manner (Chesbrough & Schwartz, 2007; Vanhaverbeke & Cloodt, 2006).

2.2.1.3 Drivers of Open Innovation: The New Division of Labour

As mentioned above, the explosion of information and knowledge in the recent years makes the problem of dispersedness of knowledge even more salient (Becker, 2001; Hayek, 1945); it makes the traditional innovation model prone to fail. In addition, a new division of labour is propelling the open innovation model. Nowadays, knowledge is widely dispersed across public and private organization and new ICT technologies support virtual collaboration, information search and communication (Teece, 2008a). Furthermore, current open innovation research puts forward four additional interconnected factors that promote the shift from a closed towards an open innovation model: the increasing availability and mobility of skilled workers, a venture capital market that endows entrepreneurs with the necessary capital to compete, external options for previously shelved ideas, and finally the increased capabilities of external suppliers (Chesbrough, 2006d; Chesbrough, 2006b).

2.2.1.4 Inbound versus Outbound Open Innovation and Archetypes of Open Innovation

Most research on open innovation differentiates between two concepts of open innovation: *inbound* where new ideas flow into an organization and *outbound* where internally developed technologies and ideas can be acquired by external organizations with business models that are better suited to commercialize a given technology or idea (Chesbrough, 2006d; p. 229).

Taking a technology-oriented perspective, *inbound open innovation* – or purposive inflows of knowledge – relates to technology exploration and innovation activities to capture and benefit from external sources of knowledge to enhance current technology developments. In literature practices such as customer involvement, external networking, external participation, outsourcing of R&D and inward licensing of IP are mentioned (van de Vrande et al., 2009). *Outbound open innovation* – or purposive outflows of knowledge – relates to technology exploitation to leverage technological capabilities of a firm outside the firm's boundaries. It includes activities such as venturing or outward licensing of IP (Chesbrough, 2006d).

Gassmann and Enkel (2004) include a third type of openness and differentiate between three archetypes of open innovation processes: Outside-in processes (1), inside-out (2) and coupled processes (3) (Gassmann & Enkel, 2004). Coupled processes combine outside-in and inside-out processes by leveraging well established relationships with innovation network partners (e.g. strategic alliances) in which give and take is critical for success (see Figure 10).

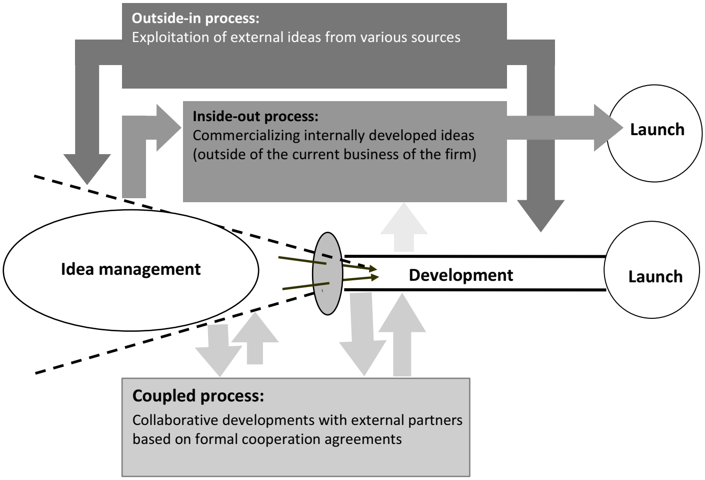

Figure 10: Archetypes of Open Innovation Processes (see Gassmann and Enkel, 2004)

2.2.1.5 Related "Boundary"-Spanning Innovation Models

In the current innovation literature, there are additional research streams that also stress the need of "active" boundary spanning innovation activities and are sometimes used synonymously for open innovation. The concept of *user innovation (or distributed innovation)* considers the user as an important actor in the innovation processes: "User of products and services – both firms and individual consumers – are increasingly able to innovate for themselves" (von Hippel, 2005; p.1). While open innovation is about value creation and profiting from innovation, "free revealing" of knowledge (without any direct financial compensation) and the contribution of autonomous individuals is a defining characteristic of openness in the user innovation paradigm (von Hippel, 2005; Reichwald & Piller, 2008; West, 2009). Moreover, a vast number of additional themes have emerged under the umbrella term *open innovation* (see in appendix chapter 12.2). This underlines the trend and interest in new innovation strategies. At the same time it stresses the need for a clear conceptualization of "openness".

2.2.2 Empirical Evidence of Characteristics and Impact of Open Innovation Strategies in Scientific Literature

Open innovation is based on practice research. Widely cited success stories on open innovation regularly treat openness as a dichotomy - "open" versus "closed" (Dahlander & Gann, 2007).
To cast light on to different kinds of openness, this research presents a r*eview* of selected *empirical research* on open innovation (Figure 11).

	1				2	3		4	5
	Innovation Search & Sources		Relationships	IP / Appropriability	External contingencies	Innovation performance measures	Quantitative causal-effect analysis (large database)	SME	Internal innovation structures/processes
Author (year)	No. of Sources	Specific source							
Chesbrough & Crowther (2006)	○	○	◐	◐	◐	○	○	○	◐
Christensen et al. (2005)	○	○	◐	◐	◐	○	○	◐	○
Dahalander & Wallin (2006)	◐	○	◐	○	○	○	○	○	○
Dittrich & Dyster (2007a, b)	○	○	●	○	○	○	○	○	○
Dodgson & Salter (2006)	◐	○	◐	◐	○	●	○	○	◐
Fabrizio (2009)	○	●	○	○	○	◐	●	○	◐
Fey & Birkinshaw (2005)	○	○	●	○	○	◐	◐	○	○
Harryson, S. (2008)	○	○	●	○	○	○	○	●	○
Henkel et al. (2006)	○	○	○	●	○	○	◐	○	◐
Lakhani et al. (2006)	●	○	○	◐	○	○	◐	○	○
Laurson & Salter (2006a)	●	○	○	○	○	●	●	○	◐
Laurson & Salter (2006b)	○	○	○	●	○	○	●	○	○
Lichtenthaler et al. (2008)	◐	○	◐	◐	◐	○	○	○	◐
Van der Vrande (2009)	◐	○	◐	◐	◐	○	○	●	○
van der Meer (2008)	○	○	◐	◐	◐	○	○	◐	◐
West and Gallagher (2006)	○	○	○	●	○	○	○	○	○

● Fully captured ◐ Partly captured ○ Not captured at all

Figure 11: Overview on Relevant Empirical Scientific Literature (2003 – 2009)

Following the idea of systematic literature review, scientific empirical papers, which were published between 2003 and mid of 2009, were analyzed[4] (Adams et al., 2006; Li, Vanhaverbeke & Schoenmakers, 2008; de Man & Duysters, 2005). The selection builds upon clear criteria: Only empirical papers that were published after 2003 were chosen[5]. In addition, empirical research papers must explicitly address the concept of open and collaborative innovation *at the firm level* (and not the project, network or industry level) and focus on *inbound open innovation*. Most importantly, papers need to be published in referred journals or

[4] EBSCO and science direct database were accessed to perform a structured literature review

[5] as 2003 was the year in which the term "open innovation" was coined by Henry Chesbrough

need to be presented at renowned, referred academic conferences[6]. Case studies in published books were not considered. Figure 11 summarizes the analysis of 16 scientific papers that empirically investigate open and collaborative innovation. Overall results reveal some major gaps and limitations both from a conceptual and empirical analysis perspective. In summary, there is no research that conceptualizes openness in a multidimensional way and at the same time investigates the performance impact based on a large scale database. Most importantly, they hardly address the link with a firm's internal innovation practices.

There are *five* major themes that shed light on relevant topics and concepts of open and collaborative innovation in existing empirical research:

- *Dimensions and facets of open and collaborative innovation strategies*

One may accept that any innovation involves some degree of openness but the question is in what ways. The analysis revealed that there are different kinds of openness that can be classified according to three dimensions: External innovation search and sources (1), relationships, co-development and networking (2), intellectual property and appropriability conditions (3). In quantitative empirical work the most elaborate measure of openness is a firm's breadth of external innovation search (Laursen & Salter, 2006). Currently, no research integrates different facets of openness. Details on the analysis of different types of openness will be discussed in more detail in chapter 2.2.3.

- *Open innovation and firm-external boundary conditions*

In a conceptual discussion, openness is regularly treated as strategic choice a firm makes (Chesbrough, 2002; Chesbrough, 2003a; Chesbrough, 2003b; Chesbrough, 2006d). As shown in Figure 11, there is little research that indicates that openness is conditioned and bounded by factors outside the firm. Christensen et al. (2005) executed a qualitative study of the current transformation of sound amplification from linear solid state technology to switch or digital technology within the consumer innovation system. He concluded that the characteristics of the innovation system may influence a firm's openness and its effect (Christensen et al., 2005). This proposes that openness may go beyond the strategic choice of the firm but this is not yet explored thoroughly.

- *Quantitative empirical research and performance impact*

Empirical and quantitative evidence on the impact of openness is scarce. There is no quantitative empirical study that has examined the causal relationship between openness and (innovation) performance. As highlighted in Figure 11, only *two* out of 16 selected studies include financial measures on innovation performance. Existing quantitative empirical research will be discussed in more detail in chapter 2.2.4.

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[6] Lakahni et al. (2006) do not fully meet all criteria as the paper is a working paper of Havard Business School; however, due to the relevance of the paper it was included

- *Open innovation strategies and specifics of SMEs*

It is claimed that in an open innovation era innovation has become more "level". Open innovation research recognizes that small firms play a prominent role in the contemporary innovation landscape (Chesbrough, 2006d). Indeed, as indicated in chapter 2.1 SMEs are by nature more open. To succeed in innovation, they have to rely on external partners and business relationships to both access new knowledge and to leverage complementary resources such as production, marketing channels and development (Bae & Gargiulo, 2004; Baum et al., 2000; Elfring & Hulsink, 2001; Vossen, 1988; Wiklund & Shepherd, 2005). However, research on open innovation in SMEs is scarce (see Figure 11). Harryson (2008) points out that small and entrepreneurial firms heavily rely on their social networks and "know-who" to get access to critical resources and assets both in the early and later phases of the innovation value chain (Harryson, Kliknaite & Dudkowski, 2008). Van der Vrande (2009) investigates different open innovation practices among Dutch SMEs (van de Vrande et al., 2009). Her study indicates that SMEs hardly rely on complex and transaction intensive practices such as IP licensing or outsourcing of R&D. SMEs leverage less resource-intensive activities such as informal networking (van de Vrande et al., 2009; p.431). Both authors point out that more in-depth research on open innovation in SMEs is required.

- *Open innovation and internal innovation practices*

While research on open and collaborative innovation focuses on the motivations for openness and the implications for performance (Fey & Birkinshaw, 2005; Laursen & Salter, 2006) there is rather limited understanding of the internal processes, structures and capabilities *enabling* external ideas to travel into and out of organizations to provide beneficial outcomes (Dahlander & Gann, 2007). Quantitative empirical studies include only measures such as expenditures for R&D and R&D training to capture absorptive capacity, which describes a firm's ability to recognize and absorb external technological knowledge. Despite the fact that many firms have established organizational routines and practices for managing innovation internally their antecedent role for capturing the value from openness has not yet been well researched. The state of research is discussed in more detail in chapter 2.3.

2.2.3 Dimensions and Measures of Open and Collaborative Innovation Strategies

The structured literature review identified three dimensions of openness. The state-of-research on these dimensions is briefly presented in the following.

2.2.3.1 External Search Strategies for Innovation Inputs

Existing empirical research indicates that a firm's capacity to exploit external knowledge for innovation purposes is manifested in its *search strategy* (Laursen & Salter, 2004, Laursen & Salter, 2006). From an open innovation perspective, search strategies describe whether firms search beyond their "internal" knowledge base (within the technological and organizational boundaries of the firm) among external sources such as customers, consumers, suppliers, research organizations or universities.

- *"Breadth" and "depth" of search strategies*

In their empirical work on open innovation (which is exceptionally rare), Laursen and Salter (2006, 2004) developed the concept of *breadth* as major dimensions of a firm's search strategy. They argue that *breadth* - representing the diversity of external innovation inputs from different types of external actors - increases the likelihood that firms adapt towards external changes and deepen the pool of innovation opportunities. The *depth* of search describes how deeply a firm draws on various external sources (Laursen & Salter, 2006). In his case study on broadcasted search of large firms via the innovation intermediary InnoCentive, Lakhani et al. (2006) showed that opening up of information about difficult and unsolved scientific problems to a large group of actors outside the firm can be an effective problem solving strategy (Lakhani et al., 2006).
The breadth of search can alleviate the problems of local search and ensures that the locus of problem solving shifts to where knowledge is stickiest (difficult to access or to move). However, the breadth of a firm's external innovation search strategy does not capture the specifics of individual partners, with whom a firm is interacting (Laursen & Salter, 2006).

- *Specific types of innovation sources*

Indeed, firms can interact with different types of organizational actors to search for and source innovation input. Since 2003, open innovation research has not investigated the relevance of *specific types* of innovation partners in a rigid manner (see Figure 11). Fabrizio (2009) provides an exceptional case of a quantitative empirical research in open innovation literature that concentrates on scientific search and the involvement of the scientific community as one specific type of external innovation sources that fosters a firm's inventive activities (Fabrizio, 2009).

2.2.3.2 External Relationships, Co-Development and Networking Strategies

A critical review of existing studies on open and collaborative innovation suggests that in addition to a firm's innovation search strategy the permeability of the firm's boundaries is dependent on the *type* and *nature of the relationships* that the organization has with its external actors (Fey & Birkinshaw, 2005; van de Vrande et al., 2009). For example, a onetime transaction will allow only little inflow and outflow of knowledge. It stresses that open innovation is not an ad-hoc approach to external innovation. Pioneers of open innovation, such as Procter & Gamble, stress that openness is not about "outsourcing" or contracting but rather about "co-development partnerships". These partnerships embody a mutual working relationship between two or more parties aimed at creating and delivering a new product, technology or service (Dodgson et al., 2006). Both a firm's networking strategies and co-development partnerships are discussed in existing empirical research on open innovation:

- *Innovation networking strategies and types of ties*

In their empirical work on open innovation Dittrich et al. (2007) conceptualize openness as the firm strategy to establish and manage external relationships via alliance and networks (Dittrich & Duysters, 2007; Dittrich, Duysters & de Man, 2007; Dittrich, 2008). They provide evidence that firms can actively shape their position in innovation networks and can leverage relationships to implement a strategic change. Their case studies on IBM and Nokia supports the proposition that open innovation is related to the establishment of *different types of relationships* of innovating firms with other organizations in order to support knowledge flows between firms; they are crucial to innovations and allow mutual innovation learning and value creation (Dittrich & Duysters, 2007). In a similar vein Harryson's work on open innovation in small high-tech firms (2008) reveals that SMEs' openness is defined by its relationships *both* for sourcing and internalization of external academic knowledge to accelerate exploration, and to develop commercialization partnerships (Harryson, 2008). In their survey among low-tech firms Chesbrough and Crowther (2006) found that firms establish "strong" relationships when they search to fill existing portfolio gaps (Chesbrough & Crowther, 2006).

- *Innovation partnerships, complementary "assets" and value creation*

Empirical research on open innovation reveals that partnerships and innovation networks are highly relevant not only to learn but also to complement a firm's innovation resources and assets via various types of innovation and operational assets. Recent case studies among Dutch SMEs, for example, show that partnerships are crucial at various stages of the innovation value chain (Christensen et al., 2005; van de Meer, 2007). Christensen et al. (2005) highlight that even in an early stage of the switch-amplifier technology, successful innovations required the alignment of usual operational types of complementary assets such as manufacturing, distribution and marketing. The commitment on both sides – both the small firms and the large partner - implies the avoidance of short-term opportunistic appropriation behaviour in order to leverage a competency in long-term relational contracting and fair and effective inter-firm cooperation (Christensen et al., 2005).

2.2.3.3 Openness, Intellectual Property and Appropriability

Regularly firms try to reduce the risk of unwanted knowledge spillovers by protecting their intellectual property and implementing a legal appropriation strategy to ensure that they reap the rewards of their inventive activities (Lakhani et al., 2006; Lakhani & Panetta, 2007; West & Gallagher, 2006). Like Gollum in "The Lord of the Rings", they become withdrawn and controlling, rather than open and collaborative, afraid that outsiders may steal their "precious" technology (Laursen & Salter, 2005). Open styles of innovation imply that firms motivate externals to contribute ideas or to elicit development collaboration. Usually this requires revealing some knowledge to outsiders. However, this results in a conflict with a firm's need to protect its intellectual property (IP) (Henkel, 2006; West & Gallagher, 2006). The disclosure paradox describes, that if firms reveal information to potential licensees or customers without paying for it, these outsiders act opportunistically and steal the idea (Dahlander & Wallin Martin W., 2006). First empirical research on open innovation and IP protection suggests that in industries with strong IPR regimes, firms might find it easier to engage with external actors (Lakhani et al., 2006). However, even in the software industry, where open source development activities build upon a free – meaning voluntary – revealing of source codes, firms can accommodate and combine free revealing and various means of protecting one's code. In his study on embedded Linux (used in embedded devices such as mobile phones, VCRs, and machine tools), Henkel (2006) showed that even in environments such as open sources where free revealing is dominant, firms can implement a selective revealing strategy combining free revealing and protection of source codes (Henkel, 2006). Thus, free revealing might be sensible thing to do and allows a firm to appropriate the returns from innovation. These empirical studies call for attention to the means of appropriating returns from a firm's innovation efforts when opening the innovation processes (Teece, 1986; Winter, 2006). Indeed, it indicates that IP protection and appropriability conditions are an elementary dimension of openness - either as strategic choice and boundary conditions (Henkel, 2006; West & Gallagher, 2006).

2.2.4 Impact of Open and Collaborative Innovation Strategies on Firm Performance

As pointed out above, empirical and quantitative evidence on the performance impact of openness is scarce; especially on SMEs. So far, the majority of empirical research has concentrated on investigating open innovation in a qualitative sense without paying attention to measuring the impact of a firm's openness on performance. Figure 11 includes only *four* empirical contributions that consider output measures; notably that only *two* studies consider financial measures on a firm's innovation performance. One of these two contributions is a *qualitative case study* that elaborates on the impact of the Connect & Develop Strategy of Procter and Gamble on firm performance (Dodgson et al., 2006). As it is an exceptional example discussing in detail the concrete financial impact of open innovation, it is described in the appendix 12.3. The remaining three quantitative empirical contributions have conceptual limitations; they do not model openness as multidimensional construct and consider only one dimension of openness (see Figure 11). Among those studies, external innovation search has been in focus. Here, Laurson and Salter (2006) provide a notable exception of existing empirical research on open innovation strategies. They statistically examine the role of breadth and depth of external search in explaining a firm's financial innovation performance (measured as share of income from new products) based on a large scale database analysis. In their study of UK manufacturers, Laursen and Salter (2006) identify an inverted U-shaped relationship and show that firms may over-search, which impedes performance (Laursen & Salter, 2006). Their research is based on the Community Innovation Survey (CIS).

Fabrizio (2009) concentrates on one specific type of external innovation source: In a quantitative database analysis of panel data of 83 firms in the biotechnology and pharmaceutical industries during the 1976-1999 (listed in Standard & Poor's Industry Surveys) he investigates search among external scientific sources in relation to internal research and its impact on invention outcome. Building open patent citations to measure inventive outcomes (invention quality and invention pace) the study confirms that access to external knowledge sources is important to guide the solution process and thus, improves the efficiency of searching and offers more timely access to research knowledge (Fabrizio, 2006). His research does not clarify whether search among external "scientific" actors has an impact on innovation performance.
Fey and Birkinshaw (2005) investigate the impact of the type of external relationships of internal R&D groups in large firms on a firm's R&D effectiveness; the survey covers firms from Sweden and the UK. R&D effectiveness is measured subjectively based on respondents' subjective evaluation of R&D effectiveness based on "quasi" metric likert scales; they do not collect financial performance measures. Concentrating on two types of relationships – contracting versus partnering – they identify that external contracting has a net negative effect on R&D performance, whereas partnering with research partners (universities) has a positive impact on R&D performance (Fey & Birkinshaw, 2005).

2.2.5 Evaluation of Existing Research

Since the publication of Chesbrough's book in 2003, the concept of open innovation has revitalized the interest of practitioners and researchers in external innovations (Chesbrough, 2006d). The definition of open innovation is obviously quite broad. This raises questions about how evidence on the impact of openness can be gathered and compared. Practice-based discussions on the open innovation usually highlight the dichotomy of openness without paying attention to different types and measures of openness (Dahlander & Gann, 2007, Huston & Sakkab, 2006). An in-depth review of empirical papers published in scientific journals (between 2003 and 2009) reveals that openness is used as an umbrella term although it is multidimensional. In summary, the review highlights different facets and styles of openness and helps to identify historical antecedents and theoretical perspectives for conceptualizing "openness". These facets can be classified according to the following dimensions: External innovation search and sources (1), relationships and networking (2), and IP protection and appropriability (3). Each dimension links to theoretical perspectives to be used to conceptualize openness in a more rigid manner. Amongst those three dimensions, external innovation search has been elaborated the most in scientific literature. However, even the established concepts of "breadth" and "depth" of external innovation search have limitations as they do not consider the distinctiveness of individual innovation sources and partners, with whom the firm is interacting. Furthermore, boundary conditions that might limit a firm's strategic choice are not sufficiently addressed and should be considered in future conceptualizations.

The review also strengthens the argument that further research is required to examine the performance impact of open innovation; especially in SMEs. While there is first evidence on the impact of external search breadth (Laursen & Salter, 2006), multivariate causal relationships between different types of openness and firm performance are not sufficiently understood. SMEs have been widely neglected in existing empirical studies although open innovation literature claims that SMEs play an even more vital role in the open innovation landscape. Finally, the role of organizational practices for innovation in helping a firm to capture the value from openness is hardly investigated. Although it is echoed in open innovation textbooks that internal innovation assets are indispensible to successfully make use of external knowledge (Chesbrough, 2006d), a more thorough understanding on the role of a firm’s organizational practices is required. As shown in Figure 11, existing empirical research hardly touches upon a firm’s internal structures and routines for innovation. This reemphasizes that further research is needed.

2.3 Absorptive Capacity and Internal Organizational Practices for Innovation

"Most of what happens in successful innovation is […] the careful implementation of an unspectacular but systematic management discipline" (Peter Drucker)[7]

To better understand the Janus-face of openness, the following section concentrates on a firm's internal assets for innovation and organizational routines and practices for innovation. In existing studies on open and collaborative innovation the concept of *absorptive capacity* is touched upon (see e.g. Laursen & Salter, 2006); and so it is introduced before reviewing the state-of-the art on organizational practices and routines for innovation.

2.3.1 Concepts and Measures of Absorptive Capacity

External knowledge needs to be (identified and) absorbed to be of value of a firm's innovation activities (Caloghirou, Kastelli & Tsakanikas, 2004; Cohen & Levinthal, 1990; Katila, 2002). The concept of *absorptive capacity* has been intensively discussed in research on organizational phenomena such as knowledge creation and learning prior to discussions on open innovation. It has become an influential construct in a number of management fields (Lenox & King, 2004; Peters & Johnston, 2009; Todorova & Durisin, 2007; Zahra & George, 2002). Cohen and Levinthal (1989, 1990) introduced the term *absorptive capacity* and argue that the ability of a firm to *recognize* the value of new, external information, *assimilate it*, and *apply it to commercial ends* is critical to a firm's innovation processes (Cohen & Levinthal, 1990; p. 128; Katila, 2002; Spithoven et al., 2009; Todorova & Durisin, 2007; Zahra & George, 2002). It is explicitly identified as an antecedent of a firm's innovation performance.

2.3.1.1 A Firm's Internal Technological Knowledge Base as a Determinant and Measure of Absorptive Capacity

A range of empirical studies suggests that absorptive capacity has an *inward* and *outward* dimension (Cohen & Levinthal, 1990; Spithoven et al., 2009). Indeed, absorptive capacity is determined by the existing (technological) knowledge base (Caloghirou et al., 2004; Cohen & Levinthal, 1990; Zahra & George, 2002). A firm's absorptive capacity is path dependent because experience and prior knowledge facilitate the use of new knowledge; in turn, absorptive capacity is cumulative (Cohen & Levinthal, 1990). Internal R&D is important to build up prior (technological) knowledge as it eases the adoption of external technologies (Cohen & Levinthal, 1990; Spithoven et al., 2009). Internal R&D and investment into internal technological

[7] see Drucker (1985)

knowledge base are important determinants of a firm's absorptive capacity. Empirical quantitative studies regularly adopt a firm's investment into the internal (technological) knowledge base as measure of a firm's absorptive capacity (see e.g. Laursen & Salter, 2006; for an overview on mostly empirical studies on absorptive capacity see Zahra & George, 2002; an excerpt of important empirical studies on absorptive capacity is shown in appendix 12.1.).

2.3.1.2 Absorptive Capacity and Organizational Routines

There have been intensive theoretical discussions on absorptive capacity. They regularly refer to a set of organizational routines and processes to absorb (technological) knowledge (Cohen & Levinthal, 1990; Nieto & Quevedo, 2005; Todorova & Durisin, 2007; Zahra & George, 2002). After the introduction by Cohen and Levinthal (1989; 1990) the concept and the related organizational routines and processes have been re-conceptualized several times (see appendix 12.1). Zahra and George (2002) for example, redefine absorptive capacity as a *dynamic organizational capability* with four dimensions that enable a firm to reconfigure its resource base and adapt to changing market conditions: "Acquiring", "assimilation", "transformation" and "exploitation" (Zahra & George, 2002). Later discussions – such as for example of Todovora and Dorosin (2007) – disagree with the reconceptualization of organizational routines and processes; in turn, the original concept as used in analysis of Cohen and Levinthal (1990) remains of considerable importance (Spithoven et al., 2009). Although theoretical discussions stress that absorptive capacity entails a range of organizational routines and practices, it is regularly operationalized as the existence and/or intensity of a company's R&D activities (Zahra & George, 2002; see appendix 12.1). In existing work the *antecedent role of organization routines* is regularly neglected although it has been put forward already in the seminal work of Cohen and Levinthal (1990).

2.3.2 Concepts and Measures of Organizational Practices and Routines for Innovation

Managerial activities and interventions are considered as crucial to balance inventive activities and commercialization (Adams et al., 2006; Davila, Epstein & Shelton, 2005; Fredberg et al., 2008; van de Meer, 2007). Ever since Nelson and Winter (1982) researchers consider managerial practices for innovation as major determinants of a firm's innovation performance (Bessant et al., 2009; Nelson et al., 1982; Pavitt, 2002). In practice, internal *managerial processes* and *semi-procedural routines* for innovation (and not for operations) have become fashionable. Managers follow the idea that innovation can be systematically managed (Barczak, Griffin Abbie & Kahn, 2009; Bessant et al., 2009; Bullinger & Engel, 2006; Bullinger, Bannert & Brunswicker, 2007; Christiansen & Varnes, 2009; Drucker, 1985). However, most work abstracts from how organizational practices can positively influence the search for and absorption of external knowledge. The following chapters present an overview on current literature and specifically empirical work on organizational practices for innovation and their conceptualization.

2.3.2.1 The Concept of Innovation Routines

Innovation routines – structures, processes, and decision rules, which allow for regular innovation activity – are central to innovation management (Bessant et al., 2009; Pavitt, 2002). A review of existing literature reveals that the concept of "innovation routines" introduced by Nelson and Winter (1982) has hardly been advanced (Nelson et al., 1982; Pavitt, 2002). Pavitt (2002) takes a rather technological perspective towards innovation routines and classifies the following "categories" (Pavitt, 2002): (1) the production of knowledge, (2) transformation of knowledge into working artefacts, (3) matching working artefacts with user requirements. In their case study research Bessant et al. (2009) investigate innovation routines in terms of phases in time and classify managerial routines along the dimension: "Searching", "Selection" and "Implementation" (Bessant et al., 2009). This reflects different practices and routines that are relevant throughout the innovation value chain (see chapter 2.1.2).

2.3.2.2 Managerial Practices in New Product Development

Quantitative research on innovation routines at an organizational level is scarce (so to say nonexistent). However, managerial practices and routines have been empirically and quantitatively investigated in New Product Development (NPD) success factor research (see for example, Cooper & Kleinschmidt, 1987). Although this body of research has been criticised for its methodological and theoretical weaknesses, it is worthwhile to briefly outline major findings (Ernst, 2002). Since more than 40 years, innovation success factor research[8] has attracted a number of different disciplines to identify *best practices* in new product development (Cooper & Kleinschmidt, 1987; Hauschildt & Walther, 2003). One major characteristic of innovation success factor research is that it investigates success factors (or barriers) at the *project level* rather than at the organizational level (see Figure 12). Due to the large amount of studies on success factors, meta-studies have been executed to summarize the main findings and critically evaluate them. An overview on major meta-studies published since 1977 can be found in appendix 12.5 (Table 29). Many of the studies claim that structured and formalized approaches towards managing innovation are crucial success factors (Barczak et al., 2009; Christiansen & Varnes, 2009; Ernst, 2002; Johne & Snelson, 1988). Ernst (2002) executed one of the most recent and thorough meta-study on new product development success factors (Ernst, 2002) and investigated success variables, which are addressed in quantitative studies on new product development success published in 1974 – 1999. Indeed, his review of empirical NPD research

[8] The overall assumption of success factor research is that there are critical success factors that significantly effect firm performance. Success factors and causal relationships are usually collected during the research process.

emphasizes the relevance of managerial practices and routines (Ernst, 2002) such as for example, the presence of a *formal (or informal) product development process*. A very recent NPD study even claims that formal processes are now “the norm” among best practices (Barczak et al., 2009). Ernst (2002) noted that *the quality of planning* and *idea management* before the development is also decisive. The necessary preparatory work comprises especially a rough evaluation of the initial ideas and the selection of the most promising process prior to entering the development phase. Successful NPD projects are *continuously evaluated* throughout the course of the projects. While Ernst (2002) suggested that a dedicated project organization is an organizational requirement, a very recent study of success factor research pointed out that there is not “one” single organizational design and structure that distinguishes top NPD performers (Barczak et al., 2009). This is in line with fact of contradictory findings of research on the appropriate organizational design for innovation and suggests that practices and routines rather than organizational structures should be focus of quantitative research (e.g. Damanpour & Gopalakrishnan, 1998; Tushman & O' Reilly, 1996; Damanpour & Wischnevsky, 2006; Freeman & Engel, 2007). NPD research concentrates on project level data which results in a major drawback: Company specific and organizational factors, which are constant over individual projects, cannot be analyzed (Ernst, 2002).

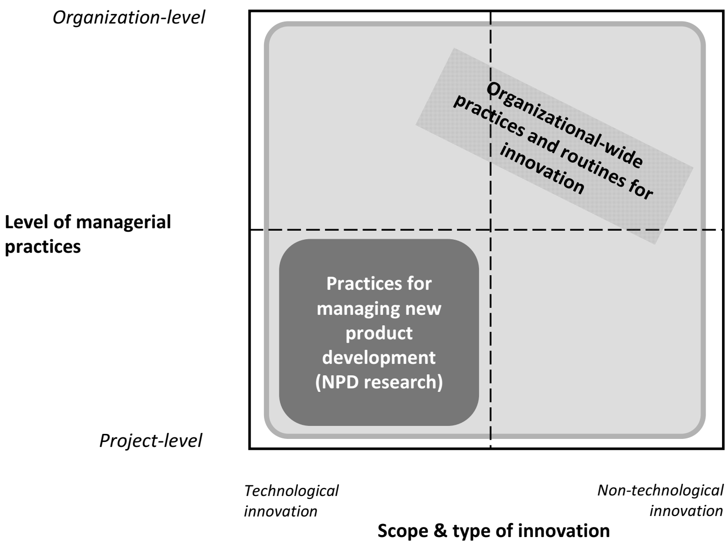

Figure 12: Scope of New Product Development (NPD) Research

2.3.2.3 Managerial Practices for Innovation at an Organizational Level

At an organizational level, an integrated framework for managing innovation cannot be identified in literature (Adams et al., 2006). Adams et al. (2006) execute a systematic literature review of innovation management frameworks and concluded that existing literature is fragmented and most models fail to take into account the organizational pervasiveness of innovation and its socio-technical connectedness (Adams et al., 2006; summary see appendix 12.6). They conclude that existing organization-wide innovation management models and measurement frameworks have mostly emerged from a rather technological understanding of innovation (see for example Chiesa et al., 1996; Wang, Lu & Chen, 2008). The review of existing frameworks indicates that coordinating routines and practices for *innovation strategy development* need to complement project specific innovation development routines at an *organizational level.* In addition, *innovation controlling* and *continuous improvement* of existing managerial practices and performance are relevant as "integrative" and coordinating routine at the organizational level to continuously adapt (Adams et al., 2006; Tang, 1998; Wong, Chin & Kwai-Sang, 2007).

Empirical research on the popular concept "innovation capability" overlaps with the discussion on organizational practices for innovation. It usually concentrates on specific functional capabilities such as *"technology"* and *"marketing"* capabilities. However, some studies also identified integrative and coordinating managerial routines as an important determinant of a firm's innovation capability (Birchall & Tovstiga, 2005; Burgelman, Kosnik & van den Poel, 2004; Koberg, Uhlenbruck & Sarason, 1996; Tang, 1999; Wang et al., 2008; Wong et al., 2007; for an overview on existing research on "innovation capability" see Sammerl, 2006). To make use of a firm's resources and assets for innovation, integrative and coordinating capabilities - both operational and dynamic ones – are required to successfully innovate. There is no consistent conceptualization and quantitative empirical analysis of such "integrative" and "coordinating" practices and routines that matter when managing innovations (Damanpour & Wischnevsky, 2006; Sammerl, 2006). This review highlights the relevance of discussions in strategic management on dynamic capabilities (Eisenhardt & Martin, 2000; Teece, 2008c).

2.3.2.4 Entrepreneurial Informal Practices versus Formalization and Discipline

The review indicates that organizational approaches and practices for enabling innovation can be differentiated along a continuum with two contrasting ends: The informal and entrepreneurial model enabling innovation via embedded routines and informal management mechanism such as culture and leadership *versus* formalized and structured approaches for managing innovation (Ernst, 2002; Freeman & Engel, 2007; van de Meer, 2007; Pavitt, 1998; Pavitt, 2002).

Referring to Schumpeter (1932) the entrepreneurial innovation model is regularly associated with young innovative firms and individuals, and contrasted with the corporate model of innovation (Schumpeter, 1912); however, "entrepreneurial spirit" can also reside in mature organizations (e.g. large giants such as Google). Entrepreneurial activities and dynamic leaders characterize entrepreneurial culture. Dynamic leaders manage and enable innovation in a very "natural" manner (Freeman & Engel, 2007; van de Meer, 2007). In empirical research the construct *entrepreneurial orientation* (EO) constitutes an organizational phenomenon that reflects a managerial capability by which firms embark on proactive and aggressive initiatives to alter the competitive scene to their advantage (Avlonitis & Salavou, 2007)). There is a vast body of empirical research on "entrepreneurship" and EO (for an overview see Wiklund et al., 2009). The impact of EO on a firm's performance and growth has been supported empirically. For example, in his empirical research among 416 Dutch SMEs, Wiklund (2009) confirms that EO has an important determining factor of firm growth and is moderated by managers' personal attitudes (Wiklund et al., 2009). Surprisingly, few entrepreneurship research studies focus on combining the EO and innovation (Avlonitis & Salavou, 2007).

In a similar manner, the relevance of *embedded organizational enablers* for innovation is highlighted in discussions on organizational culture which is viewed as internal variable that can be influenced by management (Ernst, 2003; Ernst & Kohn, 2007). In his theoretically grounded empirical study among 336 firms Ernst (2003) confirms the impact of organizational culture on a firm's performance (Ernst, 2003): He shows that "adhocracy culture", which is characterized by entrepreneurship, creative leadership, risk taking and organic processes, has a stronger impact on innovation performance than other types of organizational culture (e.g. clan culture or hierarchy culture).

The entrepreneurial and creative approach for managing and enabling innovation contrasts *structured and formalized* innovation practices (Freeman & Engel, 2007; van de Meer, 2007). Here, innovation activities are semi-procedural in nature. At a project level, the relevance of such routines is documented in new product development research (see above). At an organizational level, the impact of semi-procedural activities for innovation has hardly been analyzed based on a large-scale database and theoretically elaborated research model (Schewe, 1994).

However, there are "extreme" forms of structured management approaches, such as process management, that build upon formal organizational routines and practices. Process management, based on a view of an organization as a system of interlinked processes, involves concerted efforts to map, improve, and adhere to organizational processes (Benner, 2007; Koberg et al., 1996). Initially, a central part of total quality management (TQM) programs in the 1980s, process management practices are now applied not only as part of quality-related initiatives in manufacturing operations but also to other organizational processes, such as those concerning the selection and development of technological innovations (Benner, 2007). Benner (2009) empirically investigated how process management techniques in large incumbent firms, that entered the digital camera market in 1990s, influence a firm's technological innovation and organizational adaptation (Benner, 2009). Her results suggest that codification and routinization do not foster continuous renewal, and whether such activities spur organizational adaptation depends on the extent of change in capabilities required for the changed environment. It highlights that often externally mandated practices – such as TQM, ISO 9000, or even ERP systems in the future – may slow response when more dramatic transformation is required.

2.3.3 Evaluation of Existing Research

The concept of absorptive capacity has been an influential construct. However, conceptualizing and measuring it remains confusing (Lenox & King, 2004; Peters & Johnston, 2009; Todorova & Durisin, 2007; Zahra & George, 2002). It is regularly operationalized as the existence and/or intensity of a company's R&D activities and investment into training (Zahra & George, 2002; see appendix 12.1). Although Cohen (1990) clearly suggested that a firm's internal organizational routines for innovation may have an antecedent role, existing research has not touched upon the question whether established (mostly semi-procedural) practices for innovation help firms to benefit from openness. In contrast, there is tremendous work and empirical research that follows the notion that discipline and structure in managing innovation strengthens a firm's innovation performance. Empirical studies claim that managerial practices for innovation shape a firm's innovation performance. In practice, managerial practices for innovation are appreciated and semi-procedural innovation routines are widely used. However, this body of work on organizational practices for innovation is fragmented and shows weaknesses.

For example, NPD success factor research has some drawbacks, especially from a methodological point of view: NPD research is mostly inductive rather than deductive, and has not made any use of methodological advancement in data evaluation that has been achieved in the past several years. Neither are constructs derived based on the evaluation of existing literature and theory, nor are relevant reliability measures reported. Moreover, NPD research focuses on project level data (Ernst, 2002; Sammerl, 2006) and, thus, organizational practices for innovation need further research. Most importantly, this body of research abstracts from the question whether such practices for innovation enable a firm to benefit from openness. In summary, the review suggests that future research needs to link the conceptualization of different types of internal organizational practices – both formal and embedded ones - to the question how these practices can positively influence a firm's absorptive capacity.

3 Development of an Integrated Causal Framework for Examining Multiple Causal Relationships

The following chapters present an integrated, multidimensional and theoretically grounded conceptual framework for measuring a firm's open and collaborative strategies and its internal innovation practices, and for examining the causal effects on a firm's innovation-based value creation. It provides the basis for the translation into statistical regression models and an empirical quantitative examination of measurement constructs and causal effects based on a large database (see chapter 4). First, the principles of the modelling are presented. Second, the framework and hypotheses are developed and presented in a two staged manner. In chapter 3.2.2, the modelling takes an external view and addresses causal effects of different open and collaborative innovation strategies on a firm's innovation-based value creation. At the same time, it pays attention to external boundary conditions such as appropriability regimes and a firm's age. In chapter 3.3, the internal innovation practices are conceptualized and the causal relationships of a firm's open innovation strategies, internal managerial practices, and a firm's innovation-based value creation are detailed.

3.1 Principles of Framework Development and Conceptual Modelling

3.1.1 Conceptual and Theoretical Pluralism

A conceptual and theoretical grounding of the models provides the basis for a conceptually sound causal effect analysis (Ketchen, Thomas & Snow Charles C., 1993; Schnell et al., 1993). As shown in previous chapters, there are multiple theoretical perspectives that offer means to conceptualize open and collaborative strategies and model causal effect relationships with performance. This confirms the position of other authors (Acha, 2007; Dahlander & Gann, 2007). Thus, a mono-theoretical approach is not appropriate to model open and collaborative innovation strategies and their causal effects on firm performance. This research will consider several concepts and theoretical perspectives that emerged as relevant when reviewing the state-of-the art (chapter 2).

3.1.2 Contingent Modelling, Causal Moderation and Causal Mediation

Existing empirical research does not fully capture the complex interrelationships among open innovation strategies, internal practices and a firm's innovation performance. *Contingency theory* and *contingent modelling* offer the potential to better understand how third variables affect the relationship of open styles of innovation and innovation-based value creation (Barley, 1990; Barney, 1991a; Harrigan, 1983; Tidd, 2001). Contingency modelling is rooted in organizational theory. The original idea of contingency theory is that no single organizational structure is effective in all circumstances, and that instead there is an optimal organizational structure that best fits a given contingency, such as size, strategy, task uncertainty or technology. The basic notion is that the better the fit between the organization and contingency, the higher the organizational performance (Barley, 1990; Tidd, 2001). A contingent view has also been adopted in strategic management. There is a significant body of research on the environment-strategy and strategy-structure linkages, but few address the specific notion of innovation (Damanpour & Gopalakrishnan, 1998; Koberg et al., 1996; Mintzberg, 1991; Tidd, 2001). Contingency theory has been refined several times both on theoretical and methodological ground (Barley, 1990; Tidd, 2001). In a more general sense, contingency modelling is applied to investigate two-way interactions of two attributes – usually firm and environmental specific attributes - in explaining firm performance. It goes beyond the universal relationship for explaining complex phenomena such as performance (Kuhn, 2006; Tsai, 2009; Wiklund & Shepherd, 2005). According to Lumpkin & Dess (1996) there are different contingencies that allow explaining the interrelationship of independent variables such as firm strategies and dependent variables such as firm performance (Lumpkin & Dess, 1996) including moderating, mediating and interactive effects (see Figure 13).

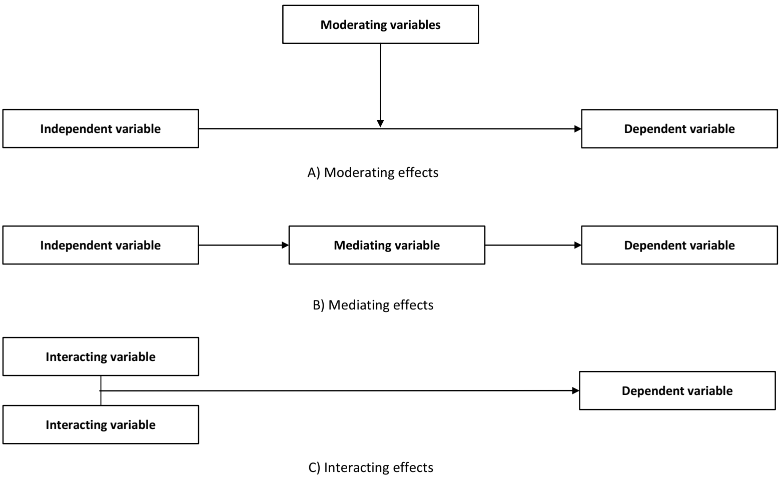

Figure 13: Classification of Contingent Modelling Strategies (see also Lumpkin & Dess, 1996)

Moderating factors influence the strengths of the relationship of an independent variable and the dependent variable. In social science such as psychology, organizational research and economics the investigation of third variables has got a longer tradition (Baron & Kenny, 1986).

However, the moderating function of third factors on the relationship of open and collaborative innovation strategies and innovation performance has not been investigated.

Mediating factors have a direct relationship with both the independent variable and the dependent variable. The moderating function of a third variable represents the generative mechanism through which the focal independent construct is able to influence the dependent construct (Baron & Kenny, 1986; Lumpkin & Dess, 1996). Quantitative, empirical research on open and collaborative innovation has not yet addressed mediating factors.

Interacting effects suggest that only a set of variables together is able to explain organizational phenomena, such as firm performance. The single variables do not directly affect the dependent variables (Lumpkin & Dess, 1996). Interacting effects are common in research domains such as psychology or economics; however, they have hardly been addressed in innovation research.

3.1.3 The Integrated Causal Framework for Examining Performance Impact

As Figure 14 shows, the framework conceptualizes relevant components and constructs in an integrated manner and details multivariate relationships among independent and dependent variables in order to *explain innovation performance and value growth*. Most importantly, the framework captures the direct effects of open and collaborative innovation strategies (I) on innovation-based value creation (II). In addition, it takes an external perspective and considers moderating effects on the causal relationship (III). Taking an internal perspective, it addresses causal mediation that represents a generative mechanism (IV).

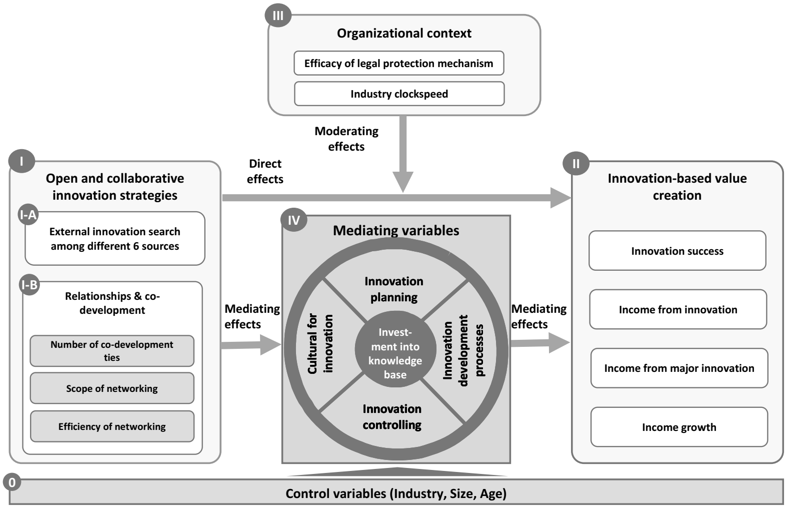

Figure 14: An Integrated Perspective of Causal Effects, Moderation and Mediation

The causal framework can be translated in mathematical models for multivariate statistical regression analyses. This allows an empirical investigation of causal effects based on a large database.

3.2 The External Perspective: Causal Effects of Open and Collaborative Innovation Strategies and Causal Moderation of Boundary Conditions

3.2.1 Theoretical Grounding of Conceptualization

Innovation based value creation is at the core of open and collaborative innovation (Vanhaverbeke & Cloodt, 2006), and thus, empirically examining the causal effect of a firm's external orientation and openness on innovation-based value creation is an important research endeavour. However, as put forward in chapter 2.2, a solid conceptualization of openness is required. A systematic review reveals that there are three dimensions of inbound open innovation strategies that are touched by existing empirical research (see 2.2.2): Innovation search and sources of innovation input (1), relationships and networking (2), and IP and appropriability strategies (3). In addition, external boundary conditions have been put forward (4). This indicates which theoretical perspectives are relevant to conceptualize open and collaborative innovation strategies and to develop propositions about causal relationships: Organizational problem solving, social network theory, co-opetitive game theory and recent extensions of the resource-based view of the firm. To model moderating factors evolutionary-based innovation theory in industrial economics is also relevant. In contrast, perspectives such as transaction cost theory or the classical market-positioning theory aren't relevant. The following conceptualization draws upon five theoretical perspectives (see Figure 15). These perspectives are briefly introduced in the following chapters.

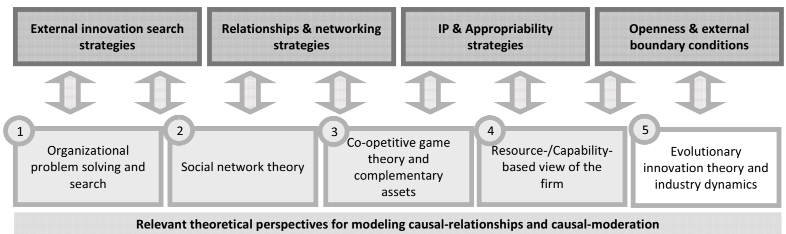

Figure 15: Relevant Theoretical Perspectives for Modelling Causal Effects and Moderation

3.2.1.1 Search and Organizational Problem Solving Theory

External search constitutes a firm's open innovation strategy. "Search" is rooted in discussions on organizational problem solving and learning, and emphasizes the importance of knowledge generation for firm performance (Levitt & March, 1988; March, 1991; Sidhu, Volberda & Commandeur, 2004). Firms can engage in a wide variety of searches such as the search for a superior organizational design, optimal manufacturing methods and for best ways to generate and implement innovations (Katila, 2002; von Hippel, 1988). Innovation search has been captured as one organizational learning process through which firms attempt to solve problems in an ambiguous world (Katila & Ahuja, 2002; p. 1183). In this context, a firm's search strategy has been defined as "organization's problem solving activities that involve the creation and recombination of (technological) ideas" (Katila & Ahuja, 2002; p. 1184). Following this perspective, search activities can occur along the continuum of exploration and exploitation. Exploration and exploitation are two different types of learning; exploration encapsulates search for new knowledge, technology, competencies, market or relations. Exploitation is the further development of existing ones (March, 1991, Levitt & March, 1988; Sidhu et al., 2004). Explorative and exploitative search vary in terms of the "distance" from the existing knowledge base of a firm. Organizations that search locally address problems that are close to their existing knowledge base, while *exploratory search* means that firm's move away from their current organizational routines and technological knowledge base (March, 1991). *Distant search* enriches the knowledge pool by adding distinctive new variations. New variations are necessary to provide a sufficient amount of choice. Distant or local search is a matter of different dimensions, such as cognitive, temporal and spatial distance. Cognitive distance has been one of the most intensively discussed dimensions in organizational learning and search. Regularly, literature describes the cognitive distance in relation to a firm's technology field and a specific technological trajectory - and exploits patent citations to measure the cognitive distance (Katila, 2002; Katila & Ahuja, 2002; Laursen & Salter, 2006; Nooteboom, 2002). Innovation search also relates to different knowledge domains such as science, technology and product-markets (von Hippel, 1988; Li et al., 2008) and ranges from supply-side and demand-side of competition (Sidhu et al., 2004). This issue seems to be highly relevant in context of open innovation as different external actors relate to different knowledge domains respectively.

3.2.1.2 Social Network Theory and Co-development Relationships

This scarce empirical work on open innovation confirms the relevance of (social) network theory to conceptualize open and collaborative innovation strategies. For example, the concepts of *embeddedness* (Granovetter, 1985) or *strengths of ties* (Granovetter, 1973) are appropriate to better understand how a firm searches for new knowledge and creates value from innovation. Embeddedness refers to the structure of a network of social relations that can affect the economic action, outcomes and behaviour of the firm and of its partners to whom the firm is directly or indirectly linked. It implies that critical transactions on which firms depend most are embedded in networks of social relationships. These relationships produce positive and unique outcomes that are difficult to imitate via others. A network perspective towards economic actions leverages the social capital metaphor that proposes that people who do better are somehow better connected (Ahuja, 2000b; Ahuja, 2000a; Burt, 2000; Gilsing, Lemmens & Duysters, 2007; Uzzi, 1997).

Network theory refers to different types of ties that describe a firm's relationships and networking strategy:

- *Strong versus weak ties:* In an innovation context, strong ties are characterized by intimate, recurrent and trustful relationships. The concept of strengths of ties is rooted in research on social interpersonal relationships (Granovetter, 1973). Strong ties – sometimes also referred as deep ties – subsume intensive knowledge and resource exchange. In turn, co-development relationships are usually strong in nature (Dittrich et al., 2007; Harryson et al., 2008; Vanhaverbeke, Duysters & Beerkens, 2002). They are generally considered to be useful when firms aim at an exploitation strategy. Weak ties, on the other hand, imply a low commitment and relationships with less familiar partners. They are characterized by only little resource and knowledge exchange (Dittrich et al., 2007). For example, when scanning for new technological trends firms do not want to engage in long-term commitments.
- *Formal versus informal ties:* Formal ties build upon formal agreements among the collaborating parties such as joint research or development agreements, licensing agreements or contractually based marketing and sales agreements. Informal ties do not build upon formal contracts and agreements; for example, expert communities and relationships resulting from completed projects represent informal ties (Powell, Koput & Smith-Doerr, 1996; Simard & West, 2006).

Network theory suggests that innovation input cannot be treated like any other input to the industrial firm's business activities that are transacted via market mechanisms (West, 2009; Chesbrough, 2006c). This contrasts the transaction cost economics (TCE) theory[9] that is regularly applied to investigate inter-organizational transactions and to decide upon the appropriate governance structure (for details on transaction cost theory see Jones, Hesterly & Borgatti, 1997; Williamson, 1987).

3.2.1.3 Co-opetitive Game Theory and Complementary Assets

The review of existing empirical work on open and collaborative innovation reveals that relationships matter and that value is conjointly created with actors that are outside the firm's

[9] Basically, TCE suggests that firms should choose for their economic exchange "arm-length" transactions (markets), hierarchy or hybrid forms (e.g. alliances, joint ventures, etc.) in order to minimize the costs of economic transactions and to cope with the threat of opportunistic behaviour (Williamson, 1987).

boundaries. Collaborative innovation strategies create value via long-term relationships rather than one-time transactions. Thus, open innovation is similar to the “value constellation” concept (Norman & Ramirez, 1993): Firms do not just add value but they co-produce value with different economic actors via non-arm length relationships and transactions (Vanhaverbeke & Cloodt, 2006). In addition, this perspective links open innovation to co-opetitive game theory and the concept of “co-opetition” (Nalebuff & Brandenburger, 1996). In co-opetition collaborating actors create value because they combine different skills, resources and competencies. But the value that is jointly created has also to be divided. This is the fundamental duality in co-opetition and in open innovation where value creation is an inherently cooperative process, and value capturing is inherently competitive (Nalebuff & Brandenburger, 1996). Thus, value creation in open innovation depends on the *relationships* and *ties* of the actors in the network. Unlike in traditional competitive strategies, in co-opetition and also in open innovation the value creation and value capturing are *interlinked*. The quality of the collaboration among players determines what “piece of the pie” they can claim.

Building upon and *extending* the ValueNet concept of Brandenburger and Nalebuff (1996), open innovation builds upon *relationships* with different types of economic actors (see Figure 16). Firms can establish linkages with suppliers, customers, individual consumers but also complementary actors offering access to *complementary assets* (Teece, 1986) such as sales channels, logistics and manufacturing processes (Chesbrough, 2006b; Vanhaverbeke & Cloodt, 2006). As discussed in chapter 2.2.3.2, SMEs regularly rely on these complementary assets in order to succeed in commercializing an innovation (see Christensen et al., 2005).

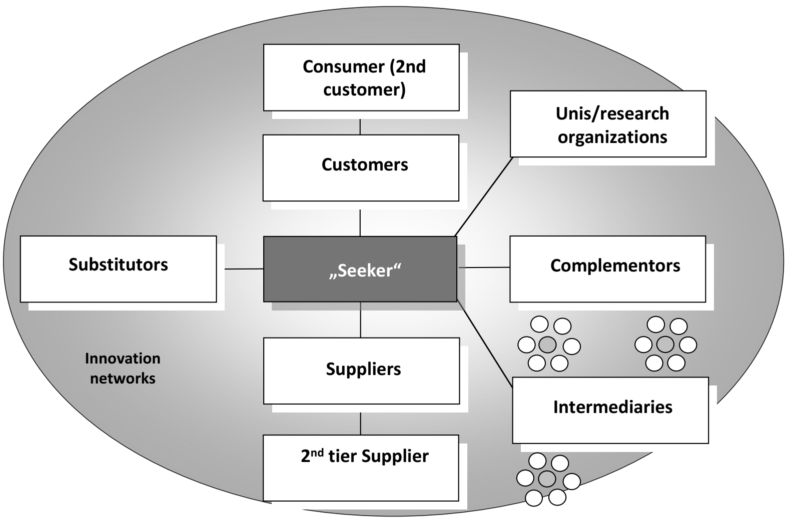

Figure 16: The Extended Value Net (see Brandenburger and Nalebuf,f, 1996)

Complementary assets are generic, specialized or co-specialized – in the sense of Teece (1986). Generic assets are general purpose assets which do not need to be tailored to the innovation of the "focal" firm in the value constellation. Specialized assets are those for which there is a unilateral dependency; co-specialized assets are those for which there is a bilateral dependence. For instance, specialized repair facilities were needed to support the introduction of the rotary engine by Madza (Teece, 1986). In open innovation, complementary assets are usually *specialized* or *co-specialized*.

3.2.1.4 The Resource-based/Capability-based View of the Firm

Open and collaborative innovation strategies can also draw upon a recent extension of the *resource-based view* of the firm, namely the *relational-based view* of the firm (Dyer et al., 1998). The highly influential *resource-based view* of the firm contends that the firm consists of a bundle of resources defined as factors that are owned and controlled by the firm. It stresses that the firm's internal resources as a source of a firm's sustainable competitive advantage. It has been a dominating theoretical concept since the 1960s to explain a firm's performance and determinants of strategic choice (Barney, 1991b; Conner & Prahalad, 1996; Kor & Mahoney, 2004; Penrose, 1959; Penrose, 1997). A firm's resources – including tangible ones such as plants, equipment, natural resources, raw materials, finished goods, and intangible ones – that are *controlled* by the firm are usually classified as physical resources (1), human resources (2) and organizational resources (3) (Barney, Wright & Ketchen, 2001). The basic premise of this view is that heterogeneous resources are idiosyncratic, difficult to transfer or copy, and in turn can be a source of sustainable competitive advantage (Barney et al., 2001; Wiklund et al., 2009). In other words, those resources and competencies that are *controlled* within the single boundaries of the firm offer the possibility to create and capture value according to unique bundles of resources they possess (Dyer et al., 1998). This strong view is mitigated by the *relational-based view* of the firm which argues that firm resources may span firm boundaries and may be embedded in inter-firm resources and routines. It highlights the importance of "network resources" such as strategic (quasi-hierarchical) inter-organizational relationships (Dyer et al., 1998). Dyer and Singh (1998) point out that bilateral-dyadic or network relationships offer a relational rent, and thus, a supernormal profit jointly generated in an exchange relationship that cannot be generated by either firm in isolation (Dyer et al., 1998).

3.2.1.5 Evolutionary-based Innovation Theory and Industrial Dynamics

Empirical research on open innovation indicates that IP and appropriability strategies are elementary dimensions of openness (Henkel, 2006; West & Gallagher, 2006). Appropriation is linked to neo-Schumpeterian and evolutionary-based theories of innovation (Arrow, 1962; Dosi, Malerba, Ramello & Silva, 2006; Levin, Klevorick, Nelson & Winter, 1987; Nelson & Winter, 1977; Teece, 1986; Winter, 2006). Authors such as Arrow (1967), Nelson (1997) and Teece

(1986) published highly influential work on the "appropriation problem" (Winter, 2006). They flag the failure of the canonical neoclassical model in appreciation the specifics of information and knowledge. According to Arrow (1967) information, that is codified knowledge, is a public good. Once it exists in a codified form, it can be copied and reproduced by others at little costs (Arrow, 1962; Hurmelinna-Laukkanen, Kyläheiko & Jauhiainen, 2007). Following the evolutionary-based models of the firm, the *appropriability regime* is considered as an important boundary condition of a firm's innovation performance. It influences a firm's incentives to invest in innovation; at the same time it determines a firm's ability to capture the profit from innovation activities (Hurmelinna-Laukkanen et al., 2007; Vega-Jurado, Gutiérrez-Garcia, Fernández-de-Lucio & Majarrés-Henríquez, 2008; Laursen & Salter, 2005; Levin et al., 1987; Teece, 1986; Vega-Jurado et al., 2008). The *appropriability regime* is defined by the *strengths of legal protection mechanism* and the nature of knowledge (Hurmelinna-Laukkanen et al., 2007; Teece, 1986). Knowledge is regularly classified as either tacit or codified (Kogut & Metiu, 2008; Teece, 1986; Teece, 2008b; Teece, 2008a).

Following the idea of evolutionary-based innovation models, environmental *dynamism* constitutes another important boundary condition of innovation (Eisenhardt & Martin, 2000; Thornhill, 2006). From an industry dynamics perspective, a particular technology regime describes the dynamics and the changes of the innovation processes as a technology moves from early embryonic stage into maturity (Castellacci, 2003; Castellacci, 2008; Nelson & Winter, 1977; Nelson et al., 1982; Utterback, 2006). In a given sectoral system, innovation activities are bounded by the industry specific paradigms and development paths (Christensen & Rosenbloom, 1995; Pavitt, 1984). The dynamism of a specific sector, meaning the uncertainty and turbulence in market and industry conditions, confines whether individual firms can benefit from innovation and appropriate value (Jacobides, Knudsen & Augier, 2006; Malerba, 2002; Utterback, 2006).

3.2.2 The Model for Examining Causal Effects and Causal Moderation

Building upon previous chapters, this section introduces the model for empirically examining the causal effects of open and collaborative innovation on a firm's innovation performance (see Figure 17). It is anchored in theoretical perspectives that were introduced in chapter 3.2.1. The framework allows measuring the direct effect of open and collaborative innovation strategies (I) subsuming innovation search (I-A) and co-development relationships (I-B) on a firm's innovation performance and value growth (II). It captures the efficacy of intellectual property rights and industry clockspeed (III) as moderating variables. The model advances prior research on innovation search significantly as it captures different types of search strategies and complements search strategies with measures on relational network that are crucial for innovation-based value creation. In addition, it considers boundary conditions of openness.

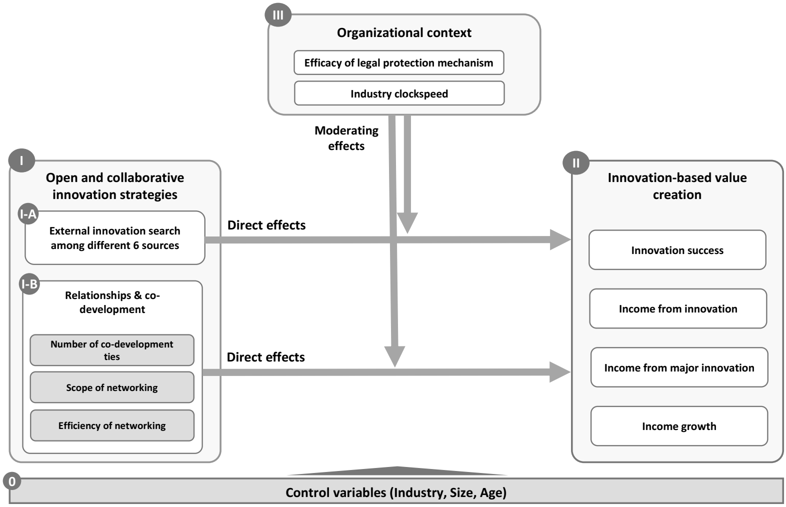

Figure 17: The Model for Examining Causal Effects of Openness and Causal Moderation

3.2.2.1 Conceptualizing Innovation Performance and Innovation-based Value Creation

As discussed in previous chapters, measuring innovation performance and value creation is challenging but crucial to support managerial decisions. As shown in Figure 18, the causal model conceptualizes innovation-based value creation as a multidimensional phenomenon. It includes *multiple measures for success* and *performance*, which makes it possible to measure the effect and impact of open and collaborative strategies on firm performance. This allows the transformation of results of causal effect analyses into management prescriptions (Tidd, 2001).
A multidimensional measurement concept advances existing empirical research that regularly relies on either input measures such as R&D expenditures, number of patents, or purely self reported performance measures (Andrew & Sirkin, 2004; Andrew, Haanaes, Michael, Sirkin & Taylor A, 2007; Andrew et al., 2008; Chandler & Hanks, 1993; Davila et al., 2005; Ernst, 2002; Hauschildt, 1991; Tidd, 2001).
The launch of an innovation captures an important event of a firm's innovation activities and represents the end of a process of problem solving, learning, and knowledge transformation (Hansen & Birkinshaw Julian, 2007; Katila, 2002; OECD/European Communities, 2005; Roper et al., 2008). The *innovation success* reflects a firm's ability to launch and commercialize innovations (Tidd, 2001; Tidd & Bessant, 2009).
A firm's *income from innovations* provides important information on the economic impact of new products and services on a firm's performance (OECD/European Communities, 2005) Capturing both incremental innovations and major innovations provides insight into how different types of external search and collaboration strategies lead to explorative or exploitative

innovation outcomes in financial terms. Incremental innovations are significantly different from major innovations. Major product or service innovations imply a discontinuous change and offer significantly new performance features to existing or new customers (O'Connor, 2008), while incremental innovations advance the process of change (OECD/European Communities, 2005). Major innovations seem to offer the greatest opportunity for performance difference and the establishment of a competitive advantage. However, the changes of success are low and it usually takes more time that investments in major innovations materialize (Schumpeter, 1912; Tushman & O' Reilly, 1996).

A firm's overall *value growth* measures a firm's value creation. For SMEs, *income growth* is considered as a crucial measure of a firm's financial performance and value creation (Almus & Nerlinger, 1999; Baum et al., 2000; Coad & Rao, 2008; Czarnitzki & Kraft, 2002; Roper, 1999; Spicer, Sadler-Smith E. & Chaston I., 2001; Szerb & Ulbert, 2004; Wiklund & Shepherd, 2005). A value growth measure offers the opportunity to investigate and quantify the effect of open and collaborative innovation strategies on a firm's value creation. This clarifies and empirically manifests whether open innovation is a new strategy to profit from and create value from innovation (Chesbrough, 2006d, Vanhaverbeke, 2006).

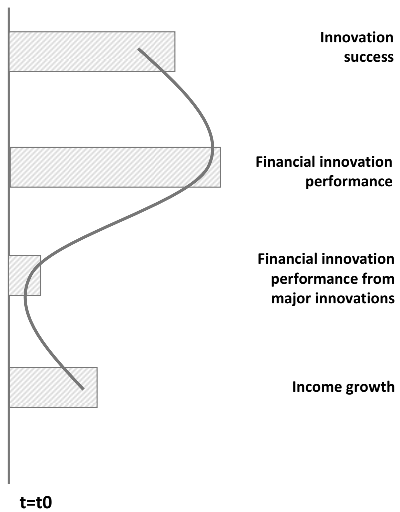

Figure 18: Example of a Firm's Performance Posture

3.2.2.2 Conceptualizing Open and Collaborative Innovation Strategies

As depicted in Figure 19, the conceptualization of open and collaborative innovation strategies combines external innovation search and network relationships. External innovation search is a means to access external innovation inputs from different knowledge domains by interaction with different innovation actors. Network relationships complement external *innovation search* and capture how a firm creates joint value with partners that complement a firm's innovation activities (Vanhaverbeke, 2006; Norman & Ramirez, 1993). *Networking and co-development strategies* create value via long-term relationships rather than one-time transactions. This makes it possible to investigate how a firm can *actively leverage* openness for innovation-based value creation. External innovation search and networking strategy are bounded by industry dynamism and a firm's appropriability regime, which may influence the possibility to appropriate value.

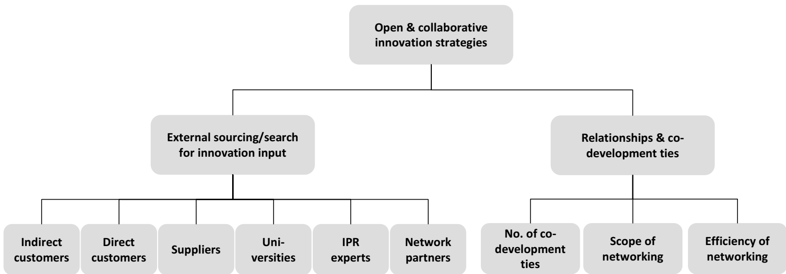

Figure 19: Conceptualization of Open and Collaborative Innovation Strategies

In the following, the model is elaborated and causal relationships are detailed. To overcome shortcomings of existing research causal relationships are transformed into quantitative hypotheses with reference to relevant theories (see chapter 3.2) and empirical studies in these respective theoretical domains.

3.2.3 Multidimensional External Search for Innovation Input and Causal Effects

External innovation search can span a range of different functions and knowledge domains (Katila, 2002; Laursen & Salter, 2006; Li et al., 2008; Sidhu et al., 2004; von Hippel, 1988). Firms can establish linkages with different actors of the value network in order to search for ideas, knowledge and information (codified knowledge), such as direct customers, indirect customers, suppliers, complementary network partners and scientific actors (Fabrizio, 2006; Nalebuff & Brandenburger, 1996; Vanhaverbeke, 2006). As put forward in theories on problem solving, the rate of "discovery" of new ideas that are of commercial value is a function of the pool, and, most importantly, the intensity and direction of search (Levitt & March, 1988). Following these theoretical perspectives, the conceptualization emphasizes the distinctiveness of each type of actor and innovation search channel. External innovation search involves *direct interaction with* external actors rather than passive search along knowledge trajectories

(Reichwald & Piller, 2008; von Hippel, 1986; von Hippel, 2005). Each search channel embraces distinct institutional norms, habits, rules, organizational practices and innovation inputs (Brown & Duguid, 1998). The interaction with each type of innovation partner is different in terms of the commercial of the innovation input and the accessibility.

3.2.3.1 External Innovation Search and Direct and Indirect Customers

The way to customer-centric innovation was paved by the shift from a manufacturing-active to customer-active innovation paradigm (Foss, Laursen & Pedersen, 2007; Rosenberg & Rosenberg, 1982; von Hippel, 1986; von Hippel, 1988). Searching for new ideas among *direct* and *indirect customers* (customers of the direct customers) goes beyond the widely discussed "customer orientation". Firms that directly interact with customers not only harness the "voice-of-the-customer" via traditional market research but interact with customers to access and acquire innovation relevant knowledge and information. In turn, the customer turns from a "value receiver" to a "value generator". Existing literature claims that interaction with customers increases the "fit-to-market" and helps firms to better understand how they can create value for the customer (Bilgram, Brem & Voigt, 2008; Hamel, 2000; Reichwald & Piller, 2006, von Hippel, 1986). One major benefit of direct interaction with customers is the access to "*sticky information"* on user needs, user context and user experience, which is tacit and difficult to articulate (Reichwald & Piller, 2008; von Hippel & von Krogh, 2006). The involvement of "indirect" customers/users (e.g. the car drivers rather than car manufacturers for automotive suppliers) may provide new insights in new business opportunities beyond existing markets (Enkel, Kausch & Gassmann, 2005). In general, customer needs are very idiosyncratic. Their innovation potential may be bounded to their previous experiences – manifesting the concept of bounded rationality; in turn, customers might concentrate on improvements of products and services they are familiar with (von Hippel, 1986; Simon, 1959). When working with "normal customers", this so called functional fixedness tends to prevent innovations that offer a totally new value proposition (von Hippel, 1986). Thus, customer inputs may be biased towards existing markets, restricting the SME to explore new business opportunities and create breakthrough innovations.

Hypothesis 1a: Search for innovation input of customers (both direct and indirect one) has a positive impact on innovation success and income from innovation

3.2.3.2 External Innovation Search and Suppliers

Traditionally, supplier management practices built on "arm-length" governance models and focus on outsourcing and cost reduction (Dyer et al., 1998). The major objective of the arm-length model was to reduce dependency from suppliers. Recently, suppliers have been identified as an important innovation partner that should be actively involved when searching for new ideas (Enkel & Gassmann, 2007). This implies that supplier interaction that goes beyond traditional contract-based supplier management (Dyer & Nobeoka, 2000). Prior research indicates that firms can benefit from the specialized (usually technological) expertise of suppliers if they involve them in new product development. They can provide ideas for improved technological solutions or process innovations (Tsai, 2009). Usually, the involvement of suppliers is to do with technological application rather than technology development (Johnsen, Phillips, Caldwell & Lewis, 2006). Thus, ideas are usually rather exploitative and close to the technological trajectory of the firm's industry rather than explorative. Suppliers concentrate on solutions and commercial value in the short-term (Chesbrough & Prencipe, 2008; Dyer et al., 1998). Their ideas might help SMEs to positively impact their success in launching innovations. However, Tsai (2009) showed that supplier collaboration does not necessarily affect a firm's innovation performance (Tsai, 2009). Managing relationships with suppliers for innovation purposes is challenging. It requires firms to motivate suppliers, to prevent them from free-riding, and to manage the risk of hostile moves (Dyer et al., 1998). The "limitations of smallness" make this quite difficult for SMEs.

Hypothesis 1b: Search for innovation input of suppliers has a positive impact on innovation success

3.2.3.3 External Innovation Search and Universities/Research Organizations

Recently, industrial firms have started to take a more "active" position to involve the scientific community and have recognized that industry-university collaboration is an important "learning relationship" (Harryson & Lorange, 2005; Harryson et al., 2008; Leydesdorff & Meyer, 2006). Small and mostly high-tech firms are often perceived as an important vehicle to commercialize ideas from universities (Fabrizio, 2006; Laursen & Salter, 2004; Harryson et al., 2008).

Both *universities and research organizations* are an important source for inventive and pre-industrial knowledge as science may significantly alter the search for inventions (Fabrizio, 2006; Fleming & Sorenson, 2004; Shinn & Lamy, 2006; Tsai, 2009). Scientific knowledge may lead to explorative search rather than local and exploitative search. Theoretical understanding of the underlying properties of technological components may facilitate effective search (Fleming & Sorenson, 2004). Universities and research organizations can support the development of new technological knowledge, and the search for breakthrough ideas (Spithoven et al., 2009). There is first empirical evidence that firms that are connected to external scientists and researchers experience greater *efficiency* when searching for new inventions. University linkages also offer more timely access to inventive trends (Fabrizio, 2009). However, there are a range of barriers to innovation search in university-industry relationships, such as lack of resources, cultural differences, long-term oriented scientific research versus exploitation oriented research of industrial organizations, incompatible rewards systems with focus on publishing versus "protecting" results, and risk related to obtaining control over university inventions via IP rights (Harryson et al., 2008). Appropriating the financial value from ideas of research partners is usually not feasible in the short-term or mid-term because SMEs need to build up internal knowledge (Fabrizio, 2006; Spithoven et al., 2009).

Hypothesis 1c: Search for innovation input of universities has a negative impact on innovation-based value creation

3.2.3.4 External Innovation Search and IPR Experts

In an open innovation context, intermediaries play a direct role in innovation in itself (Arora, Fosfuri & Gambardella, 2001; Chesbrough, 2006c; Gans & Stern, 2002; Sousa, 2008). New service providers ranging from online market places to idea scouts and patent brokers facilitate search for external innovation inputs (Nambisan & Sawhney, 2007). In SME markets, "traditional" intermediate service providers such as technology transfer and knowledge brokering services support the search for external knowledge (Bennett & Robson, 2005; Santamaría, Nieto & Barge-Gil, 2009). Experts on intellectual property rights (IPR) may provide crucial information services that help to bridge the gap between a technology opportunity and its successful commercialization (Bessant & Rush, 1995). They may support search for technological trends and ideas outside the firm's boundary services; they may also provide ideas on how to appropriate value from a firm's knowledge assets (Bader, 2006; Bessant & Rush, 1995; Bessant, 1999; Bennett & Robson, 2005; Turok & Rako, 2000; Vega-Jurado et al., 2008). If legal IP protection matters, SMEs usually have to rely on external IPR experts as they can hardly handle the complex rules and regulations of patent protection. Engaging with IPR experts is costly; it requires a firm to invest financial resources and time. Interaction with IPR experts may make it more difficult to quickly move an idea to the commercialization stage. However, if SMEs involve IPR experts, it indicates their strong interest to protect their (mostly technological) knowledge assets, to develop ideas on how to appropriate returns from them, or to use external R&D (Hurmelinna-Laukkanen et al., 2007; Jauhiainen & Hurmelinna-Laukkanen, 2008). They may also learn how they can transform their idea into a value proposition without competing in the product market but cooperating with established firms through the market for ideas (Chesbrough, 2003a; Gans & Stern, 2002).

Hypothesis 1d: Search for innovation input of IPR experts has a positive effect on income from innovation

3.2.3.5 External Innovation Search and Network Partners

Network relationships also offer an important means to mutual learning which is not just internal but relates to the types of relationships a firm has established with other organizational actors. If firms have established network relationships, there is usually a mutual understanding among partners (Dittrich et al., 2007; Harryson, 2008; Vanhaverbeke et al., 2002). This may ease the generation of new ideas and their absorption. In addition, n*etwork and co-development partners* offer SMEs access to complementary innovation assets and also operational complementary assets such as manufacturing, marketing and access channels (Christensen et al., 2005; van de Meer, 2007; Teece, 1986; Teece, 2006; Vanhaverbeke & Cloodt, 2006). As a result, ideas created in a collaborative innovation setting, might be exploited more easily as access to complementary assets (both innovation and operational assets) can be considered already in the early phases. Complementarities of assets and knowledge of network partners may facilitate the generation of new valuable ideas and their absorption. The involvement of network partners may positively influence both innovation efficiency and financial performance.

Hypothesis 1e: Search for innovation input of network partners has a positive effect on innovation success and income from innovation

3.2.4 Dual Involvement of External Innovation Sources and Interaction Effects

Firms can establish linkages with different actors to access different types of knowledge domains (Katila, 2002; Katila & Ahuja, 2002; Laursen & Salter, 2006; Li et al., 2008; Sidhu et al., 2004; von Hippel, 1988). Each search channel is distinct and relates to different types of search domains (Brown & Duguid, 1998). The combination of different search channels and "cross-functional" learning may provide access to different but complementary information; thus, it may enhance a firm's exploration and exploitation activities (Sidhu et al., 2004). However, there is also some risk in involving different types of actors at the same time (Li et al., 2008). For example, if there is dual search both among network partners and scientific knowledge among universities, extensive learning about new solution principles and market-functions is required. Involving network partners at this stage might be extremely challenging and costly. Network partners cause a risk of contractual hazard (Gans & Stern, 2002). In a similar manner, dual involvement of both complementary network partners and customers may increase the risk of contractual hazard. In contrast, dual consideration and involvement of scientific and market actors may spur the innovation process. Johnsen et al. (2006) showed that there is a positive effect if SMEs involve academic partners and customers simultaneously to better understand application areas and market functions of newly generated knowledge (Johnsen et al., 2006).

Hypothesis 2a: Dual involvement of two different external innovation sources will show a significant effect on innovation performance and value growth

Hypothesis 2b: Dual involvement of science and network partners might have a negative effect of innovation performance and value creation

Hypothesis 2c: Dual involvement of customers and complementary network partners might have a negative effect of innovation performance

Hypothesis 2d: Dual involvement of universities and consumers might have a positive effect on a firm's innovation performance and value creation

3.2.5 Innovation Relationships, Networking and Causal Effects

Of course, knowledge doesn't really flow – it tends to be sticky (von Hippel, 1986). Case studies on open innovation practices point out that firm's relationships are a constituting dimension of openness (Fey & Birkinshaw, 2005; p. 600-601; Vanhaverbeke & Cloodt, 2006; van de Vrande et al., 2009). This evidence confirms the relevance of theoretical perspectives that stress inter-organizational relationships such as "value constellations", the relational view of the firm, and social network theory (Granovetter, 1973; Nalebuff & Brandenburger, 1996; Norman & Ramirez, 1993). There are three variables that constitute a firm's innovation relationships: The number of co-development ties, the scope of collaborative partnerships, and the efficiency of the network relationships.

3.2.5.1 Number of Co-development Ties

Social network and alliance theory suggests that firms can establish different types of ties that shape their networking strategy: Strong versus weak, and formal versus informal ties (Granovetter, 1973; Uzzi, 1997). Strong ties subsume intensive knowledge and resource exchange (Granovetter, 1973; Dittrich et al., 2007; Harryson et al., 2008; Vanhaverbeke et al., 2002). Research on networks and alliances provides evidence that a large number of relational ties - and especially strong ones - impacts firm performance (Baum et al., 2000; 2005). This is in line with the relational-based view of the firm that highlights the relevance of a firm's relationships that offer relational rents (Dyer et al., 1998). A well-established portfolio of partnerships embeds critical resources and can offer a competitive advantage; especially to SMEs network relationships are crucial (Barney et al., 2001; Grant, 1996; Wiklund et al., 2009). Network relationships influence their capabilities as well as others' perception of their capabilities as they are sending favourable signals to the market. In his quantitative study among

Biotech start-ups, Baum (2000) showed that the size of the alliance network at founding has a positive effect on performance and growth of small firms. The partner network alleviates the liabilities of "smallness" because the knowledge and resources of the SMEs' partners may compensate their lacking experience and power (Baum et al., 2000). Following the concept of value constellations and "complementary assets" (Nalebuff & Brandenburger, 1996; Teece, 1986; Vanhaverbeke, 2006), innovation partners provide access to innovation assets (such as R&D assets). Thus, the number of co-development partnerships may positively affect a firm's innovation-based value creation.

Hypothesis 3a: A large number of co-development ties may have a positive effect on a firm's innovation performance and value creation

The relational view of the firm suggests that the size of co-development partnerships has a positive effect on firm's innovation performance. However, at some stage maintaining these relationships requires too much effort and attention. Following the problem solving and attention based perspective of the firm, managers need to concentrate their energy, effort and mindfulness on a limited number of issues (Simon, 1959). Consequently, a poor allocation of attention and resources may lead to too many co-development activities. This is specifically true for SMEs that suffer from the liability of smallness (Brüderl & Schüssler, 1990; Brüderl, Preisendörfer & Ziegler, 1996).

Hypothesis 3b: There is an inverted U-shaped relationship between the size of the co-development ties and a firm's innovation performance

3.2.5.2 Scope (and Depth) of Networking

Firms may leverage co-development partnerships either in the early or the latter phases of the innovation value chain, or in both phases (Dittrich & Duysters, 2007; Harryson, 2008; Vanhaverbeke & Cloodt, 2006). Recent case studies among Dutch SMEs, for example, show that partnerships are crucial at various stages of the innovation value chain (Christensen et al., 2005; van de Meer, 2007). Network and alliance theory suggest that if firms engage deeply with external partners there will be more intensive mutual exchange of knowledge, assets and resources (Bullinger, Auerhammer & Gomeringer, 2004; Dittrich & Duysters, 2007; Enkel & Gassmann, 2005; Granovetter, 1973; Harryson, 2008; Laursen & Salter, 2006; Vanhaverbeke et al., 2002). Long-term relationships create a mutual understanding that facilitates successful collaboration (2005). As a result, the managerial distance (not necessarily the technological distance) might be reduced (Nooteboom, 1999; 2005). This spurs learning and allows more effective and efficient knowledge transformation. At the same time the transfer of know-how and innovative ideas among SMEs and co-development partners is fraught with ambiguity. Long-term cooperative innovation arrangements may have negative implications, locking firms into unproductive processes where know-how and other resources are wasted (Walter, Ritter & Riesenhuber, 2007). Thus, a wide scope and depth of co-development partnerships might have a positive impact on innovation success rather than on innovation-based value creation.

Hypothesis 3c: The scope of co-development partnerships has a positive effect on a firm's innovation success

3.2.5.3 Efficiency of Networking

SMEs regularly rely on a range of network relationships but not all of them are about collaborative innovation. For example, there are network partners that are important for operational activities such as marketing, sales or production (Becker, Knackstedt & Pfeiffer, 2008; Nalebuff & Brandenburger, 1996; Norman & Ramirez, 1993; Teece, 1986). These partnerships may provide access to complementary operational assets already in the development phase of an innovation (Teece, 1986; Vanhaverbeke & Cloodt, 2006). In his case study research Christensen et al. (2005) showed that even in an early stage of the switch-amplifier technology, successful innovations required not only the alignment of three complementary innovation assets: science-based assets, high-tech product design assets, and lead-user assets, *but also* usual operational types of complementary assets such as manufacturing, distribution and marketing. To succeed in innovation and create value SMEs need to establish relationships to access complementary innovation assets *and* other social, technical and commercial assets that would usually take several years of operational experience to acquire (Christensen et al., 2005). Network theory and alliance research suggests that the efficiency of a firm's networking strategy influence firm performance (Baum et al., 2000; Burt, 2000; George, Zahra, Wheatley & Khan, 2001). If SMEs leverage their operational partner relationships as co-development partner, they can exploit synergies. This may positively affect their innovation performance.

Hypothesis 3d: The efficiency of networking has a positive effect on a firm's innovation performance

3.2.6 Appropriability Regime, Industry Clockspeed and Moderating Effects

As pointed out above, a firm's external environment may constitute a contingency factor of a firm's open innovation strategy. The appropriability regime, and specifically the IP protection scheme, is one factor that might constrain how firms open up to external influences and whether openness affects performance. In addition, industry dynamism is a second relevant factor that is considered as a boundary condition.

3.2.6.1 Moderating Effect of the Legal IP Protection Scheme

As discussed in chapter 2.2.3 external search and more intense co-development activities imply that firms reveal some knowledge to outsiders. Especially, if firms collaborate deeply – e.g. in conjoint development projects – there will be intensive exchange of knowledge, mutual dependency and reciprocity (Dittrich & Duysters, 2007; Granovetter, 1973). However, this results in a conflict with a firm's objective to appropriate returns from an innovation (Henkel, 2006; Hurmelinna-Laukkanen et al., 2007; Levin et al., 1987; Teece, 1986; West & Gallagher, 2006). The *strength of legal IP protection mechanism* (efficacy) is one constituting variable of the appropriability regime (Hurmelinna-Laukkanen et al., 2007; Teece, 1986). The appropriability regime influences the ability to capture profit from innovation (Vega-Jurado et al., 2008; Laursen & Salter, 2005; Levin et al., 1987; Teece, 1986; Vega-Jurado et al., 2008).

When searching for new ideas among different actors, the relevance of the strengths of the legal protection scheme is prevalent. In case of strong IP schemes, SMEs might be facilitated in external search as it elicits outsiders to participate (Chesbrough, 2003a; Graham & Mowery, 2006; Lakhani & Panetta, 2007). In case of a weak IP protection scheme, the tacitness of internal technical competencies can actually strengthen the appropriability conditions (Hurmelinna-Laukkanen, Sainio & Jauhiainen, 2008; Hurmelinna-Laukkanen et al., 2007). Prior research suggests that IP protection hinders the involvement of scientific partners due to incompatible reward systems among science and research versus industry (Fleming & Sorenson, 2004; Harryson, 2008).

However, the IP protection scheme interplays with the need to access complementary assets and to align with other players in the value chain (Christensen et al., 2005; Gans & Stern, 2002; Teece, 1986). The ability to appropriate returns from innovation depends on two factors of the appropriation environment: The appropriation regime and control over complementary assets. Thus, the value of the innovation might be smaller if the appropriability scheme is weak and when specialized complementary assets are controlled by other larger players (Teece, 1986). Referring to co-opetitive game theory, Gans and Stern (2003) are particularly concerned with the problem of contractual hazard that occurs when firms engage with owners of complementary assets. That is, even if the IP protection scheme is strong, small firms face the paradox of disclosure (Arrow, 1962) and the problem of strong bargaining power (Gans & Stern, 2002).

Hypothesis 4: The strengths of the IP protection scheme has a moderating effect on the relationship of open and collaborative innovation strategies and innovation-based value creation

Hypothesis 4a: The effect of involving universities or research organizations is negatively moderated by the strengths of the IP protection scheme

Hypothesis 4b: The effect of efficient networking strategies is negatively moderated by the strengths of the IP protection scheme

3.2.6.2 Moderating Effect of Dynamism and Industry Clockspeed

Dynamism also characterizes a firm's innovation environment. Dynamism refers to the degree of uncertainty and turbulences in market and industry conditions. It is related to the rate of change in two dimensions: product-markets and technologies (Damanpour & Wischnevsky, 2006; Eisenhardt & Martin, 2000; Tidd, 2001; Thornhill, 2006; Utterback, 2006). The industry clockspeed might also moderate the effect of external search and collaboration (Eisenhardt & Martin, 2000; Fine, 1999; Malecki, 1981; O'Connor, Ravichandran & Robeson, 2008). It represents an environmental moderator that constitutes how firms search – exploratory or exploitative (Jansen, van den Bosch & Volberda, 2005) and also whether they can realize the potential performance impact to be gained from open styles of innovation (Jacobides et al., 2006; Robinson, 1998). In line with Teece (1986), access to complementary assets might be even more critical if product lifecycles are short (Teece, 1986).

Hypothesis 5: Industry clockspeed has a moderating effect on the relationship of open innovation strategies and innovation-based value creation

3.3 The Internal Perspective: Modelling Organizational Practices for Innovation and Causal Mediation

The following chapter presents the model for measuring mediating and complementary effects. It takes an internal perspective.

3.3.1 Theoretical and Conceptual Grounding

A firm's *absorptive capacity* has been an influencing concept describing a firm's ability to absorb external knowledge (Caloghirou et al., 2004; Cohen & Levinthal, 1990; Lenox & King, 2004; Todorova & Durisin, 2007); especially technological ones. However, the antecedent role of internal organizational practices and routines is regularly neglected (Cohen & Levinthal, 1990). In addition, research on organizational practices and routines abstracts from the question whether organizational routines for innovation such as formal innovation controlling, performance measurement and stage-gate systems positively influence a firm's external idea sourcing and absorption. The review of existing quantitative empirical research revealed that existing models, concepts and measures for organization-wide innovation routines are fragmented, show conceptual weaknesses and lack empirical validity (see chapter 2.3.3). It also highlights the organizational pervasiveness of managerial practices and the need to link such practices with the concept of absorptive capacity. To ensure a sound modelling of organizational innovation routines, relevant theoretical and conceptual perspectives are discussed in the following. First, the most recent conceptualization of absorptive capacity is presented to link internal innovation routines to different components of absorptive capacity. Afterwards, organizational practices are reflected from those theoretical perspectives that guided the modelling of causal effects (see chapter 3.2.1. and Figure 20).

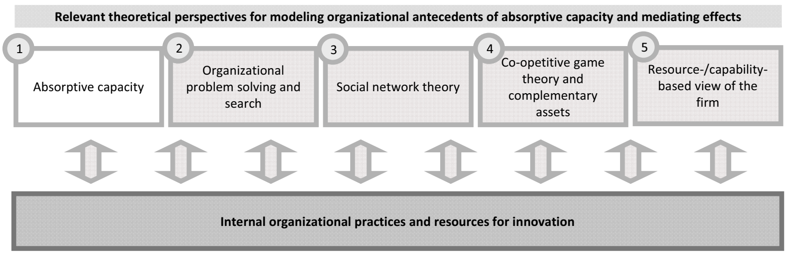

Figure 20: Relevant Theoretical Perspectives for Modelling Causal Mediation

3.3.1.1 Absorptive Capacity and its Major Components

Internal organizational practices for innovation relate to different dimensions of *absorptive capacity*. Thus, it is worthwhile to recap on the key components of this construct. Following the most recent and most in-depth re-conceptualization of Todorova and Durisin (2007) there are four major components with a clear temporal dimension (see Figure 21): "Recognition of the value", "Acquisition", "Transformation" or "Assimilation", and "Exploitation" (Todorova & Durisin, 2007). The authors re-emphasize the importance of the first component "recognition of the value" of external knowledge. While acquisition mainly directs attention to intensity, speed, and effort, the ability to learn and identify new knowledge depends to a great extent on the ability to value it (Todorova & Durisin, 2007). The use of insights from system dynamics strengthens the modelling of absorptive capacity (Todorova & Durisin, 2007).

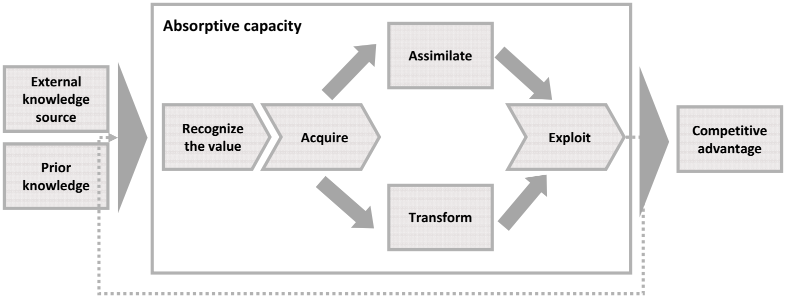

Figure 21: Major Dimensions of Absorptive Capacity based on Todovora (2007)

Internal organizational antecedents of absorptive capacity cannot be neglected (see Cohen & Levinthal, 1990; p. 131). The conceptualization of organization-wide innovation practices can be enriched by four additional theoretical perspectives (see Figure 20)

3.3.1.2 *Innovation Routines in Organizational Problem Solving*

Learning and problem solving thinking support the conceptualization of open and collaborative innovation strategies (see chapter 521H3.2). At the same time, they help to better understand the idea of internal managerial practices for innovation. Schumpeter (1912) already noted that organizations require well defined routines and managerial practices for the support and direction of their innovation efforts (see Schumpeter, 1912; Pavitt, 2002). This is in line with the definition of innovation management introduced in chapter 2.1.1.3 (see also Adams et al., 2006; Hauschildt, 2004). The notion of "routines" was first coined by Nelson and Winter (1982) as part of a more realistic interpretation of what managers actually do in a messy and changing world (Nelson et al., 1982; Pavitt, 2002). Innovation routines must accomplish managerial tasks in the corporate innovation system (Pavitt, 2002). The fundamental uncertainty surrounding innovation activity is uncertainty about its results but there may also be strong patterns of a highly predictable nature in the activity (Nelson et al., 1982; p. 132). Thus, Nelson and Winter (1982) emphasize routines and heuristics in organizational learning processes and proposed to assimilate to the concept of routine all of the patterning of organizational activity that the observance of heuristics produces, including the patterning of particular ways of attempting to innovate (Nelson et al., 1982).

Theoretical discussions on exploration and exploitation in organizational problem solving suggest that increased routinization and coordination in an organization's activities may drive innovation, especially incremental innovations which are perceived as exploitative in nature (Benner, 2007; March, 1991). However, there is a controversy whether organizational routines can foster exploration and major innovation (Benner, 2007). Following Nelson and Winter (1982) essential managerial tasks in innovation can be achieved through a variety and combination of routines, some of which may be formal, and others organizationally embedded (Nelson et al., 1982; Pavitt, 2002: 119). This highlights the relevance of both *formal* and *"embedded"* coordination mechanism such as culture.

3.3.1.3 Co-opetitive Game Theory and Organizational Innovation Practices

Co-opetitive game theory and value constellations are crucial for strategy making (see chapter 3.2.1.3). At the first sight this might not be relevant when taking an "inward perspective" of open innovation. However, a thorough understanding of "how value is created" in a firm's value networks is required when searching for external innovation inputs. A firm's strategy processes guide managerial actions when searching for external innovations (Nalebuff & Brandenburger, 1996). Thus, co-opetitive game theory indirectly influences the conceptualization of managerial practices for innovation. It emphasizes internal routines that help to "recognize the value" of external innovation inputs, such as strategy making.

3.3.1.4 Social Network Theory and Internal Knowledge Transformation Processes

Network theory and the concept of social capital explain how internal knowledge transformation and coordination mechanism influence a firm's innovation performance and value creation (Brown & Duguid, 2006; Brown & Duguid, 1998; Uzzi, 1997). Following the social network perspective social integration mechanisms build connectedness and shared meaning. Thus, they support all processes of knowledge absorption including knowledge transformation and assimilation (Todorova & Durisin, 2007). Both strong and weak types of intra-organizational ties characterize internal innovation practices, shape embedded practices, and may also influence a firm's value innovation performance (Granovetter, 1973; Granovetter, 2005). At the same time, they relate to all components of absorptive capacity.

3.3.1.5 The Resource-based/Capability-based View of the Firm

As discussed above, the resource-based view of the firm emphasizes internal resources. It stresses that resources *controlled* by the firm are the main source of a competitive advantage and sustainable organizational performance (Barney, 1991a; Birchall & Tovstiga, 2005; Brown & Eisenhardt, 1995; Galanakis, 2006; Goffin & Mitchell, 2005; Tidd, 2001; Vega-Jurado et al., 2008; Wiklund & Shepherd, 2005). The *capability/competency-based view* (these terms are usually used interchangeable) and the knowledge-based view expands the static view of resources and stresses the relevance of intangible and "implicit" assets as a source of competitive advantage (Grant, 1996; Leonard-Barton, 1992). The knowledge-based and capability-based view stresses that organizational capabilities as a source of competitive advantage depend more on *integrative mechanism such as routines* and other formal and informal coordinating mechanisms rather than specialized knowledge of employees (Grant, 1996; Birchall & Tovstiga, 2005). From an internal view, the *dynamic capability perspective* is another important extension of the resource-based theory (Eisenhardt & Martin, 2000; Wiklund et al., 2009). Dynamic capabilities refer to ‘‘the firm’s processes that use resources - specifically the processes to integrate, reconfigure, gain and release resources - to match and even create market change’’ (Eisenhardt & Martin, 2000, p. 1107; Teece, Pisano & Shuen, 1997). They can be defined as a “second-order” or higher level capability that enables a firm for strategic renewal and innovation. Despite the idiosyncratic nature of dynamic capabilities, Eisenhart (2000) claims that specific dynamic capabilities – such as the new product development processes – exhibit common features that are associated with effective processes across firms (Eisenhardt & Martin, 2000). Although there is some ambiguity in the terminology of capabilities and competencies, there is consensus that these capabilities result *from actions of (senior) managers* to ensure learning, integration, and, when required, reconfiguration and transformation—all aimed at sensing and seizing new opportunities as markets and technologies evolve. It indicates that *organization-wide managerial routines and practices* to adapt, integrate and reconfigure a firm’s resources are more important than the specialized knowledge base of the firm (O'Reilly & Tushman, 2004; Westkämper & Dunker, 2004). Following Teece et al. (1997) there are three types of internal organizational processes that constitute a firm’s “meta-capabilities”: coordination and integration (a rather static concept), reconfiguration (a transformational concept); and learning (a dynamic concept). They can be further detailed in s*trategic coordination, operative coordination, culture* and *learning* (Teece et al., 1997).

3.3.2 Modelling Internal Managerial Practices for Innovation as Mediators of Open and Collaborative Innovation Strategies

The review of existing research and relevant theoretical perspectives clearly indicates that internal innovation practices range from embedded and informal practices through to formal practices (Pavitt, 2002; Teece et al., 1997). In addition, theory suggests that innovation practice include coordination, re-configuration and learning practices (Teece et al., 1997). Following the discussion on dynamic capabilities, it can be distinguished between: strategic coordination, operative coordination, culture and learning practices. They constitute a firm’s meta-processes to adapt over time.

Most importantly, the discussion on the construct absorptive capacity suggests that organizational practices need to be linked to the respective components of a firm’s absorptive capacity (see Figure 22).

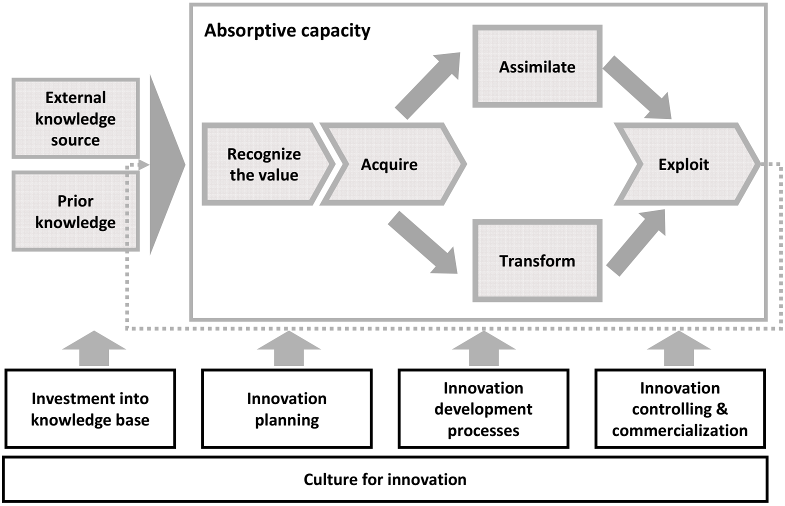

Figure 22: Relation of a Firm's Managerial Practices for Innovation and Absorptive Capacity

As a result, the following major dimensions of internal innovation practices are conceptualized: Investment into the internal knowledge base (1), innovation planning (2), innovation development processes (3), innovation controlling (4) and culture for innovation (5). These components represent the most important innovation practices taking place along the innovation chain (see chapter 2.1.2).

The causal mediation is captured as *generative mechanism* that is between the relationship of independent and dependent variables. The causal model depicted in Figure 23 provides the basis for empirically examining the interplay of open and collaborative innovation strategies, internal innovation practices and innovation-based value creation.

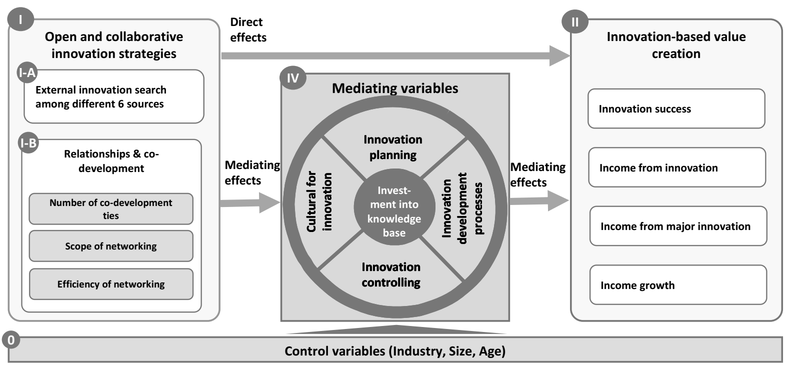

Figure 23: Causal Model of Mediating and Complementary Effects

In the following the extended causal effect model is elaborated in more detail. Both the direct effects and mediating are theoretically discussed. The theoretical perspectives and concepts introduced are guiding the discussion.

3.3.3 Internal Innovation Practices and their Interplay with Openness in Explaining Innovation-based Value Creation

3.3.3.1 Innovation Planning

A strong vision for innovation and an innovation strategy is the backbone of innovation at the firm level. A strategic approach towards innovation implies that innovation is explicitly anchored in the corporate vision and strategy (Abell, 1980; Adams et al., 2006; Burgelman, Maidique, Christensen & Wheelwright, 2004; Hauschildt, 2004; Pfeiffer, 1971; Porter, 1996). An innovation strategy drives the identification of future business opportunities and the exploration of new technologies, solution principles or market functions (Adams et al., 2006; March, 1991). Following the knowledge-based view of the firm, innovation strategies aim to enhance, extend, and complement firms' competencies and technological knowledge-bases. In turn, innovation strategy defines how a firm can better leverage its internal competencies to develop a new product or service (Grant, 1996). They also have to identify the value of new external information and knowledge ranging from new customer needs to new technological developments (Cohen & Levinthal, 1990; Nelson & Winter, 1977; Todorova & Durisin, 2007). The actual strategy process is more complex and requires strategic coordination and reconfiguration (Teece et al., 1997). Formal routines for identifying future business opportunities and mapping it with internal competencies and capabilities are essential for innovation strategy making (Adams et al., 2006; Goffin & Mitchell, 2005; Mintzberg, 1991; Mintzberg, Quinn & Ghoshal, 1995; Pfeiffer, 1971; Wong et al., 2007). Semi-procedural mechanisms and routines for innovation planning and ideation are argued to support a firm in both exploration and exploitation of new opportunities (Bessant et al., 2009; Bullinger & Engel, 2006; Goffin & Mitchell, 2005; Tidd, 2001). In summary, it can be assumed that innovation planning has a positive impact on a firm's innovation performance. At the same time, it may also mediate the impact of open innovation strategies.

Hypothesis 6a: Innovation planning positively effects innovation-based value creation and mediates the effect of openness

3.3.3.2 Innovation Development Processes

Formal systems and procedures for new product development have become fashionable; the benefits of systematic processes have been well documented in NPD research (Brown & Eisenhardt, 1995; Bullinger & Engel, 2006; Cooper & Kleinschmidt, 1987; Cooper, 2008).

Managerial systems such as the stage-gate model are rooted in engineering disciplines. In turn, they best support the development of new products and processes (Cooper, 2008; Ernst, 2002; Schewe, 1994). Formal systems and processes for service and business model innovations are equally important (Christensen, Johnson & Kagermann, 2009). Managerial systems are "social technologies" that support managers to coordinate and integrate the development of innovations in a structured manner (Christiansen & Varnes, 2009). They guide decisions and goal-oriented actions (Benner & Tushman, 2002; Cooper, 2008; van de Meer, 2007). From an innovation problem solving perspective, innovation routines enable the management of complexity and uncertainty of innovation activities (March, 1991; Nelson & Winter, 1977). Development routines correspond to the second dimension of absorptive capacity. They are organizational antecedents to assimilate and transform new knowledge (Todorova & Durisin, 2007). Opening the innovation processes increases the complexity of problem solving activities in the innovation system; thus, it makes the coordination of activities more difficult (Baldwin & Clark, 2005; Fuller & Moran, 2001; Maula, Keil & Salmenkaita, 2006). Just like absorptive capacity helps to assimilate technological knowledge, support development processes the coordination of external and internal innovation activities.

Hypothesis 6b: Innovation development processes positively effects innovation-based value creation and mediates the effect of openness

3.3.3.3 Innovation Controlling

Ideas need to be turned into valuable outcomes such as new products, processes, services, or new business models (Tidd & Bessant, 2009). To exploit innovation potential firms need to measure and manage innovation projects and processes in an *efficient* and goal-oriented manner (Adams et al., 2006; March, 1991). NPD Research claims that clearly defined measures and targets for timing, resources and quality are essential (Brown & Eisenhardt, 1995; Ernst, 2002; Hauschildt, 2004; Schewe, 1994). Indeed, managing time and resources is one of the most critical tasks in managing innovation projects as previous research has shown that not meeting the time-to-market can have a negative impact on profits (Goffin & Mitchell, 2005). Measuring performance is specifically important when launching and commercializing individual innovations (Adams et al., 2006; Bullinger & Engel, 2006). However, it is one of the most challenging managerial tasks (Andrew et al., 2007; Chiesa et al., 1996; Hauschildt, 2004). Following the idea of process management, routine-like communication, regular review of strengths and weaknesses, and regular interaction of different disciplines involved throughout the innovation value chain, help to improve the efficiency, speed, and the ability to reconfigure activities (Benner, 2007; Goffin & Mitchell, 2005; Westkämper & Alting, 2000). Controlling is both the final and (through a feedback loop) the first stage of the management cycle (Ritter & Gemünden, 2003). Thus, it fosters continuous learning (Simon, 1959; Teece et al., 1997).

Formal systems for project management, controlling and learning routines are "heuristics" that may affect innovation performance (Teece et al., 1997; Wong et al., 2007). Innovation controlling may act as organizational antecedent to the fourth dimension of absorptive capacity (to "exploit") and helps to turn external and internal knowledge into value (Todorova & Durisin, 2007).

Hypothesis 6c: Innovation controlling positively influences innovation-based value creation and mediates the effect of openness

3.3.3.4 Culture for Innovation

In addition to formal practices, culturally embedded practices direct activities of individuals of an organization, and ensure that managerial tasks for innovation are executed (Nelson et al., 1982; Pavitt, 2002). From a dynamic capability perspective, culture can be a governance system mediating on the individuals' behaviour without relying on more administrative methods (Eisenhardt & Martin, 2000; Teece et al., 1997). Culture influences managerial decision throughout the innovation process (Ernst & Kohn, 2007; Ernst, 2002; van de Meer, 2007; Wong et al., 2007). At an organizational level an innovation culture embodies a strong reputation for "being" innovative (Goffin & Mitchell, 2005) serving as an asset that can create a competitive advantage (Baum et al., 2000; Teece et al., 1997). Similar to the "adhocracy culture", a culture for innovation implies and emphasizes freedom to try out "new things" (Amabile & Khaire, 2008; Ernst, 2002). If such openness for new ideas is inherited in values, beliefs and assumptions, culture fosters the exploration of new knowledge (Anderson & West, 1996). At the same time, entrepreneurial spirit and risk taking characterize a culture for innovation. It enables the exploitation of new ideas and directs individuals' activities in order to turn ideas into commercial value (Schumpeter, 1912). From a temporal perspective, a culture for innovation is linked to both the early and the later components of absorptive capacity (Todorova & Durisin, 2007), and thus, it may mediate the effect of openness.

Hypothesis 6d: Culture for innovation positively affects innovation-based value creation and mediates the effect of openness

3.3.3.5 Investment into Knowledge Base

From a resource-based view, financial innovation assets are crucial assets as they provide resource slacks. They offer the opportunity to experiment and engage in more risky innovation projects; thus, they may create a competitive advantage (Barney, 1991a; Teece et al., 1997; Wiklund et al., 2009). Following the idea of organizational slack and strategy as resource-endowment, investment into the knowledge base may directly positively influence innovation performance. A firm's investment into the future gives a rough idea about its internal learning activities and aspiration to explore (Cohen & Levinthal, 1990; Laursen & Salter, 2006). Organizational learning theory argues that learning is path dependent. Thus, a firm's prior investments into innovation provide an indication of its prior knowledge building activities. Cohen and Levinthal (1990) argue that a firm's prior knowledge (technological knowledge) eases the identification of the value of external knowledge. Thus, financial innovation assets and investments are argued to be antecedents of absorptive capacity. They enable firms to create value from openness (Cohen & Levinthal, 1990; Laursen & Salter, 2006; Todorova & Durisin, 2007; Zahra & George, 2002).

Hypothesis 6e: Investment into knowledge base positively affects innovation-based value creation and mediates the effect of openness

4 Multivariate Statistical Modelling, Measures and Data Collection

In the previous chapters a theoretically grounded causal framework was modelled conceptualizing multivariate causal relationships of open innovation strategies and innovation-based value creation; it considers both external contingency factors and internal innovation practices as mediators. The framework details causal relationships via directional and quantitative hypotheses. Thus, the conceptual framework provides the basis for the statistical modelling and empirical inference of causal effects. As indicated in chapter 1.4.3, causal effect analysis and measurement is the most valuable but also the most challenging scientific activity; especially when dealing with complex problems such as a firm's economic performance and value creation (Greene, 2000; Tidd, 2001). Multivariate statistical methodologies and techniques make it possible to quantitatively investigate effects of independent constructs and variables on dependent variables. However, an appropriate specification of the statistical model and the selection of the appropriate statistical technique is a prerequisite of a successful causal effect analysis. The following chapters discuss multivariate statistical modelling for examining causal effects and performance prediction. They will pay attention to complex regression models that deal with two specific types of dependent variables that are relevant in this research, namely limited dependent and ordinal variable. These types of variables have to be dealt with in order to operationalize the causal framework via regression models. Finally, measures, data collection and data validation issues are discussed.[10]

4.1 Causal Relationships Analysis and Multivariate Regression Modelling

Multivariate regression analysis subsumes statistical techniques for simultaneously modelling and analyzing multiple measurements on objects under investigation, when the focus is on examining the *relationship* between a single dependent variable and several independent (predictor) variables (Backhaus, Erichson, Pinke, Weiber, Rolf, Plinke & Weiber, 2008; Hair, 1998).

4.1.1 Characteristics of Multivariate Regression Modelling

The use of multivariate regressions exposes the *relative importance* of the various determinants of firm performance and allows predictions to be made. Multivariate regression allows

[10] For a detailed introduction into multivariate statistical analysis, it is referred to fundamental literature, such as e.g. Backhaus, Erichson, Pinke, Weiber, Rolf, Plinke & Weiber (2008); Greene (2004); Hair (1998); Hair (2010); Maddala (1990); Wooldridge (2002)

investigating the effect of several independent variables simultaneously and estimating the effect of each single variable on the dependent measure, holding all other variables fixed. The goal of empirical multivariate regression analysis is to determine whether a change in one variable, say x_i causes a change in the dependent variable y_i. Following the idea of probability, the notion of “ceteris paribus” – that is, holding all other relevant factors fixed – is at the crux establishing a causal relationship (Wooldridge, 2002).

Multivariate regression models build upon regression functions that describe a *statistical relationship* of independent variables and a dependent variable and not a *deterministic* one (Greene, 2000; Hair, 1998). The generic form of a multivariate regression model is:

$$y_i = f\left(x_{i1}, x_{i2}, \ldots . x_{iK}\right) + \varepsilon_i ; i = 1, \ldots ., N$$

Statistical regression models cater for the randomness in economic and social life and include a random disturbance. The underlying functional relationship is an approximate. The term ε_i is a random disturbance, so named because it “disturbs” otherwise stable relationships (Greene, 2000; Long, 1997). The goal of multivariate regression modelling is to find the best fitting and most parsimonious, yet conceptually reasonable model to describe the relationship between an outcome and a set of independent variables (Hosmer & Lemeshow, 1989). Regression analysis has a range of advantages to other statistical techniques such as correlation analysis. The fact that one event follows another or two factors co-vary does not mean that they cause each other (de Vaus, 2001; Hair, 1998).

4.1.2 Specification of Regression Models and Regression Techniques

The ability of regression techniques to expose the mechanisms or business processes by which individual factors influence business performance, however, depends on the regression modelling approach adopted (Greene, 2000; Hair, 1998; Urban & Mayerl, 2008). On the one hand, the statistical regression models should be in line with the conceptual framework (This regularly results in a model dilemma as the statistical regression model is only a simplified representation of the theoretical model). On the other hand, the statistical model should conform to the characteristics of the empirical data.

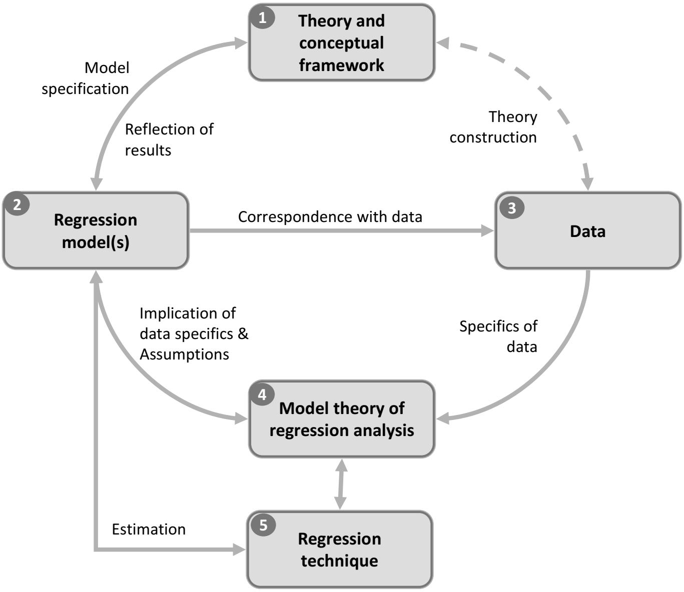

Figure 24: Specifics of Multivariate Regression Modelling (see Urban & Mayerl, 2008)

As shown in Figure 24, the interdependence of the conceptual framework (1), the regression models (2), model theory of regression analysis (3), the characteristics of the data (4), and regression techniques (5) are considered in the detailing of the regression model and the selection of the statistical regression technique. A theoretically grounded conceptual model and directional hypotheses (1, see Figure 26) provide the basis for sound regression modelling (see chapter 3). Limits of empirical data require theory construction. The regression models (2, see Figure 26) are derived from the conceptual framework and the direction hypotheses and specify the variables and measures. In addition, the regression models correspond with the empirical data and the sample (3 in Figure 26; see also chapter 4.7.). To select the appropriate regression technique, this research draws upon model theory of regression analysis (4, in Figure 26); it takes into account the specifics of the empirical database and considers the implication on the regression model. This allows selecting the appropriate regression technique (5). After the estimation of the regression model (link 5 to 2 in Figure 26), the assumptions of the regression model are investigated ensuring that solid causal inferences are drawn (link 4 to 2 in Figure 26). In a final step, the results of the estimated regression model are evaluated and reflected in the lights of the conceptual model and its directional hypotheses (Creswell, 2009; Hair, 1998; Urban & Mayerl, 2008).

4.2 Linear Regression Models and Ordinary Least Square Estimation

The classical *linear regression model* is a widely used statistical regression model (Hair, 1998; Long, 1997). Here, the underlying functional relationship is linear. For a sample N of random observations, the regression model is defined as following:

$$y_i = f(x_{i1,} x_{i2,} ....x_{iK}) + \in_i = \beta_0 + \beta_1 x_1 + ...\beta_K x_{iK} + \varepsilon_i;\ i = 1,...N$$

Where y_i is the dependent variable, x_i are independent variables, and ε_i is a stochastic error. Both the dependent and the independent variable are metric in nature. The subscript *i* is the observation number from N random observations. βi through β_k are parameters - so called regression coefficients - that indicate the effect of a given x on y. β_0 is the intercept (Hair, 1998; Long, 1997). The set of weighted independent variables forms the regression variate, a linear combination of the independent variable that best predicts the dependent variable (Hair, 1998). In matrix notation this can be written for all observations as following:

$\mathbf{y} = \mathbf{X\beta} + \boldsymbol{\varepsilon}$; where

$$\mathbf{y} = \begin{pmatrix} y_1 \\ . \\ . \\ y_N \end{pmatrix}; \mathbf{X} = \begin{pmatrix} 1 & x_{11} & . & x_{1K} \\ . & . & . & . \\ . & . & . & . \\ 1 & x_{N1} & . & x_{NK} \end{pmatrix}; \boldsymbol{\beta} = \begin{pmatrix} \beta_0 \\ \beta_1 \\ . \\ \beta_k \end{pmatrix}; \boldsymbol{\varepsilon} = \begin{pmatrix} \varepsilon_1 \\ . \\ . \\ \varepsilon_N \end{pmatrix}$$

If one defines $\mathbf{x}_i$ as the *i*-ths row of $\mathbf{X}$, the regression model for each individual y_i can be written as following:

$$y_i = \mathbf{x_i \beta} + \varepsilon_i$$

4.2.1.1 Assumptions of Multivariate Linear Regression Models

Multivariate linear regression models build upon five major assumptions (Backhaus et al., 2008; Greene, 2000; Hair, 1998; Long, 1997). To make a causal claim and to ensure sound statistical inferences, these assumptions need to be thoroughly inspected once the regression model is estimated:

- *Linearity:*

One assumption is that y is linearly related to $\mathrm{x_i}$ through the regression coefficients β . However, the modelling of non-linear relationships between the x and y is possible through the inclusion of transformed variables (see below in chapter 4.4).

- *Multicollinearity:*

A second major assumption is that the variables x_i are linearly independent. This implies that none of the variables x_i is a linear combination of the remaining variables x_i (Mathematically, the matrix **X** requires a full rank). If there is linear dependency, there is the problem of *multicollinearity*. *Multicollinearity* has a negative impact on the goodness of the fit of the model. Yet in most situations, some degree of multicollinearity is unavoidable. For example, when including moderating and interaction effects (see chapter 4.4).

- *Zero Condition Mean of* $\boldsymbol{\varepsilon}$:

The statistical error $\boldsymbol{\varepsilon}$ can be thought of as an intrinsically random unobservable influence on the dependent variable. One basic assumption of the linear regression model is that the conditional expectation of the error is 0; formally,

$$E(\varepsilon_i | \mathbf{x_i}) =, \text{ for all } i.$$

This implies that for a given set of values for the variables x_i, the error is expected to be 0. The assumption implies that the conditional expectation of y given x is a linear combination of the variables x_i :

$$E(y_i | \mathbf{x_i}) = E(\mathbf{x_i}\boldsymbol{\beta} + \varepsilon_i | x_i) = \mathbf{x_i}\boldsymbol{\beta} + E(\varepsilon_i | \mathbf{x_i}) = \mathbf{x_i}\mathbf{b}$$

- *Homoskedastic and Uncorrelated Errors:*

In linear regression models, the errors are assumed to be homoskedastic, which means that for a given **x**, the errors have a *constant* variance. Formally,

$$\mathrm{Var}(\varepsilon_i | \mathbf{x_i}) = \sigma^2, \text{ for all } i.$$

If the variance differs across the observations, the errors are heteroskedastic. The errors are also assumed to be uncorrelated across observations, so that for two observations *i* and *j*, the covariance between ε_i and ε_j is 0. Heteroskedasticity may arise in numerous applications, in both cross-section and time-series data (Wooldridge, 2002). It is well known that the presence of heteroskedasticity in the disturbance leads to consistent but inefficient estimates and a inconsistent covariance matrix. To overcome this problem of heteroskedasticity, econometric literature suggests a more robust covariance matrix estimator which is consistent in the presence of heteroskedasticity (White, 1980).

- *Normality:*

A final important assumption of the linear regression model is that error terms are normally distributed when conditioned on the variables x_i. The violation of this assumption negatively influences the fit of the estimation. For example, a kernel density test helps to identify whether the errors are normally distributed or not (Cox, 2).

4.2.1.2 Least Square Estimation Method and the Gauss-Markov Theorem

The *method of least squares* is used to estimate the statistical relationship and fit the estimated values with the observed values. In turn, it is regularly referred to as ordinal least squares regressions (or OLS regressions). The best fit in the least squares sense minimises the sum of the squared residuals (the difference between an observed and the value provided by the model). The *Gauss-Markov Theorem* states that in the classical linear regression model, the least squares estimator b is the best linear unbiased estimator (BLUE) of ß (Backhaus et al., 2008; Greene, 2000; Hair, 1998). The *Roa-Blackwell Theorem* states that in the classical regression model with normally distributed disturbances, the least squares estimator ß has the minimum variance of all unbiased estimators (Greene, 2000). Overall, the least squares estimation is a powerful technique that produces an estimator with desirable statistical properties in many cases (Greene, 2000).

4.2.1.3 Misfit of Ordinary Least Square Estimation for Limited Dependent Variables

In a range of situations, the class of linear unbiased estimators becomes a bit restrictive. For example, if the dependent variable is binary, ordinal, nominal, count, truncated or censored, the OLS estimation is regularly not appropriate (Greene, 2000; Long, 1997; Maddala, 1990). For example, Long (1997) provides a range of examples, describing the misfit of OLS regression models for binary or ordinal dependent variables (Long, 1997). More complex regression models are required to deal with the specifics of such dependent variables that may cause a violation of assumptions of multivariate linear regression models (Long, 1997; Maddala, 1990). A detailed discussion of state-of-the art of multivariate regression modelling for more complex regression problems is beyond the scope of this research. However, the dependent variables used in this research are censored and ordinal, and thus, required estimation techniques are addressed in chapter 4.3.

4.2.1.4 Goodness of Fit and Statistical Inference

A well-fitting regression model results in predicted values close to the observed values. In this research, the most commonly used measure of accuracy (goodness of fit) for regression models is used; the so called *coefficient of determination (R^2)*. It investigates how well the regression line fit to the data and indicates whether and how well the model explains movements in the dependent variables (Greene, 2000; Hair, 1998). Calculated as the squared correlation between the real and predicted values of the dependent variable, it represents the combined effect of the entire variate (several independent variables plus intercept) in explaining the dependent variable.

$$R^2 = \frac{\left[\sum_i (y_i - \bar{y})(\hat{y}_i - \bar{y}\right]^2}{\left[\sum_i (y_i - \bar{y})^2\right]\left[\sum_i (\hat{y}_i - \bar{y})^2\right]}$$

This measure can be used to assess one individual regression model; but it also allows measuring the improvement made when more independent variables are added. Indeed, in this research a high R² is less relevant as the causal relationships between different independent variables and the dependent variable are in focus. It is more important to understand which factors have a significant effect or improve the accuracy of the model rather than the overall fit of the model. No one would expect that a firm's openness or internal practices for managing innovation can fully predict firm performance.

Statistical tests are required to test the accuracy and reliability of the model. They are a pre-requisite to infer statistically sound causal relationships. In multivariate regression modelling such statistical tests take two basic forms: Testing *of the overall model* (coefficient of determination) and testing of the statistical significance of *each regression coefficient*. In this research, the latter is even more important.

An F-test is executed to test whether the variation explained by the regression model is higher than the baseline prediction. The F-test evaluates the null hypothesis that all regression coefficients are equal to zero versus the alternative that at least one does not. An equivalent null hypothesis is that R² equals zero.

$$H_o = \beta_1 = \beta_2 = \ldots.\beta_K = 0$$

A significant F-test indicates that the observed R-squared is reliable, and is not a spurious result of oddities in the data set. Thus, the F-test examines the overall significance of the model and determines whether the proposed relationship between the response variable and the set of predictors is statistically reliable (For further details please see Greene, 2000). Formally, the F-Ratio value can be written as following:

$$F = \frac{\left(\boldsymbol{\beta}'\mathbf{X}'\mathbf{y} - \mathbf{N}\bar{\mathbf{y}}'\right) / K - 1}{\mathbf{y}'\mathbf{y} - \boldsymbol{\beta}\mathbf{X}'\mathbf{y} / N - K}$$

It is also important to investigate the significance of each individual coefficient. A t-test is applied to test the significance of each individual coefficient; it investigates whether there is a significant relationship between the individual independent variable and the dependent variable. The t-test evaluates the null hypothesis that the coefficient equals zero versus the alternative hypothesis that the coefficient is unequal to zero. For one individual coefficient, this can be written as following:

$H_o : \beta_1 = 0; H_1 : \beta_1 \neq 0$

(details on t-statistics are discussed in Backhaus et al., 2008; Hair, 2010; Long, 1997; Urban & Mayerl, 2008). If the t-test results are significant, the null hypothesis can be denied.
For both the F-test and the t-test, conventional standards of statistical significance are applied to decline the null hypotheses for each individual coefficient. Three significance levels are considered: p<0.1; p<0.05 and p<0.01 (Urban & Mayerl, 2008).

4.3 Regression Models for Censored and Ordinal Variables

Roughly, a limited dependent variable is a variable whose range is restricted in some important way or is categorical in nature. Variables that are limited to their range because of some underlying stochastic choice mechanism require more complex regression models and estimation methods (Long, 1997; Maddala, 1990). As regression models in this research consider the specifics of censored and ordinal dependent variables, model theory and regression techniques addressing the specifics of these variables are discussed in the following chapters.

4.3.1 Censored Data and Regression Modelling

Tobit regression models allow estimating causal effects in case of censored data and corner solution outcomes. The following chapters introduce specifics of such regressions and discuss assumptions, goodness of fit and statistical inference.

4.3.1.1 The Problem of Data Censoring and Specification of Tobit Models

C*ensored dependent variables* describe situations when the variable to be explained is partly continuous but has positive probabilities mass at one more points. For example, the variable innovation performance that is usually measured as share of new products (or services) of total revenue is partly continuous but has positive probability mass at the point “zero” (no income from innovation) (Wooldridge, 2002). It is worth pointing out that *censored samples* are particularly different from *truncated samples* (see Table 2*)*: In case of the truncated regression model, one does not have any observations on either the explained variable or the independent variables if the variable is above (or below) a threshold. In case of the censored regression model, one has data for the independent variable for all observations. As for the explained variable, one actually has observations for some, but for the others it is only known whether or not they are above (or below) a certain threshold. This is the situation considered by Tobin (Greene, 2000; Maddala, 1990; Tobin, 1958).

Table 2: Differences between Censored and Truncated Samples (Maddala, 1990)

Sample	Dependent variable	Independent variable
Censored	Dependent variable y is *known exactly* only if some criterion defined in terms of the value of y is met, such as y> τ	Independent variable x values are observed for all of the sample, regardless of whether y is known exactly
Truncated	Dependent variable y is *observed* only if some criterion defined in terms of the value of y is met, such as y> τ	Independent variables are observed only if y is observed

If a distribution is censored on the left, observations with values at or below τ are set to τ_y (most often they are equal zero).

$$y_i = \begin{cases} y_i* & \text{if } y_i* > \tau \\ \tau_y & \text{if } y_i* \leq \tau \end{cases}$$

If y* is normal, then the probability of an observation being censored is

Pr (Censored) = $\Pr(y* \leq \tau) = \Phi(\frac{\tau - \mu}{\sigma})$

And the probability not being censored is

Pr (Uncensored) = $1 - \Phi\left(\frac{\mu - \tau}{\sigma}\right) = \Phi\left(\frac{\tau - \mu}{\sigma}\right)$

Tobin (1958) devised what became known as the tobit (Tobin's probit) or censored normal regression for situations in which y is observed for values greater than 0 but is not observed (*censored*) for values of zero or less (Tobin, 1958). The standard tobit model is a latent model and is defined as:

$$y_i = \begin{cases} y_i* = \mathbf{x_i \beta} + \varepsilon_i & if\ y_i* > 0 \\ 0 & if\ y_i* \leq 0 \end{cases}$$

The initial discussion of the tobit model focused on problems such as households purchases for durable goods (Tobin, 1958). For example, if one has survey data on consumer expenditures, you may find that most households report zero expenditure on automobiles or major household goods during one year. Thus, there will be a lot of observations concentrated around zero. It is regularly argued that there is a latent variable y_i^* that cannot be observed and constitutes threshold expenditures (e.g. the price for the cheapest car) (Maddala, 1990; Tobin, 1958). As pointed out by Wooldrige (2002) applications of censored regression modelling fall in *two categories*: In true censoring, there is a quantitative variable y_i^*. If this variable were observed for everyone in the population, one could apply OLS. However, data censoring arises in that y_i^* is censored from above and/or below. Data censoring is not the only application of censored regression modelling. In addition, there are kinds of response variables that are called *corner solution outcomes*. To describe the situation of corner solution, let y_i be an observable choice or outcome describing economic agents, an individual or a firm, with the following characteristics: y_i takes on the value zero with positive probability but is a continuous random variable over strictly positive values. When imagining economic agents solving optimization problem, for some agents the *zero* would be an optimal choice (Wooldridge, 2002). That is, it is not just data observability that is the issue. As shown in the following chapters, this research deals with corner solution outcomes.

In the typical tobit model, censoring relates to the value “zero”. In a more general sense, y_i^* is a latent variable that is observed for values greater than τ and censored otherwise. The tobit model can also be generalized to take into account censoring both from above and/or below (Maddala, 1990). Assuming that the disturbance is distributed normally, the probability of being censored in the tobit model is:

$$\Pr(Censored|x_i) = \Phi(\frac{\tau - \mathbf{x}_i\boldsymbol{\beta}}{\sigma}) = \Phi(-\delta_i)$$

$$\Pr(Uncensored|x_i) = \Phi(\frac{\mathbf{x}_i\boldsymbol{\beta} - \tau}{\sigma}) = \Phi(\delta_i)$$

Here, the standard notation for the probability distribution function (pdf) and cumulative probability distribution (cdf) functions of the normal distribution $N(\mu,\sigma^2)$ is used (ϕ is the pdf, Φ is the cdf).

4.3.1.2 Estimation of Tobit Regression Models

Authors such as Maddala (1990) or Wooldrige (2002) show that OLS using the entire sample or OLS using the subsample for which y> 0 are both (generally) inconsistent estimators if the dependent variable is censored (Greene, 2000; Maddala, 1990; Wooldridge, 2002). It will yield a downwards-biased estimate of the slope coefficient and an upwards-biased estimate of the intercept. To estimate the tobit model, the maximum likelihood estimation technique offers an alternative (Greene, 2000; Tobin, 1958; Wooldridge, 2002). The log likelihood equation for uncensored observation can be written as:

$$\ln L_u(\beta,\sigma^2) = \sum_{Uncensored} \ln \frac{1}{\sigma}\phi\left(\frac{y_i - \mathbf{x}\boldsymbol{\beta}}{\sigma}\right)$$

For censored observations, one can compute:

$$\ln L_C(\beta,\sigma^2) = \sum_{Censored} \ln \Phi\left(\frac{\tau - \mathbf{x}\boldsymbol{\beta}}{\sigma}\right)$$

Combining the results, the log likelihood for the tobit regression model censored at τ is:

$$\ln L\ (\beta, \sigma^2 \big| \mathbf{y}, \mathbf{X}) = \sum_{Uncensored} \ln \frac{1}{\sigma} \phi\left(\frac{y_i - \mathbf{x\beta}}{\sigma} \right) + \sum_{Censored} \ln \Phi\left(\frac{\tau - \mathbf{x\beta}}{\sigma} \right)$$

The two parts correspond to the classical regression for the non-limited observations and the relevant probabilities for the limited observations, respectively. Estimation is easily carried out in a standard maximum likelihood estimator framework (Greene, 2000; Long, 1997; Wooldridge, 2002). Using the software program STATA allows estimating tobit regression models efficiently. The idea behind maximum likelihood parameter estimation is to determine the parameters that maximize the probability (likelihood) of the sample data. Although the methodology for maximum likelihood estimation is simple, the implementation is mathematically intense. Using today's computer power, however, mathematical complexity is not a big obstacle (for further details on maximum likelihood parameter estimation see Greene, 2000). Takeshi Amemiya (1973) has proven that the likelihood estimator suggested by Tobin for this model is consistent (see Maddala, 1990).

4.3.1.3 Assumptions of the Tobit Regression Model

Assumptions of multivariate linear regression modelling cannot be directly transferred to the tobit regression model (see also Backhaus et al., 2008; Greene, 2000; Hair, 1998; Long, 1997). The tobit model is a non-linear model and estimated with maximum likelihood. There are three assumptions that are relevant for tobit regressions (Brännäs, Kurt & Laitila, 1989; Greene, 2000; Maddala, 1990).

- *Multicollinearity*:

As for OLS regressions, multicollinearity needs to be carefully investigated when estimating tobit regression models. *Multicollinearity* has a negative effect on the models accuracy. Statistical procedures to investigate multicollinearity are different for tobit models. Instead of investigating the variance inflation factor (VIF), the covariance matrix of the regression coefficients is inspected.

- *Homoskedastic and Uncorrelated Errors:*

In tobit regression modelling, the errors are also assumed to be *homoskedastic*. As pointed out above, heteroskedasticity may arise in numerous applications, in both cross-section and time-series data (Greene, 2000; Wooldridge, 2002). If the error terms are heteroskedastic, the maximum likelihood estimator (MLE) is inconsistent (Arabamazar & Schmidt, 1981; Maddala, 1990). Although some authors draw quite pessimistic conclusions, there is evidence that given severity of heteroskedasticity, it causes less inconsistency in the censored model than in the truncated model. Moderate heteroskedasticity does not cause serious inconsistencies (Arabamazar & Schmidt, 1981).

- *Normality:*

As for the linear regression model, the tobit model assumes that error terms are *normally distributed*. The violation of this assumption negatively influences the fit of the estimation; and thus, it needs to be thoroughly inspected. For example, a kernel density tests helps to identify whether the errors are normally distributed or not (Arabamazar & Schmidt, 1981; Cox, 2).

4.3.1.4 Goodness of Fit of the Model and Statistical Inference

As for multivariate linear regression models, the goodness of the model fit needs to be investigated allowing statistical inference to be made. There are hypotheses and statistical tests that can be used with any model estimated with maximum likelihood (Long, 1997). As for linear regression models, both the significance of the overall model and the significance of each coefficient is tested. As discussed above, scalar measure for goodness of fit are widely accepted in OLS regressions; however, they are less applicable and robust in estimations with maximum likelihood (Long, 1997). This can provide only a rough measure of the adequateness of the model.

The basic measure of how well the maximum likelihood estimation fits is the *Log Likelihood Value*, similar to the sum of squares values used in multiple regressions. The Log Likelihood can be used to compare between equations for the change in fit (Backhaus et al., 2008; Hair, 2010). While in linear regression models the *coefficient of determination* R^2 is the standard measure of fit, there is no precise measure of determination in censored regression models. There are scalar measures that are referred to as Pseudo R^2 (Hair, 2010; Long, 1997) to provide a similar scalar measure as for the linear regression model. For example, there is the McFadden Pseudo R^2 that suggests an analogy to explain the variation in the linear regression models. Alternative Pseudo R^2s were suggested by Nagelkerke and Cox-Snell. In this research the Pseudo R^2 by Nagelkerke is reported; it is considered superior to Pseudo R^2 McFadden or Pseudo R^2 Cox-Snell (Long, 1997). In this research, it is more important to understand which factors have a significant effect or improve the accuracy of the model rather than the overall fit of the model. The Pseudo R^2 Nagelkerke allows comparing two models and assessing the change of fit (Long, 1997).

As for OLS regression, statistical tests are required to test the accuracy and reliability of the model. They are a pre-requisite to infer statistically sound causal relationships. To do so, both *the overall significance of the model* and significance of *each regression coefficient is investigated.* The *Likelihood Ratio (LR) Chi-Squared test* allows testing the hypothesis that all regression coefficients are equal to zero versus the alternative that at least one does not. It tests the difference between the full model (with predictors) and the constant only model (Backhaus et al., 2008; Hair, 2010; Long, 1997). Alternative tests may use the Wald statistic (Wooldridge, 2002); however, the LR test has been adopted in this research as suggested in econometric literature (Long, 1997). A *t-test* is applied to test the significance of the effect of *each individual* *coefficient* (Hair, 2010; Backhaus et al., 2008; Long, 1997). The term "effect" refers to a change in an outcome for a change in an independent variable, holding all other variables constant. The t-test evaluates the null hypothesis that the coefficient equals zero versus the alternative hypothesis that the coefficient is unequal to zero. If the t-test results are significant, the null hypothesis can be denied. For both tests, the LR Chi-Squared test and the t-test, common standards and significance levels are applied to falsify the null hypotheses (see discussion on OLS regression).

4.3.2 Ordinal Dependent Variables and Regression Modelling

If a dependent variable is ordinal, its categories can be ranked from low to high but the distance between adjacent categories are unknown. For examples, innovation success can be measured in different categories representing a firm's success in introducing innovations and launching a new product. Often, ordinal dependent variables are treated as if they were interval. However, there are examples that such regressions provide misleading results (Long, 1997). Thus, this research adopts a regression technique catering for the specifics of ordinal data.

4.3.2.1 Specification and Identification of Ordered Logit Models

Ordinal dependent variables and the study of how an ordered response variable depends on a set of regressors (independent variables) have been widely discussed in existing econometric and statistical literature. One way to model such data is to assume that the ordered response is the discrete version of a continuous latent variable for which a linear regression model holds (Hosmer & Lemeshow, 1989; Long, 1997). In general, a latent regression model for ordinal data can be derived by mapping a latent variable y* ranging from - ∞ to + ∞ to an observed variable y. As shown in Figure 25, the latent variable is divided into J intervals that are actually observed.

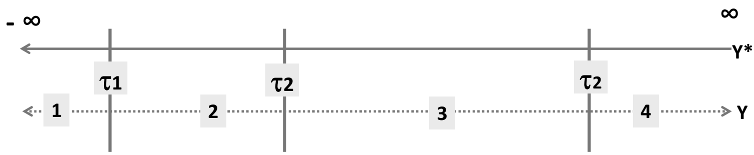

*Figure 25: Mapping of y and Latent Variable y**

The various τ_i -s represent cut points or thresholds and the extreme categories are defined by open-ended intervals with τ_0 =-∞ and τ_J =-∞. Following existing literature, there are different approaches for estimating the ordinal logistic model (Fuks & Salazar, 2008; Long, 1997): Proportional odds (1), partial proportional odds (2) and generalized logit (3). The ordinal logit model – also called proportional odds model (POM) - is the most widely used latent ordinal regression model. It was first discussed in social science in the 1960s (Long, 1997; McCullagh, 1980). In the ordinal logit model the variable y is thought of providing incomplete information about the underlying variable y* according the measurement equation:

$$y_m = m \text{ if } \tau_{m-1} \le y_i^* < \tau_m; for\ m = 1\ to\ J$$

The line of approach of the proportional odds model is to assume that the ordinal data is the discretized version of an underlying continuous variable which depends on a covariate as in a linear regression model, which can be written as following:

$$y_i{*} = \mathbf{x_i}\boldsymbol{\beta} + \varepsilon_i$$

The fundamental assumption in the ordinal logistic model with proportional odds is that the relationship between each pair of groups of the dependent variable is the same, i.e., the coefficients which describe the association between the smaller categories versus the higher ones (or vice-versa) are the same. This assumption is regularly referred to as assumption of "parallel slopes" (Bender & Groueven, 1997; Hosmer & Lemeshow, 1989; Long, 1997).
Under the additional assumption that the disturbance ε has a standard logistic distribution with the cumulative distribution function (cdf)

$$F(t) = \frac{e^{(\varepsilon)}}{1+e^{(\varepsilon)}} = \frac{\exp(\varepsilon)}{1+\exp(\varepsilon)},$$

it follows that the cumulative probability of the outcome being less than or equal than m equals:

$$\Pr(y_i \le m | \mathbf{x_i}) = \Pr(\varepsilon_i \le \tau_m - (\mathbf{x}'\boldsymbol{\beta})) = \frac{\exp(\tau_m - \mathbf{x}'\boldsymbol{\beta})}{1+\exp(\tau_m - \mathbf{x}'\boldsymbol{\beta})}$$

This model is non-linear. Considering the assumption of a logistic distribution of the disturbance the probability that the observed value y is m has a simple equation (Long, 1997):

$$\Pr(y_i = m | \mathbf{x_i}, \boldsymbol{\beta}, \boldsymbol{\tau}) = F(\tau_m - \mathbf{x}'\boldsymbol{\beta}) - F(\tau_{m-1} - \mathbf{x}'\boldsymbol{\beta}) = \exp(\tau_m - \mathbf{x}'\boldsymbol{\beta})$$

A logistic transformation of this non-linear model results in the so called "logit equation":

$$logit\left[\Pr(y_i = m | \mathbf{x_i}, \boldsymbol{\beta}, \boldsymbol{\tau})\right] = \tau_m - \mathbf{x}'\boldsymbol{\beta}$$

The *ordinal logit model* is often interpreted in terms of odds[11] ratio for cumulative probabilities (Long, 1997). The odds that an outcome is m or less versus great than m given x are

$$\Omega_m(\mathbf{x}) = \frac{\Pr(y_i \le m | \mathbf{x_i}, \boldsymbol{\beta}, \boldsymbol{\tau})}{1-\Pr(y_i \le m | \mathbf{x_i}, \boldsymbol{\beta}, \boldsymbol{\tau})} = \frac{\Pr(y_i \le m | \mathbf{x_i}, \boldsymbol{\beta}, \boldsymbol{\tau})}{\Pr(y_i > m | \mathbf{x_i}, \boldsymbol{\beta}, \boldsymbol{\tau})}$$

[11] Odds is a common approach in probability theory for expressing the likelihood that an event occurs (see Long (1997))

For the ordered logit model, the odds have a simple equation:

$$\Omega_m(\mathbf{x}) = \frac{\Pr(y_i \le m \mid \mathbf{x_i}, \boldsymbol{\beta}, \boldsymbol{\tau})}{\Pr(y_i > m \mid \mathbf{x_i}, \boldsymbol{\beta}, \boldsymbol{\tau})} = \exp(\tau_m - \mathbf{x}\boldsymbol{\beta})$$

In turn, this model is regularly referred to as proportional "odds" model. In statistical literature this ordered logit regression model is also discussed as extension of the ordinary logistic model (McCullagh, 1980).

If one or more βs differ between the classes, the hypothesis of proportional odds is violated. Both the partial proportional odds and generalized ordered logit model relax this assumption. In the partial proportional odds model, one subset of βs varies across the classes while another subset of βs remains fixed. The generalized ordered logit model completely relax this assumption and do not constrain the βs at all (Fuks & Salazar, 2008; Long, 1997).

4.3.2.2 Estimation of the Ordered Logit Model

Since the dependent variable is unobserved and latent, the model cannot be estimated with OLS (Long, 1997). Maximum likelihood estimation is adopted to estimate ordinal regression models and specifically the *ordered logit model*. As pointed out, in the logit model the errors are assumed to have a logistic distribution. It is an extremely flexible and easily used function (Hosmer & Lemeshow, 1989). Assuming that the observations are independent, the likelihood equation is:

$$L(\boldsymbol{\beta}, \boldsymbol{\tau} \mid \mathbf{y}, \mathbf{X}) = \prod_{i=1}^{N} p_i = \prod_{j=1}^{J} \prod_{y_i=1} \Pr(y_i = j \mid \mathbf{x_i}, \boldsymbol{\beta}, \boldsymbol{\tau})$$

Taking logs, the log likelihood equation can be written as following:

$$\ln L(\boldsymbol{\beta}, \boldsymbol{\tau} \mid \mathbf{y}, \mathbf{X}) = \sum_{j=1}^{J} \sum_{y_i=j} \ln\left[F(\tau_j - \mathbf{x_i}\boldsymbol{\beta}) - F(\tau_{j-1} - \mathbf{x_i}\boldsymbol{\beta})\right]$$

This equation can be maximized with numerical methods to estimate both the cut points and the individual coefficients (Long, 1997; Maddala, 1990). In this research STATA offers routines to estimate the ordered logit model efficiently.

4.3.2.3 Assumptions of Ordered Logit Models

There are three assumptions that are relevant for *ordered logit models.*

- *Assumptions of proportional odds:*

As discussed, it implies that the odds ratio is the same for all categories (Long, 1997). It is recommended to estimate the three competing ordinal regression models– proportional odds, partial proportional odds, and generalized logit models and to compare them with regards to the Akaike Information Criteria (AIC) and Schwarz's Bayesian Information Criterion (BIC) (Fuks & Salazar, 2008; Hosmer & Lemeshow, 1989; Long, 1997).

- *Logistic distribution of error term* ε :

Secondly, the ordered logit model assumes that the error term ε has a *logistic distribution* with a mean of 0 and a variance of $\pi^2/3$. The ordered probit model would be an alternative choice; however, the choice is largely of convenience. An interpretation of the parameters in terms of odds requires the ordered logit model. In turn, it was chosen for this research.

- *Multicollinearity*:

Finally, the ordered logit model assumes that there is no *multicollinearity* (see above) (Hair, 2010). *Multicollinearity* has a negative effect on the models accuracy. The VIF factor is inspected for independent variables to exclude problems of *multicollinearity.*

4.3.2.4 Goodness of Fit and Test of Significance

As for multivariate linear regression models, the goodness of the model fit needs to be investigated allowing statistical inference to be made. In addition, statistical tests are required to test the accuracy and significance of the overall model and each individual coefficient.
The so called *-2 Log likelihood value (-2 LL)* reflects the probability that the estimated values fit the empirical data (Hair, 2010). The measure -2LL is also called deviance and is comparable to the coefficient of determination in ordinal least square regressions (OLS). In addition, the *Pseudo R² Nagelkerke* is reported. There is no precise measure of determination in ordered logit regression models. Just like for the tobit regression model, a comparison of the respective Pseudo R² Nagelkerke provides an idea about the contribution of one model over and above another, and about improvements in terms of accuracy. To investigate significance of the overall ordered logit model the *likelihood ratio (LR) chi-squared test* is applied. As suggested in model theory of regression, a *Wald-test* is applied to test the significance of each individual coefficient/odds ratio (Backhaus et al., 2008; Hosmer & Lemeshow, 1989; Long, 1997). For both tests common standards and significance levels are applied to falsify the null hypotheses.

4.3.2.5 Interpretation

The interpretation of βs of the latent regression model is not straightforward. To determine the effect of change in x_k x by δ , then

$$\frac{\Omega_m(\mathbf{x}, x_k + \delta)}{\Omega_m(\mathbf{x}, x_k)} = \exp(-\delta \times \beta_k) = \frac{1}{\exp(\delta \times \beta_k)};$$

If x_k changes by 1, the odds ratio equals exp (-β_k). In turn, odds ratios can be easily interpreted (Hosmer & Lemeshow, 1989; Long, 1997).

4.4 Moderating and Mediating Effects in Multivariate Regression Modelling

4.4.1 Moderating and Interaction Effects

It could be argued that almost any causal claim implies a set of conditions that need to be satisfied before a purported cause is sufficient to bring about this effect; thus multiplicative interaction models are highly relevant (Cohen, 1983). In regression analysis, the function of third variables as moderator or interaction term has a relatively long tradition in quantitative research in social and economic science (Greene, 2000; Hair, 1998; Urban & Mayerl, 2008). *Moderation* and *interaction* implies that the causal relation between an independent (let's say x) and a dependent variable (y) changes as function of the moderator variable (Baron & Kenny, 1986). Stated differently, a multiple regression formulation involving variables a moderating effect of z on the relationship between x and y would be said to exist if the regression of y on *x, z,* and *xz* (a cross-product of x and *z) showed a statistically significant effect for the xz* term (Stone & Hollenbeck, 1984). The moderator is integrated as compound variable formed by multiplying independent variable and the moderating variable (Hair, 1998). Considering only two variables - an independent and a moderating variable - the basic moderation model can be written as following:

$$y = \beta_0 + \beta_1 x + \beta_2 z + \beta_3 xz + \varepsilon_y$$

Interacting effects (see chapter 3) are modelled in a similar manner via multiplicative interaction models. Both the independent variables and the multiplicative terms are included in a step-wise manner.

In the linear regression model, the linear hypothesis represents a gradual, steady change in the effect of the independent variable on the dependent variable as the moderating changes (Baron & Kenny, 1986). Moderating and interacting effects can also be applied to tobit and ordered logit regression models (see Laursen & Salter, 2006; Mackinnon & Dwyer, 1993; Maddala, 1990). The moderating regression model is considered superior to the subgroup method (Stone & Hollenbeck, 1984). Advocates of the moderating regression method argue that the presence of a moderating effect is determined in three steps: First a model having only main effects terms is estimated; secondly, a model having both main effects terms and the interaction term is estimated; the comparison of the change in the R^2 (or Pseudo R^2) and the significance of the model suggest that that moderation is presence (e.g., Cohen, 1983).

For both moderating and interactive effects, the magnitude of higher-order effects cannot be evaluated separately from the lower-order terms. Both the significance and direction of the direct effects of the universal effects and the two-way interaction terms have to be taken into account. For example, the universal effect may counteract the effect of the interaction variables. This research adopts a common practice to visualize how significant interactions affect the dependent variable: First, one enters selected values of the interaction terms into the regression equation and then plots these values against the resulting values of the dependent variable. Such plots show the effect of one selected variable, given different combinations of values for other variables (Cohen, 1983).

4.4.2 Mediating and Indirect Effects – The Baron and Kenny Technique

Whereas moderator variables specify when certain effects will hold, mediators speak to how or why such effects occur. For example, external factors such as the IP efficacy scheme may moderate the effect of a firm's open innovation strategy on performance, and this effect is in turn mediated by internal processes and practices (Baron & Kenny, 1986). Although mediation is an important phenomenon in innovation, it is hardly investigated in quantitative studies. To test mediation this research refers to the mediating regression technique that was first proposed by Baron and Kenny's (1986). In the original article of 1986, it is argued that three regression equations need to be estimated: First, regressing the mediator on the independent variable (1); second, regressing the dependent variable on the independent variable (2); and third, regressing the dependent variable on both the independent variable and on the mediator (3) (Baron & Kenny, 1986). Separate coefficients should be estimated for each regression model. Considering only one independent variable, the dependent variable and one mediating variable, the regression models can be written as following:

Model 1: $m = \beta_1 + \alpha x + \varepsilon_1$

Model 2: $y = \beta_2 + \tau\ x + \varepsilon_2$

Model 3: $y = \beta_3 + \tau' x + \beta_4 m + \varepsilon_3$

According to the original article of Baron and Kenny (1986) the following conditions must hold, to establish mediation: First the independent variable must affect the mediator in the first equation (1), second the independent variable must affect the dependent variable in the second equation (2); and third the mediator must affect the dependent variable in the last equation (3). If these conditions all hold in the prediction, then the effect of the independent variable must be less in the third equation than in the second equation. The second condition stating that the independent variable needs to significantly affect the dependent variable was relieved in later discussions (see e.g. Shrout & Bolger, 2002). Both the direct and the mediating effects operate together and may cancel each other out in the estimation of the total effect and so they appear as a non-significant effect of the manipulation.

Perfect mediation holds if the independent variable has no direct effect if the moderating is entered in the equation (τ'=0). If the direct effect is only partly mediated there are indirect effects and direct effects (Figure 26). Perfect mediation is a rare phenomenon (Urban & Mayerl, 2008).

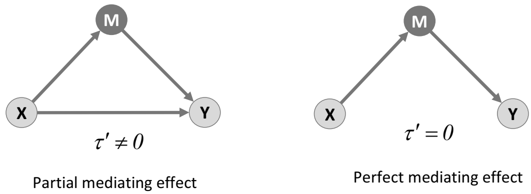

Figure 26: Partial Mediation versus Perfect Mediation

4.4.3 Non-linear Effects

Inspection of residuals may indicate that there is a curvilinear effect (U-shaped) of the independent variable on the dependent variable. For example, Laursen & Salter (2006) assumed an inverted U-shaped relationship of openness and firm performance (Greene, 2000; Laursen & Salter, 2006). A curvilinear model with one turning point can be modelled via the inclusion of a squared component of the independent variable. This approach has been widely adopted in economic research to investigate non-linear effects. Non-linear effects can be interpreted as special cases of interacting effects (Hair, 2010)

4.5 Statistical Analysis of Measurement Constructs and Exploration of Search Strategies

Causal effect modelling and multivariate regression analyses to infer causality is the primary focus of this research. To represent complex phenomena such as innovation routines in multivariate regression models, factor analysis allows validating complex constructs and reducing the number of variables. In addition, firm's search strategies are explored via cluster analysis to identify external innovation search patterns of SMEs.

4.5.1 Factor Analysis and Empirical Identification of Complex Measures

To manage the complexity of causal effects, multivariate analysis is required to group individual variables into components (Hair, 1998). Factor analysis is an important multivariate statistical methodology to investigate the convergence of individual items into components. In this research, principle component analysis (PCA) is applied to identify components of internal practices and routines for innovation.

4.5.1.1 Objectives of Exploratory Factor Analysis

Factor analysis is an interdependence technique whose primary purpose is to define the *underlying structure among the variables* in the analysis (Hair, 1998; Greene, 2000). It is a multivariate statistical methodology in order to group individual variables into components (Hair, 1998). Factor analysis investigates the convergences of individual variables to highly interrelated sets of variables called "factors". On the one hand, these factors reduce the number of variables. On the other hand, factors respond to concepts that cannot be adequately described by a single measure (e.g. different innovation routines and practices represent a sum of different concepts that may not be expressed in one individual variable) (Hair, 1998). Exploratory factor analysis is applied to investigate the convergence of the different components of internal innovation routines and practices. It reduces the number of variables for measuring a firm's internal innovation practices and prevents that irrelevant (non-discriminative) variables are included (Hair, 1998; de Jong & Marsili, 2006).

4.5.1.2 Preparatory Tests and Assumptions

The critical assumptions underlying factor analysis are more conceptual than statistical. Indeed, the assumption that the underlying structure does exist in the set of selected variables is an important one. From a statistical point of view, departures from normality, homoskedasticity, and linearity apply only to the extent that they diminish the observed correlations. In fact, some degree of multicollinearity is desirable because the objective is to identify interrelated sets of variables. To exclude nonessential multicollinearity that results purely from scaling, existing literature suggests the standardization of variables prior the factor analysis (Hair, 1998).
Preparatory tests are required to investigate whether there are sufficient correlations in the data matrix in order to justify factor analysis. Following existing literature, this research examines the measure sampling adequacy (MSA) for each individual variable. It states to which extent the initial variable fit together and provides an indication whether the factor analysis is making sense (Backhaus et al., 2008; Hair, 1998). In addition, the Barlett-Test (Test of Sphericity) is applied. It is a widely accepted preparatory test that examines the entire correlation matrix and provides the statistical evidence that the correlation matrix has significant correlations among at least some of the variables (Backhaus et al., 2008; Hair, 2010).

4.5.1.3 Extraction Method and Selection Criteria

Component analysis – also known as Principle Component Analysis (PCA) - is applied to *extract* components of innovation routines for innovation (Backhaus et al., 2008; Hair, 1998; Hair, 2010). Component analysis considers the total variance and derives factors that contain small proportions of unique variance, and, in some instances, error variances. It has been chosen due to the following reason: Component analysis is most appropriate if one wants to summarize most of the original information in a minimum number of factors (Hair, 1998; Hair, 2010). A critical step in factor analysis is selecting the right number of factors. The *latent root criterion* for the selection of the factors was selected. It requires the *eigenvalues* to be greater than one for those factors to be selected (see also Hair, 1998). Finally, the interpretation of factors is essential. A first inspection of the "un-rotated" factor matrix is a critical step. Most importantly, orthogonal rotation methods simplify the interpretation. The VARIMAX rotation is chosen in this research. It maximizes the sum of variances of required loadings of the factors. It has proven to be successful as an analytic approach in obtaining an orthogonal rotation of factors (Hair, 2010). Software packages SPSS and STATA supported the efficient rotation of factor matrices.

4.5.2 Cluster Analysis and Patterns of Firm Strategies

To describe external innovation search of SMEs this research constructs an empirical taxonomy. Unlike typologies, which are purely conceptually constructed, taxonomies describe SMEs external innovation search strategies empirically (Dess, Newport & Rasheed, 1993; DeSarbo, Benedetto, Song & Sinha, 2005; de Jong & Marsili, 2006). This would not be possible without an object methodology such as statistical cluster analysis.

4.5.2.1 Objective of Cluster analysis and Cluster Analysis Procedure

Cluster analysis has the primary purpose to define the underlying structure among objects rather than variables. The overall objective is to group those objects that are highly similar into clusters. Objects in the same cluster are more similar to one another than they are to objects in other clusters. Clustering models are best applied if one is searching for a "natural" structure among the observations based on a multivariate profile. Cluster analysis is not a statistical inference technique in which parameters are assessed as representing a population. As such, it has strong mathematical properties but not statistical foundations. In this research it is used to describe a firm's strategies rather than investigating effects of a firm's openness on firm performance (Backhaus et al., 2008; Hair, 1998). As suggested in recently published innovation research (see for example de Jong & Marsili, 2006; Lichtenthaler, 2008; van de Vrande et al., 2009), this research follows a structured clustering procedure (see e.g. Backhaus et al., 2008; Hair, 1998).

4.5.2.2 Cluster Variables, Clustering Design and Investigation of Assumptions

The selection of the variables and the similarity measure is an important step in the cluster analysis (Hair, 2010; Ketchen & Shook, 1996). The selection of variables should ideally have some theoretical foundations. However, it is not required if the focus lies on exploring patterns rather than predicting relationships and cluster types (Ketchen & Shook, 1996). If cluster variables or constructs are metric or interval scaled, distance measures are most appropriate (Hair, 1998). Since cluster analysis groups elements such that the distance between groups along all clustering variables is maximized, variables with large ranges are given more weight and may dominate the definition of clusters. To overcome this problem, variables were standardized. This allows variables to contribute equally (Hair, 2010; Ketchen & Shook, 1996). Assumptions such as normality, linearity and homoskedasticity that are so important in statistical modelling of causal effects have little bearing on cluster analysis (Backhaus et al., 2008; Hair, 1998). One major assumption that needs to be investigated is multicollinearity (Hair, 1998).

4.5.2.3 Selection of Clustering Algorithm and Determination of the Number of Clusters

The selection of the appropriate clustering algorithms is critical to the effective use of cluster analysis. In generally, one can differentiate between hierarchical and non-hierarchical cluster algorithms. Following research and literature on clustering algorithms, this research applies a combination of hierarchical and non-hierarchical cluster analysis techniques as this helps to obtain more stable and robust taxonomies (Backhaus et al., 2008; Ketchen & Shook, 1996). Relevant studies in innovation research that also deal with the construction of taxonomies and the description of firm's strategies in practice have also relied on such a combination (de Jong & Marsili, 2006; van de Vrande et al., 2009).

In this research the starting point of the clustering is the hierarchical cluster algorithm as the centroids of a hierarchical solution set the initial solution for the non-hierarchical clustering algorithm. *Hierarchical cluster analysis* involves a series of N-1 clustering decisions (N = number of observations) that combine observations into a hierarchy or a *treelike structure*. It represents a combination of a repetitive clustering process and a clustering algorithm to define the similarity between clusters with multiple members. It generates a complete set of cluster solutions ranging from single member clusters to one-cluster where all observations are in a single cluster. It offers the researcher a means to compare the different clusters and help in judging how many clusters should be retained. The *Ward* algorithm, a hierarchical method, is superior to other agglomerative clustering algorithms and can be applied to metric and interval data (Milligan & Sokol, 1980). It is based on a squared Euclidian distance. In the Ward procedure, the selection of which two clusters to combine is based on which combination of clusters minimize the within-cluster sum of squares across the complete set of disjoint or separate clusters (see Hair, 1998).

The hierarchical cluster analysis is combined with *the K-Means* procedure. It is a *non-hierarchical clustering procedure* that assigns objects into clusters once the number of cluster is specified. The algorithm builds upon cluster seeds as starting point. Afterwards observations are assigned to cluster seeds based on similarity (Hair, 1998). The algorithm is also significantly

sensitive to the initial selected cluster centres. While some K-means procedure use randomly selected starting points, this research employs centroids of an initial hierarchical solution (Milligan & Sokol, 1980). A combination of K-Means and Ward increases validity of solutions (Ketchen & Shook, 1996).
The selection of the number of clusters in the hierarchical cluster analysis was based on the inspection of the "elbow" of the graph plotting the agglomeration coefficient on a y-axis and the number of clusters on x-axis (Backhaus et al., 2008; Ketchen & Shook, 1996). The agglomeration coefficient is a numerical value at which various cases merge. In addition to empirical judgement of the appropriate cluster solution, the number is judged from a theoretical perspective.

4.5.2.4 Interpretation and Validation

Reliability can be improved by combining multiple cluster algorithms (Ketchen & Shook, 1996). In addition, existing literature suggests applying variance analysis to test whether there is a significant difference between the clusters. The analysis of variance (ANOVA) provides a statistical test whether the means of several cluster groups are all equal (Hair, 1998; Ketchen & Shook, 1996). Using cluster variables provides criterion-related validity. Finally, existing statistical literature suggest profiling the clusters to describe how cluster differ from each other in relevant dimensions and to interpret the cluster results. Non-clustering variables are used to describe the clusters in more detail.

4.6 Overview on Major Analyses Phases

Statistical analyses are implemented in three major phases (see Figure 27). The first phase subsumes exploratory and preparatory statistical analyses. It explores external innovation search patterns to provide a better understanding how firm's search for innovation inputs among different types of actors. In addition, measures of internal innovation practices were composed in preparation of regression analyses. Factor analysis was applied to empirically extract components of internal innovation practices and to validate the measurement framework developed in chapter 3. These first exploratory analyses are preparing the statistical estimation of causal effects and multivariate regression analyses to infer causality. Regression analyses are the central element of this research. They can be subdivided in two major phases: Thus, the first phase of regression analyses, estimates statistical models taking an external perspective and examining causal effects and causal moderation. In the second phase, causal mediation was in focus and mediating regression analyses were estimated to examine the interplay of openness and internal innovation practices in explaining innovation performance and value growth.

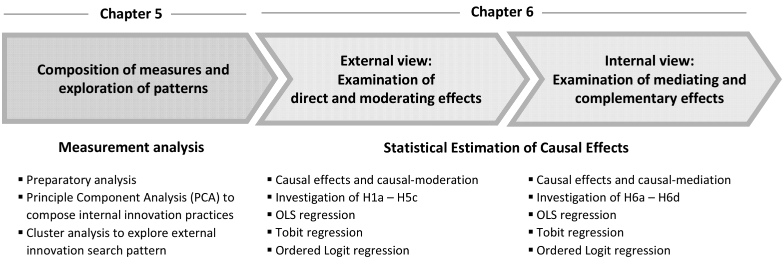

Figure 27: Major Analyses Phases

4.7 Measures

In the following, the measures adopted in the regression models are introduced. They are operationalized in accordance with the conceptual framework introduced in chapter 3.

4.7.1 Dependent Variables: Measuring Innovation–based Value Creation

There are four dependent variables (see *dimension II* in Figure 14):

- *Innovation Success – Success of Innovation Launch:*

The variable aims at indicating the firm's success in launching their innovation. It measures the percentage of innovation projects where the launch specific targets have been met. By definition it ranges from 0 to 100 percentages. An analysis of the distribution of this variable reveals that data is rather categorical rather than continuous. Probabilities are "bulked" at categorical threshold of 10 percent points. Thus, this variable has been re-coded into 11 categories (Cat= 0, …,10). Data of firms that did not specify any targets was excluded from the sample in regressions with innovation success as the dependent variable. As suggested in chapter 4.3.2, ordinal logit models are applied to estimate causal effects.

- *Innovation Performance – Share of Income from Innovation:*

The variable captures a firm's average innovation performance over the last 4 years as a share of income from new products/services that are not older than 3 years. Data is collected over the last 4 years and thus, the average income from new products/services represents a proxy of a firm's innovation performance. This operationalization is in line with the OSLO manual and existing cited research offering the possibility to capture the financial impact of innovation (OECD/European Communities, 2005). By definition, this variable range between 0 and 100 percentage. This variable exemplifies a corner solution problem in regression modelling. It takes on the value zero with positive probability but is a continuous random variable over strictly positive values. Some firms do not aim for product or service innovations and so "0" is an optimal choice (and following the wording of Maddala (1990), they do not participate in the process under investigation). However, they fall in the same group of firms that show a value of "0" because they don't earn any money from new products that they have been developing. Due to the censoring of this dependent variable at the lower level, a tobit modelling approach is appropriate.

- *Major Innovation Performance – Share of Income from Major Innovation:*

To measure a firm's performance in *exploration* (see chapter 3.2.1.1) and creating value from "major" innovations, a measure is used that captures the average share of income from major products or services innovations that have been introduced to the market no longer than 3 years ago (As discussed in 3.2.2 major innovations imply a significant performance difference and a discontinuous change either in the market or the technology dimension of innovation). Again, data of the last four years is used to calculate a proxy of a firm's innovation performance in financial terms. By definition, this variable range between 0 and 100 percentage and represents a corner solution. Thus, tobit regressions are applied.

- *Income Growth:*

The average growth rate in income over the last 4 years was chosen as a proxy to measure a firm's value growth (Czarnitzki & Kraft, 2002; Füglistaller, 2004; Murphy, Trailer & Hill, 1996; Pleitner & Jakl, 2002; Szerb & Ulbert, 2004). In research on firm growth, income growth is the most regularly used measure to capture firm performance (e.g. Delmar et al., 2003; Wiklund et al., 2009). In this research, average growth rate is based on a linear approximation of the increase of the income over the last 4 years. As suggested by Weinzimmer (1998) a beta coefficient is preferable proxy as it dampens the effect of any significant outlier (Weinzimmer et al., 1998). The beta coefficient is divided by the average income over the last 4 years as a relative growth measure is superior to absolute growth measures (Delmar et al., 2003; Hölzl, 2009; Renz, 2004). This measure is a continuous variable that is neither limited nor categorical. The skewness is in acceptable bounds. In turn, it can be justified to apply OLS regressions.

4.7.2 Independent Variables: Measuring a Firm's Open and Collaborative Innovation Strategies

As discussed in chapter 3.2, this research concentrates on two dimensions of independent measures of a firm's open and collaborative innovation strategy (see *dimension I* in Figure 17).

4.7.2.1 External Innovation Search among Individual Search Channels

Interactions with each of six types of innovation partners are measured individually. The intensity of interaction with the respective source to search for new ideas is measured on a likert scale from 1=not at all to 7=regularly (see *dimension I-A* in Figure 17).

4.7.2.2 Relationships and Co-development Strategies

There are three different measures that capture a firm's relationships and co-development strategies (see *dimension I-B* in Figure 17).

- *Number of co-development ties:*

Following prior research (see e.g. Baum et al., 2000 etc.), the number of partners with which the SME has collaborated in at least one innovation project over the last 3 years provides insight into a firm's strong co-development ties. Regression models include the ratio of total number of co-development partners and total number of employees as a proxy of a firm's co-development ties. A transformation of this variable was not required.

- *Scope (and depth) of networking:*

Networking can take place throughout each phase of the innovation value chain, both in the early and the latter phases (see chapter 3.2). The depth of networking in each individual phase is measured on a likert scale ranging from 1 to 7 describing the relevance of innovation partnerships in each phase respectively. A composed measure combining the depth of networking of each individual phase is a proxy for a firm's scope of networking. The convergence of the measure is confirmed and can be described as "marvellous". Crombach's alpha=0.999[12] statistically confirms the consistency of this latent variable. It appears to have a high statistical validity (Backhaus et al., 2008).

- *Efficiency of networking:*

To measure the efficiency of networking a proxy measure is used: The ratio of number of innovation partners with at least one collaborative innovation project within the last 3 years and the total number partners they are in regular contact with and exchange information. By definition, this variable has a lower bound of 0 and an upper bound of 100 percentages.

4.7.3 Contingent and Moderating Variables

Two moderating measures are considered (see *dimension III* in Figure 17):

- *Strengths of appropriability regime (efficacy of legal IP protection):*

Following existing discussion on appropriability regimes, it seems appropriate to concentrate on the strengths of legal protection via patents as en exogenous variable that cannot directly be influenced by managerial actions (Hurmelinna-Laukkanen et al., 2007; Laursen & Salter, 2005). A binary variable was implemented measuring the efficacy of patent protection.

- *Industry dynamism:*

As suggested by prior research (Fine, 1999; O'Connor, 1998, Shapiro, 2006) the rate of new product introduction is an appropriate measure of so called "industry clockspeed". As SMEs usually do not offer a large number of different product groups, this research concentrates on

[12] Crombach's alpha is measuring the consistency of a composite measure; see Backhaus et al. (2008)

the average product lifecycle of the most important product/service group (those with the highest contribution to a firm's current performance). A binary variable classifies industry dynamism in high dynamism (average length of product lifecycle less than 60 months) and low dynamism (average length of product lifecycle more than 60 months).

4.7.4 Mediating Variables – Internal Innovation Practices and Routines

As shown in Figure 23, organizational practices and routines for innovation are modelled as mediating factors (see *dimension IV*). More fundamentally, there is no generally accepted measure of internal innovation practices. Based on the theoretical and conceptual discussions, existing measures are advanced to capture internal organizational antecedents of openness. A set of 13 variables addresses the five components of formal and embedded innovation practices: innovation planning, innovation development processes, commercialization and controlling, investment into knowledge base and culture. Each component reflects different dimension of internal managerial practices for innovation. Multi-item measures were used to operationalize the components. Items have interval or metric scales. Factor analysis was applied to compose the different dimensions and examine the validity of the compound measures.

4.7.5 Control Variables

The model includes control variables to consider external factors that describe the technological opportunity of the industry environment and organizational characteristics. Firm size was introduced as control variable (Acs & Audretsch, 1987). An investigation of shape of the distribution suggests a transformation. In turn, the control variable is the natural logarithm of the number of employees. In addition, age is included as control variable. As the assumption of normality is not satisfied, firm age was included as the natural logarithm of the years passed since foundation. Finally, seven industry dummy variables were used to capture environmental characteristics and account for different propensities to innovate across industries. Indicator coding was applied and knowledge intensive services were selected as a comparison group (Hair, 1998; Hair, 2010).

4.8 Data Collection, Sampling and Data Preparation

4.8.1 Data Collection and Sampling

This research draws upon a coherent set of firm-level data of one benchmarking database on innovation management in SMEs. The benchmarking database was build up in a European initiative aiming for improving innovation management in SMEs. The so called IMP³rove initiative was financially supported by the European Commission. It is lead by an internal consortium consisting of a research organization and top management consultancy and additional small innovation support service providers[13]. The benchmarking data were collected between April 2007 and August 2009 with the assistance of trained personnel that were well familiar with the benchmarking questionnaire.

4.8.1.1 Benchmarking and Administered Data Collection Process

Data was collected in an administered manner and based on a structured process. Key informants of SMEs were the main source of information. The owner or CEO of the SME completed the benchmarking questionnaire with the support of an innovation coach (Bertrand & Mullainathan, 2001; Hair, 2010; Mayer, 2002; Sidhu et al., 2004). The data collection and benchmarking process subsumed three major phases: In the preparation phase the innovation coach introduced the objectives of the benchmarking questionnaire, key terms and constructs in order to increase the consistency and quality. After the preparation phase, the questionnaire was filled in online with the support of the innovation coach. Preventive software functions reduced the number of invalid data. After the completion of the benchmarking questionnaire, a benchmarking report was generated. In the final phase, the innovation coach analyzed the benchmarking report and discussed the results during an on-site visit. During this on-site visit the coach also double-checked the consistency of the benchmarking data (Diedrichs, Engel & Wagner, 2006; Engel, Diedrichs & Brunswicker, 2008). Most importantly, the coach identified measures for improving a firm's innovation performance.

4.8.1.2 Piloting and Pre-testing of Benchmarking

To ensure the interpretability, reliability and validity of the measurement instrument the measurement instrument was developed and tested in several cycles (Engel et al., 2008). Prior to the development of questionnaire and the operationalization of the constructs, the research team executed a state-of-the art review on existing measurement instruments and diagnostic tools for innovation management in SMEs. In addition, guidelines such as OSLO manual, existing surveys such as CIS and conceptual discussion on innovation management measurement were reviewed (Adams et al., 2006). Based on the evaluation of state-of-the art, the research team developed a new questionnaire advancing existing measurement approaches. It covers input, output and process measures of organizational innovation management (Adams et al., 2006). This questionnaire was discussed with innovation management experts in the consortium and members of the advisory board. The benchmarking questionnaire was piloted in a modular manner. First, so called "dry-runs" were executed with selected SMEs in Germany to test the acceptance of the questionnaire. Both "innovative" (recent innovation award winners) and "non-

[13] A.T.Kearney and Fraunhofer IAO constitute the European Coordination Team; for more information on the initiative please visit www.improve-innovation.eu

innovative" SMEs from manufacturing and ICT sectors were selected to pre-test the paper-based questionnaire. After an adaption of the questionnaire, a pre-test was executed with 85 SMEs in four European countries including Finland, France, Germany and Romania. Here, the testing followed the structured benchmarking process that was supported via an online questionnaire. Feedback of the piloting was collected, assessed and resulted in further improvements of the questionnaire, the measurement design, validation functions of the software and the process. The timeframe for preparation and completion of the assessment phase was one day on average. The on-site visit lasted three to five hours (Engel et al., 2008).

4.8.1.3 Sampling Characteristics

The sample includes profit-oriented organizations from all 25 European countries plus Switzerland. To develop a representative sample, the data collection was carefully planned regarding the geographic scope, industry focus and size of the SMEs. Examples of sampling criteria are: Sectors with high share of GDP, sectors with high job creation potential, balance of small and medium-sized firms, balance of small and young firms. So called national coordinators supported the recruiting of a specific number of SMEs in proportion to the respective GDP of that country. For example, France, Italy, Germany and UK had to acquire the largest number of SMEs. A second distinguishing factor was the industry sector. NACE codes classes with a high innovation potential were grouped into eight industry groups including both high-tech and low-tech sectors (Engel et al., 2008). Both types of firm were included in the regression analysis as recent studies indicate that low-tech firms have also adopted more open approaches towards innovation (Chesbrough & Crowther, 2006). The sampling was not restricted to innovative firms only. Both regional and national databases where accessed to contact firms. In addition, the network of national coordinators and associated innovation service providers was leveraged to pre-list potential firms.

More than 30,000 firms that met the sampling criteria were contacted (see Figure 28). In addition, SMEs could apply directly online to participate in the benchmarking. If they meet the minimum participation criteria, they were contacted by a coach to start the benchmarking phase. 3,000 SMEs participated in the benchmarking. 2,212 successfully completed the benchmarking questionnaire. 1,680 were visited on site. After thorough data validation a benchmarking dataset of 1,489 was available for regression analysis.

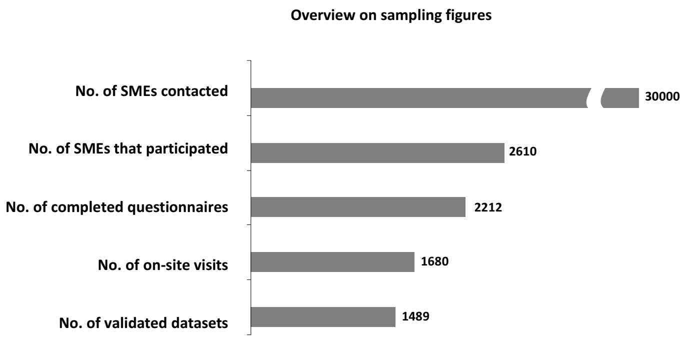

Figure 28: Overview of Sampling Statistics (Source IMP³rove www.improve-innovation.eu)

The ratio of number of variables and total sample size indicates a high statistical power. It is close to the ideal value of 50:1 suggested by Hair (2010).

4.8.2 Data Validation and Preparation

Robust results were important for this research. Thus, different measures supported data validation and preparation for empirical modelling. First, the validation focused on consistency analysis collected during on-site visits. Second, the internal consistency of each individual questionnaire was scrutinized. Thirteen criteria were defined to analyze the completed datasets. For example, figures such as age and size of the firm of the introduction section were cross checked with information on employment data of the last year that were filled in a later section of the questionnaire. Inconsistent datasets were completely removed from the datasets. Third, the data preparation concentrated on the shape of the distribution of each individual variable and construct specified above. As suggested by Hair (1998, 2010), this research investigated skewness, kurtosis and outliers. Outliers that extremely deviate from the mean – more than 2 times of the standard deviation – were removed (Hair, 1998; Hair, 2010). For each individual regression model additional data investigation was necessary. Some variables had some additional missing values and so a smaller dataset was used if necessary.

5 Validation of Measurement Instrument and Exploration of Innovation Search Patterns

5.1 Description of Sample and Firm Characteristics in Terms of Openness and Performance

The next section describes the sample and characterizes firms in terms of their level of external innovation search and networking. It also provides an overview of firms' innovation performance and growth.

5.1.1 Industry, Size and Age Distribution

The sample consists of rather small and young firms. On average, they employ 23 people (employees as head counts on payroll) and are 14 years in business (mean values for both size and age). Table 3 presents the characteristics of the dataset in terms of industry, size and age class. Among the industry groups KIS, Machinery/Equipment and ICT/Electrical/Optical show the highest representation in the dataset. Firms from the KIS sector represent the subsample containing the youngest and smallest firms. Firms from Machinery/Equipment sectors represent more mature and larger firms.

Table 3: Firm Characteristics in Terms of Industry Class, Size and Age (SD= Standard Deviation)

No	Industry group	No. of firms	Age in years (median)	SD of age	Size in no. of employees (median)	SD of size
1	Biotechnology/Pharmaceuticals/ Chemicals	143	20	31.16	28	127
2	Food and beverages	80	16.5	34.77	46.5	241
3	ICT/Electrical/Optical	314	11	22.43	18	132
4	Knowledge intensive services (KIS)	435	8	18.02	12	99
5	Machinery /Equipment	380	22.5	30.70	40	139
6	Space/Aeronautics	94	18	27.87	55	146
7	Textile	43	20	44.54	54	72
	Total	**1489**	**14**	**27.73**	**23**	**135**

5.1.2 Level of External Innovation Search and Co-development

Data on six types of sources for innovation were collected for each individual firm in the sample: Direct customers, indirect customers, suppliers, complementary network partners, IPR experts and universities. Key informants (owner or CEO) stated how regularly they actively involve the respective partners to collect and generate new ideas and suggestions for new solutions. They assessed the involvement of each type of source on seven point likert scale anchored with 1=not at all and 7=very regularly. If access to a specific source was not available, answers were labelled as "not applicable". Table 4 reports the level of external search and co-development intensity across the overall sample.

Table 4: Level of External Search and Co-development across the Overall Sample

Dimensions of open and collaborative innovation strategies	No of datasets	Mean	SD
Intensity of innovation search (individual sources)			
Direct customer	1483	4.70	1.94
Indirect customers	1466	3.82	2.09
Suppliers	1476	3.80	2.03
Universities/research	1445	3.08	2.11
IPR Experts	1433	2.48	1.94
Network partners	1449	3.87	2.08
Relationships and co-development intensity			
Number of co-development ties (in relation to total no. of employees)	1462	0.29	0.45
Scope of networking (across the innovation value chain)	1232	4.43	1.46
Efficiency of networking	1489	0.62	0.39

As one may have expected, customers are the most important source for innovation for European SMEs. The mean value of 4.7 (based on a seven-point likert scale) points out that SMEs actively involve customers to generate new ideas (Laursen & Salter, 2006; von Hippel, 1988). Innovation network partners are also considered as an important source of innovation. This indicates that SMEs rely on partners to access complementary innovation assets and at the same time to access new ideas (Christensen et al., 2005). SMEs hardly involve IPR experts and research partners in order to search for new scientific knowledge.

The lower part of Table 4 describes the level of relationships and co-development strategies among European SMEs. They constitute another important dimension of open and collaborative innovation strategies and complement innovation search. On average, SMEs have 0.09 co-development partners per employee (median value). This variable ranges from 0.00 to 2.05 co-development partners per employee (min and max value). It is worth pointing out that firms may increase their innovation resources by up to 200 % to complement their internal assets (max value).

European SMEs show a relatively wide scope of networking. They involve co-development partners in all three phases: idea management, development and commercialization. Key informants stated how intensively they involve (formal) co-development partners throughout the innovation value chain. They assessed whether partners enhance their innovation activities in the respective phase on a seven-point likert scale ranging with 1=very low to 7=very high. On average, the scope of networking across all phases of the innovation value chain is 4.43 (mean). Table 5 presents the depth of networking and co-development activities for each individual phase. SMEs involve their formal co-development partners most actively during development phase.

Table 5: Scope of Innovation Networking

Depth of innovation networking across individual phases	**No of datasets**	**Mean**	**SD**
Opportunity identification and idea management	1232	4.30	1.814
Development	1232	4.69	1.577
Launch and commercialization	1232	4.28	1.725
Total	**1232**	**4.43**	**1.46**

The efficiency of networking – the third variable describing a firm's relationships - is 62 % on average (median).

5.1.3 Level of Innovation Success, Innovation Performance and Growth

This research is about value creation from innovation and causal effects of firm strategies and practices on innovation performance and growth. Thus, it is worthwhile to describe the sample in terms of a firm's innovation success, innovation performance and income growth.

Table 6 describes European SMEs in terms of innovation input and output measures. European SMEs spend about 2 % of their income on innovation. Results show that expenditures for innovation are highest among the firms from industry group 3 (ICT/Electrical/Optical). On average, ICT firms spend 8 % of their income on innovation (median values).

The share of income from innovation - new products and services, which have been introduced no longer than four years before income is reported - is around 17 % across the overall sample (median value). When calculating the average performance over the last four years, SMEs from industry group 3 (ICT/Electrical/Optical) generated the highest share of income from innovations (25 % share of innovation income). They are closely followed by SMEs from industry group 4 (KIS). As one may have expected, SMEs from industry group 1 (Biotechnology/Pharmaceuticals/Chemicals) and industry group 6 (Space/Aeronautics) generated a lower share of innovation income. This indicates the difference in the industry clockspeed and in the rate of new product/service introduction in these industries.

When considering all industry groups, SMEs achieved an average income growth rate of 10 % (the beta value is based on income data of the last four years; median values are reported). SMEs from industry group 4 (KIS) show the highest average growth rate, closely followed by SMEs from industry group 3 (ICT/Electrical/Optical). The average growth rate of SMEs from these two industry groups was 17 % and 11 % respectively. The average income growth rate in industry group 1 (Biotechnology/Pharmaceuticals/Chemicals) was also relatively high (8 %). The total sample shows an employment growth rate with a median value of 6 %; this is slightly lower than the income growth rate of the total sample. Again, the KIS sector showed the fastest growth over the last four years (median value of 13 %). It shows that SMEs from this industry group employed additional people and accumulated additional resources and knowledge (Baum et al., 2000; Bruneel, Clarysse & Wright, 2009).

Table 6: Innovation Performance and Value Growth across Different Industry Groups

No	Industry group	Expenditures for innovation (median; as share of total income)	Share of income from innovation (median)	Share of major innovation* (median)	Average income growth (median)	Average growth in employment (median)
1	**Biotechnology/Pharmaceuticals/ Chemicals**	0.03	0.14	0.30	0.08	0.04
2	**Food and beverages**	0.01	0.18	0.42	0.10	0.04
3	**ICT/Electrical/Optical**	0.08	0.25	0.40	0.11	0.07
4	**Knowledge intensive services (KIS)**	0.05	0.23	0.41	0.17	0.13
5	**Machinery /Equipment**	0.02	0.14	0.36	0.09	0.05
6	**Space/Aeronautics**	0.01	0.10	0.30	0.07	0.03
7	**Textile**	0.02	0.15	0.41	0.07	0.07
	Total	**0.03**	**0.17**	**0.38**	**0.10**	**0.06**

* as share of total income from innovation

Not only financial output of innovation matters to understand innovation-based value creation. A firm's success in launching an innovation is another important indicator. It helps to better understand how open and collaborative innovation strategies impact a firm's success in turning an idea into an innovation project, moving it to the commercialization stage and successfully launching it. There are ten different performance categories describing a firm's success in launching an innovation. Category 0 includes firm's that have not met project targets in any of their innovation projects that they have launched over the last three years. All categories from 1 through to 10 describe firms with different profiles in terms of innovation success. Each category spans a 10 % range of success rates; the higher the category the higher the success rate. Figure 29 profiles the success of the sample in launching innovations. It presents the share of firms within each success category. 16.9 % of firms in the sample are in category 5. In this category, 41 to 50 % of projects that were launched over the last three years met their targets. This category contains the largest share of the sample. 15.9 % of SMEs are in category 8 where the average success rate of innovation launches was between 71 to 80 %. 15.8 % of SMEs met their launch specific targets in nearly all of the projects and so they are assigned to category 10.

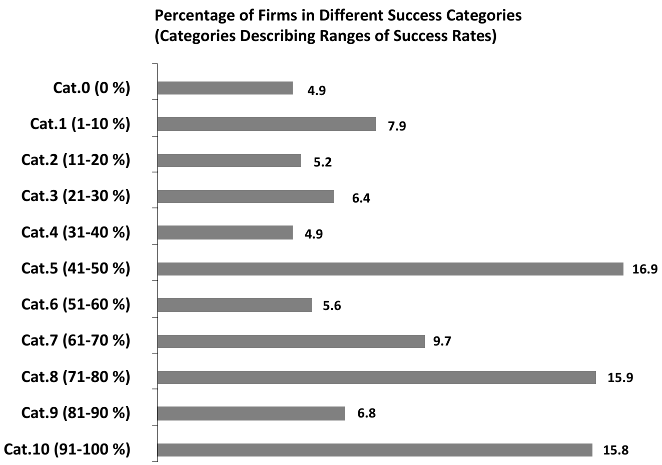

Figure 29: Innovation Success: Distribution of Firms across 10 Success Categories (N=1158)

5.2 Composition of Measures of Internal Innovation Practices via Exploratory Factor Analysis

5.2.1 Objectives and Specification of Factor Analysis Design

As shown in chapter 3, managerial practices for innovation cannot be measured with just one single variable. From a theoretical point of view, managerial practices for innovation are complex and have many dimensions and meanings. For adequate representation, multiple measures are required (Hair, 1998). To overcome shortcomings in existing research, exploratory factor analysis (Hair, 1998) was used to investigate the convergence of individual items, and to confirm the validity of the theoretically derived measurement framework (Hair, 1998; Hair, 2010). Details on principle component analysis (PCA) were discussed in chapter 4.5.1. The conceptual framework (see chapter 3.2) guided the selection of the 13 appropriate variables that measure innovation practices at the firm level. It suggests that there is some underlying structure among the individual variables (13 variables). Only metric and interval scales were used.

5.2.2 Preparation, Assumptions and Validity of Results

Required preparatory analyses were executed. All variables were standardized to increase content validity and to exclude nonessential multicollinearity (purely due to scaling). Measure of Sampling Adequacy (MSA) analyses show that there are sufficient correlations in the data matrix. It justified the application of factor analysis. For 12 variables the MSA was higher than 0.7. Only one variable was close to 0.5 ($p<0.001$). The Bartlett test of the sphericity and the Kaiser-Meyer-Olkin (KMO) measure was applied to justify the factor analysis. KMO and Barlett-test results meet common standards (KMO=0.779; p(Barlett)=0.000) and suggest the suitability of factor analysis. As discussed in chapter 4.5.1, Principle Component Analysis (PCA) with VARIMAX rotation was used to *extract* components of innovation routines for innovation (Backhaus et al., 2008; Hair, 1998; Hair, 2010).
A first inspection of the “un-rotated” factor matrix suggested that there are five factors. The final number of factors was extracted once the results were rotated. The *latent root criterion* supported the selection of the factors (see chapter 4.5.1). As a result, a 5-dimensional measurement solution was obtained explaining 65.52 % of the overall variance.

5.2.3 Results of Factor Analysis and Description of Components

Table 7 presents the rotated factor matrix with the factor loadings for each variable respectively. Five factors were extracted. The measurement analysis confirms the content validity of conceptual discussion in chapter 3.3. Managerial routines and practices for innovation can be classified as either strategic or operational coordination activities. In addition, culture is an embedded practice that governs a firm's innovation activities (see Teece et al., 1997). Routines and activities that enable a firm to build its knowledge base converged into a distinct construct. The interrelation of the results of factor analysis and conceptual framework are shown in Figure 30.

Table 7: Rotated Matrix with Factor Loadings

No	Variables	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
1	Systematic management and controlling of innovation launch	0.801				
2	Systematic project controlling and quality management	0.767				
3	Systematic process management and controlling of process parameters	0.700				
4	Systematic project review	0.528			0.300	
5	Clear vision linked to innovation		0.817			
6	Systematic development of an innovation strategy		0.775			
7	Systematic process for development of non-product innovations			0.835		
8	Systematic process for development of product/service innovations			0.821		
9	Perceived relevance of improving innovation management				0.781	
10	Perceived performance in innovation management				0.701	
11	Cultural readiness		0.470		0.529	
12	Expenditures for innovation over the last 4 years					0.804
13	Budget for long-term oriented project			0.343		0.614

The components show a clear temporal dimension. This reveals that they are linked to different components of absorptive capacity and may constitute organizational antecedents of absorptive capacity. In addition, they are clearly linked to different phases of the innovation value chain respectively (see chapter 2.1.2.). In addition, the components reflect both the explorative and exploitative character of innovation practices. While practices and routines in the early phases are exploratory in nature, the later phases are more exploitative. In the following, each component and the related variables are described.

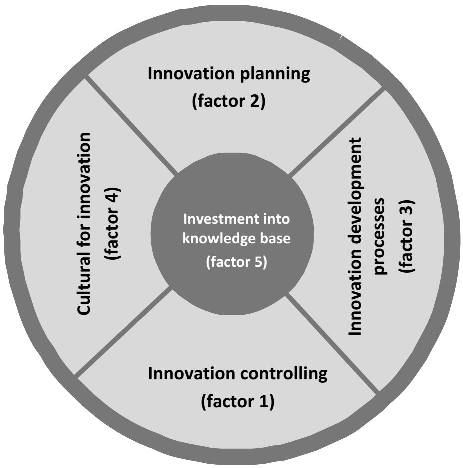

Figure 30: The Components of Internal Innovation Practices and the Empirical Reference Factor

In the following, each component and the related variables are described.

5.2.3.1 Innovation Planning (Factor 2)

Factor analysis merged similar variables into factor 2 and empirically confirms the content validity of the component *innovation planning* (see chapter 3.3.3.1). It combines two multiple-item measures (measure 5 and 6) into one component. These variables show a high factor loading of 0.775 and 0.817. Measure 5 relates to a firm's vision (a rather embedded concept and routine). The second multidimensional measure (measure 6) captures routines for developing and implementing an innovation strategy. Such routines enable firms to explore new business opportunities and mapping it with internal capabilities in a goal-oriented manner. The second measure is also linked to a firm's routines and practices for strategic implementation such as idea generation (Bessant et al., 2009; Goffin & Mitchell, 2005; Tidd, 2001). This confirms that innovation strategy making and ideation are strongly linked and cannot be separated. Interestingly, measure 11 (cultural readiness) shows a relatively high factor loading (0.47). This indicates that innovation strategy making as "formal" routine is linked to culture that represents an "embedded" governance mechanism for innovation.

In summary, factor 2 captures a firm's routines and practices for developing an innovation strategy that turns a vision for innovation into reality. It describes "meta-capabilities" to coordinate innovation activities at a strategic level, to explore new opportunities for innovation and map it with internal capabilities, and to implement a vision for innovation in a goal-oriented manner (Grant, 1996). Thus, innovation planning may represent an organizational antecedent for identifying and also assessing the value of new external information (Cohen & Levinthal, 1990; Nelson & Winter, 1977; Todorova & Durisin, 2007).

5.2.3.2 Innovation Development Processes (Factor 3)

PCA also confirmed the content validity of *innovation development processes* (see chapter 3.3.3.2). Results in the factor loading matrix confirm that innovation development processes describe a distinct component of a firm's organizational practices for innovation (Table 7). It combines two measures that investigate the degree of formalization of a firm's development processes both for product innovations and non-product innovations (measure 7 and measure 8). Formal systems and processes for product development such as the stage-gate model are widely known and regularly addressed in existing research on innovation practices (Cooper & Kleinschmidt, 1987). Measure 7 addresses such development processes for product innovations. Measure 8 complements this measure and addresses formal systems and processes that facilitate and coordinate the development of non-product innovations (such as services, process or business models). Both measures measure the degree of formalization based on structured likert scales. They show a factor loading higher than 0.8.

Overall, this construct captures the degree of formalization of innovation development processes. It investigates whether a firm is disciplined and relies on formal systems when coordinating and integrating the development of innovations (Christiansen & Varnes, 2009). In practice such practices are employed to better assess and mitigate risk (Benner & Tushman, 2002; Cooper, 2008; van de Meer, 2007). From an innovation problem perspective, such processes represent heuristics that support the coordination of interfaces of different actors involved in the development of an innovation, both internal and external ones, and help to partition tasks and knowledge (von Hippel, 1990). Thus, the component is clearly linked to the components "transformation" and "assimilation" of absorptive capacity (Todorova & Durisin, 2007).

5.2.3.3 Innovation Controlling (Factor 1)

A third factor combines variables measuring operational practices. PCA empirically supports the relevance of *innovation controlling* that was proposed in chapter 3.3.3.3. As shown in Table 7, factor 1 summarizes four measures that relate to this type of organizational practices for innovation. Measure 1, measure 2 and measure 3 address routines that enable for process efficiency, speed and target implementation. They show a relatively high factor loading ranging from 0.7 to 0.801. These variables capture routines that make project and process targets explicit and increase efficiency via operational coordination of innovation processes in an end-to-end manner. Measure 1 addresses operational routines in the commercialization phase. In the later stages of the innovation value chain measuring targets and controlling innovation activities is extremely important. It shows a high factor loading of 0.801. In addition, systematic project controlling and quality management describe whether firms are disciplined in managing individual innovation projects. This is addressed in measure 2 which shows a factor loading of 0.767. Measure 3 addresses routines for managing the innovation value chain in an integrated and efficient manner. It has a factor loading of 0.700. These routines rely on process measures that are collected and reviewed on a regularly manner. Such measures are established to improve yields, reduce waste and to drive time-to-market and other lead times such as idea-to-development.

The relevance of continuous learning steaming from systematic innovation project and process controlling is confirmed by a relatively high loading of 0.528 of measure 4 (Simon, 1959; Teece et al., 1997). Following the idea of process management, measure 4 investigates routine-like communication activities, regular review and “lessons learned” routines (Goffin & Mitchell, 2005). Measure 4 also loads on factor 4 which indicates the linkage with embedded routines for innovation.

Overall, innovation controlling is linked to the component “exploitation” of the concept absorptive capacity. It can be perceived as an organizational antecedent of the exploitation of technological or market knowledge. It coordinates a firm’s processes in an end-to-end manner and should increase the success of implementing an innovation independent from the fact whether it includes internal or external ideas (Todorova & Durisin, 2007).

5.2.3.4 Culture for Innovation (Factor 4)

Culture for innovation converged as a separate construct and empirically confirms the relevance of embedded governance mechanism (as proposed in chapter 3.3.3.4). As shown in Table 7 the component includes three measures that describe a firm’s culture for innovation at an organizational and individual level (Teece et al., 1997).

This component subsumes two measures (measure 9 and measure 10) that address the *organizational dimension*. They show a factor loading of 0.781 and 0.701 respectively. They measure whether innovation and innovation management are reflected in a firm’s cultural values at an organizational level (Goffin & Mitchell, 2005). It investigates to which degree innovation is embedded in cultural values and implicit norms governing the activities of individual actors (Schein, 1985). Such corporate values mediate individuals’ behaviour and can be influenced only indirectly.

In addition to an organizational dimension there is an *individual dimension* of culture for innovation. Measure 11 is multidimensional and indicates that the dimension culture for innovation relates to different attitudes, beliefs and characteristics of individual members within the organization at different hierarchy levels (Ernst, 2003). Measure 11 shows a factor loading of 0.529. It considers both explorative and exploitative elements of a firm’s culture for innovation. On the one hand, organizational culture implies creativity and openness for new idea of individual members. On the other hand, organizational culture measures an entrepreneurial spirit of individuals. It addresses those entrepreneurial capabilities of individuals of different hierarchy levels that make it possible to take an idea to a commercial end (Schumpeter, 1912; Wiklund, 1999). This conceptualization is line with prior research performed by Ernst (2003) on organizational culture and innovation. Following his argumentation, a culture that is associated with innovation is characterized by entrepreneurship, creative leadership, and risk taking (Ernst, 2003; Ernst & Kohn, 2007). The composition of culture for innovation extends the concept of entrepreneurial orientation (Lumpkin & Dess, 1996) which is not necessarily linked to innovation. To conclude, the factor *culture for innovation* overcomes shortcomings in existing NPD research and literature on structured innovation management (Ernst, 2002). Existing literature is purely concerned with actions that could be viewed as results of a specific culture. For example, the possibility for employees to use a proportion of their working time to work on their own ideas could be viewed as the result of their organizational culture that fosters innovation. In contrast, this measurement approach is concerned with measures for cultural variables that lie behind the actions that can be observed.

5.2.3.5 Investment into Knowledge Base (Factor 5)

Finally, factor analysis extracted one distinct component that measures a firm's financial investment into innovation. It summarized two measures in factor 5 confirming the validity of the component *investment into knowledge base*. Measure 13 investigates a firm's activities in the past to develop their knowledge base (factor loading 0.804). It measures a firm's expenditures for innovation. This measure is in line with the widely used measure of R&D expenditures. Measure 14 complements this measure and investigates a firm's investment into future innovation activities to build their innovation capability. It shows a factor loading of 0.614. Financial resources are slack resources that drive experimentation and exploration (Barney, 1991a; March, 1991; Wiklund et al., 2009). This convergence confirms the path dependent nature of learning and knowledge building. Following existing conceptual discussions of absorptive capacity, these knowledge building activities may represent important antecedents of absorptive capacity (Cohen & Levinthal, 1990; Laursen & Salter, 2006; Todorova & Durisin, 2007; Zahra & George, 2002).

5.3 Exploration of Strategic Types of External Innovation Search

5.3.1 Objectives and Specifics of Cluster Analysis

To explore open innovation search patterns cluster analysis was applied. All six types of sources were considered as cluster variables to describe how firms search for external innovation search. Variables were standardized to increase content validity and to exclude nonessential multicollinearity purely due to scaling. The clustering procedure is described in detail in chapter

4.5.2. It combines hierarchical and non-hierarchical cluster algorithms. First, Ward method was the starting point of the clustering. As depicted in Figure 31 the "elbow criterion" suggested choosing the "five-clusters" solution (Backhaus et al., 2008). Thus, the "four-groups", "five-groups" and the "six-groups" solutions from this initial cluster analysis were taken into consideration to apply the K-Means cluster algorithm.

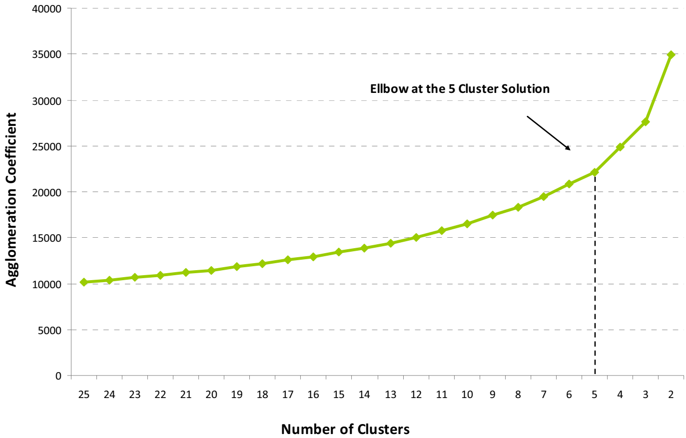

Figure 31: Cluster Agglomeration Coefficient

Afterwards, a K-Means cluster analysis was performed to determine the final cluster profiles. In addition, results were investigated from a theoretical perspective. The initial clustering revealed that the "five-groups" solution is conceptually the most appropriate one (Backhaus et al., 2008). K-Means analysis confirmed the "five-groups" solution and confirmed the content validity.

5.3.2 Results of Cluster Analysis and Description of Search Types

Table 8 presents the results of the cluster analysis and profiles each cluster. These cluster solutions provide an idea about how these SMEs combine different types of innovation partners to access external ideas.

These different types of external innovation search patterns can be described as following:

- *Technology-oriented searcher (cluster 1):*

Firms in cluster 1 are characterized by a relatively high degree of interaction and search for scientific, technological and pre-commercial knowledge among *universities and research organizations* and *IPR experts (*degree of interaction with universities and research organizations and IPR experts is beyond average). They may be dedicated to protect their knowledge, source external R&D, or search for new means to commercialize their technological competencies. They also rely on innovation inputs form their network partners that complement their own resources and capabilities. However, they do not put a large emphasis on search via linkages with customers or linkages with suppliers.

- *Supply-chain searcher (cluster 2):*

Firms in cluster 2 are characterized by a relatively intensive interaction with direct customers (direct customers only) and suppliers in comparison to other external sources. Taking a closer look into the relative weight of the respective source, data reveals that these firms rely on “traditional” supply-chain linkages and do not search for complementary innovation inputs among network partners. In addition, their innovation activities do not rely on input from sources generating pre-commercial and future-oriented knowledge such as universities and research organizations.

- *Closed innovator (cluster 3):*

Type 3 follows a rather introvert innovation strategy. SMEs in cluster 3 do not actively interact with external sources to search for new innovation inputs and to learn. Neither do they rely on inputs from actors of their value chain (customers or suppliers) nor do they search for new knowledge among complementary actors. They are also characterized by an innovation performance below average (see Table 10).

- *Application-oriented and demand-driven searcher (cluster 4):*

Cluster 4 represents the largest cluster in terms of number of SMEs. SMEs of type 4 are application-oriented innovation searchers drawing upon customers, suppliers and also network partners to get access to new ideas. In addition, distant indirect customers are an important input source in relation to other sources. However, these firms do not search for pre-commercial and future-oriented (rather science and technology-oriented) knowledge among universities and research organizations.

- *Full-scope searcher (cluster 5):*

Firms in cluster 5 show a strong external orientation in innovation search and a “balanced” portfolio of external sources. Indeed, they draw upon all six sources to get access to new ideas and new knowledge. Unlike other types, SMEs of type 5 show a very strong interaction with universities/research organizations and IPR experts. This indicates that they investigate new technologies and search for new and pre-commercial knowledge.

Table 8: Results of Cluster Analysis

	Mean values					
Cluster variable	**Total sample**	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**
Direct customers	4.70	4.53	5.38	2.04	5.52	5.87
Indirect customers	3.82	3.37	2.00	2.53	5.60	5.35
Suppliers	3.80	2.99	3.91	1.96	4.71	5.41
Universities/research	3.08	5.04	1.67	1.56	1.75	5.36
IPR experts	2.48	2.72	1.40	1.37	1.54	5.24
Network partners	3.87	4.48	2.61	2.37	4.31	5.50
No of firms	**1411**	**271**	**275**	**279**	**300**	**286**

5.3.3 Profiling and Validity

An overview of the five types of "idea searchers" and different search patterns is shown below (Figure 32). It reveals how SMEs combine different types of external innovation sources when searching for new innovation opportunities outside their organizational boundaries.

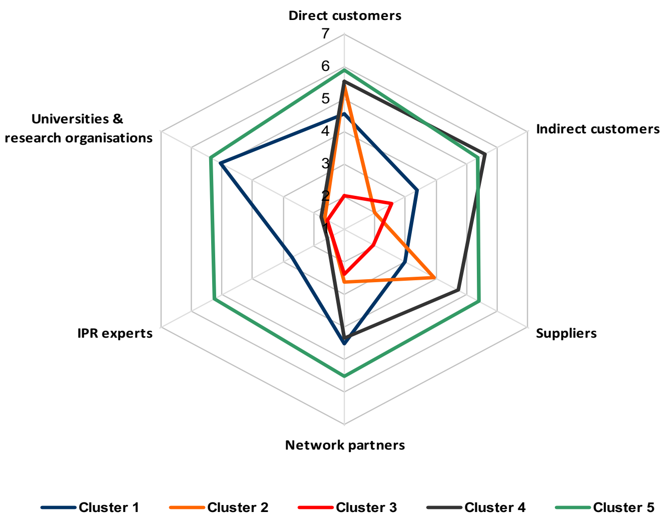

Figure 32: Cluster Profiles: Strength of Involvement of Each Individual Source/Mean Values

The combination of two cluster algorithms confirmed the content validity of the clusters as both algorithms revealed the same search types. Another basic requirement for confirming the validity of the cluster analysis is that there is a significant difference between the clusters for each variable used to cluster the sample (Hair, 1998). To analyze the difference among the clusters, variance analysis was applied as discussed in chapter 4.5.2.4 (see also Hair, 2010). As shown in Table 9, the variance analysis confirmed a significant difference between the five groups for all variables used for clustering the SMEs (p< 0.01 for all 6 cluster variables).

Table 9: Results of Variance Analysis

Cluster variable	Mean total sample	SD	F test (df=4)
Direct customers	4.70	1.94	363.977***
Indirect customers	3.82	2.09	344.558***
Suppliers	3.80	2.03	203.862***
Network partners	3.87	2.08	167.714***
IPR experts	2.48	1.94	514.666***
Universities/Research	3.08	2.11	743.674***

F test applied: * p<0.1*, ** p<0.05, *** p<0.01

To increase the value of the cluster analysis, clusters were profiled. Table 10 describes each cluster in terms of the performance measures: innovation success, innovation performance and income growth. Profiling the clusters suggests that a firm's external innovation search strategy, and specifically the combination of different external innovation sources, shapes a firm's innovation-based value creation. It provides a rationale for causal relationship analyses.

Table 10: Profiling of Clusters in Terms of Performance Measures

	Median values					
Cluster variable	**Total sample**	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**
Innovation success (success rate in %)	60	50	60	50	70	70
Share of income from innovation (of total income)	0.171	0.1758	0.15	0.112	0.159	0.248
Share of income from major innovation (of total income)	0.025	0.0299	0.007	0.0115	0.0112	0.069
Average yearly income growth	0.100	0.0927	0.0918	0.1037	0.1059	0.1222
No of firms	**1411**	**271**	**275**	**279**	**300**	**286**

6 Results of Statistical Estimation and Empirical Examination of Multivariate Causal Relationships

Previous chapters suggest that there are different open styles in innovation. Statistical estimation of causal effects, causal moderation and causal mediation is a central objective of this research to make a claim about the performance impact of different types of open and collaborative innovation strategies. The following chapters present the results of multivariate regression analyses. They empirically examine the conceptual framework and directional hypotheses proposed in chapter 3 by estimating multivariate statistical regression models. As discussed in chapter 4, sound statistical regression modelling is important for accurate causal inference.

6.1 Overview on Multivariate Regression Models and Investigation of Assumptions

Before presenting the results, this chapter provides an overview of all types of statistical regression models and introduces the estimation procedure. In addition, this chapter presents the results of the investigation of the assumptions for OLS, tobit and ordered logit regressions.

6.1.1 Overview on Regression Models and Structure of Investigation

To investigate the causal relationships detailed in the conceptual framework presented in chapter 3, regression analyses are presented in a two staged manner. As shown in Table 11, statistical regression models split into two groups.

The first group of statistical models – model 1 through to model 5 - takes an *external perspective* and addresses direct, interaction and moderating effects. Empirical investigations of these models concentrate on causal effects and causal moderation that are detailed in hypotheses discussed in chapter 3.2.2. Model 1 investigates the direct effects of multidimensional external innovation search and model 2 addresses complementary effects of different external innovation sources. Results are presented in chapter 6.2.1. Model 3 captures both external innovation search and co-development strategies (see chapter 6.2.2). Model 4 and model 5 consider moderating effects of appropriability conditions and industry clockspeed respectively (model 4 and model 5).

The second group of regression models takes an *internal perspective* and examines the interplay of openness and internal innovation routines in explaining a firm's innovation-based value creation. Here, empirical investigation concentrates on mediating and complementary effects. Model i1, model i3 and model ii investigate the preconditions required to perform mediating regression analyses. Results are briefly summarized in chapter 6.3.1. Model 6 allows estimating mediating regression analyses. It is linked to hypotheses on mediating factors presented in chapter 3.3. Results of mediating regression analyses are presented in chapter 6.3.2. Table 11 provides an overview on the different causal relationships addressed, their link with the overall conceptual framework, the related statistical regression model and hypotheses.

Table 11: Overview on Regression Models

Causal relationships	Dimensions in conceptual framework	Regression models	Related hypotheses
Effects of control variables	0	Model 0	-
Internal perspective			
Direct effects and complementary effects of multidimensional external innovation search	I-A, II	Model 1 and Model 2	Group 1 & 2
Direct effects of external innovation search and co-development strategies	I (I-A, I-B), II	Model 3	Group 3
Moderating effects of appropriability conditions and industry clock speed	I (I-A, I-B), II, III	Model 4 and Model 5	Group 4
External perspective			
Testing of conditions of mediating regressions:			-
1) Direction effects of openness on mediating variables	I (I-A, I-B),IV	Model i1 and Model i3	
2) Direct effects of mediating variables on dependent variables	II, IV	Model ii	
Mediating and complementary effects of innovation practices	I (I-A, I-B), II, IV	Model 6	Group 5

An appropriate specification of each statistical model and the selection of the appropriate statistical technique is a prerequisite of successful causal effect estimation. The statistical model needs to be conforming to the characteristics of the empirical data captured. As discussed in chapter 4, the nature of the dependent variable and the probability distribution may require more complex regression procedures. The regression modelling captures the idiosyncratic nature of the dependent variables. *Ordered logit regression models* are estimated to explain the dependent variable innovation success. Results of regression analysis present the odds-ratio to ease the interpretation of the results. *Tobit regression model*s are required to estimate the effects for two censored dependent variables – income from innovation and major income from innovation. Regression models estimating the effect on the dependent variable income growth are modelled and estimated as OLS regressions.

6.1.2 Investigation of Assumptions and Goodness of Fit Measures

To draw proper causal inferences, the investigation of assumptions is an important step in regression modelling (Greene, 2000; Long, 1997). The assumptions for all types of regression models were inspected (for details on the assumptions of each type of regression see chapter 4).

Results of regression models to investigate the assumptions for model 3 (including all independent variables) and model 6 (including all independent and mediating variables) are presented in the appendix 12.7. These models are the most critical regression models as they contain all important variables.

6.1.2.1 Investigation of Assumptions of OLS and Goodness of Fit Measures

To explain a firm's income growth, OLS regression models were estimated. To ensure that proper inferences are drawn, assumptions of OLS regressions were thoroughly inspected (see chapter 4.2.1.1).

To check for potential problems of *multicollinearity* the VIF factors were calculated; it is a common measure to investigate multicollinearity. For all independent and control variables in model 3 and model 6 the VIF factors are in acceptable bounds. The mean VIF for model 3 is 1.49. The max VIF is 1.79. For model 6, the mean VIF is 1.36. The max VIF is 1.92. Thus, the problem of multicollinearity can be rejected considering these relatively low VIF factors. A widely accepted upper limit is a VIF of 10. Even if one assumes a lower value of 5, problems of multicollinearity can be rejected (Hair, 1998; Urban & Mayerl, 2008 p. 232).

Residuals were investigated to address the problem of *heteroskedasticity.* As discussed, OLS makes the assumption that variance of the error terms is constant. To investigate this assumption, the fitted values were plotted against the residuals to visually inspect whether the residuals have a constant variance (see appendix 12.7.1). In the plotting, the pattern suggested that the problem of heteroskedasticity cannot be rejected. In turn, a Breusch-Pagan (Cook-Weisberg) test was performed (Breusch & Pagan, 1979; Jarque & Bera, 1980; Urban & Mayerl, 2008). Results indicate the presence of heteroskedasticity in the disturbance of the model; this is a common problem in cross-sectional data. The presence of heteroskedasticity may lead to consistent but inefficient parameter estimates in OLS regression. To prevent that faulty inferences are drawn, methods for correcting for heteroskedasticity were applied. A robust estimation of the model variance was performed as suggested in econometric literature (Long & Ervin, 2000; White, 1980). Following the seminal work of White (1980), a covariance matrix estimator was used, which is consistent even in the presence of heteroskedasticity, but does not rely on a (possible incorrect) specific formal model of the structure of the heteroskedasticity. Thus, even if heteroskedasticity could not be fully eliminated proper inferences can be drawn (White, 1980). In STATA this estimator is known as Huber/White/sandwich estimate.

In OLS regressions, residuals are assumed to be *normally distributed*. To investigate this assumption, the cumulated probabilities of the residuals were plotted against the normal distribution (Urban & Mayerl, 2008). In addition, the kernel density plot was generated (Cox, 2). A visual inspection suggests that this assumption is met; both for model 3 and 6 (see appendix 12.7.1).

The *assumption of linearity* is also a crucial one. OLS regression estimation makes the assumption of linear relationships between the independent variables and the dependent variables. The most straightforward approach to investigate this assumption is to plot the standardized residuals against each of the independent variables (Urban & Mayerl, 2008). No significant non-linear pattern was identified except for those variables where non-linearity was specifically addressed in the hypotheses (see appendix 12.7.1).
The goodness of fit is reported for each regression model – ranging from model 0 to model 6. The *coefficient of determination (R^2)*, the *adjusted R^2*, the results of the *F-Test* and *t-tests* are presented when discussing the results in the following chapters. A comparison of the respective R^2 provides an idea about the contribution of one model over and above another and improved accuracy (see chapter 4.2.1.4).

6.1.2.2 Investigation of Assumptions of Tobit Model and Goodness of Fit Measures

Tobit models are applied to deal with corner solution outcomes. The tobit model does not rely on OLS estimation and thus, assumptions and especially means to investigate these assumptions are slightly different from procedures of OLS regression. To investigate potential problems of misspecification, this research investigates those assumptions that are relevant for tobit regressions as pointed out in economic literature (Amemiya, 1984; Maddala, 1990; Sigelman & Zeng, 1999; Wooldridge, 2002).
The problem of *multicollinearity* was investigated by inspecting the covariance matrix of coefficients (Urban & Mayerl, 2008). The results suggest that the values of the coefficients are in acceptable bounds and so the problem of multicollinearity can be rejected (see appendix chapter 12.7).
In addition, the problem of *heteroskedasticity* was investigated (Brännäs et al., 1989). The fitted values were plotted against the real values. A visual inspection indicates that heteroskedasticity does not cause a problem.
In tobit regressions *normal distribution of the residuals* is also assumed. The cumulated probabilities of the residuals were plotted against the normal distribution. In addition, the kernel density plot was generated. Results suggest that there is no severe deviation from the normality assumption.
The *goodness of fit*, the significance of the overall model and each individual coefficient is reported for each individual model. *Pseudo R^2* (Nagelkerke), *Likelihood-Ratio* (LR), results of *Likelihood Ratio (LR) chi-square* test and *t-test* are presented due to reasons discussed in chapter 4.3.1. A comparison of the respective Pseudo R^2 (Nagelkerke) provides an idea about the contribution of one model over and above another and the improved accuracy.

6.1.2.3 Investigation of Assumptions of Ordered Logit Models and Goodness of Fit Measures

Ordered logit regressions are appropriate to cater for the specifics of ordinal dependent variables. Three assumptions were discussed in chapter 4.3.2.

From a conceptual perspective, the *proportional odds assumption* seems to be reasonable (see discussion in chapter 4.3.2; see also Bender & Groueven, 1997; Long, 1997). To test this assumption of the proportional odds, all three models – proportional odds, partial proportional odds, and generalized logit – were estimated and compared via the Akaike Information Criteria and Schwarz's Bayesian Information Criterion. Results suggested that the proportional odds assumption is met (Fuks & Salazar, 2008).

The *assumption of logistic distribution of the error term* is rather arbitrary in the sense that they cannot be tested, but they are necessary to identify the model (Long, 1997).

Multicollinearity was investigated prior to estimating the ordered logit model via OLS regression. VIF factors were all below 5 and thus, in acceptable bounds (Hair, 2010).

Measures to assess the *goodness of fit* and the significance of regression estimations are reported for each individual model. *Pseudo R^2* (Nagelkerke), *-2 Log likelihood value (-2 LL)*, results of the *likelihood ratio (LR) chi-squared test* and the *Wald test* are reported too for each model respectively (see chapter 4.3.1.). A comparison of the respective Pseudo R^2 (Nagelkerke) provides an idea about the contribution of one model over and above another and improved accuracy.

6.2 The External Perspective: Causal Effects of Open and Collaborative Innovation Strategies and Moderation of Organizational Context

The following chapters present the results of statistical estimation of regression models addressing direct and moderating effects. Chapter 6.2.1 presents the results of the direct effects of external innovation search (model 1). Model 2 estimates the effects of dual involvement of two different innovation sources. Afterwards, model 3 enriches external innovation search with parameters addressing a firm's relational ties to provide a more holistic picture on a firm's openness. Results are presented in 6.2.2. To better understand whether external boundary conditions matter and limit a firm's open styles of innovation, model 4 and model 5 include moderating effects; they are reported in chapter 6.2.3.

6.2.1 Performance Impact of Multidimensional External Innovation Search

External innovation search is an important process of innovation problem solving. Each search channel is distinctive and is a crucial variable of open and innovation search. In addition, the combination and interaction of different search channels describes a firm's open and collaborative innovation strategy. To provide a distinct and detailed picture on causal effects, *direct* and *interaction effect* of individual external innovation search directions on a firm's innovation performance and value creation. The effects are investigated in a three-staged regression analyses: First, the *base model (model 0)* is estimated. Second, *model 1* estimates the direct effect of a firm's interaction with each individual innovation sources on the dependent variables (model 1). Finally, *model 2* includes interaction variables combining two innovation sources. It reveals complementary and contradictory effects of such combinations. The regression modelling and statistical estimation considers the specifics of the dependent variables.

6.2.1.1 Direct and Interaction Effects of External Innovation Search on Innovation Success

Table 12 presents the results of ordered logit regressions. For each regression model the "odds-ratios" are presented. In the base model, there is no effect of the control variables age, size or industry on the success of launch (see model 0).

Model 1 makes a significant contribution over and above model 0 suggesting that there is an external innovation search as a causal effect on innovation success (see difference between R^2 Nagelkerke of model 1 and model 0). Three odds values are significant and larger than 1.0. Results show that the involvement of *indirect customers, suppliers* and *complementary network partners* has a positive and significant effect on a firm's innovation success. This supports hypothesis 1a and indicates that *indirect customer* involvement positively influences innovation success (odds ratio= 1.0895, $p<0.01$). Indirect customers – more distant sources along the value chain – offer insights about "real" customer problems, required market functions to be performed and most importantly, feedback on new innovations. An early involvement of indirect customers provides access to sticky information that is difficult to articulate and at the same time offers SMEs an early understanding of the limits of new products and services (Harrison & Waluszewski, 2008; Reichwald & Piller, 2008; von Hippel & von Krogh, 2006).

Interestingly, the involvement of *direct customers* does *not* show a significant effect. In turn, it cannot be concluded that the involvement of direct customers is beneficiary when developing and launching a new innovation. So it is not the traditional "market-side" learning that helps a firm to successfully complete an innovation project and to successfully launch an innovation but rather more "distant" learning.

Results confirm hypothesis 1b. *Supplier involvement* shows a positive effect on a firm's success of launch (odds ratio=1.0701; $p<0.05$). Results confirm what has been suggested in prior research: Firms can benefit from the specialized (usually technological) expertise of suppliers if they involve them in innovation activities. Their ideas are usually easy to exploit and close to the technological trajectory of the firm's industry. Thus, firms can significantly benefit from "supply-side" search (Tsai, 2009).

Involvement of *universities* shows a significant and negative effect (odds ratio < 1). This supports hypothesis 1c. It suggests that that interaction with scientific partners may have a negative effect on a firm's innovation success. While universities may provide the opportunity to accumulate new knowledge, university involvement may negatively affect the efficiency of the innovation processes. Too much reliance on external sources of new pre-commercial knowledge seems to be a hindrance.

Interestingly, the involvement of *IPR experts* shows a negative and significant effect on a firm's innovation success. The odds-ratio is significant and smaller than 1 (odds ratio= 0.9064, p<0.01). It suggests that interaction with IPR experts may negatively influence the efficiency of the innovation activities (see hypothesis 1d); it may hinder a firm to successfully move an idea from its inception to the commercialization phase; maybe simply because of resource constraints and delay of activities as obtaining patent protection is inherently costly (Jauhiainen & Hurmelinna-Laukkanen, 2008; Kitching & Blackburn, 1999). Results suggest that the involvement of *network partners* is extremely valuable for SMEs and thus, they support hypothesis 1e. The ordered logit regression analysis reveals a significant and positive effect of the variable involvement of network partners (odds ratio=1.1532; p<0.01). A higher degree of network partner involvement increases the probability that a firm belongs to a higher success category (ranging from a success category 0 to category 10). For example, if a firm increases its involvement by one degree on a likert scale of 1 to 7, the probability that it belongs to a higher success category increases by roughly 15 %. The predicted probability of success of launch of firms from machinery industry is shown in Figure 33.

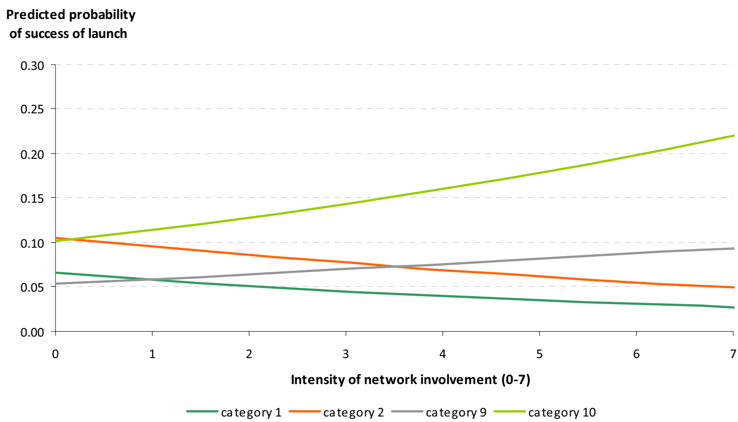

Figure 33: Relationship between Innovation Success and Network Partner Involvement

Network partners usually complement the SME's resources and assets. In addition, network relationships are usually characterized by mutual understanding and well established communication and interaction channels. Due to the peculiarities of these search channels, it is easier to generate, absorb, and exploit new ideas.

Table 12: Ordered Logit Regressions Explaining Success of Launch (External Innovation Search)

Independent & interaction variables	**Model 0**	**Model 1**	**Model 2**
	Odds ratio (s.e.)	Odds ratio (s.e.)	Odds ratio (s.e.)
External innovation search			
Direct customers		1.0283 (0.0339)	1.0367 (0.0352)
Indirect customers		**1.0895*** (0.0318)**	**1.0884*** (0.0325)**
Suppliers		**1.0701** (0.0327)**	**1.0563* (0.0333)**
Universities/research		**0.9470* (0.0303)**	**0.9303** (0.0317)**
IPR experts		**0.9064*** (0.0312)**	**0.8492*** (0.0361)**
Network partners		**1.1532*** (0.0357)**	**1.1565*** (0.0365)**
Interaction variables			
Uni & direct customer			0.9999 (0.0199)
Uni & indirect customer			0.9996 (0.0160)
Uni & supplier			1.0155 (0.0164)
Uni & network partners			1.0225 (0.0165)
Uni & IPR experts			1.0213 (0.0156)
IPR & customer			1.0236 (0.0224)
IPR & indirect customer			1.0178 (0.0183)
IPR & supplier			1.0128 (0.0183)
IPR & network partners			0.9911 (0.0184)
Network p. & direct customer			1.0038 (0.0167)
Network p. indirect customer			1.0179 (0.0157)
Network & supplier			1.0099 (0.0158)
Supplier & direct customers			1.0035 (0.0159)
Supplier & indirect customers			**0.9653** (0.0138)**
Direct cust. & indirect cust.			1.0073 (0.0158)
Control variables			
Age_ln	1.0467 (0.0633)	1.0190 (0.0638)	1.0077 (0.0640)
Size_ln	0.9934 (0.0472)	1.0285 (0.0501)	1.0503 (0.0522)
Industry_dummies [ref KIS]		**Space 1.4746* (0.3366)**	**Space 1.5608* (0.3623)** **Mach 1.3074* (0.2039)**
No. of observations	1153	1098	1098
Chi Square	6.67	**62.05*** **	**93.00*** **
Loglikelihood	-2626.5344	-2477.1118	-2461.6378
Pseudo R² (Nagelkerke)	0.006	**0.056*** **	**0.082*** **

*p<0.1, **p<0.05, ***p<0.01

Table 12 also presents the results of ordered logit regression for model 2 that includes interaction variables of two types of innovation sources. Different innovation sources may be either complementary or contradictory. Model 2 makes a significant contribution over and above model 1 supporting hypothesis 2a asserting that dual involvements have significant effects – either positive or negative ones. Interestingly, there is only *one* significant interactive effect on a firm's innovation success. The dual involvement of indirect customers and suppliers *shows a significant negative effect* (odds ratio < 1.0; p<0.05). Involving indirect customers may positively affect a firm's innovation success (see above). However, a dual involvement of indirect customers and existing suppliers is contradictory rather than complementary. There might be a "gap" between the new customer demands and the technological capabilities of suppliers to perform these functions. The nature of direct and indirect effects is visualized in Figure 34.

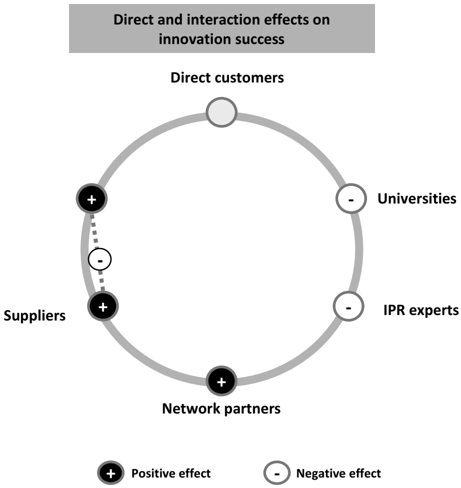

Figure 34: Direct and Interaction Effects on Innovation Success

6.2.1.2 Direct and Interaction Effects of Innovation Search on Innovation Performance

Tobit regressions of model 1 and model 2 explain the effect of external innovation search on income from innovation. Results are presented in Table 13. When estimating the control model, results indicate that the control variables firm age and firm size affect a firm's income from innovation (see model 0). As one may expect, the share of income from innovation is negatively influenced by a firm's age. The younger and smaller the firm is, the higher the estimated innovation performance. However, the effect saturates over time. Model 0 indicates industry effects: Firms from ICT show a significant higher share of income from innovation (in comparison to the KIS sector). As one may have expected, Biotech shows a significantly lower share of income. Longer product lifecycles are directly reflected in the share of income from new products.

Model 1 makes a significant contribution over model 0 (R^2 Nagelkerke Model 0 of 0.134 versus R^2 Nagelkerke Model 1 of 0.177). This indicates that external innovation search affects a firm's innovation performance. In summary, there are three types of innovation sources that matter: *direct customers, IPR experts and network partners*. Involvement of each of these three innovation partners reflects different styles of openness that positively influence the financial income stream gained from new products and services.

First, involvement of *direct customers* shows a significant and positive effect (c.= 0.0104, $p<0.1$). This supports hypothesis 1a and re-emphasizes the relevance of market learning for SMEs. If firms perceive their customers not just as "value receivers" but rather as "value generators" (Reichwald & Piller, 2008, von Hippel, 1988), the fit-to-market and also the perceived value of the innovation may increase. This may significantly propel innovation activities and impact innovation performance in financial terms.

Interestingly, active *supplier involvement* does not influence a firm's income from innovation. To create value, market-side search and interaction is more valuable rather than supply-side learning. Thus, results are in line with Tsai (2009) who also did not find a significant and positive effect of supplier involvement on a firm's innovation performance (Tsai, 2009).

The effect of involvement of *universities* is negative but not significant. Thus, one cannot assume that explorative search for new pre-commercial knowledge may negatively influence a firm's innovation performance in financial terms.

The effect of involvement of *IPR experts* is also significant and positive (although it is marginal; c.=0.0109 $p<0.1$). This supports hypothesis 1d asserting that interaction with IPR experts may positively influence a firm's innovation-based value creation. This suggests that if SMEs work with IPR experts, they may also learn about the competitive technologies and also about new means to transform their idea into a value proposition; for example, via cooperating with established firms through the market for ideas (Gans & Stern, 2002).

The parameter measuring a firm's involvement of *network partner* shows a significant and positive effect on financial innovation performance (c.= 0.0240, $p<0.001$). This is in line with hypothesis 1e that asserts that external search among network partners positively affects a firm's income from innovation. It indicates that if firms leverage co-development partnerships when searching for new ideas, they can positively shape their financial impact from innovation. Such network relationships offer access to complementary innovation and operational assets that are crucial to create value from innovation (Christensen et al., 2005; Teece, 1986).

Model 2 estimates the effect of combinations of different types of sources on a firm's innovation performance. It makes a significant contribution over model 1. Table 13 indicates that 6 interaction variables measuring combinations of two different innovation sources have a significant effect on a firm's innovation performance. This supports the hypothesis 2a asserting that the dual involvement of two innovation partners is either positive or negative.

Table 13: Tobit Regressions Explaining Income from Innovation (External Innovation Search)

Independent & interaction variables	**Model 0**	**Model 1**	**Model 2**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.5745*** (0.0308)**	**0.5654*** (0.0320)**	**0.5878*** (0.0328)**
External innovation search			
Direct customers		**0.0104* (0.00580)**	**0.0137** (0.0061)**
Indirect customers		-0.0023 (0.00520)	-0.0029 (0.0053)
Suppliers		0.0033 (0.00556)	0.0020 (0.0056)
Universities/research		-0.0054 (0.00591)	-0.0052 (0.0061)
IPR experts		**0.0109* (0.00650)**	**0.0148** (0.0073)**
Network partners		**0.0240*** (0.00553)**	**0.0214*** (0.0057)**
Interaction variables			
Uni & direct customer			0.0032 (0.0032)
Uni & indirect customer			**0.0060** (0.0028)**
Uni & supplier			**-0.0064** (0.0028)**
Uni & network partners			-0.0036 (0.0027)
Uni & IPR experts			0.0010 (0.0029)
IPR & customer			**0.0139*** (0.0038)**
IPR & indirect customer			**-0.0059* (0.0033)**
IPR & supplier			0.0001 (0.0033)
IPR & network partners			0.0051 (0.0035)
Network p. & direct customer			**-0.0066** (0.0028)**
Network p. indirect customer			-0.0002 (0.0025)
Network & supplier			0.0025 (0.0027)
Supplier & direct customers			-0.0011 (0.0028)
Supplier & indirect customers			0.0002 (0.0025)
Direct cust. & indirect cust.			**-0.0077*** (0.0027)**
Control variables			
Age_ln	**-0.0795*** (0.0111)**	**-0.0696*** (0.0112)**	**-0.0638*** (0.0111)**
Size_ln	**-0.0189** (0.0090)**	**-0.0239*** (0.0092)**	**-0.0281*** (0.0091)**
Industry_dummies [ref KIS]	**ICT 0.0567** (0.0279)**	**ICT 0.0510* (0.0238)**	**ICT 0.0462* (0.0281)**
	Bio -0.0632 (0.0368)**	**Bio -0.0807** (0.0367)**	**Bio -0.0834** (0.0372)**
No. of observations	1442	1365	1365
No. of left censored data	187	175	175
No. of non censored data	1255	1190	1190
No of right censored data	0	0	0
Chi Square	132.53	166.69	216.09
Pseudo R^2 (Nagelkerke)	**0.134*** **	**0.177*** **	**0.225*** **
*p<0.1, **p<0.05, ***p<0.01			

The nature of the effects is shown in Figure 35. On the one hand, there are *two positive effects* revealing those innovation sources that are complementary; such dual involvements may help firms creating value from combining different types of external innovation inputs and knowledge: First, the interaction variable measuring the dual involvement of *universities* and *indirect customers* shows a positive and significant effect. There is a significant and marginal positive effect in model 2 (c.=0.0060, p<0.05). If firms involve both universities and indirect customers simultaneously, they increase the probability of a higher innovation performance. This supports hypothesis 2d asserting that dual interaction with universities and market actors may have a positive effect on the financial income stream from innovation. Universities offer the opportunity to effectively search for new inventions, e.g. new technological solution principles. Experimentation with indirect customers complements this activity. It may significantly spur the innovation process as SMEs learn about the value of these technological solution principles and may test whether they perform the appropriate market functions. Second, the interaction variable measuring the dual involvement of *IPR experts* and *customers* shows a significant and marginal positive effect (c.=0.0139, p<0.05). Technology exploration and pre-commercial search should be combined with market-side learning to ensure that value is created. While both the involvement of IPR experts and direct customers positively shape innovation performance individually (positive direct effects), the simultaneous involvement of both types of innovation partners may improve innovation performance even further.

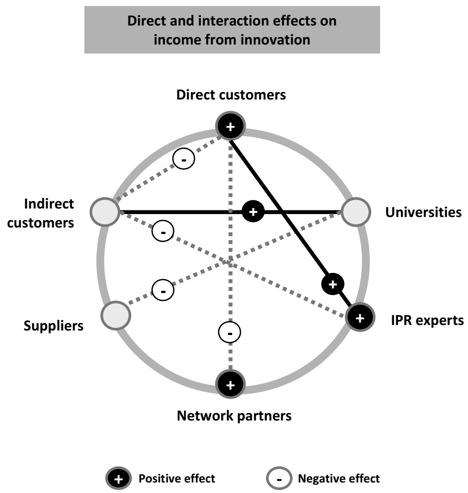

Figure 35: Direct and Interaction Effects on Income from Innovation

On the other hand, the model identifies *four negative effects* that are significant. This reveals that there are innovation sources that are rather contradictory. First, the dual involvement of *universities* and *suppliers* seems to have a negative effect (c.=-0.0064, p<0.05). This suggests that interaction with suppliers may not be supportive when working with universities to search for new technological and inventive trends. Suppliers do not support SMEs in turning pre-industrial knowledge into new products and services that generate additional income streams. Second, the combination of *IPR experts* and *indirect customers* is also contradictory (c.= -0.0059, p<0.1). The combination of technology exploration and market exploration seems to be contradictory and too difficult to handle for SMEs. While the dual involvement of IPR experts and direct customers is beneficiary, exploration in two dimensions – technology and market – might not be.

Third, the dual involvement of *network partners* and *customers* has a slightly negative effect (c.=-0.0066, p<0.01). It indicates that the dual search for complementary innovation inputs and customer insight is risky and challenging. This supports hypothesis 2c arguing that the dual involvement of network partners and customers is risky. In such a situation, SMEs may face the problem of moral hazard as network partner may directly engage with the customer. Fourth, the dual involvement of *direct* and *indirect customers* has negative impact on innovation performance (c.=-0.0077, p<0.001). It suggests that the combination of market exploitation and exploration is challenging and shapes a firm's innovation performance in a negative way.

6.2.1.3 Direct and Interaction Effects of External Innovation Search on Major Innovation Performance

Table 14 presents the results of tobit regressions explaining the relevance of different external search strategies in explaining a firm's major innovation performance. In model 0, firm age and firm size show a significant and negative effect on innovation performance. As one may have expected, the younger and smaller the SME is, the higher the share of income from major innovation. However, the effect of age and size saturates over time.

Model 1 makes a significant contribution over model 0 (see Pseudo R^2 Nagelkerke for model 1 and model 2). This suggests that there are external search strategies that positively affect a firm's financial performance in major innovations; even though they are more risky.

There are two types of actors that matter when aiming for breakthrough innovations: N*etwork partners* and *IPR experts*. Results put forward that these actors are highly valuable innovation partners that may shape a firm's innovation activities in a sustainable manner.

The positive effect of *IPR expert involvement* is in line with hypothesis 1d. IPR experts may positively influence a firm's innovation activities when engaging in more risky innovations. One may assume that if SMEs work with IPR experts, they are usually dedicated to protect their IP or to access external R&D. If they involve IPR experts, they may also learn about new means to transform their idea into a value proposition (Gans & Stern, 2002). This is even more important when firms work on major innovations. Results also support hypothesis 1e asserting that *network partners* matter when searching for new ideas; this proposition seems to hold even if firms aim for major innovations. An active involvement of network partners may be highly beneficial when developing new products and services of high novelty.

Table 14: Tobit Regressions Explaining Income from Major Innovation (External Inno. Search)

Independent & interaction variables	Model 0	Model 1	Model 2
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.2595*** (0.0291)**	**0.2630*** (0.0300)**	**0.2692*** (0.0309)**
External innovation search			
Direct customers		0.0013 (0.0055)	0.0059 (0.0058)
Indirect customers		0.0048 (0.0049)	0.0041 (0.0050)
Suppliers		-0.0011 (0.0052)	-0.0015 (0.0053)
Universities/research		0.0035 (0.0056)	0.0002 (0.0058)
IPR experts		**0.0142** (0.0061)**	**0.0171** (0.0069)**
Network partners		**0.0114** (0.0052)**	**0.0119** (0.0054)**
Interaction variables			
Uni & direct customer			0.0048 (0.0031)
Uni & indirect customer			0.0025 (0.0026)
Uni & supplier			-0.0009 (0.0027)
Uni & network partners			0.0026 (0.0026)
Uni & IPR experts			-0.0021 (0.0027)
IPR & customer			**0.0096*** (0.0036)**
IPR & indirect customer			**-0.0062** (0.0031)**
IPR & supplier			-0.0000 (0.0030)
IPR & network partners			-0.0032 (0.0032)
Network p. & direct customer			**-0.0049* (0.0027)**
Network p. indirect customer			0.0014 (0.0024)
Network & supplier			-0.0000 (0.0025)
Supplier & direct customers			0.0006 (0.0027)
Supplier & indirect customers			-0.0010 (0.0023)
Direct cust. & indirect cust.			**-0.0044* (0.0026)**
Control variables			
Age_ln	**-0.0669*** (0.0106)**	**-0.0566*** (0.0107)**	**-0.0541*** (0.0106)**
Size_ln	**-0.0148* (0.0086)**	**-0.0213** (0.0087)**	**-0.0224** (0.0087)**
Industry_dummies [ref KIS]			
No. of observations	1458	1381	1381
No. of left censored data	564	529	529
No. of non censored data	894	852	852
No of right censored data	0	0	0
Chi Square	84.55	107.54	133.86
Pseudo R^2 (Nagelkerke)	**0.089*** **	**0.119*** **	**0.147*** **

*p<0.1, **p<0.05, ***p<0.01

Network relationships offer access to complementary innovation and operational assets that are crucial to create value from innovation; especially if innovation shows a higher degree of novelty. A highly novel product or service requires new capabilities and access to complementary assets which are usually not owned by the SME (Christensen et al., 2005; Teece, 1986). It also confirms that the external search for major ideas should take place in settings where there are complementarities and mutual understanding. Indeed, complementary search is a highly valuable strategy.

Interestingly, *direct and indirect customers* do not matter for major innovation activities. It cannot be asserted that market-side learning is highly valuable when engaging in more risky innovations. This might have to do with the functional fixedness of “normal customers” (von Hippel, 1986). *Suppliers* do not matter either when firms engage in major innovations.

In summary, opening up to external influences is also of value when engaging in more risky and major innovations. However, firms need to be more selective and should build on more trustworthy search channels.

Just like in previous sections, model 2 estimates the effect of parameters measuring the dual involvement of two different innovation actors. Model 2 is significant and makes a contribution over and above model 1, Pseudo R^2 (Nagelkerke) of model 2 is larger than Pseudo R^2 (Nagelkerke) of model 1). As shown in Figure 36, there are *four interaction variables* that have a significant effect on a firm’s major innovation activities. This supports hypothesis 2a that argues that dual involvements have significant effects – either positive or negative ones. It confirms that there are complementary and contradictory effects when involving two external innovation actors simultaneously in major innovation.

Results revealed *one positive* effect of dual involvement: The combination of *IPR experts* and *direct customers* shows a significant and slightly positive effect (c.=0.0096, $p<0.01$). It suggests that technology exploration and market exploitation is complementary. In contrast, results indicate that there are *three contradictory* effects. First, the parameter measuring the dual involvement of *IPR experts* and *indirect customers* is contradictory. The interaction variable shows a significant but negative effect. Such a combination may require dual learning which is exploratory in two dimensions – technology and markets. For SMEs this may be very difficult to perform and implement. Second, the dual involvement of *network partners* and *customers* shows a significant and slightly negative effect. This supports hypothesis 2c. It puts forward that the combination of network partners and customers might put a firm’s ability to profit from innovation at risk. If products or services are in the early phases of their lifecycle it can be assumed that SMEs may face the risk of moral hazard. Their network partners may directly engage with the customer and “invent around”. Third, the dual involvement of *direct customers* and *indirect customers* is also contradictory. The interaction variable shows a significant and slightly negative effect. This implies that a strong market orientation has a negative impact on a firm’s income from major innovation.

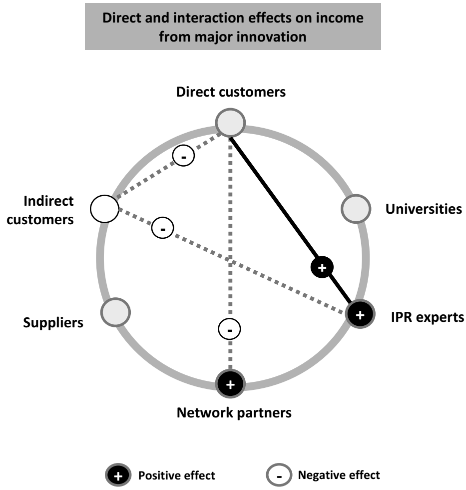

Figure 36: Direct and Interaction Effects on Income from Major Innovation

6.2.1.4 Direct and Interaction Effects of External Innovation Search on Income Growth

OLS regression models were applied to estimate the effect of external innovation search on a firm's income growth. Results are presented in Table 15. All models are statistically significant. Model 0 includes the control variables only. When estimating the control model firm age has a significant and negative effect on firm's income growth. The younger a firm is, the higher its income growth. This effect saturates over time. Firm size does not show a significant effect. So it cannot be assumed that firm size is explaining a firm's average growth in income. Only one industry dummy showed a significant effect. The dummy variable *Space* shows a negative and marginal significant effect (c.=-00582, p<0.1). It indicates that SMEs in the space or aeronautics sector show a lower average beta indicator for income growth than SMEs in knowledge intensive services (KIS).

External innovation search activities have a significant but only a marginal effect on a firm's income growth; model 1 makes hardly any contribution over and above model 0. This shows that it is difficult to directly transform external search strategies into income growth. It remains a key managerial challenge. As shown in Table 15, there are two significant effects that point out which innovation actors are valuable innovation sources.

IPR expert involvement shows a significant and positive effect (c.=0.0105, p<0.05). This is in line with hypothesis 1d which asserts that working with IPR experts provides access to external R&D, new ideas for commercialization internal assets and technologies. For example, IPR experts might be a valuable source when following a technology licensing strategy (rather than product strategy), especially if SMEs decide to compete in the so called market for ideas (Gans & Stern, 2002).

Involvement of universities has a significant and negative effect on a firm's income growth (c.=-0.0093, p<0.05). This supports hypothesis 1c. These results underline the difficulties of SMEs in translating ideas that result from collaboration with universities (or research organization) into economic value and income growth.

Table 15: OLS Regressions Explaining Income Growth (External Innovation Search)

Independent & interaction variables	**Model 0**	**Model 1**	**Model 2**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.5047*** (0.0229)**	**0.5038*** (0.0245)**	**0.5106*** (0.0256)**
External innovation search			
Direct customers		-0.0041 (0.0043)	-0.0024 (0.0046)
Indirect customers		-0.0052 (0.0039)	-0.0057 (0.0040)
Suppliers		0.0060 (0.0042)	0.0057 (0.0043)
Universities/research		**-0.0093** (0.0044)**	**-0.0093** (0.0046)**
IPR experts		**0.0105** (0.0049)**	**0.0148*** (0.0056)**
Network partners		0.0052 (0.0041)	0.0036 (0.0043)
Interaction variables			
Uni & direct customer			0.0034 (0.0024)
Uni & indirect customer			-0.0011 (0.0021)
Uni & supplier			**-0.0036* (0.0022)**
Uni & network partners			-0.0004 (0.0021)
Uni & IPR experts			-0.0010 (0.0022)
IPR & customer			**0.0051* (0.0029)**
IPR & indirect customer			-0.0004 (0.0025)
IPR & supplier			-0.0018 (0.0025)
IPR & network partners			-0.0034 (0.0026)
Network p. & direct customer			-0.0025 (0.0022)
Network p. indirect customer			-0.0006 (0.0019)
Network & supplier			**0.0041** (0.0020)**
Supplier & direct customers			-0.0012 (0.0021)
Supplier & indirect customers			0.0020 (0.0019)
Direct cust. & indirect cust.			-0.0008 (0.0020)
Control variables			
Age_ln	**-0.1314*** (0.0082)**	**-0.1308*** (0.0086)**	**-0.1290*** (0.0087)**
Size_ln	0.0093 (0.0066)	0.0090 (0.0069)	0.0077 (0.0070)
Industry_dummies [ref KIS]	**Space -0.0582* (0.0317)**	**Space -0.0564* (0.0331)**	**Space -0.0664** (0.0334)**
No. of observations	1441	1364	1364
R^2	**0.1979*** **	**0.2015*** **	**0.2127*** **
Adjusted R^2	**0.1934*** **	**0.1933*** **	**0.1956*** **

*p<0.1, **p<0.05, ***p<0.01

Although one may argue that involvement of universities supports technological and inventive exploration, results suggest that there is a range of barriers to turn this learning into growth. Usually, SMEs have to build up resources and capabilities internally in order to identify potential market functions to be performed with this new scientific knowledge. In addition, there are additional barriers that make it more difficult to appropriate financial value. For example, it is often difficult to obtain control over university inventions.

In summary, statistical estimation of model 1 indicates that external innovation search is not sufficient to significantly affect a firm's income growth. To create value from external innovations, firms may need to leverage networking and co-development strategies and internal innovations (see following chapters).

As in previous chapters, model 2 includes both direct effects and interaction variables measuring the effect of dual combinations of two external innovation sources. As shown in Table 15, model 2 is estimated as OLS to explain a firm's income growth. It is significant and makes a marginal, significant contribution over model 1.

As shown in Figure 37, there are three interaction terms that show a significant effect in model 2: There are *two positive* effects and *one negative* effect. First, the dual involvement of *IPR experts* and *customers* shows a positive effect on firm's income growth (c.=0.0051, $p<0.1$). As in previous regressions, it suggests that technology exploration and market exploitation is complementary and enables SMEs to turn technological search into financial return and growth.

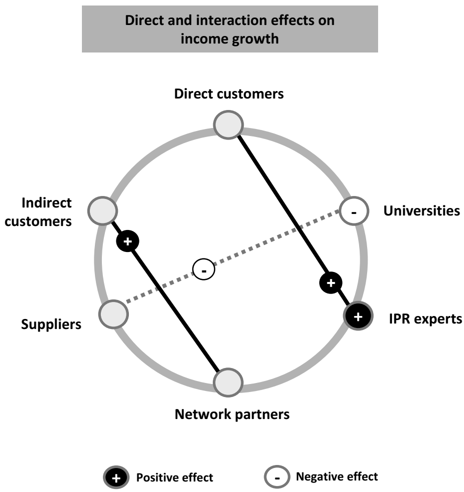

Figure 37: Direct and Interaction Effects on Income Growth

Second, the parameter measuring the dual involvement of *network partners* and *suppliers* also shows a significant and marginal positive effect (c.=0.0041, $p<0.05$). This reveals a "true" interaction effect. None of the two independent variables showed a significant effect in model 1 and model 2. However, the dual involvement of both actors simultaneously shows a significant effect. Third, the parameter measuring the dual combination of *universities* and *suppliers* shows a significant and negative effect. This result underlines that a strategy combining interaction with science partners and technology search via suppliers is not a winning strategy. The contradictions may result from the different maturity levels of innovation inputs of these two innovation sources: Scientific input is pre-industrial and can usually hardly be turned into financial impact while suppliers focus on short-term financial impact.

6.2.2 Performance Impact of Relationships for Innovation and Co-development Strategies

As pointed out before, a firm's relationships and co-development ties constitute an additional important dimension of open and collaborative strategies. It complements external innovation search and stresses that open innovation is not transactional but relational. The causal effects are discussed in hypotheses group 3. To provide a more comprehensive picture on open and collaborative innovation strategies, regression model 3 estimates the effects of both external innovation search (I-A) and relationships (I-B) on a firm's innovation performance and value creation. Thus, it departs from model 1 as it captures a richer picture of open and collaborative innovation strategies.

6.2.2.1 Direct Effects of Innovation Search and Co-development Strategies on Innovation Success

In Table 16, results of model 3 are presented. Model 3 makes a significant contribution over model 1 (see R^2 Nagelkerke of model 3 in comparison to model 1). It indicates that relationships and co-development ties add to the effect of external innovation search on innovation success. Just like in prior regressions in chapter 6.2.1, results indicate that the involvement of *indirect customers, suppliers, network partners,* and *IPR experts,* has a significant effect on a firm's innovation success independent from a firm's relational ties and networking strategies. As discussed in chapter 6.2.1.1 the involvement of the former three actors shows a significant positive effect. In contrast, the involvement of IPR experts reveals a significant and negative effect.

A closer look into the results of the effect of a firm's relationships and co-development ties confirms the relevance of close collaboration and interaction with network partners. The variable *scope of networking* shows a significant and positive effect on a firm's innovation success (odds ratio =1.0913, $p<0.1$). It confirms hypothesis 2b. It suggests that if firms deeply engage with complementary network partners in both the early and later phases of the innovation value chain, the probability of success of collaborative innovation projects is higher. Intensive networking and collaboration creates mutual understanding and may positively affect knowledge access, transformation and exploitation; in turn, it may increase the efficiency of a firm's innovation processes. Interestingly, neither the *number of a firm's co-development ties* nor the *efficiency of a firm's networking* show a significant effect on a firm's innovation success. It is not the size of the network that positively influence the successful commercialization but the quality and the intensity of co-development activities.

Table 16: Ordered Logit Regressions Explaining Innovation Success (Search & Relationships)

Independent variables	**Model 0**	**Model 1**	**Model 3**
	Odds ratio (s.e.)	Odds ratio (s.e.)	Odds ratio (s.e.)
External innovation search			
Direct customers		1.0283 (0.0339)	1.0409 (0.0381)
Indirect customers		**1.0895*** (0.0318)**	**1.0850*** (0.0342)**
Suppliers		**1.0701** (0.0327)**	**1.0684** (0.0354)**
Universities/research		**0.9470* (0.0303)**	0.9585 (0.0324)
IPR experts		**0.9064*** (0.0312)**	**0.9102*** (0.0328)**
Network partners		**1.1532*** (0.0357)**	**1.1392*** (0.0397)**
Relationships			
No. of co-development ties			0.9772 (0.1608)
Scope of networking			**1.0913* (0.0519)**
Efficiency of networking			1.2528 (0.2333)
Control variables			
Age_ln	1.0467 (0.0633)	1.0190 (0.0638)	1.0488 (0.0713)
Size_ln	0.9934 (0.0472)	1.0285 (0.0501)	1.0127 (0.0578)
Industry_dummies [ref. KIS]		**Space 1.4746* (0.3366)**	
No. of observations	1153	1098	957
Chi Square	6.67	**62.05*** **	**68.86*** **
Loglikelihood	-2626.5344	-2477.1118	-2152.0038
Pseudo R² (Nagelkerke)	0.006	**0.056*** **	**0.070*** **
*p<0.1, **p<0.05, ***p<0.01			

6.2.2.2 Direct Effects on Innovation Performance

Table 17 presents the results of tobit regression for model 3. Model 3 makes a significant contribution over and above model 1. It indicates that a firm's relationships are additive to a firm's external search. Both in model 3 and model 1, three types of innovation sources show significant effects: *direct customers, network partners* and *IPR experts*. If SMEs consider these sources when searching for new innovation inputs, this increases the probability of a higher share of income from new products and services. The effect of *network partner involvement* is partly mediated by the variables measuring a firm's relationships and co-development strategies. This underlines hypothesis 1c asserting that a firm's relationships and relational ties improve a firm's search activities. Indeed, external search is also defined by a firm's relational networks which facilitate the identification of new knowledge and the access to new knowledge (Granovetter, 1973; Dittrich & Duysters, 2007).

Table 17: Tobit Regressions Explaining Innovation Performance (Search & Relationships)

Independent variables	**Model 0**	**Model 1**	**Model 3**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.5745*** (0.0308)**	**0.5654*** (0.0320)**	**0.4848*** (0.0396)**
External innovation search			
Direct customers		**0.0104* (0.00580)**	**0.0145** (0.00641)**
Indirect customers		-0.0023 (0.00520)	-0.0069 (0.0057)
Suppliers		0.0033 (0.00556)	0.0019 (0.0061)
Universities/research		-0.0054 (0.00591)	-0.0088 (0.0062)
IPR experts		**0.0109* (0.00650)**	**0.0118* (0.0068)**
Network partners		**0.0240*** (0.00553)**	**0.0186*** (0.0063)**
Relationships			
Number of co-development ties			**0.1102*** (0.0291)**
Scope of networking			-0.0087 (0.0082)
Efficiency of networking			**0.0554* (0.0331)**
Control variables			
Age_ln	**-0.0795*** (0.0111)**	**-0.0696*** (0.0112)**	**-0.0554*** (0.0123)**
Size_ln	**-0.0189** (0.0090)**	**-0.0239*** (0.0092)**	-0.0117 (0.0107)
Industry_dummies [ref. KIS]	**ICT 0.0567** (0.0279)** **Bio -0.0632** (0.0368)**	**ICT 0.0510* (0.0238)** **Bio -0.0807** (0.0367)**	**ICT 0.0571* (0.0304**)
No. of observations	1442	1365	1125
No. of left censored data	187	175	126
No. of non censored data	1255	1190	999
No of right censored data	0	0	0
Chi Square	132.53	166.69	148.55
Pseudo R^2 (Nagelkerke)	**0.134*** **	**0.177*** **	**0.194*** **

*p<0.1, **p<0.05, ***p<0.01

The relevance of relationships and co-development ties is confirmed in the tobit regression. A firm's relational ties for innovation enable a firm to create value from innovation. The parameter *number of co-development ties* (0.1102, p=0.01) shows a significant and positive effect. This supports hypothesis 3a asserting that a larger number of co-development ties positively affects firm's innovation performance. Just like prior research on networks and alliances has identified a positive effect of a larger number of strong relational ties impacts firm performance, results emphasize the positive effect of a firm's innovation ties on innovation-based value creation (Baum et al., 2000; 2005). This indicates that the idea of the relational-based view of the firm can be transferred to innovation-based value creation (Dyer et al., 1998). The parameter *efficiency of networking* (c.=0.0554, p<0.1) also shows a significant and positive effect. This supports the hypothesis 3d asserting that the *efficiency of a firm's networking* positively affects innovation performance. If SMEs wants to create value from innovations, they need to establish relationships for accessing complementary innovation assets *and* other social, technical and commercial assets that would usually take several years of operational experience to acquire. Operational partners should also be leveraged as innovation partners.

In chapter 3.2.5 it is argued that firms may "over-network" and that the positive effect of a large co-development partner network may saturate. It is proposed that there is a tipping point. To estimate the non-linear relationship a squared-term was entered in the tobit regression (see Model 3^2 in the appendix 12.8). There is strong support of an inverted U-shaped relationship. First, the variable *number of co-development ties* is significant. Second, the squared term is significant as well and has a negative effect. Figure 38 depicts that if SMEs have too many co-development partners there are decreasing returns. This supports hypothesis 3b.

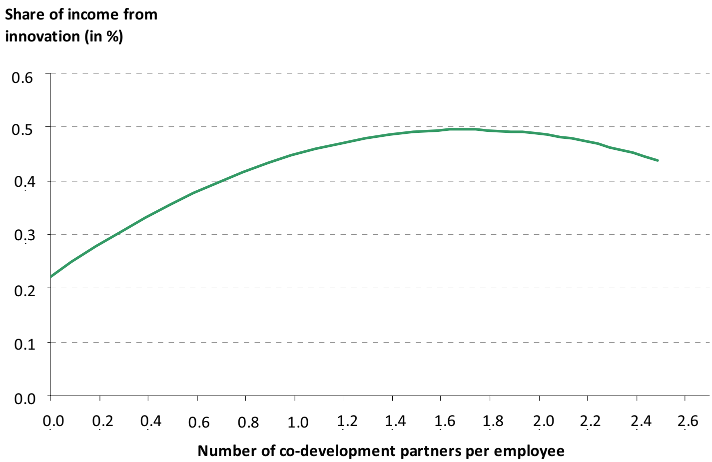

Figure 38: Predicted Relationship between Innovation Performance and Number of Co-development Partners (Illustrative for KIS Sector)

From Figure 38, it can be seen, that in Knowledge Intensive Services (KIS), the point where the size of co-development networks may have a negative effect – what could also be called "tipping point" - is roughly at 1.7 partners per employee. However, the model predicts negative returns; thus, it can only be concluded that there are decreasing returns.

6.2.2.3 Direct Effects on Major Innovation Performance

Table 18 presents the results of tobit regressions to investigate the effect of both innovation search and co-development on a firm's performance in major innovations. Model 3 makes a significant contribution over and above model 1.

Table 18: Tobit Regressions Explaining Major Innovation Performance (Search & Relationships)

Independent variables	**Model 0**	**Model 1**	**Model 3**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.2595*** (0.0291)**	**0.2630*** (0.0300)**	**0.2094*** (0.0369)**
External innovation search			
Direct customers		0.0013 (0.0055)	0.0077 (0.0060)
Indirect customers		0.0048 (0.0049)	0.0023 (0.0053)
Suppliers		-0.0011 (0.0052)	-0.0054 (0.0056)
Universities/research		0.0035 (0.0056)	-0.0011 (0.0058)
IPR experts		**0.0142** (0.0061)**	**0.0141** (0.0063)**
Network partners		**0.0114** (0.0052)**	0.0058 (0.0058)
Relationships			
Number of co-development ties			**0.0485* (0.0265)**
Scope of networking			0.0112 (0.0077)
Efficiency of network ing			**0.0562* (0.0312)**
Control variables			
Age_ln	**-0.0669*** (0.0106)**	**-0.0566*** (0.0107)**	**-0.0443*** (0.0116)**
Size_ln	**-0.0148* (0.0086)**	**-0.0213** (0.0087)**	**-0.0208** (0.0100)**
Industry_dummies [ref. KIS]			**Mach 0.0588** (0.0294)**
			Textile 0.1347 (0.0604)**
No. of observations	1458	1381	1137
No. of left censored data	564	529	416
No. of non censored data	894	852	721
No of right censored data	0	0	0
Chi Square	84.55	107.54	96.48
Pseudo R^2 (Nagelkerke)	**0.089*** **	**0.119*** **	**0.133*** **
*p<0.1, **p<0.05, ***p<0.01			

In model 3, one variable of *external innovation search* has a significant effect. When comparing model 3 and model 1, results reveal that in model 3 only one parameter of external innovation search is significant. *IPR experts involvement* shows a significant and positive effect on a firm's income from major innovation in both models (c.=0.0141, p<0.01). The effect is independent from a firm's relational ties. In contrast, the effect of *networking partner involvement* is not significant in model 3 when entering variables on relationships and co-development ties in the equation. This suggests that major innovations are associated with close interactions that are embedded in a firm's co-development relationships. Formal and well established relationships (so rather "closed" network ties) may enable the successful search for inputs for major innovations that can be turned into value. Complexity, risk and uncertainty of more major innovations may require more established relationships.

Two variables of the dimension *relationships* have a significant effect. Thus, the relevance of complementary partnerships and co-development ties for major innovations is confirmed in the tobit regression. Just like in the previous chapter, the parameter *number of co-development ties* (c.= 0.0485, p<0.1) and the *efficiency of the networking* (c.= 0.0562, p<0.1) show significant and positive effects. Indeed, results confirm hypothesis 3a. It is not surprising that the positive effect of a large number of co-development partners in model 3 is weaker than in model 1. As one may have assumed firms need to be more selective and have to rely on specialized, high-quality relationships if the product or service is in the early lifecycle stage. However, the access to operational assets is equally important for major innovations. Results also confirm hypothesis 3b asserting that there is an inverted U-shaped relationship between the *number of co-development ties* and a firm's income from major innovation (see model 3^2 in the appendix 12.8).

6.2.2.4 Direct Effects on Income Growth

To provide a more comprehensive picture on the effect of open and collaborative innovation on a firm's income growth, OLS regressions were applied to estimate model 3. Table 19 presents the results of OLS regressions estimating model 3. Model 3 makes hardly any contribution to the base model (when comparing the adjusted R^2). This confirms the weak effect of open styles of innovation on income growth.

Table 19: OLS Regressions Explaining Income Growth (Search & Relationships)

Independent & variables	**Model 0**	**Model 1**	**Model 3**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.5047*** (0.0229)**	**0.5038*** (0.0245)**	**0.4623*** (0.0304)**
External innovation search			
Direct customers		-0.0041 (0.0043)	-0.0015 (0.0048)
Indirect customers		-0.0052 (0.0039)	-0.0065 (0.0043)
Suppliers		0.0060 (0.0042)	0.0016 (0.0046)
Universities/Research		**-0.0093** (0.0044)**	**-0.0093** (0.0047)**
IPR experts		**0.0105** (0.0049)**	**0.0124** (0.0051)**
Network partners		0.0052 (0.0041)	0.0049 (0.0047)
Relationships			
Number of co-development ties			**0.0459** (0.0217)**
Scope of networking			-0.0032 (0.0061)
Efficiency of networking			0.0182 (0.0248)
Control variables			
Age_ln	**-0.1314*** (0.0082)**	**-0.1308*** (0.0086)**	**-0.1206*** (0.0095)**
Size_ln	0.0093 (0.0066)	0.0090 (0.0069)	0.0106 (0.0081)
Industry_dummies [ref. KIS]	**Space -0.0582* (0.0317)**	**Space -0.0564* (0.0331)**	
No. of observations	1441	1364	1124
R^2	**0.1979*** **	**0.2015*** **	**0.2016*** **
Adjusted R^2	**0.1934*** **	**0.1933*** **	**0.1893*** **
*p<0.1, **p<0.05, ***p<0.01			

Just like in model 1, two variables of *external innovation search* show a significant effect. *IPR experts* and *universities* shape a firm's income growth. As discussed before, *IPR expert* involvement is valuable and may positively shape a firm's growth. In contrast, the involvement of *universities* (and research organizations) is risky and may even negatively influence a firm's income growth. These are independent from a firm's relational ties.
There is one significant effect related to a firm's *relationships.* Results confirm the importance of relational ties and co-development strategies for creating value from openness. As hypothesis 3a asserts, the *number of co-development ties* has a significant and positive causal effect on firm's income growth (c.=0.0459; $p<0.05$) It confirms the relevance of relational assets that help a firm to appropriate financial value and to grow.

6.2.3 Moderating Effects of Efficacy of IP Protection and Industry Clockspeed

The investigation of boundary conditions of a firm's openness is a central focus of this research. As argued above, two boundary conditions are highly important in an open innovation setting: The strength of the *appropriability regime (IP protection efficacy)* and the *dynamism of a firm's innovation environment (clockspeed)*. These factors may condition a firm's openness and its effect. Causal moderations are discussed in hypotheses group 4 and 5. Causal moderation analyses complement prior regression models. They clarify whether open innovation strategies are constrained by a firm's industry context and whether openness is a strategic choice a firm can make.
To investigate the moderating effects of both the strength of the legal IP protection scheme and the industry clockspeed model 4 and model 5 include moderating effects conceptualized as compound variables (also called interaction variables). As discussed in chapter 4.4, the magnitude of higher-order regression coefficients (as opposed to statistical significance) cannot be evaluated separately from lower-order terms but have to be assessed conjointly. In the following, model 4 estimates the moderating effects of legal IP protection scheme. Model 5 estimates the moderating effect of industry clockspeed. To determine the moderating effect, model 3 is estimated first. Afterwards, incremental effects in model 4 and 5 are assessed (Hair, 1998; Hair, 2010; Wiklund & Shepherd, 2005).

6.2.3.1 Moderating Effects on Innovation Success

Table 20 presents the results of ordered logit regression analysis examining the moderating effects of both the strengths of the appropriability scheme (model 4) and the clockspeed on the relation between openness and innovation success (model 5).
Model 4 makes a significant contribution over model 3 (see Pseudo R^2 Nagelkerke of both models in Table 20). Results suggest that the appropriability condition has a direct influence on a firm's innovation success. The variable *strengths of the appropriability regime* (IP protection

efficacy) shows a significant and negative effect (odds ratio 0=0.5809; $p<0.001$). A high efficacy of the legal protection is associated with a lower innovation success.
The moderating regression revealed two significant moderating effects. This supports hypothesis 4 stating that the appropriability regime moderates the influence of different types of openness on innovation-based value creation. There is one *positive* and one *negative moderating effect*. Results indicate that the effect of *supplier involvement* on a firm's success in launching an innovation is *positively* moderated by the efficacy of the IP protection scheme (odds ratio =1.1749, $p<0.001$). That is, the interaction with suppliers is eased if there is stronger IP protection scheme. As suppliers usually do not have the control over complementary assets and have a relatively low bargaining power, the risk of contractual hazard is rather low. In turn, a strong IP protection scheme changes the relationship between a firm's interaction with suppliers and innovation success in a positive manner.
In contrast, the IP protection efficacy negatively moderates the effect of a firm's *co-development ties*. The effect of the interaction variable is significant and negative (odds ratio = 0.5810; $p<0.01$). If there is a high efficacy of IP protection, a larger co-development network shows a negative effect on a firm's innovation success. This confirms that IP management puts a burden on a firm's collaborative innovation activities and hinders SMEs to extract the value from it. One may conclude that IP protection and IP management is too difficult, costly and resource-intensive for SMEs with a large co-development network as there is intensive knowledge exchange and mutual knowledge flows. Hypothesis 4a and 4b was not supported in these regressions.
Model 5 makes a significant (marginal) contribution over model 3. This supports hypothesis 5 for the dependent variable innovation success which asserts that clockspeed constraints the effect of different types of open and collaboration strategies. There are three significant moderating effects. *Two* have a positive effect and *one* is negative. The effect of active involvement of three types of sources - *network partners, IPR experts and universities* - seems to be bounded by industry dynamism. In model 5, the main effect of involvement of *network partners* does not show a significant effect suggesting that network partners do not significantly influence innovation success if product lifecycles are long. In contrast, if product lifecycles are shorter than 60 months, the involvement of network partners is more valuable than in environments where product lifecycles are longer (odds ratio = 1.1514, $p<0.01$).
It can be concluded that in dynamic environments access to complementary assets is even more critical than in more stable environments. As a result the involvement of network partners is even more critical. This result is in line with theoretical discussions on complementary assets (Teece, 1986).

Table 20: Ordered Logit Regressions Explaining Innovation Success (Moderating Effects)

Independent & moderating variables	**Model 3**	**Model 4**	**Model 5**
	Odds ration (s.e.)	Odds ratio (s.e.)	Odds ratio (s.e.)
External innovation search			
Direct customers	1.0409 (0.0381)	1.0082 (0.0542)	0.9890 (0.0502)
Indirect customers	**1.0850*** (0.0342)**	**1.0853* (0.0512)**	**1.0940** (0.0464)**
Suppliers	**1.0684** (0.0354)**	0.9757 (0.0468)	1.0709 (0.0476)
Universities/research	0.9585 (0.0324)	**0.9161* (0.0480)**	1.0203 (0.0464)
IPR experts	**0.9102*** (0.0328)**	1.0034 (0.0624)	**0.8522*** (0.0406)**
Network partners	**1.1392*** (0.0397)**	**1.1130** (0.0564)**	1.0614 (0.0510)
Relationships			
No. of co-development ties	0.9772 (0.1608)	1.3170 (0.2664)	0.9729 (0.2286)
Scope of networking	**1.0913* (0.0519)**	1.1110 (0.0796)	**1.1283* (0.0728)**
Efficiency of networking	1.2528 (0.2333)	1.0689 (0.2946)	1.3604 (0.3519)
Moderating effects-1			
Appropriability conditions		**0.5809*** (0.0809)**	
Appr.& direct customers		1.0767 (0.0789)	
Appr. & indirect customers		0.9944 (0.0634)	
Appr. & suppliers		**1.1749** (0.0776)**	
Appr. & network partners		1.0063 (0.0709)	
Appr. & IPR experts		0.8950 (0.0694)	
Appr. & Universities		1.1139 (0.0779)	
Appr.& Efficiency of network		1.3323 (0.4981)	
Appr. & Scope of networking		0.9506 (0.0914)	
Appr. & No. of co-develop. ties		**0.5810 ** (0.1558)**	
Moderating effects -2			
Clockspeed			0.8955 (0.1165)
Clocks.& direct customers			1.1067 (0.0805)
Clocks. & indirect customers			1.0096 (0.0645)
Clocks. & suppliers			0.9914 (0.0655)
Clocks. & network partners			**1.1514** (0.0794)**
Clocks. & IPR experts			**1.1582** (0.0859)**
Clocks. & Universities			**0.8631** (0.0589)**
Clocks.& Efficiency of network			0.8675 (0.3250)
Clocks. & Scope of networking			0.9281 (0.0894)
Clocks. & No. of co-develop. ties			1.0492 (0.2886)
Control variables			
Age_ln	1.0488 (0.0713)	1.0812 (0.0746)	1.0558 (0.0729)
Size_ln	1.0127 (0.0578)	1.0169 (0.0585)	1.0026 (0.0582)
Industry_dummies [ref. KIS]		**Space 1.6189* (0.4045)**	
		Mach 1.3366* (0.2332)	
No. of observations	957	957	957
Chi Square	**68.86*** **	**98.08*** **	**84.11*** **
Loglikelihood	-2152.0038	-2137.3934	-2144.3774
Pseudo R^2 (Nagelkerke)	**0.070*** **	**0.098*** **	**0.085*** **
*p<0.1, **p<0.05, ***p<0.01			

The involvement of *IPR experts* is also contingent upon the dynamics in the innovation environment. The interaction variable of IPR expert involvement and clockspeed is significant and positive (odds ratio = 1.1582, p<0.01) while the main effect in model 5 is negative (odds

ratio = 0.8522, $p<0.01$). Results suggest that if lifecycles are long, the involvement of IPR experts has a negative influence on innovation success. In contrast, in more dynamic environments the collaboration with IPR experts is not so much a cause for concern as it may even have a positive effect on a firm's innovation success.
A third significant moderating effect relates to the involvement of *universities*. The moderating effect is significant but negative (odds ratio = 0.8631; $p<0.01$). In addition, the main effect of the parameter involvement of universities is actually positive (even though it is not significant). This clearly indicates that in high clockspeed environments, the involvement of universities is unfolding its negative impact on a firm's success in successfully launching an innovation. If environments are turbulent, it might not be beneficial to draw upon knowledge from science and university partners. Or put in another way, SMEs should not get too dependent of external R&D and technology sources if they act in turbulent environments.

6.2.3.2 Moderating Effects on Innovation Performance

Table 21 presents results of tobit regressions to estimate the moderating effects on the interrelationships of open innovation strategies and innovation performance. Again, the moderating variables (compound variables) are added into the equation.
Model 4 estimates the moderating effects of the strengths of appropriability regime. A comparison of the R^2 Nagelkerke of model 3 and 4 reveals that it makes a significant contribution over model 3. This supports the proposition that the effect of openness on a firm's innovation performance is bound by the IP protection scheme (hypothesis 4). Interestingly, the strength of the IP protection scheme shows no direct significant effect.
There is only *one* significant moderating effect: The interaction variable of *efficiency of networking* and strength of appropriability regime shows a negative and significant effect (c. = -0.2194, $p < 0.01$). In model 4, the main effect of the parameter *efficiency of networking* is significant and positive (c.=0.16848; $p<0.001$) suggesting that in environments with a weak appropriability regime operational partners should be involved as innovation partners. However, the effect of the interaction variable is counteracting this positive effect. If the appropriability scheme is strong, a high efficiency of networking may even negatively shape a firm's innovation performance. This supports hypothesis 4b.
When collaborating with operational partners for innovation purposes and involving them directly in development activities, there is also the risk that these firms gain control over the innovation developed by the SME. Codified knowledge is much easier to transfer and to replicate than tacit knowledge. Thus, even if the SME holds a patent, the knowledge can be replicated easily and large firms can innovate "around" by leveraging their own complementary assets.

Table 21: Tobit Regressions Explaining Innovation Performance (Moderating Effects)

Independent & moderating variables	**Model 3**	**Model 4**	**Model 5**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.4848*** (0.0396)**	**0.4657*** (0.0403)**	**0.4944*** (0.0448)**
External innovation search			
Direct customers	**0.0145** (0.00641)**	**0.0187** (0.0090)**	**0.0269*** (0.0086)**
Indirect customers	-0.0069 (0.0057)	-0.0103 (0.0083)	-0.0119 (0.0074)
Suppliers	0.0019 (0.0061)	0.0047 (0.0087)	-0.0053 (0.0079)
Universities/Research	-0.0088 (0.0062)	-0.0098 (0.0091)	**-0.0136* (0.0082)**
IPR experts	**0.0118* (0.0068)**	0.0014 (0.0113)	**0.0238*** (0.0088)**
Network partners	**0.0186*** (0.0063)**	**0.0201** (0.0089)**	0.0111 (0.0084)
Relationships			
No. of co-development ties	**0.1102*** (0.0291)**	**0.1020*** (0.0357)**	**0.0813** (0.0390)**
Scope of networking	-0.0087 (0.0082)	-0.0175 (0.0122)	-0.0029 (0.0107)
Efficiency of networking	**0.0554* (0.0331)**	**0.1648*** (0.0469)**	**0.0922** (0.0443)**
Moderating effects-1			
Appropriability conditions		0.0166 (0.0247)	
Appr.& direct customers		-0.0076 (0.0128)	
Appr. & indirect customers		0.0065 (0.0114)	
Appr. & suppliers		-0.0051 (0.0119)	
Appr. & network partners		-0.0052 (0.0127)	
Appr. & IPR experts		0.0185 (0.0143)	
Appr. & Universities		0.0041 (0.0125)	
Appr.& Efficiency of network		**-0.2194*** (0.0654)**	
Appr. & Scope of networking		0.0178 (0.0165)	
Appr. & No. of co-develop. Ties		0.0215 (0.0498)	
Moderating effects-2			
Clockspeed			-0.0013 (0.0233)
Clocks.& direct customers			**-0.0268** (0.0128)**
Clocks. & indirect customers			0.0098 (0.0115)
Clocks. & suppliers			0.0174 (0.0121)
Clocks. & network partners			0.0173 (0.0125)
Clocks. & IPR experts			**-0.0292** (0.0138)**
Clocks. & Universities			0.0121 (0.0125)
Clocks.& Efficiency of network			-0.0874 (0.0659)
Clocks. & Scope of networking			-0.0145 (0.0168)
Clocks. & No. of co-develop. ties			0.0537 (0.0491)
Control variables			
Age_ln	**-0.0554*** (0.0123)**	**-0.0531*** (0.0123)**	**-0.0583*** (0.0125)**
Size_ln	-0.0117 (0.0107)	-0.0123 (0.0107)	-0.0119 (0.0107)
Industry_dummies [ref. KIS]	**ICT 0.0571* (0.0304)**	**ICT 0.0602** (0.0306)**	**ICT 0.0537* (0.0304)**
No. of observations	1125	1125	1125
No. of left censored data	126	126	126
No. of non censored data	999	999	999
No of right censored data	0	0	0
Chi Square	148.55	164.54	162.18
Pseudo R^2 (Nagelkerke)	**0.194*** **	**0.213*** **	**0.210*** **

*p<0.1, **p<0.05, ***p<0.01

Given the regression coefficient of the tobit model, Figure 39 plots the effect of the parameter *efficiency of networking* on a firm's income from innovation considering different appropriability conditions – a strong IP protection scheme and a weak IP protection scheme (binary variable). The nature of the interaction indicates that if the IP protection efficacy is weak the parameter *efficiency of networking* has a positive impact on a firm's innovation performance. The slope of the line is positive. One may argue that under the conditions of weak IP protection efficacy knowledge is tacit and difficult to transfer across firm boundaries. As a result, openness and strong interweavement with partners has a positive effect on a firm's innovation performance. In contrast, a strong IP protection efficacy makes the transfer of knowledge much easier. If the IP protection efficacy is strong, a high efficiency of a firm's innovation networking strategy has a negative impact on a firm's innovation performance. Under such conditions, complementary partners may represent a "risk" for appropriating the value from opening the innovation processes.

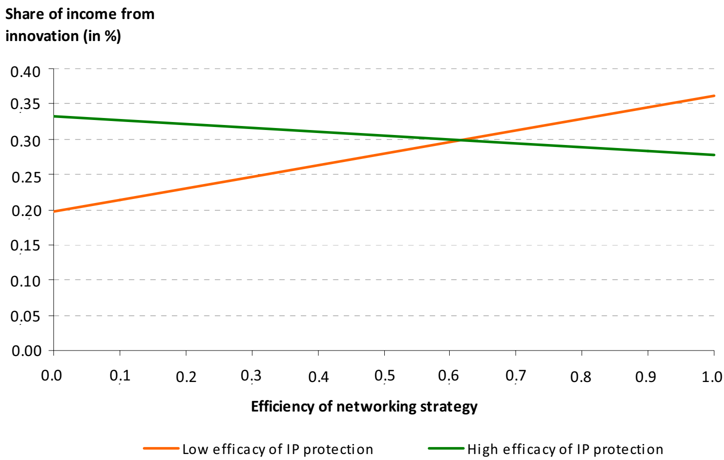

Figure 39: Moderation on Relationship of Efficiency of Networking and Innovation Performance by Strengths of IP Protection Scheme

Model 5 estimates the moderating effects of the industry clockspeed. It makes a significant contribution over and above model 3. This supports the hypothesis that openness is bounded by industry dynamism (hypothesis 5). The parameter clockspeed does not show a direct significant effect.

There are *two* interaction variables that show significant effects. First, the interaction variable of the parameters clockspeed and *customer involvement* show a significant and negative effect (c. = -0.0268; $p<0.05$). To determine the nature of the interaction effect, the main effects and the interaction term must be considered jointly. The main effect of the parameter customer involvement is significant and positive (c.=0.0269, p<0.01). This indicates that if industry clockspeed is low (meaning product lifecycles are long), customer involvement shows a positive effect. However, the negative effect of the interaction variable counteracts this effect. To better describe the nature of the moderating effect, the influence of customer involvement on a firm's innovation performance against different types of product lifecycles is plotted.

Figure 40 depicts the moderating effect and clarifies that customer involvement does not have a positive effect on a firm's innovation performance if industry lifecycles are relatively short (shorter than 60 months).

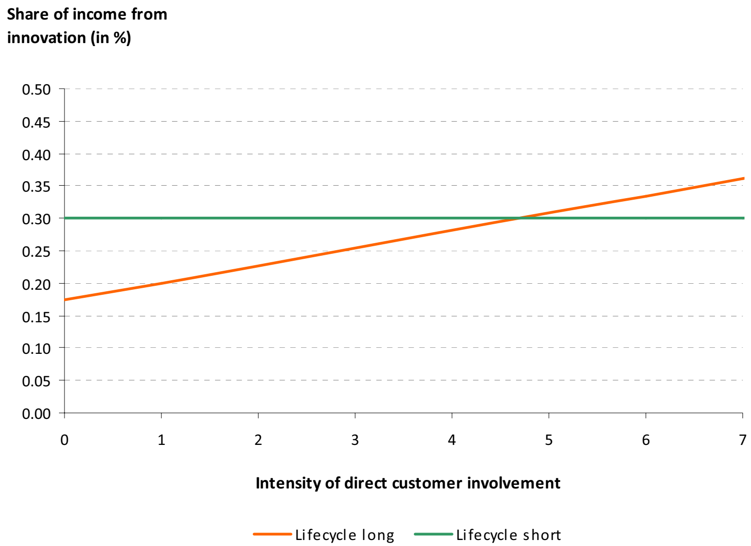

Figure 40: Moderation on Effect of Customer Involvement on Innovation Performance by Industry Clockspeed

Second, the interaction term of *IPR expert involvement* and industry clockspeed shows a significant and negative effect in the tobit regression (c.=0.0292, p<0.05). The direct effect of IPR expert involvement is significant and positive (c.=0.0238, p<0.01). However, this positive effect is counterbalanced by the significant and negative effect of the interaction variable. If the clockspeed is relatively high (meaning that product lifecycles are shorter than 60 months), the positive effect of interaction with IPR experts does not unfold. In dynamic environments, IPR expert involvement may even negatively shape a firm's innovation performance. It can be concluded that too much reliance on external technology and IPR experts may negatively shape the financial innovation performance.

6.2.3.3 Moderating Effects on Major Innovation Performance

If firms aim for major innovations – new products or services that are in the early stage of the product lifecycle – industry dynamism and the strength of the appropriability regime may also constrain how firms open up to external influences and how openness affects financial innovation performance (Thornhill, 2006; Damanpour & Wischnevsky, 2006; Tidd, 2001). Table 22 presents the results of the tobit regression analyses for the dependent variable *income from major innovation*. It shows estimates of model 4 and 5, which include moderating variables in the equations.

Model 4 makes a significant contribution over and above model 3. A comparison of R^2 Nagelkerke of model 3 and 4 reveals that there are moderating effects. This supports hypothesis 4 which suggests that the relationship between openness and innovation performance is bounded by the appropriability regime; specifically by the efficacy of IP protection. Interestingly, the appropriability regime does not show any significant direct effect on a firm's major innovation performance.

There is only *one* interaction variable that shows a significant effect. The interaction variable of *efficiency of networking* and the strengths of the appropriability regime shows a significant and negative effect. To interpret the nature of the effect, both the main effect and the interaction effects were considered conjointly. Efficiency of networking shows a *significant and positive* effect (c.=0.1620; $p<0.01$). In addition, the interaction variable has a *significant negative* influence on the share of income from major innovation (c.= -0.2182; $p<0.01$). This indicates that in environments with a relatively weak appropriability regime, a highly efficient networking strategy shows a positive effect. The negative effect of the interaction variable of high IP efficacy and efficiency of networking counteracts this positive effect. This supports hypothesis 4b asserting an efficient networking strategy is negatively moderated by a strong IP protection scheme. If appropriability regimes are weak, SMEs should implement an efficient networking strategy and directly involve their operational partners in the innovation activities. Such partnerships may offer access to crucial operative complementary assets such as marketing channels, production resources, and also brand reputation, which are highly relevant in the early stages of the product's lifecycle (Teece, 1986). In contrast, a strong appropriability regime constrains the positive influence of efficient networking strategies. If an efficient networking strategy is accompanied by a strong appropriability regime, it may even be counterproductive to involve operational partners in the development of major innovation. Even if SMEs hold a patent, they face the risk that their operational partners can easily replicate the inventions. Again, hypothesis 4a was not supported.

Table 22: Tobit Regressions Explaining Major Innovation Performance (Moderating Effects)

Independent & moderating variables	**Model 3**	**Model 4**	**Model 5**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.2094*** (0.0369)**	**0.1924*** (0.0376)**	**0.1415*** (0.0419)**
External innovation search			
Direct customers	0.0077 (0.0060)	0.0075 (0.0085)	0.0076 (0.0082)
Indirect customers	0.0023 (0.0053)	-0.0050 (0.0077)	0.0036 (0.0070)
Suppliers	-0.0054 (0.0056)	-0.0085 (0.0081)	-0.0054 (0.0074)
Universities/Research	-0.0011 (0.0058)	0.0056 (0.0085)	0.0048 (0.0078)
IPR experts	**0.0141** (0.0063)**	0.0007 (0.0105)	**0.0198** (0.0082)**
Network partners	0.0058 (0.0058)	0.0019 (0.0083)	-0.0052 (0.0078)
Relationships			
No. of co-development ties	**0.0485* (0.0265)**	0.0306 (0.0325)	**0.0854** (0.0356)**
Scope of networking	0.0112 (0.0077)	0.0112 (0.0115)	**0.0268*** (0.0102)**
Efficiency of networking	**0.0562* (0.0312)**	**0.1620*** (0.0445)**	0.0679 (0.0429)
Moderating effects-1			
Appropriability conditions		0.0135 (0.0232)	
Appr.& direct customers		0.0028 (0.0120)	
Appr. & indirect customers		0.0145 (0.0106)	
Appr. & suppliers		0.0080 (0.0110)	
Appr. & network partners		0.0059 (0.0118)	
Appr. & IPR experts		0.0207 (0.0132)	
Appr. & Universities		-0.0114 (0.0117)	
Appr.& Efficiency of network		**-0.2182*** (0.0618)**	
Appr. & Scope of networking		0.0020 (0.0154)	
Appr. & no. of co-develop. ties		0.0476 (0.0452)	
Moderating effects-2			
Clockspeed			**0.0751*** (0.0218)**
Clocks.& direct customers			0.0024 (0.0119)
Clocks. & indirect customers			-0.0020 (0.0107)
Clocks. & suppliers			-0.0019 (0.0111)
Clocks. & network partners			**0.0259** (0.0115)**
Clocks. & IPR experts			-0.0108 (0.0126)
Clocks. & Universities			-0.0105 (0.0116)
Clocks.& Efficiency of network			-0.0247 (0.0618)
Clocks. & Scope of networking			**-0.0429*** (0.0155)**
Clocks. & No. of co-develop. ties			-0.0525 (0.0445)
Control variables			
Age_ln	**-0.0443*** (0.0116)**	**-0.0408*** (0.0115)**	**-0.0345*** (0.0117)**
Size_ln	**-0.0208** (0.0100)**	**-0.0204** (0.0100)**	**-0.0197** (0.0100)**
Industry_dummies [ref. KIS]	**Mach 0.0588** (0.0294)**	**Mach 0.0542* (0.0300)**	**Mach 0.0701** (0.0292)**
	Textile 0.1347 (0.0604)**	**Textile 0.1275** (0.0603)**	**Textile 0.126** (0.0599)**
No. of observations	1137	1137	1137
No. of left censored data	416	416	416
No. of non censored data	721	721	721
No of right censored data	0	0	0
Chi Square	96.48	117.17	124.67
Pseudo R^2 (Nagelkerke)	**0.133*****	**0.159*****	**0.169*****

*p<0.1, **p<0.05, ***p<0.01

In Table 22, model 5 estimates the moderating effects of clockspeed and dynamism. Model 5 makes a significant contribution over and above model 3. This supports hypothesis 5 arguing that industry clockspeed is moderating the effect of a firm's open innovation strategies on innovation performance. The parameter measuring industry clockspeed has a direct and significant effect. It suggests that high industry dynamism is associated with a higher rate of new products that are at an early product lifecycle stage. In addition, there are *two* interaction terms that show a significant effect.

The effect of *network partner involvement* is bounded by innovation clockspeed. To understand the moderating effect, both the universal effects and the interacting effects are evaluated. A closer look into model 3 and model 5 reveals that, in general, network partners are not a relevant source for new ideas for major innovations. In model 3 there is no significant effect. Even if one controls for the innovation clockspeed and dynamism in model 5, there is no significant effect. This suggests that if clockspeed is rather low (and product lifecycles are longer than 60 months), the effect of network partner involvement is not significant. However, if innovation clockspeed is higher and the product lifecycles are relatively short, network partners become a relevant source for new ideas for breakthrough innovations. The interaction effect of clockspeed and involvement of network partners shows a significant and positive effect (c.=0.0259, $p<0.05$). It points out that if involvement of network partners (to identify new ideas) is accompanied by high industry dynamism, there is a positive effect on a firm's income from major innovation.

The second significant interacting effect relates to the firm's *scope of networking*. In model 5, the direct effect of scope of networking is positively influencing income from major innovation. If there is little dynamism in the innovation environment (clockspeed is low), firms can benefit if they work very closely with innovation partners on major innovation. However, if a wide scope of networking is accompanied by shorter product lifecycles and higher innovation dynamism, there is a negative effect on a firm's share of income from innovation. As shown in Table 22, the interaction effect is significant and negative (c.= -0.0429, $p<0.01$).

6.2.3.4 Moderating Effects on Income Growth

OLS regressions are performed to investigate whether IP protection efficacy or industry clockspeed moderate the effect of openness on a firm's income growth. Table 23 presents the results of OLS regressions estimated for model 4 and model 5. Both models make a significant but only marginal contribution over and above model 3. This suggests that moderating effects exist but are only marginal (see hypothesis 4 and hypothesis 5 respectively).

As in prior regression, model 4 investigates the moderating effect of the strengths of IP protection. The universal effect of the legal IP protection efficacy is not significant.

Table 23: OLS Regressions Explaining Income Growth (Moderating Effects)

Independent & moderating variables	**Model 3**	**Model 4**	**Model 5**
	coef (s.e.)	coef (s.e.)	Coef (s.e.)
Intercept	**0.4623*** (0.0304)**	**0.4512*** (0.0312)**	**0.4730*** (0.0343)**
External innovation search			
Direct customers	-0.0015 (0.0048)	**-0.0157** (0.0069)**	0.0045 (0.0064)
Indirect customers	-0.0065 (0.0043)	0.0016 (0.0063)	-0.0045 (0.0056)
Suppliers	0.0016 (0.0046)	0.0087 (0.0066)	0.0011 (0.0059)
Universities/Research	**-0.0093** (0.0047)**	**-0.0164** (0.0069)**	**-0.0149** (0.0062)**
IPR experts	**0.0124** (0.0051)**	**0.0153* (0.0086)**	**0.0157** (0.0068)**
Network partners	0.0049 (0.0047)	0.0090 (0.0067)	0.0100 (0.0063)
Relationships			
No. of co-development ties	**0.0459** (0.0217)**	0.0294 (0.0266)	**0.0713** (0.0288)**
Scope of networking	-0.0032 (0.0061)	-0.0059 (0.0090)	-0.0009 (0.0079)
Efficiency of networking	0.0182 (0.0248)	0.0132 (0.0353)	0.0241 (0.0332)
Moderating effects-1			
Appropriability conditions		-0.0234 (0.0188)	
Appr.& direct customers		**0.0279*** (0.0097)**	
Appr. & indirect customers		-0.0137 (0.0086)	
Appr. & suppliers		-0.0145 (0.0090)	
Appr. & network partners		-0.0113 (0.0096)	
Appr. & IPR experts		-0.0019 (0.0109)	
Appr. & Universities		0.0137 (0.0095)	
Appr.& Efficiency of network		0.0039 (0.0492)	
Appr. & Scope of networking		0.0058 (0.0123)	
Appr. & no. of co-develop. ties		0.0453 (0.0373)	
Moderating effects-2			
Clockspeed			-0.0134 (0.0176)
Clocks.& direct customers			-0.0139 (0.0097)
Clocks. & indirect customers			-0.0056 (0.0087)
Clocks. & suppliers			0.0026 (0.0092)
Clocks. & network partners			-0.0116 (0.0095)
Clocks. & IPR experts			-0.0096 (0.0105)
Clocks. & Universities			0.0141 (0.0095)
Clocks.& Efficiency of network			-0.0177 (0.0497)
Clocks. & Scope of networking			-0.0045 (0.0126)
Clocks. & No. of co-develop. ties			-0.0547 (0.0369)
Control variables			
Age_ln	**-0.1206*** (0.0095)**	**-0.1186*** (0.0096)**	**-0.1222*** (0.0097)**
Size_ln	0.0106 (0.0081)	**0.0139* (0.0081)**	0.0110 (0.0081)
Industry_dummies [ref. KIS]			
No. of observations	1124	1124	1124
R^2	**0.2016*****	**0.2142*****	**0.2124*****
Adjusted R^2	**0.1893*****	**0.1949*****	**0.1930*****
*p<0.1, **p<0.05, ***p<0.01			

Among the interaction variables, only *one* shows a significant effect: The interaction variable of strengths of appropriability regime and *customer involvement* shows a significant and positive effect (c.= 0.0279; $p<0.01$). To interpret the effects both the direct and the higher-order effects have to be assessed simultaneously. The direct effect of customer involvement is *significant and* *negative effect* (c.=-0.0157, $p<0.05$). This suggests that if the appropriability regime is weak (and IP protection is ineffective), customer involvement may have a negative influence on income growth. It indicates that the stickiness of knowledge hinders firms to create value from innovations that build upon customer involvement. However, the effect of the interaction term counteracts this negative effect. If customer involvement is accompanied by a strong IP protection scheme, customer involvement is a successful strategy and positively shapes a firm's growth.

Table 23 also presents the results of the moderating OLS regressions for model 5 estimating the moderating effect of clockspeed on the relationship between openness and income growth. None of the interaction term shows a significant effect. So, results do not suggest that clockspeed constrains the role of openness in explaining a firm's growth.

6.3 The Internal Perspective: Mediating and Complementing Effects of Internal Practices for Innovation

A central focus of this research is to investigate the mediating and complementary effects of internal innovation practices and assets on the relationship between open and collaborative innovation strategies and innovation-based value creation. Statistical estimation of mediating effects clarify *how* open and collaborative innovation strategies interplay with internal innovation practices in explaining a firm's innovation-based value creation.

6.3.1 Examination of Conditions of Mediating Regression Analysis

The mediating regression techniques proposed by Barron & Kenny's (1986) allows for investigation of causal mediation. Internal innovation practices represent the mediating variables in regression models discussed in the following section. They comprise five components: *Innovation planning, innovation development, innovation controlling, culture for innovation and investment into knowledge base* (see chapter 5.2). As discussed in more detail in chapter 4.4, there are three assumptions to be met to perform a mediating regression analysis. The estimation of regression models of type 1 and type 3 in previous chapters provide evidence that there is a significant relationship between open and collaboration strategy and firm performance. In addition, two other causal relationships need to hold: First, there need to be a significant relationship between the independent variables (open and collaborative innovation strategies) and the mediating variables. Second, significant relationships between the mediating variables and the dependent variables should be identified. To test these conditions, two additional regression models are estimated. Models of type i are estimated including model i1 and model i3 to investigate the first pre-condition. They estimate the effect of the independent variables on the mediating variables (see chapter 6.1.1). Model ii investigates the second pre-condition: It examines the effect of each of the five mediating factors on the dependent variables (see chapter 6.1.1). Results of testing these conditions are briefly presented in the following (details on the regression analysis are presented in the appendix).

6.3.1.1 Relationship between Independent Variables and Mediating Variables

First, the causal relationship between the independent variables and the mediating variables is investigated. Regression analyses are used to investigate the significance of the causal relationship as they are superior to correlation analysis. Considering the nature of the dependent variables, OLS regression is appropriate to investigate the causal effects of open and collaborative innovation strategies on the mediating variables. Figure 41 depicts the causal relationship of the independent variables and the five mediating factors that were of interest.

Neither the magnitude nor the directions of the effect of individual parameters were in focus. The overall objective was to investigate whether there is any significant relationship. If there is, it provides the rationale for performing mediating regression analyses. Both the overall significance of the model and the significance of individual variables were investigated.

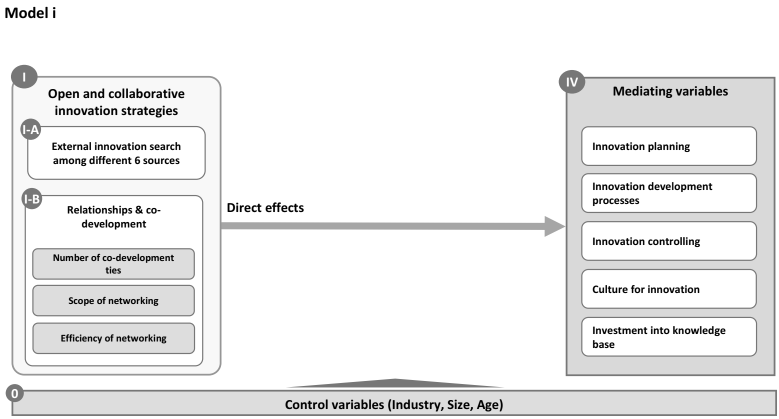

Figure 41: Causal Effect Relationships of Independent and Mediating Variables (Model i1 und i3)

OLS regressions are estimated for all five factors of internal innovation routines. First, the control model (model i0) was estimated containing only the control variables. Second, the model on innovation search (model i1) and the model capturing both innovation search variables and relationship are estimated (model i3). Results show convincing causal effects of open and collaborative innovation strategies on a firm's internal innovation routines. The F-Test revealed that all regression models are significant at the significance level of 0.01. The measure of validity and goodness of fit - the adjusted R^2 - indicate that open and collaborative innovation strategies explain nearly 20 % of the variance of a firm's internal innovation practices. When investigating the effect of individual independent variables, there were significant effects. Results are reported in the appendix chapter 12.9. Results suggest that open and collaborative innovation strategies do affect a firm's internal innovation. This provides the necessary condition for performing mediating regression analysis.

6.3.1.2 Direct Effects of Mediating Variables on Dependent Variables

In addition, the direct effects of internal innovation practices on the dependent variables were estimated. To perform mediating regression analysis and to investigate the antecedent role of internal innovation routines, causal relationships depicted in Figure 42 need to hold (model ii).

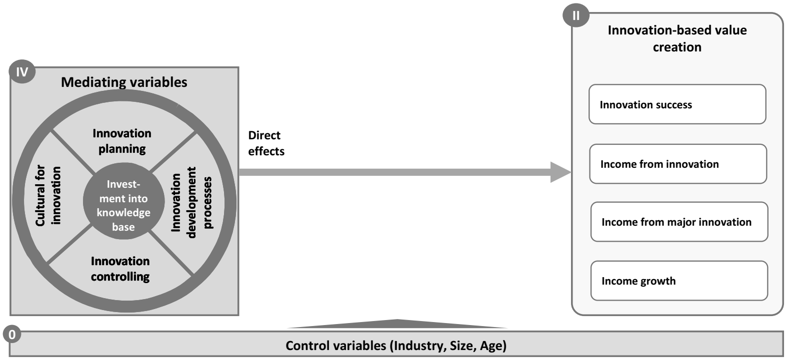

Figure 42: Causal Effect Relationships of Mediating and Dependent Variables (Model ii)

Results of regression estimations are presented in the appendix (see chapter 12.9.1.1). Models of type ii include all mediating variables. For each dependent variable separate regression models are estimated.

First, an ordered logit model is estimated to investigate the effects of the mediating variables on a firm's innovation success. The model is significant. Three factors show a significant and positive effect ($p<0.01$): *Innovation controlling, innovation development processes* and *culture for innovation.* Innovation planning and investment into internal knowledge base do not show a significant effect on innovation success.

Second, tobit models are estimated to assess the effect of the mediating factors on the share of income from innovation (and also major innovation). In both cases, model ii is significant. When examining the significance of individual parameters, four significant and positive effects were identified ($p<0.01$). Except for innovation development processes *all* factors significantly affect a firm's innovation performance.

Finally, OLS regressions estimate the direct effects of internal innovation routines on a firm's income growth. Again, the overall model is significant. Three factors show a significant and positive effect on the dependent variable ($p<0.01$): *Innovation planning, culture for innovation* and *investment into the internal knowledge base.*

In summary, results support the pre-conditions for performing mediating regression analyses.

6.3.2 Mediating and Complementary Effects of Organizational Innovation Practices

Prior chapters have provided the rationale for performing mediating regression analyses. Following the procedure of Baron and Kenny (1986) and its extensions (Shrout & Bolger, 2002), the prerequisites for entering both the independent and the mediating variables in one equation are met (see chapter 4.4). The following chapters present three regression models that were estimated for each dependent variable. The control model is presented as a reference model in the tables. In the second column, estimates of model 3 capturing the effect of the independent variables - a firm's open and collaborative innovation strategies – are shown. The third column of each table contains estimates for model 6. Model 6 includes both the independent variables (open and collaborative innovation strategies) and the mediating variables (internal innovation routines) simultaneously. Comparing the estimation of both model 3 and model 6 offers the possibility to investigate and interpret the mediating effect of internal innovation routines. If there is a mediating effect, then the effect of the independent variable must be less in the third equation than in the second equation. As in prior chapters, regression analyses consider the specific nature of the dependent variables.

6.3.2.1 Mediating Effects on Innovation Success

Results of the ordered logit regressions estimating the effects for the dependent variable *innovation success* are presented in Table 24. Model 6 makes a significant contribution over model 3 suggesting that there are both *strong mediating and complementary effects* (Pseudo R^2 Nagelkerke increases from 0.070 in model 3 to 0.259 in model 6). Indeed, internal organizational innovation practices help to leverage openness for a higher innovation success. In total, five parameters of openness are mediated. When including the mediating variables in model 6, two relationships between openness and innovation success, which are significant in model 3, are turned into non-significant relationships in model 6. This suggests that these effects are fully mediated by internal organizational practices for innovation. They have turned into "non-significant" effect in model 6 ($p>0.1$). The relationship between three parameters measuring a firm's openness and innovation success are partly mediated.

The effect of *supplier involvement* is not significant in model 6. It is fully mediated by internal innovation practices. If SMEs want to leverage *supplier involvement*, internal innovation routines play a significant role in order to successfully move innovations to the commercialization stage. The positive effect of the parameter *scope of networking* is fully mediated (the coefficient is non-significant in model 6). If firms draw deeply from co-development partners both in the early phases and the later phases of the innovation process, proficiency in managing innovations are crucial in order to create value from external innovations.

In addition to full mediation, there is partial mediation for the remaining variables that are significant in model 3. The positive relationships between *indirect customers involvement* and innovation success is only slightly mediated by a firm's organizational practices for innovation. When comparing model 6 and model 3, the significance has only slightly decreased and the magnitude of the positive effect is reduced only marginally. These results indicate that hardly any of the five practices for innovation helps to leverage such distant search among indirect customers.

Table 24: Ordered Logit Regressions Explaining Innovation Success (Mediating Regressions)

Independent & mediating variables	**Model 0**	**Model 3**	**Model 6**
	Odds ratio (s.e.)	Odds ration (s.e.)	Odds ratio (s.e.)
External innovation search			
Direct customers		1.0409 (0.0381)	0.9761 (0.0370)
Indirect customers		**1.0850*** (0.0342)**	**1.0826** (0.0360)**
Suppliers		**1.0684** (0.0354)**	1.0325 (0.0354)
Universities/research		0.9585 (0.0324)	0.9783 (0.0340)
IPR experts		**0.9102*** (0.0328)**	**0.9229** (0.0346)**
Network partners		**1.1392*** (0.0397)**	**1.0709* (0.0379)**
Relationships			
Number of co-development ties		0.9772 (0.1608)	0.9951 (0.1665)
Scope of networking		**1.0913* (0.0519)**	1.0534 (0.0519)
Efficiency of networking		1.2528 (0.2333)	0.9566 (0.1791)
Innovation practices- Mediators			
Innovation planning			1.0549 (0.0711)
Innovation development process			**1.2238 ***(0.0813)**
Innovation controlling			**3.2108*** (0.2817)**
Culture for innovation			**1.4307*** (0.1000)**
Invest. in internal knowledge			0.9952 (0.0597)
Control variables			
Age_ln	1.0467 (0.0633)	1.0488 (0.0713)	1.0131 (0.0707)
Size_ln	0.9934 (0.0472)	1.0127 (0.0578)	0.9572 (0.0572)
Industry_dummies [ref KIS]			
No. of observations	1153	957	933
Chi Square	6.67	68.86	275.97
Loglikelihood	-2626.5344	-2152.0038	-1922.6075
Pseudo R^2 (Nagelkerke)	0.006	**0.070*****	**0.259*****

*p<0.1, **p<0.05, ***p<0.01

In a similar manner, the positive effect of the parameter *network partner involvement* on a firm's innovation success is partly mediated by internal innovation routines. When comparing model 6 and model 3, the significance of the effect in model 3 is reduced in model 6 (from $p<0.01$ to $p<0.1$) and the magnitude of the effect in model 3 has decreased marginally in model 6 (from odds. ratio = 1.132 to 1.0709). This suggests that internal innovation routines complement the positive effect of external search among network partners in achieving a higher innovation success. However, they do not represent those managerial practices that make sure that external ideas and suggestions from partners are successfully and efficiently identified and integrated with internal innovation assets. Different practices may be required for translating these external ideas.

The regression analyses revealed which organizational practices for innovation facilitate firms to realize the potential benefits and impact of openness on innovation success. Three out of five factors of organizational practices for innovation help exploiting externally (and internally) generated ideas and innovation assets for a higher innovation success: *Innovation development processes, innovation controlling* and *culture for innovation.*

The factor *innovation development processes* shows a significant and positive effect in the ordered logit regression of model 6 (odds=1.2238, p<0.01). This supports hypothesis 6b.

Results indicate that formal development processes guide innovation activities and help managers to coordinate and integrate development activities that include external ideas. When opening up to external influences for innovation, formal processes and system are important heuristics that guide innovation problem solving and decision making. They define the interfaces and input channels for external innovation inputs and, in turn, they ensure that external ideas are accessed, efficiently transformed and successfully combined with internal innovations. In addition, the factor *innovation controlling* shows a significant and strongly positive effect on a firm's innovation success (odds ratio = 3.2108; p<0.01). This confirms hypothesis 6c which asserts that such routines are important antecedents of a firm's ability to exploit external or collaboratively developed ideas (Todorova & Durisin, 2007). Indeed, formal practices and structures for innovation controlling show the strongest mediating effect. Routine-like performance measurement and regular project reviews are highly important in order to integrate internal and external innovation activities efficiently. They ensure that innovations move to the commercialization stage quickly and successfully. They have an instrumental role in managing the inflow of new ideas across organizational boundaries.

The factor *culture for innovation* also shows a significant and positive effect (odds ratio= 1.4307, p<0.01). This confirms hypothesis 6d which proposes that culture is an embedded governance mechanism for innovation. A culture for innovation may foster and govern internal innovations. In addition, these findings confirm that culture influences attitudes and managerial actions towards integrating external ideas and combining it with existing internal knowledge (Lichtenthaler & Ernst, 2006). These regressions show that culture for innovation is supporting the exploitation of new ideas (and not just the exploration). A culture balancing openness to new ideas and entrepreneurial spirit drives exploitation. In SMEs, it seems to be an important governance system mediating on the individuals' behaviour without relying on more administrative methods (Teece et al., 1997). It helps to reduce the managerial and cognitive distance among partners. It may also act as "reputation" for being "innovative" that puts SMEs in a stronger position when interaction with external partners (Baum et al., 2000; Teece et al., 1997). Interestingly, the factor *innovation strategy and planning* has no significant and positive effect in model. Thus, one cannot assume that those semi-procedural mechanisms and routines for innovation planning may support a firm to mediate and complement the effect of openness on a firm's innovation success. It is worth it to point out that a firm's *investment into the knowledge base* does not show a significant effect on a firm's innovation success either. So it cannot be confirmed that a firm's internal knowledge base does not affect innovation success – neither purely internally developed nor collaboratively developed ones.

6.3.2.2 Mediating Effects on Innovation Performance

Table 25 presents the results of the tobit regression for the dependent variable income from innovations. A comparison of model 3 and 6 reveals that there are mediating and complementary effects. Model 6 makes a significant contribution over model 3 (Pseudo R^2 Nagelkerke changes from 0.194 to 0.322) and supports the proposition that internal organizational practices matter to create value from openness. Three positive and significant effects of a firm's openness on income from innovation are fully mediated by organizational innovation practices; two effects are partly mediated. In addition, there are two suppressor effects suggesting counteracting effects of the direct effects and the mediating effects (Urban & Mayerl, 2008).

The significant effects in model 3 of the parameter *direct customers involvement* and *IPR expert involvement* became non-significant once mediating variables were included (see model 6). In addition, the parameter *efficiency of networking* has a non-significant effect in model 6 ($p<0.01$). This indicates that these variables are fully mediated by internal innovation practices. It can be concluded that if firms want to benefit from ideas provided by customers and external IPR advisors internal organizational practices and routines are important "facilitators" or "enablers" in order to benefit from these strategies.

The effect of involving *network partners* to search and source new ideas is only partly mediated (The significance level reduces from $p<0.01$ to $p<0.1$ and the magnitude of the effect reduces from c.= 0.0186 to c.= 0.0109). In a similar manner, the effect of the *number of a firm's co-development ties* is also reduced in model 6 suggesting a partial mediation. This suggests that if firms interact with co-development partners to search and to co-develop innovations, internally-oriented managerial practices may only slightly help a firm to benefit from this strategy; but most probably not completely. While they directly affect a firm's innovation activities they do not necessarily constitute those organizational antecedents that help firms to transform and integrate ideas that come from co-development partners.

Interestingly, the mediation analyses reveal two "suppressor effects" for the parameter involvement of *universities* and *scope of networking.* In model 6, the direct effect of involvement of *universities* is negative suggesting that SMEs will not be able to create economic returns from searching and sourcing ideas from universities; they may actually suffer from university involvement unless they have established internal managerial practices for innovation. A firm's internal organizational practices for innovation counterbalance the negative effect of scientific search. This suggests that internal innovation practices for innovation help to turn relationships with scientific partners into a positive effect on a firm's performance.

In a similar way, the mediating regression reveals a significant and negative effect of the parameter of *scope of networking*. This suggests that it is quite risky to engage in intensive networking both in the early and latter phases of the innovation process (the direct effect is negative). If firms rely heavily on input from external innovation partners, internal organizational practices are highly important as they counteract this negative effect.

Table 25: Tobit Regressions Explaining Innovation Performance (Mediating Regressions)

Independent & mediating variables	**Model 0**	**Model 3**	**Model 6**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.5745*** (0.0308)**	**0.4848*** (0.0396)**	**0.4839*** (0.0389)**
External innovation search			
Direct customers		**0.0145** (0.00641)**	0.0045 (0.0063)
Indirect customers		-0.0069 (0.0057)	-0.0091 (0.0056)
Suppliers		0.0019 (0.0061)	-0.0004 (0.0059)
Universities/research		-0.0088 (0.0062)	**-0.0119** (0.0061)**
IPR experts		**0.0118* (0.0068)**	0.0081 (0.0066)
Network partners		**0.0186*** (0.0063)**	**0.0109* (0.0061)**
Relationships			
Number of co-development ties		**0.1102*** (0.0291)**	**0.0638** (0.0282)**
Scope of networking		-0.0087 (0.0082)	**-0.0185** (0.0080)**
Efficiency of networking		**0.0554* (0.0331)**	0.0358 (0.0318)
Innovation practices- Mediators			
Innovation planning			**0.0465*** (0.0112)**
Innovation development process			0.0058 (0.0110)
Innovation controlling			**0.0793*** (0.0112)**
Culture for innovation			**0.0731*** (0.0116)**
Invest. in internal knowledge			**0.0590*** (0.0103)**
Control variables			
Age_ln	**-0.0795*** (0.0111)**	**-0.0554*** (0.0123)**	**-0.0436*** (0.0119)**
Size_ln	**-0.0189** (0.0090)**	-0.0117 (0.0107)	**-0.0223** (0.0106)**
Industry_dummies [ref KIS]	**ICT 0.0567** (0.0279)** **Bio -0.0632** (0.0368)**	**ICT 0.0571* (0.0304)**	
No. of observations	1442	1125	1108
No. of left censored data	187	126	123
No. of non censored data	1255	999	985
No of right censored data	0	0	0
Chi Square	132.53	148.55	253.80
Pseudo R^2 (Nagelkerke)	**0.134*** **	**0.194*** **	**0.322*** **

*p<0.1, **p<0.05, ***p<0.01

Four factors of a firm's internal innovation practices (see the innovation wheel in chapter 5.2.3) were identified as relevant organizational antecedents of absorptive capacity and "facilitators" of open and collaborative innovation strategies; they help a firm to create financial returns from open innovation strategies: *Innovation planning, innovation controlling and commercialization, culture for innovation, investment into the knowledge base.* These factors embrace both formal and embedded practices for innovation. They mediate and complement the causal effect of a firm's open and collaborative innovation strategies.

While the factor *innovation planning* didn't show a mediating and complementing effect on a firm's innovation success, this factor shows a significant and positive relationship with a firm's income from innovation (c.=0.0465; $p<0.01$). This confirms hypothesis 6a which asserts that semi-procedural routines for innovation planning help a firm to identify and assess the value of relevant external innovation. It helps to identify future business opportunities and mapping external innovation capabilities with internal capabilities (Cohen & Levinthal, 1990; Grant, 1996). Interestingly, the factor *innovation development processes* did not show a significant and positive effect (so hypothesis 6b cannot be supported for the dependent variable income from innovation). Formal systems for *innovation controlling* are also important to create financial impact from innovations that include both external and internal innovation input. It is worth it to point out that this effect is relatively strong (c.=0.0793, $p<0.01$). This supports hypothesis 6c. It suggests that SMEs need disciplines and heuristics for measuring and managing innovation projects in an integrated manner. Such routines are crucial to integrate external innovation inputs into internal activities and manage internal innovation activities and their interfaces with collaboration partners. The effect of the factor *culture for innovation* is also significant and positive (c.= 0.0731, $p<0.01$). This supports the proposition that culture is an important mediating factor (hypothesis 6d). It governs internal innovation activities and at the same time, allows firms to better manage interfaces with external organizational actors when searching and accessing external information or engaging in co-development activities.

Finally, hypothesis 6e is also confirmed. The factor *investment into knowledge base* shows a significant and positive effect (c.=0.0590, $p<0.01$). As suggested in prior innovation studies on absorptive capacity, a firm's prior knowledge is an important determining factor of firm's ability to absorb external knowledge (Cohen & Levinthal, 1990; Laursen & Salter, 2006). These results clearly indicate that firms need to invest internally to reap the rewards from openness; openness does not substitute internal innovation resources (which suggests that a transaction cost perspective towards open innovation is not appropriate; Williamson, 1987).

6.3.2.3 Mediating Effects on Major Innovation Performance

Previous chapters showed that firms need to adopt different open and collaborative innovation strategies when aiming for major innovations. Hence, the interplay with internal innovation practices may also be different. Table 26 reports the results of mediating regressions for the dependent variable major innovation performance (measured as share of income from major innovation). Model 6 makes a significant contribution over and above model 3 (Pseudo R^2 Nagelkerke increases from 0.133 to 0.247). Thus suggests that there are mediating effects.

When comparing the effects in model 3 and model 6 one can easily identify that all significant relationships between openness and major innovation performance are fully mediated by a firm's organizational practices for innovation.

Table 26: Tobit Regressions Explaining Major Innovation Performance (Mediating Regressions)

Independent & mediating variables	**Model 0**	**Model 3**	**Model 6**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.2595*** (0.0291)**	**0.2094*** (0.0369)**	**0.2072*** (0.0366)**
External innovation search			
Direct customers		0.0077 (0.0060)	-0.0018 (0.0059)
Indirect customers		0.0023 (0.0053)	0.0001 (0.0052)
Suppliers		-0.0054 (0.0056)	-0.0038 (0.0055)
Universities/research		-0.0011 (0.0058)	-0.0058 (0.0057)
IPR experts		**0.0141** (0.0063)**	0.0010 (0.0061)
Network partners		0.0058 (0.0058)	-0.0010 (0.0057)
Relationships			
Number of co-development ties		**0.0485* (0.0265)**	0.0084 (0.0258)
Scope of networking		0.0112 (0.0077)	-0.0016 (0.0076)
Efficiency of networking		**0.0562* (0.0312)**	0.0487 (0.0302)
Innovation practices- Mediators			
Innovation planning			**0.0409*** (0.0105)**
Innovation development process			0.0154 (0.0103)
Innovation controlling			**0.0499*** (0.0105)**
Culture for innovation			**0.0664*** (0.0111)**
Invest. in internal knowledge			**0.0634*** (0.0096)**
Control variables			
Age_ln	**-0.0669*** (0.0106)**	**-0.0443*** (0.0116)**	**-0.0316*** (0.0113)**
Size_ln	**-0.0148* (0.0086)**	**-0.0208** (0.0100)**	**-0.0315*** (0.0100)**
Industry_dummies [ref KIS]		**Mach 0.0588** (0.0294)**	**Mach 0.0630** (0.0282)**
		Textile 0.1347 (0.0604)**	**Textile 0.1222** (0.0610)**
No. of observations	1458	1137	1120
No. of left censored data	564	416	408
No. of non censored data	894	721	712
No of right censored data	0	0	0
Chi Square	84.55	96.48	182.89
Pseudo R^2 (Nagelkerke)	**0.089*****	**0.133*****	**0.247*****
*p<0.1, **p<0.05, ***p<0.01			

None of the parameters that have a significant effect in model 3 show significant effects in model 6. Hence, there is perfect mediation (Baron & Kenny, 1986). It clearly indicates that a firm's internal innovation routines and assets are a major prerequisite when opening to external influences in "major innovation activities". Proficiency in managing innovations internally is highly valuable when it comes to more risky and complex innovation endeavours. Four types of organizational practices for innovation mediate the positive effect of openness on major innovation performance. They provide the translation of understanding between organizations engaging in external innovation search or collaboration: *Innovation controlling, innovation planning, innovation culture* and *investment into internal knowledge base*. As shown in Table

26, these factors show a significant and positive effect when regressing the share of income from major innovation on the independent and mediating variables.

When firms work on major innovation activities, semi-procedural routines for innovation planning are highly valuable; the factor *innovation planning* shows a significant and positive effect on income from major innovation (c. = 0.0409, $p<0.01$). It helps the firm to identify the value of external innovation inputs and at the same time also directs a firm's innovation activities and decisions in co-development partnerships. Such routines ensure that managers make better strategic choices when planning and implementing an open and collaboration strategy. So hypothesis 6a can be confirmed. As in prior regressions, the factor *innovation development processes* did not show a significant and positive effect (so hypothesis 6b cannot be supported for the dependent variable income from major innovation). In addition, *innovation controlling* is extremely valuable when firms engage in major and more risky innovations and open their innovation activities (c.=0.0499, $p<0.01$). Formal routines help firms to reduce complexity and uncertainty of major innovation activities that imply discontinuities both from a market and technological perspective and are uncertain in multiple dimensions. Exploration reduces variation. Thus, internal routines need to counterbalance variation and complexity.

Culture for innovation also shows a significant and positive effect (c.=0.0664, $p<0.01$). The effect is even stronger when estimating the mediating effect on a firm's major innovation performance as compared to the regression above estimating the effects on a firm's innovation performance. This emphasizes the relevance of culture as means to successfully identify, access, transform, and exploit external ideas and technologies.

As one might have expected, a firm's *investment into the knowledge base* is also a crucial mediating factor (c.=0.0634; $p<0.01$). This suggests that firms cannot reduce their own internal investments in innovation and cannot understand open innovation as "outsourcing" strategy. The opposite is true, investments in innovations are equally important when engaging in open and collaborative innovations.

6.3.2.4 Mediating Effects on Income Growth

Table 27 presents the results of the OLS regression estimating the causal mediation for the dependent variable *income growth*. Model 6 makes a significant and marginal positive contribution over model 3 (see adjusted R^2). A closer look reveals that there are both mediating and complementary effects.

The positive relationship between the size of the co-development network (*number of co-development ties*) and income growth is fully mediated. In contrast, the positive effect of the parameter *IPR expert involvement* is only partly mediated. That is, formal and embedded organizational practices cannot fully explain how firms create value when they ask IPR experts for innovation support. Just like in prior regressions, the mediation analysis reveals a "suppressor effects" for the parameter *involvement of universities/research organizations.* Both in model 6 and model 3, the effect of *involvement of universities* is negative but in model 6 the direct effect shows a larger magnitude. This indicates that a firm's internal organizational practices for innovation counterbalance the negative effect of scientific search on income growth. However, they cannot fully alleviate the problem.

Table 27: OLS Regressions Explaining Income Growth (Mediating Regressions)

Independent & mediating variables	**Model 0**	**Model 3**	**Model 6**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.5047*** (0.0229)**	**0.4623*** (0.0304)**	**0.4330*** (0.0308)**
External innovation search			
Direct customers		-0.0015 (0.0048)	-0.0018 (0.0048)
Indirect customers		-0.0065 (0.0043)	-0.0048 (0.0043)
Suppliers		0.0016 (0.0046)	0.0017 (0.0046)
Universities/research		**-0.0093** (0.0047)**	**-0.0133*** (0.0047)**
IPR experts		**0.0124** (0.0051)**	**0.0118** (0.0051)**
Network partners		0.0049 (0.0047)	0.0061 (0.0047)
Relationships			
Number of co-development ties		**0.0459** (0.0217)**	0.0337 (0.0217)
Scope of networking		-0.0032 (0.0061)	-0.0055 (0.0062)
Efficiency of networking		0.0182 (0.0248)	0.0181 (0.0245)
Innovation practices - Mediators			
Innovation planning			0.0123 (0.0087)
Innovation development process			-0.0071 (0.0085)
Innovation controlling			-0.0011 (0.0087)
Culture for innovation			**0.0158* (0.0090)**
Invest. in internal knowledge			**0.0368*** (0.0081)**
Control variables			
Age_ln	**-0.1314*** (0.0082)**	**-0.1206*** (0.0095)**	**-0.1141*** (0.0095)**
Size_ln	0.0093 (0.0066)	0.0106 (0.0081)	**0.0144* (0.0083)**
Industry_dummies [ref KIS]	**Space -0.0582* (0.0317)**		
No. of observations	1441	1124	1095
R^2	**0.1979***	**0.2016***	**0.2247***
Adjusted R^2	**0.1934***	**0.1893***	**0.2088***
*p<0.1, **p<0.05, ***p<0.01			

When looking into the relevance of managerial practices for innovation, one can easily identify that only two out of five managerial practices are organizational antecedents. Unlike in prior regressions formal and semi-procedural routines do not show a significant effect. I*nnovation planning, innovation development processes,* and *innovation controlling* do *not* significantly shape a firm's ability to turn openness into value growth. Results emphasize that embedded practices and financial resources make a difference. When comparing model 3 and 6, results confirm that a firm's culture for innovation mediates and complements the effect of openness (c.=0.0158, p<0.1). This outcome supports hypothesis 6d. It indicates that culture is an important driver of a firm's long-term growth as it directs innovation activities of individuals towards the achievement of innovation objectives and targets. It is also an important antecedent of successful collaborative innovation and helps to turn them into long-term value. At an organizational level an innovation culture embodies a strong "reputation" for being "innovative" serving as an "asset" that can create a competitive advantage. It may help to overcome the liability of smallness. In turn, it directly and indirectly influences a firm's income growth. This result is in line with prior studies that show that "entrepreneurial" culture is driving innovation performance (Ernst, 2003; Goffin & Mitchell, 2005; Sammerl, 2006). In addition, the estimation of model 6 confirms that a firm's investment into the knowledge base partly mediates the effect of openness on income growth. It confirms that financial innovation assets and investment are antecedents of successful transformation and exploitation of both external and internal knowledge. Even in the long-term, internal capability building remains crucial when opening innovation processes (Cohen & Levinthal, 1990; Laursen & Salter, 2006; Todorova & Durisin, 2007; Zahra & George, 2002).

7 Conclusions, Implications and Critical Discussion

Firms have revitalized their interest in tapping into innovation sources outside their organizational boundaries to sustain their innovations. They can make a choice among a range of different innovation partners ranging from customers, suppliers, universities, advisors to complementary network partners. This research showed that they do. The statistical examination of causal relationships of different types of open and collaborative innovation strategies and innovation-based value creation was unique as it takes a multidimensional perspective towards openness, and considers its interplay with both *external* and *internal* factors. Based on a comprehensive and theoretically grounded framework this research statistically examined multivariate causal relationships, causal moderations and causal mediations. It is the first quantitative research that examines open and collaborative innovation based on a large set of firm-level data of SMEs creating theoretical and practical results of high objectivity and accuracy.

7.1 External Perspective: Implications for Theory and Practice on Open and Collaborative Innovation Strategies

In summary, the results of quantitative multivariate examination of multivariate causal relationships *explain* the relationship between different types of open and collaborative innovation strategies and innovation-based value creation in a profound and fine-grained manner. Figure 43 shows that causal inference successfully supported those hypotheses that examine the effect of openness and environmental contingencies. Reaching these results, this research has made some significant conceptual and empirical contribution to existing theory and practice of open and collaborative innovation.

The results strongly suggest that openness is not a dichotomic concept – open versus closed. Openness and specifically external innovation sourcing should be considered as multidimensional interactions with different types of innovation partners. It matters with whom firms interact when searching for new ideas. Some innovation sources positively affect a firm's innovation performance, while others do not. In general, complementary network partners are highly valuable partners for SMEs. Furthermore, the dual involvement of some external innovation partners has a positive effect. However, some combinations imply contradicting effects of two types of innovation sources. As a result, it makes a difference how firms involve different innovation partners simultaneously. In addition, a firm's relational ties shape a firm's innovation performance and value growth. A major implication of the examination of moderating effects is that the impact of a firm's external idea sourcing and co-developments is conditioned and bounded by factors outside the firm. Openness goes beyond a strategic choice of the firm as the industry clockspeed and the appropriability conditions confine how firms open up their innovation processes and whether they benefit from open styles of innovation.

Hypotheses			**Dependent variable**			
Nr		**Causal relationship addressed in hypotheses**	**Success of launch**	**Income from innovation**	**Income from major innovation**	**Income growth**
1a	✓	Effect of involvement of direct customers	○	+	○	○
1a	✓	Effect of involvement of indirect customers	+	○	○	○
1b	✓	Effect of involvement of suppliers	+	○	○	○
1c	✓	Effect of involvement of universities/research organizations	-	-	○	-
1d	✓	Effect of involvement of IPR experts	-	+	+	+
1e	✓	Effect of involvement of network/co-development partners	**+**	**+**	**+**	○
2a	✓	Number of combinations of two external innovation sources that are complementary	0	2	1	2
2a	✓	Number of combinations of two external innovation sources that are contradictory	1	4	3	1
2b	(✓)	Effect of dual involvement of universities and network/co-development partners	○	○	○	+
2c	✓	Effect of dual involvement of direct customers & network/co-development partners	○	-	-	○
2c	(✓)	Effect of dual involvement of indirect customers & network/co-development partners	○	○	○	+
2d	(✓)	Effect of dual involvement of universities and direct/indirect customers	○	+	○	○
3a	✓	Effect of size of co-development network	○	**+**	**+**	**+**
3b	✓	Saturation of effect of the size of the co-development ties		✓	✓	✓
3c	✓	Effect of scope of networking	+	-	-	○
3d	✓	Effect of efficiency of networking strategies	○	**+**	**+**	**+**
4	✓	Number of moderating effects of efficacy of IP protection	2	1	1	1
5	✓	Number of moderating effects of industry clockspeed	3	2	1	0

\+ Positive significant effect ○ No significant effect ✓ Hypothesis is confirmed

\- Negative significant effect **○** Strong effect (✓) Hypothesis is partly confirmed

Figure 43: Overview of Results of Statistical Examination of Causality - External Perspective

This research also identified that the nature of the involvement with external innovation partners affects the success of innovation launch, income from innovation, income from major innovation, and income growth differently. As shown in Figure 43, this reveals a *trade-off*. Only *networked searching* – meaning the involvement of network/co-development partners when searching for new ideas – positively affects three dimensions of innovation performance. Complementary network partners and well established interaction channels are extremely valuable when SMEs open up their innovation activities and propel both innovation performance and value-creation in innovation. In addition, the involvement of IPR experts seems to be a promising strategy. If SMEs search for means to protect IP, to access and source external R&D or to identify new means to commercialize internal technological knowledge, IPR experts are a critical source. They may shape a firm's innovation-based value creation in multiple ways.

7.1.1 The Role of Different Types of Open and Collaborative Innovation Strategies

Results point out the relevance of different types of external innovation sources. Three types of innovation sources matter for a firm's success in commercializing innovations: *Indirect customers* – distant sources along the value chain – may impact a firm's innovation success. However, one cannot assume that traditional "market-side" sourcing among *direct customers* helps a firm to successfully launch an innovation; results suggest that more "distant" sourcing matters. To achieve a high success in launching innovations, SMEs can also benefit from *supply-side searching* for new ideas, as suppliers concentrate on solutions that can be commercialized in the short-term. The interaction with *complementary network partners* is extremely valuable as it builds upon well established relationships and mutual understanding, which drive innovation efficiency. In contrast, the involvement of *IPR experts* may slow the efficiency of the innovation processes and may negatively affect a firm's innovation success. As assumed, "pre-commercial learning relationships" with *universities* negatively affect the efficiency of innovation. In addition, dual involvement of different innovation actors is not beneficial when aiming for a high innovation success. The dual involvement of indirect customers and suppliers may actually negatively affect a firm's innovation success.

A different picture emerges when one looks into the effect of openness on a firm's financial innovation performance: *Network partners* are the most relevant innovation source to ask for new ideas when aiming for a higher share of income from innovations. They offer well functioning interaction channels that are crucial to combine and transform inputs from different knowledge domains. They also offer access to complementary assets that are critical to create value from an idea (Christensen et al., 2005; Teece, 1986). *Direct customers* are also valuable partners and should be exploited as "value-generators"; it was found that market-side searching rather than supply-side searching positively affects a firm's share of income. In addition, SMEs may also benefit from insights gained when working with *IPR experts* because they may learn about new means to transform their idea into a value proposition. However, the interaction with *universities* is somewhat risky. If SMEs search in highly pre-commercial domains, they get locked in and may struggle with turning ideas into value. However, a firm's innovation practices and routines can offer a remedy to mitigate this risk. *Dual involvement* of different innovation partners may shape a firm's innovation either in a positive or negative sense. Results emphasize that negative effects steaming from dual involvements outweigh positive effects. For example, the simultaneous involvement of customers and complementary network partners is a risky strategy and may negatively influence a firm's innovation posture (Gans & Stern, 2002). It is worth it to point out that those firms that involve IPR experts can benefit from a simultaneous involvement of direct customers. Results do not support the idea that the dual involvement of universities and customers is valuable. Apparently, existing and direct customers are not ready for innovations that build on new scientific and technological knowledge.

Results suggest that if firms work on major innovations, which are in an early lifecycle stage and offer significantly new performance features to the customer, they need to be more selective when searching for new ideas. More focused external innovation search strategies are associated with such risky and uncertain innovations. Results emphasize that there are only two types of partners that may positively affect performance in major innovation endeavours: *Network partners and IPR experts*. Furthermore, the simultaneous involvement of one of these partners with customers in innovation projects aiming for major innovations is not recommended as it may put a firm's innovation at risk.

This research also shows that openness to external influences is difficult to directly translate in income growth. Direct effects are only marginal. Interestingly, results support the idea that technology strategies rather than product strategies might be a valuable growth strategy. It confirms that SMEs should consider external technology sourcing or new commercialization strategies such as technology licensing, and thus, should work closely with IPR experts.

Results emphasize that asking for ideas is not sufficient in order to make knowledge flow across organizational boundaries. As shown in Figure 43, a firm's *relational ties and networking strategies* shape a firm's innovation performance and value growth. It confirms that a firm's network ties matter as they ensure that the value from openness is captured. A firm's intensity of co-development activities significantly shapes innovation success. Innovators need to build on strong ties, high quality partnerships and very close collaboration to move quickly to the commercialization phase; if a successful launch is in focus, it's not about the number of co-development partners. However, the analysis revealed that if SMEs clinch too much and work too closely with their partners they may get locked in and put their financial returns from innovation at risk. Formal innovation practices might help them to counterfeit this risk of not reaping the rewards from collaboratively developed innovations.

In contrast, a *large co-development network* for innovation shapes a firm's innovation performance in financial terms. A large co-development network creates "relational value" and has a positive effect on a firm's income from innovation; only if SMEs have too many co-development partners there are decreasing returns. In case firms aim for major product and service innovations that are in the early stages of their lifecycle, well established relationships (so called "closed" network ties) that build upon well established interaction channels and complementarity of competencies are even more crucial. Results also imply that SMEs need to leverage their network ties wisely and efficiently when aiming for a higher financial innovation performance. They suggest that operational partners should be leveraged as innovation partners to get access to operational assets such as marketing channels in an efficient manner.

7.1.2 External Boundary Conditions and Implications for Open Innovation Strategies

Causal moderation analyses complement causal effects analyses. As shown in Figure 43, this research reveals that openness is not just about the strategic choice of the firm (Barley, 1990; Christensen et al., 2005). Industry clockspeed and appropriability conditions confine how openness and co-development activities impact performance.

For example, the *strength of the appropriability scheme* shapes the impact of a firm's open innovation strategies significantly. A strong appropriability scheme, meaning a strong efficacy of the IP protection, makes knowledge easier to replicate and also to transfer across organizational boundaries. Thus, even if SMEs hold a patent, operational partners can invent "around". Under such conditions, the involvement of operational partners as innovation partners represents a large risk. Innovative firms – especially small ones – might not reap the rewards from co-development activities. This is specifically relevant if SMEs aim for major innovations that represent a significant performance difference and offer compelling value propositions to the customer. In such cases, SMEs face the problem of principle hazard that owners of complementary assets expropriate the innovators codified knowledge. In contrast, under conditions of weak appropriability schemes the involvement of operational partners is actually highly beneficial (as knowledge is more tacit and more difficult to replicate) and offers valuable access to complementary assets such as marketing channels.

In addition, *industry dynamism and clockspeed* also significantly shape the impact of a firm's open and collaborative innovation strategies. For example, the active involvement of co-development partners is even more important if product lifecycles are short. Interestingly, industry dynamism also shapes the role of customer involvement. The positive effect of customer involvement unfolds only if dynamism is moderate or low. In turbulent environments an active involvement of customers is not associated with a higher innovation performance. Furthermore, if firms deeply engage in collaboration activities and at the same time act in turbulent environments, they are faced with problems of negative returns from innovation.

7.2 Internal Perspective: Implications for Theory and Practice of Managerial Routines and Organizational Facilitation of Innovation

Openness and inter-organizational interaction pose new managerial challenges. This research argues that a firm's managerial practices for innovation are organizational antecedents of absorptive capacity and “facilitators” of open innovation strategies. Established internal innovation routines and capabilities may (or may not) help a firm to benefit from interaction with external innovation partner. This research conceptualized five different components of organizational innovation practices, namely *innovation planning, innovation development processes, innovation controlling, culture for innovation* and *investment into knowledge base.* They measure practices for managing innovation at an organizational level. They adequately represent the multidimensionality of managerial practices for innovation. Factor analysis empirically composed these factors and ensured that there is a high consistency and homogeneity among different measures within one component. It composed five dimensions of *high content validity,* which correspond to the managerial practices in the “empirical world”. By doing this, results made a major step forward towards an empirically validated framework for identifying and measuring internal organizational practices for innovation. It advances existing frameworks for measuring organizational innovation practices. As a result, it significantly contributes to the literature on innovation management and innovation routines (Bessant et al., 2009; Pavitt, 2002). It is worth pointing out that it overcomes major conceptual and methodological weaknesses of existing research - such as NPD success factor research – and managerial practices (see chapter 2.3.2). In addition, the conceptualization of these five components of organizational practices for innovation is linked to different dimensions of absorptive capacity (Todorova & Durisin, 2007). Results open the black box of absorptive capacity and the antecedent role of innovation practices (regularly referred to as “processes”) in creating impact from external-oriented innovation strategies (Cohen & Levinthal, 1990; Nelson et al., 1982). The mediating modelling examined an under-researched issue, and enriched the understanding whether and which organizational practices for innovation help a firm to benefit from different kinds of openness.

This research investigated hypotheses that address the mediating and complementary effects of different types of organizational practices for innovation embracing strategic, operational and embedded ones. Results reveal that a firm’s internal managerial practices are highly relevant. As shown in Figure 44, causal inference highlighted numerous mediating and complementary effects. Indeed, a firm’s internal innovation practices make a difference and are enormously shaping a firm’s innovation-based value creation. The mediating regression model and mediating hypotheses proposed in chapter 3 were empirically supported. In addition, new insights and additional fine-grained findings on causal mechanism could be drawn.

Overall, results emphasize that firms will only gain the potential of external innovation inputs if they are proficient in managing innovation internally. Results emphasize that a firm’s organizational practices and internal assets for innovation are at least as important as open styles of innovation.

Statistical analyses identified which practices lie in the causal pathway between open and collaborative innovation strategies and innovation-based value creation; they revealed *which* *types of openness* are mediated. That is, they provide an answer to the question which type of open innovation strategy is best supported by internal organizational practices for innovation.

Hypotheses			**Dependent variables**			
Nr		**Causal relationship addressed in hypotheses**	**Success of launch**	**Income from innovation**	**Income from major innovation**	**Income growth**
		Number of direct effects of different types of openness that are strongly/partly mediated	2/2	1/1	3/0	1/1
6a	✓	Complementary and mediating effect of innovation planning	○	●	●	○
6b	✓	Complementary and mediating effect of development processes for innovation	●	○	○	○
6c	✓	Complementary and mediating effect of innovation controlling and commercialization	●	●	●	○
6d	✓	Complementary and mediating effect of culture for innovation	●	●	●	●
6e	✓	Complementary and mediating effect of investment into knowledge base	○	●	●	●

● Significant effect ○ No significant effect ✓ Hypothesis is confirmed

Figure 44: Overview of Results of Statistical Examination of Causality – Internal Perspective

Results clearly point out that involvement of actors along the value chain – meaning either customers or suppliers - can be best leveraged if firms are proficient in managing innovation at an organizational level. This research also provides the evidence that managerial practices for innovation are extremely valuable in order to move a co-development project efficiently to the commercialization stage, in case firms draw more deeply among external partners. Another major finding was that a firm's managerial practice for innovation can offer a remedy to mitigate this risk steaming from interactions with universities (and research organizations) or very deep co-development activities.

Results confirm the notion that both formal and embedded managerial practices are important to capture the value from openness. In general, formal and operational routines for measuring the performance of innovation activities from the inception of the idea to the commercialization phase are extremely important. Indeed, SMEs need to have discipline throughout the innovation value chain to integrate external and internal innovation. At the same time, a culture for innovation is an important governance mechanism to affect a firm's innovation efficiency, innovation performance and growth.

The relevance of each of the five components of innovation practices varies depending on the aspired impact. *Innovation controlling, innovation development processes* and *a culture for innovation* help to make use of openness for a higher innovation success. In contrast, if firms want to create financial impact from openness and achieve a higher income from new products, the following four practices are important *innovation planning, innovation controlling, culture for innovation and investment into knowledge base.* Indeed, semi-procedural routines for innovation strategy making and firm's investment to nurture the internal knowledge base are extremely important to leverage openness for a higher financial performance. Openness and external search is *not* substituting a firm's internal innovation and knowledge building activities but requires a firm to invest internally. In general, managing innovation internally is even more demanding if firms open up to external influences for achieving a higher income from innovation. It requires more than just operational proficiency in managing innovation. Strategic coordination and internal investments are also highly valuable when firms engage in major innovations that are more risky. Proficiency in managing innovations internally supports the translation between external and internal innovations if firms develop major innovations that are in the early stage of the product/service lifecycle. Without them, open innovation strategies cannot materialize at all and put a firm's investment at risk.

Finally, results reveal that a *firm's culture for innovation* and *financial resources* propel the effect of open innovation strategies on a firm's growth. Findings of this research suggest that culture and entrepreneurial leaders are important governance mechanisms that support small firms in making use of external innovations and turn them into firm growth (Macpherson & Holt, 2007). Indeed, formal operational practices for innovation such as innovation controlling are not sufficient to turn open innovation strategies into growth strategies. Entrepreneurial leaders are those that build weak ties, connect with innovation partners and leverage "formal and strong ties" for a firm's growth. Financial resources provide the financial slack to experiment and to build the internal - mostly technological - knowledge required to absorb external knowledge.

To conclude, SMEs might miss innovation opportunities if they do not open up to external influences and co-development activities. However, they need to be proficient in managing innovation internally both in a formal and "embedded" way. To create value operational proficiency is not sufficient. Strategic coordination, financial dedication towards innovation and culture for innovation should be successfully in place; if not SMEs risk the benefits of openness leaking outside of their firm boundaries.

7.3 Critical Evaluation of Research Results

This research developed a framework of multiple causal relationships between open and collaborative innovation strategies and firm's innovation-based value creation. Most importantly, it empirically examined this framework to statistically infer causal relationships. In summary, results allowed answering all four research questions and overcame major limitations in existing research (see chapter 1.2.1). Following the idea of *statistical explanation* it successfully integrated a *theoretical and pragmatic scientific objective.*

From a theoretical perspective, this research was explanatory in nature. A quantitative quasi-random experimental research design defined the structure of enquiry and *statistically inferred* multiple causal effect relationships in a rigid manner (de Vaus, 2001). Reflecting the results from a theoretical and explanatory perspective, there are *significant strengths:*

First, a thorough conceptual framework and a set of propositions guided the statistical examination of causal relationships. Overcoming limitations of inductive reasoning, the construction of this causal framework was theoretically grounded in relevant theories (see chapter 3). In summary, the consideration of *interaction effects* among innovation sources, *causal moderation* and *causal mediation* for explaining the four dimensions of innovation-based value creation is a major strength of the framework and related causal regression models. Such higher-order relationships go *beyond universal relationships* for explaining performance.

Second, constructs and measures significantly advance existing measures that are quite “naïve” (for example, binary measures or those focusing purely on search along technological trajectories). Measures capture the multidimensionality of open and collaborative innovation. By modelling organizational practices for innovation as antecedents of absorptive capacity it proposed a new measurement framework that is superior to widely used proxy measures such as R&D expenditures (see chapter 2.3.). These internal practices were empirically composed and showed a high *content validity* and *reliability* (see chapter 5.2).

Third, a large sample of 1,489 firm-level data was the basis of multivariate statistical analyses. It ensured *external validity* and *generalizability* of the results (Munch & Verkuilen, 2005)).

Fourth, multivariate regression analyses took into consideration the specifics of the dependent variable and ensured a higher reliability of the results. A series of regression models were estimated via multivariate OLS, tobit and ordered logit regressions which supported the hypotheses and revealed additional highly valuable insights (see chapter 7.1 and 7.2). S*tatistical conclusion validity* was ensured as assumptions of each regression model were thoroughly scrutinized. Statistical tests of the significance of the individual coefficient and the overall regression model allowed solid causal inference. Although this research was not about prediction, results of these statistical examinations may actually support the development of quantitative causal models used in strategic planning or simulation models (Hillbrand, 2008).

Finally, both the research process and the research results were documented ensuring a high transparency of the research activities undertaken and made them *intersubjectively traceable.*

Despite the significance of the findings there are some limitations and restrictions:

First, the causal relationship framework itself and the related measures were constrained, partly by the empirical database used. For example, it did not allow for the analysis of each firm’s technological knowledge (e.g. patents) and the identification and measurement of the impact of “really new” innovations that disrupt existing industries. In addition, additional measures about the financial flows among partners when searching for innovation were not available.

Second, the research used a newly developed instrument as existing survey instruments (such as the CIS) are limited. Thus, scales were not used by other researchers in prior studies.

Third, the reliability of the regression results was not yet tested with a new sample drawn from the population. A longitudinal study was not executed as insufficient time had passed.

Fourth, data were drawn from key informants in SMEs only. Indeed, the data could have been enriched with additional sources such as patent databases.

A fifth limitation resulted from the fact that regression modelling did not fully exploit techniques and models for a more fine grained analysis of mediating effects. For example, statistical methods such as path analysis could have not been used to provide even more detailed insight into mediating effects.

In summary, all these limitations offer great potential for future research (see chapter 8).

From a *pragmatic perspective*, results show significant strengths: In today's innovation environment, managers are regularly confronted with the question whether and how they should open up to external influences to spur and sustain their innovation activities. However, opening up to external innovation sources and co-developments is costly and requires some significant investment. In the lights of this area of conflict, results of causal effect relationships help managers to analyze, design, implement or adapt a firm's strategic approach towards external innovation. It provides answers to questions such as: Who to involve? How to combine different innovation partners? What is the risk involved? How deeply should one draw upon external innovation partners? Which strategy works best depending on the environmental context? Do existing managerial practices for innovation actually support managers to reap the rewards from openness? What is the expected impact of different styles of openness? On the one hand, the causal framework helps to analyze a firm's current style of openness, external boundary conditions and internal organizational practices. It reveals a firm's currents profile. At the same time, empirically validated causal effect relationships support the decision and implementation of the right *"means"* to create financial impact from openness. Overall, the empirical results of this dissertation support managerial actions to develop and implement open innovation strategies and to adapt a firm's managerial practices and structures for innovation in a goal-oriented manner.

However, there are also some practical *limitations*. Research results cannot be directly transformed into "social technologies" and management tools that are fully *customized* towards the context of each individual firm. While results offer relevant input for strategic planning they cannot directly be transferred into quantitative planning models to be used internally. In empirical research a trade-off had to be made between the number of selected domains, the level of detail and the generalizability of the results (Dess et al., 1993). Finally, the causal analysis emphasized the benefits to be gained from complementary network partners. However, it does not detail the specific mechanisms and potential managerial actions for managing relationships with different actors in a firm's eco-system to co-create value. There is great potential for future research.

8 Future Research

This thesis made significant contributions both in a scientific and practical way. At the same time, it paved the way for future research on open and collaborative innovation in SMEs, and posed further questions and research topics. Future research should elaborate results presented based on the same research design and database, and also via complementary research strategies – both in a conceptual and pragmatic way.

Building upon the European database of innovation management, future research may advance these findings with more fine-grained analyses of mediating, moderating and higher order interaction effects. An analysis of individual mediating effects (e.g. via path analysis) would shed light on the question how firms should prioritize their managerial innovation practices depending on the style of openness and the type of innovation partner they are working with. As research results revealed that industry-context (such as appropriability scheme and industry clock speed) constitutes a highly relevant boundary condition, future statistical analyses should take a closer look into external and sector-specific factors. For example, technological opportunities, complexity of products and characteristics of a firm's value-system could be included in the framework. Indeed, "configurations" of strategic open innovation styles could be developed in a deductive manner (Miller, 1987).

Another theme to be addressed is the centrality of a firm's organizational lifecycle in open innovation and its interplay with organizational practices and routines. SMEs usually go through different lifecycle phases and mature over time. Indeed, it would be of high value to investigate the relevance of different styles of openness and different types of innovation partners throughout the organizational lifecycle.

To draw more detailed conclusions on causal mechanisms, a longitudinal study should be performed. It may provide more detailed insights about the sequencing of firm strategies, internal practices and innovation-based value creation.

Future research should also consider these research results when building simulation models.

In addition, causal models for strategic planning and performance measurement of open innovation strategies are a relevant future research area. Indeed, further research should address in more detail managerial models for managing and measuring the impact of open and collaborative innovation activities. While these research results provide detailed insight about causal relationships at an aggregated level, more customized causal models should be developed and tested in practice that performance indicators adapted towards the individual firm.

Finally, further research is required to answer the question *how* SMEs should manage complementary relationships for innovation. In-depth case studies and action research will help to open the black box of managerial practices required to combine input from different organizations and knowledge domains, and to co-create value in innovation value networks.

9 Abstract

The recent discourse in innovation management highlights that traditional models of innovation are prone to fail to sustain a firm's innovation performance. It pays high attention to "open innovation" as new innovation paradigm. Indeed, open innovation has vitalized the firm's interest to tap into external innovation sources. Prominent case studies of well-known multinationals such as Procter & Gamble, Philips or IBM demonstrate that firms from different sectors have discovered the value to be gained from searching for new ideas outside of their firm's boundaries. They suggest that firms should involve a wide range of different actors – such as customers, suppliers or universities – to succeed in innovation. While existing literature indicates that "openness" has become highly influential in firms' innovation strategies, it does not sufficiently explain whether and how different open styles of innovation affect a firm's innovation performance and growth. This dissertation opens the black box of different "open styles" of innovation strategies and overcomes major limitations in existing research. It empirically examines multivariate causal relationships between different types of open and collaborative innovation strategies and innovation-based value creation. It is the first quantitative empirical research that statistically infers these causal relationships and is based on 1,489 firm level data of European small and medium-sized enterprises (SMEs). A rigid quantitative observational research design and solid multivariate regression modelling allow making such causal claims which can hardly be made in case study or action research.

Departing from a structured review of existing empirical research, this research introduces a theoretically grounded framework detailing multivariate causal relationships between open and collaborative innovation strategies and firm's innovation success, innovation performance and income growth. It is unique as it takes into consideration both *external factors*, which may constrain a firm's strategic choice, and *internal factors*, which may facilitate open and collaborative innovation strategies. Indeed, openness may challenge the way firms manage innovation internally. The conceptualization of five types of organizational practices and their integration as "mediators" is a differentiating factor of the developed framework and its directional hypotheses.

In preparation of the discussion of causal relationships this research presents an empirical exploration of six types of external search strategies revealing that SMEs engage in open and collaborative innovation. It also emphasizes that there are different "kinds" of openness and provides the empirical rationale for performing fine-grained analyses of the performance impact of openness. In addition, five dimensions of organizational innovation practices were statistically composed. By doing this, this dissertation makes a major step forward towards an empirically validated framework for identifying and measuring organizational practices for innovation including strategic, operational and culturally embedded ones.

The empirical examination of the causal framework is the major contribution of this research. It is implemented via multiple regression models. To make proper causal claims, logit and tobit regression models take into consideration the specific nature of measures. In summary, statistical analyses present results of high validity, reliability and generalizability that examine causal relationships in a fine-grained manner, support proposed hypotheses and reveal additional insights.

Empirical analyses concentrating on the *external perspective* thoroughly examine the impact of different open styles of innovation. Results strongly suggest that open styles of innovation do shape a firm's performance both in a positive and negative way. However, "openness" is not a dichotomic concept – open versus closed – but should be considered as multidimensional interactions with different types of innovation partners and a firm's co-development relationships. It matters how firms open up their innovation processes, with whom and how they interact when searching for new ideas and whether they engage in dense co-development partnerships. Some innovation sources positively affect a firm's innovation performance, whilst others do not. Furthermore, it makes a difference how firms involve various innovation partners simultaneously. A major implication of the examination of moderating effects is that openness goes beyond a firm's strategic choice as the industry clockspeed and the appropriability conditions confine whether firms can benefit from open styles of innovation.

Empirical analyses taking an *internal perspective* reveal the role of internal innovation practices and assets as "facilitators" of open and collaborative innovation. Most importantly, mediating regression analyses clarify that a firm's internal organizational practices for innovation enable a firm to realize the impact to be gained from open and collaborative innovation strategies. They represent organizational antecedents of a firm's ability to successfully search, transform and exploit external innovation inputs. To create value from openness operational proficiency in managing innovation internally is not sufficient. Strategic coordination, financial dedication towards innovation, and a culture for innovation should be successfully in place.

In summary, this dissertation makes significant contributions not only in a theoretical but also a pragmatic way. Results represent managerial prescriptions and guide managerial actions to develop and implement open innovation strategies and organizational practices for innovation with a high impact on innovation performance and firm growth.

10 Zusammenfassung

Um dem immer höheren Innovationsdruck Stand zu halten, suchen Unternehmen nach neuen Innovationsansätzen. „Open Innovation“ steht nun im Mittelpunkt der Diskussion zu einem erfolgreichen Innovationsmanagement. Der Trend hin zu „Open Innovation“ löste in den letzten Jahren bei vielen Unternehmen ein verstärktes Interesse daran aus, Innovationspotentiale außerhalb der Unternehmensgrenzen systematisch zu erschließen. Fallbeispiele von Procter & Gamble, Philips oder IBM zeigen auf, dass erfolgreiche Unternehmen unterschiedlicher Branchen die Vorteile einer gezielten Einbindung von unterschiedlichen Organisationen außerhalb der eigenen Unternehmensgrenze – wie zum Beispiel Kunden, Zulieferern oder auch Universitäten – für die eigene Innovationsleistung erkannt haben. Die wissenschaftliche Literatur belegt das Interesse von Unternehmen an „Offenheit“ im Innovationsmodell sehr deutlich. Dies erklärt aber noch nicht, ob und inwiefern sich offene Innovationsstrategien tatsächlich auf den finanziellen Erfolg und die Wertschöpfung eines Unternehmens auswirken.

Diese Dissertation beschäftigt sich mit dem Einfluss von verschiedenen Arten von Offenheit im Zusammenspiel mit internen Innovationspotentialen auf den Innovationserfolg, die finanzielle Innovationsleistung und auch das Unternehmenswachstum. Sie adressiert damit wesentliche Lücken der bisherigen Forschung. Die Arbeit versteht Offenheit nicht als dichotomes Konzept - offen versus geschlossen. Sie untersucht mehrdimensionale kausale Zusammenhänge zwischen offenen und kollaborativen Innovationsstrategien und der innovationsbasierten Wertschöpfung. Es ist die erste empirische Forschungsarbeit, die statistisch solche solche Wirkungszusammenhänge, basierend auf unternehmensbezogenen Daten von rund 1500 europäischen kleineren und mittleren Unternehmen (KMUs) nachweist. Ein quantitatives Forschungsdesign und eine fundierte multivariate Regressionsmodellierung ermöglichen es, kausale Zusammenhänge geltend zu machen. Ausgehend von einer strukturierten Analyse des Stands der empirischen Forschung wird ein theoretisch fundiertes kausales Konzept eingeführt. Die Besonderheit dieses Konzeptes liegt darin, dass es eine nach außen gerichtete und eine unternehmensinterne Sichtweise integriert. Zum einen können umfeld- und industriespezifische Faktoren die Wirksamkeit von offenen Innovationsstrategien einschränken. Zum anderen spielen interne Innovationsstrukturen und -potentiale eine Rolle, da ein offener Innovationsansatz auch hohe Anforderungen an das Management von Innovationen innerhalb des Unternehmens stellt. Die Berücksichtigung von organisationsinternen Innovationskompetenzen als Mediatoren, im Sinne von vermittelnden Faktoren, trägt der Bedeutung des Zusammenspiels von nach außen gerichteten Innovationsstrategien und internen Innovationspotentialen Rechnung.

In Vorbereitung der Untersuchung der kausalen Zusammenhänge präsentiert die Arbeit eine empirisch abgeleitete Typologie von Suchstrategien, welche die Offenheit der Unternehmen bei der Suche nach Innovationsimpulsen beschreiben. Diese Typologie macht deutlich, dass die externe Suche nach Ideen sehr wichtig ist, aber auch sehr unterschiedlich umgesetzt wird. Es werden des Weiteren fünf statistisch abgeleitete Faktoren zur Messung von organisationsinternen Innovationspraktiken vorgestellt und damit ein empirisch validiertes Instrument zur Analyse des organisatorischen Innovationsmanagement eingeführt.

Die Modellierung und statistische Untersuchung der kausalen Zusammenhänge, die den Kern der Arbeit bilden, sind in mehreren Regressionsmodellen umgesetzt. Um die Beschaffenheit der Messgrößen zu berücksichtigen und belastbare Ergebnisse sicher zu stellen, werden OLS-, Logit- und Tobit-Regressionsmodelle verwendet. Die Ergebnisse zeichnen sich durch eine hohe Validität, Reliabilität und Generalisierbarkeit aus, bestätigen die im Kausalmodell spezifizierten Hypothesen und liefern neue, zusätzliche Erkenntnisse.

Die Ergebnisse zeigen die kausale Wirkung von Offenheit auf die Innovationsleistung im Detail auf. Sie machen auch deutlich, dass Offenheit mehrdimensional ist und dass die Auswirkung auf die Innovationsleistung von der Entscheidung abhängt, wie ein Unternehmen sich entlang der Wertschöpfungskette öffnet, welchen Innovationspartner es einbindet um Zugang Innovationsbeiträgen zu erhalten, und ob es auf engverzahnte Entwicklungspartnerschaften setzt. Einige Innovationsquellen beeinflussen die Innovationsleistung positiv, andere stellen ein Risiko für den Innovationserfolg des Unternehmens dar. Darüber hinaus spielt auch die Kombination von unterschiedlichen Innovationsquellen für die Steigerung des Innovationserfolgs eine Rolle. Außerdem ist Offenheit mehr als nur eine strategische Entscheidung. Das Industrieumfeld, und insbesondere die Wirksamkeit von Schutzrechten und die Innovationsdynamik, schränken die Wirkung von offenen Innovationsstrategien auf die Innovationsleistung ein.

Die Ergebnisse bestätigen auch die Bedeutung des Blicks nach „innen“ und stellen die Bedeutung von systematischen Innovationskompetenzen innerhalb der Organisation für „Open Innovation“ klar heraus. Mediatorische Regressionsanalysen belegen, dass interne Innovationsstrukturen und -ressourcen die organisatorische Voraussetzung für die Absorptionsfähigkeit der externen Innovationsimpulse schaffen. Sie sind notwendig, um die potentielle Leistungssteigerung von offenen Innovationsstrategien zu realisieren. Dabei genügt eine rein operative Ausrichtung der organisatorischen Innovationsprozesse und -routinen nicht.

Diese Dissertation leistet nicht nur in theoretischer, sondern auch in praktischer Hinsicht einen wichtigen Beitrag. Sie liefert empirisch fundierte Entscheidungsgrundlagen und Leitlinien für die Gestaltung von offenen und kollaborativen Innovationsstrategien. Die Ergebnisse der Arbeit unterstützen das Innovationsmanagement dabei, die Öffnung der Innovationsaktivitäten unter der Berücksichtung der internen organisatorischen Rahmenbedingungen so zu gestalten, dass sich eine positive Wirkung auf die Innovationsleistung und die Wertschöpfung eines Unternehmens entfalten kann.

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12 Appendices

The appendices complement the main dissertation document. They include chapters on terminology, further details concerning the review of relevant existing empirical work, and results of statistical analyses, which are not presented in the main section of the document.

12.1 Definition of SMEs and Related Terminology

The term SME is regularly used interchangeable with concepts such as new venture/start-up, high-tech start-up, entrepreneurial firm (or entrepreneur) and high growth firm. These concepts describe subgroups or special types of SMEs. To clarify what is meant by these terms and concepts, they are briefly described:

- *New venture/start-up:* The term new venture (or start-up) refers to a newly founded firm. Newly founded firms represent *young* and small enterprises. As prior research on small firm growth has shown, newly founded firms achieve the maturity level usually not until eight and twelve years after their foundation (Christmas, Bauerschmidt & Hofer, 1998; Mata & Portugal, 1994). Indeed, a critical phase is the founding process, which is addressed in research domains related to new venturing and entrepreneurship (Wiklund et al., 2009).
- *High-tech/high-technology start-up*: High-tech start-ups comprise new ventures/start-ups in so called "high-tech" industries. Although there has been a controversial debate on the definition of high-tech industries (Almus & Nerlinger, 1999; Grimpe & Sofka, 2009; Kaynak & Hartley, 2005; Pavitt, 1984; Vega-Jurado et al., 2008), an emerging definition refers to high-tech businesses which are characterized by a heavier R&D investment and depend on innovation in science and technology.
- *Entrepreneurial firm:* An entrepreneurial firm is one that engages in product-market innovation, undertakes somewhat risky ventures, and is first to come up with '*'proactive''* innovations, beating competitors to the punch (Miller 1983 in Wiklund & Shepherd, 2005). There is a longstanding tradition attributing the growth of *small firms* to their entrepreneurial activity (Wiklund et al., 2009). Thus, the construct *entrepreneurial orientation* (EO) is an organizational dimension that describes proactive and small firms quite well (Avlonitis & Salavou, 2007; Lumpkin & Dess, 1996).
- *Gazelles/High-growth firms:* Rapidly growing firms (high-growth firms) depict a significantly higher growth in terms of size or sales than their peers (Delmar et al., 2003; Weinzimmer et al., 1998). Only a few newly founded firms grow very fast and also survive for a longer period of time – these are so called gazelles (Hölzl, 2009).

12.2 Comparison of Open Innovation and Related Concepts

As mentioned in chapter 2.2.1.5, there are additional research streams that stress the relevance of *active boundary* spanning innovation activities – just like the open innovation paradigm. In some situations, they are used as synonyms of open innovation, though there are conceptual differences. The concept of *user innovation (or distributed) innovation* considers the user as an important actor in the innovation processes: "User of products and services – both firms and individual consumers – are increasingly able to innovate for themselves" (von Hippel, 2005; p.1). The user innovation paradigm has received the broadest application in the study of open source software, which arose in the 1980s as an alternative means of production for an information good, in which (stereotypically) the software is developed by a loosely organized federation of individual users (West, 2009). In the user innovation paradigm *free revealing* of knowledge (without any direct financial compensation) is a defining characteristic of openness in the innovation (von Hippel, 2005; Reichwald & Piller, 2008). The idea has also been applied in other consumer industries such as music and sports (West, 2009; Reichwald & Piller, 2008). The current discussion of user innovation mostly focuses on the contribution of autonomous individuals rather than organizational actors (West, 2009). Whilst open innovation emphasizes profit and competitive advantage, user innovation focuses on consumer welfare (Chesbrough, 2003b; Chesbrough, 2003d). Concepts such as *interactive value creation, co-creation* are in line with the idea of user innovation that contrasts the traditional "manufacturing-active paradigm" with the "consumer-active paradigm". The latter stresses the active participation of individuals in the innovation process and value creation (Reichwald & Piller, 2006; von Hippel, 2005).

Recently, terms like *crowd-sourcing and community-based* innovation are raised in discussions on openness and open innovation. These concepts consider the collective intelligence of a large (often open) group of individuals as a great potential to solve problems and a complementary "asset" in the innovation value creation process (Fredberg et al., 2008). Online communities can constitute an important external source for those firms that manage to establish a constructive relationship with them (Dahlander et al., 2008).

Although these concepts share some communality with open innovation, it is important to point out that open innovation is per se a profit maximizing strategy. In turn, free revealing of knowledge is not the defining dimension of "openness" as it is in the context of user innovation (West, 2009; Pénin, 2008). In addition, business-to-business interactions are in focus rather than the interaction and "openness" of individuals.

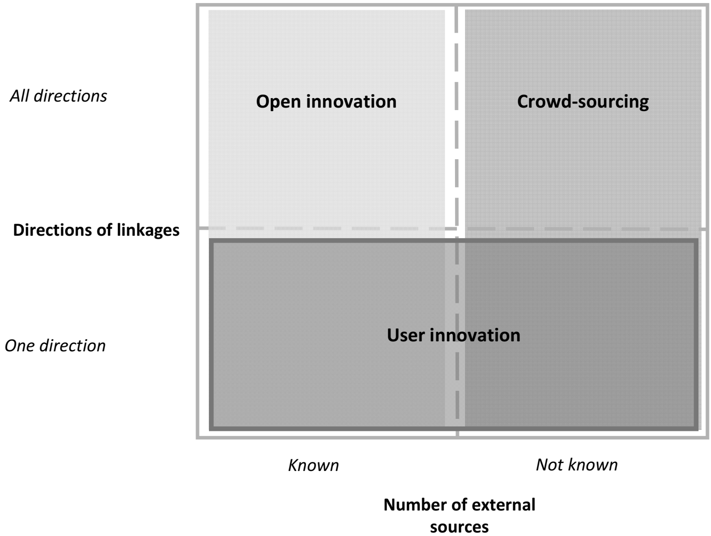


Figure 45: Overlap among Different Boundary Spanning Concepts

In addition to user-oriented concepts of open innovation, the discussion on open innovation is characterized by a range of similar terms such as "networked innovation" (Harryson & Kliknaite, 2006) or "collaborative" innovation (Tsai, 2009). They indicate the relevance of "innovation networks" and inter-organizational relationships to implement an open innovation strategy. Other authors refer to "creation nets" pointing out the relevance of value networks, eco-systems and "long-term relationships" with external firms to shape innovations of partners in order to profit from innovation (Brown & Hagel, 2006). Indeed, the current discussion on open innovation is characterized by a vast number of themes and practices, and has received contributions from various research streams.

12.3 The Case Study of Procter and Gamble: Evidence on the Impact of Open and Collaborative Innovation

Background Information: Procter & Gamble (P&G) is one of the world's largest and most successful consumer businesses and provides consumer products in the area of pharmaceuticals, cleaning suppliers, personal care, and pet suppliers. It serves consumers in more than 180 countries, with net sale of over $40 billion and nearly 100,000 employees. Products include world leading brands such as Pampers, Pringles, Ariel and Tide[14] (Huston & Sakkab, 2006; Dodgson et al., 2006). It has a substantial R&D organization, with over 6,500 scientists. It spends 5$ million in R&D and registers 8 patents a day. In 2006, it owned over 29,000 patents with another 5,000 added every year. As it operates in an intensively competitive market, P&G is forced innovating its product range. As it experienced lower than expected sales growth throughout the 1990s, it recognized that it needed to significantly increase its innovation rate to meet sales growth targets. At the same time, the management was realizing that costs of investment in R&D were increasing much faster than sales growth. Despite this increase in costs, the management team agreed that innovation should remain its core strategy. An analysis of its existing innovation model revealed, that it was not learning enough from the outside world.

The Open Innovation Strategy of P&G: In 1999, P&G launched a new strategy to increase its growth through innovation. One major aim was to stimulate innovation by making P&G's internally focused R&D more outward focused (it is worth to point out that P&G's success in the past also built upon making connections – from candles to soap, from animal fat in soap to the first of all vegetable shortening; this led to discoveries in emulsifiers and surfactants, used today in products such as shampoos and dishwashing liquids). P&G systematically implemented new organizational practices to access external expertise that is spread out across the world. Nowadays, it has successfully moved from "Research & Develop" to "Connect & Develop" (Dodgson et al., 2006; Huston & Sakkab, 2006). Its open innovation strategy is mostly inbound oriented and builds upon all three dimensions discussed in chapter 2.2: External innovation search among a range of different and diverse innovation sources (1), relationships and co-development partnerships (2), IP and appropriability strategy (3). The emphasis is on improving innovation problem solving by accessing external expertise and solution sources. To implement its strategy it relies on a range of new organizational practices and IT-technologies (Enkel & Gassmann, 2009). Overall, the new strategy required a tremendous organizational change as P&G was mostly inward focused in the past. In the past, only 15 % of new products had elements that originated from outside P&G. In the change program P&G set the goal to achieve

[14] See Procter and Gamble website, http://www.pg.com/en_US/company/core_strengths.shtml

a contribution rate of external ideas of nearly 50 % among the products in the product pipeline. In 2006, 45 % of the initiatives in the product development portfolio have elements that were discovered externally (Dodgson et al., 2006; Huston & Sakkab, 2006).

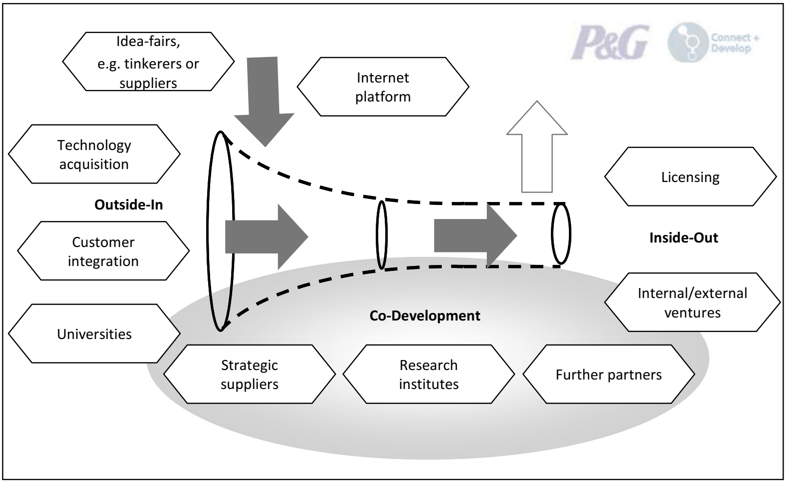


Figure 46: Open Innovation Practices implemented by P&G; see Enkel & Gassmann (2009)

Furthermore, idea market places and the involvement of innovation intermediaries were a driving force of the open innovation strategy. P&G has been instrumental in creating and supporting a number of web-based intermediaries which link externally solutions to internal problems, such as InnoCentive.Com, Yet2.Com and NineSigma (Dodgson et al., 2006; Lakhani & Panetta, 2007).

Impact of Open Innovation Strategy: The changes due to P&G's new innovation strategy were occurring rapidly. Within six years, P&G managed to improve its R&D productivity by nearly 60 % (Huston & Sakkab, 2006; RTM, 2007). According to the senior executives of P&G, the innovation success rate has more than doubled, whilst the cost of innovation has fallen. R&D investments as percentage of sales went down from 4.8 % in 2000 to 3.4 % in 2006. Between 2004 and 2006, P&G launched more than 100 new products that built upon external innovation inputs and solutions generated via external and broadcasted search (Dodgson et al., 2006; Huston & Sakkab, 2006).

12.4 Conceptualizations and Measures of Absorptive Capacity

As discussed in chapter 2.3.1, there are various conceptualizations of absorptive capacity. Operationalizations and measures of absorptive capacity vary across studies. Table 29 presents an excerpt of influential studies on the concept of absorptive capacity.

Table 28: Excerpt of Influential Studies on Absorptive Capacity (see also Zahra & George, 2002)

Author	Study/Sample	Theoretical lens	Treatment/ modelling	Operationalization
Cohen & Levinthal (1989, 1990)	2302 business units from in 297 industrial companies in U.S	Organizational learning; economic theory	Absorptive capacity is used as predictor of innovative activity; relates R&D spending/sales with absorptive capacity	R&D intensity; responsiveness of R&D to learning incentives (relevance, ease, and appropriability); impact on R&D expenditure of certain characteristics of the learning environment
Boynton, Zmud & Jacobs (1994)	132 units with similar information technology (IT) mainframe	Organizational learning	Absorptive capacity as a predictor of the extent of management IT use	1. Management IT knowledge of business processes and the value of information technology 2. Managerial IT process effectiveness
Szulanski (1996)	271 respondents comment on 122 transfers of 38 practices/ technologies involving 8 firms	Organizational knowledge / strategic management	Absorptive capacity as predictor of effective transfer of best practices within the firm	9 measures that capture the ability to value, assimilate, and apply new technology (set of items rated on a scale from 1 to 5)
Veugelers (1997)	290 Flemish firms with active R&D units in the Netherlands between 1992 and 1993	Organizational knowledge / innovation	Absorptive capacity is a moderator of level of innovative activity	absorptive capacity is (1) R&D department fully staffed; (2) R&D departments with doctorates; (3) R&D departments engaged in fundamental research
Cockburn & Hender-son (1998)	68196 publications in scientific journals Ten large	Industrial/or-ganization economics	Absorptive capacity as predictor of research productivity Examines the relationship between public R&D, private	Not a direct operationalization of absorptive capacity but is reflected by number of scientific publications; total publications per dollar spent on R&D per year
Kim (1998)	Case study of a manufacturing firm (Hyndai Motor Co.)	Organizational learning theory; organizations as learning systems	Organizational learning is a function of absorptive capacity: it is the capacity to assimilate knowledge (for imitation) and create new knowledge (for innovation)	Changes in firm orientation toward use of assimilated technology: transition from technology assimilation to imitate to development of internal R&D functions to innovate
Zahra & George (2002)	Theoretical analysis (Literature review)	Dynamic capability perspective	Reconceptualization of absorptive capacity (absorptive capacity) as a set of organizational routines and processes by which firms acquire, assimilate, transform, and exploit knowledge to produce a dynamic organizational capability	Efficiency factor (ŋ)= R-absorptive capacity/ P-absorptive capacity where R-absorptive capacity – realized absorptive capacity, P-absorptive capacity – potential absorptive capacity. The efficiency factor suggests that firms vary in their ability to create value from their knowledge base because of variations in their capabilities to transform and exploit knowledge.

12.5 Innovation Success Factor Research

The identification of success factors in New Product Development (NPD) has received a high level of popularity over the last 40 years (Ernst, 2003; Cooper & Kleinschmidt, 1987). In this period more than 60 studies have been published that try to identify "best practices" in innovation and especially new product development (Hauschildt & Walther, 2003). These studies regularly focus on "successful" or "unsuccessful" new product development projects or programs rather than the organizational innovation system. Considering the high failure rate of new products and the general dissatisfaction of managers with returns gained from investment into innovation, NPD studies are of practical relevance to management in order to benchmark and improve their existing NPD performance (Andrew et al., 2007; Barczak et al., 2009; Brown & Eisenhardt, 1995; Ernst, 2002; Henard & Szymanski, 2001; Rothwell, 1992; Schewe, 1994). To consolidate the results, more than 10 meta-studies have reviewed and critically evaluated the results of good practice studies. The most important meta-studies are reported below (Table 29); these studies provide the basis for the review of existing NPD research presented in the main part of the document.

Table 29: Excerpt of Important Meta-studies of Innovation Success Factor Research

Author (Year)	Type of Study	Focus of study
Rothwell (1977)	Metastudy 1956 – 1976	Success factors and barriers of innovation
Johne & Snelson (1988)	Metastudy 1979 – 1987	Success factors of new product programs
Schewe (1991)	Metastudy 1968-1989	Identification of barriers and key success factors of innovation management
Hausschild (1993)	Metastudy 1963-1991	Success factors of innovation management; factors that can be influenced by management
Rothwell (1992)	Review: Complementation of his review of 1977	Success factors of the 5th generation of the innovation process
Brown & Eisenhardt (1995)	Metastudy: 1969 - 1995	Success factors in new product development
Balachandra & Frair (1997)	Metastudy: 1964-1991	Review of contingency factors on the relationship between determinants and innovation success
Rüdiger (1997)	Metastudy: 1975 – 1996	Critical review of studies of Cooper and Kleinschmidt
Souitaris (1999)	Metastudy: 1963-1991	Determinants of technological innovation
Henard & Syzmanski (2001)	Metastudy: 1980 – 1997	Quantitative meta analysis of determinants of product innovation success
Ernst (2002)	Metastudy: 1974 – 1999	Factors of New Product Development Success
Barczak et al. (2009)	Study	Success factors of New Product Development

12.6 Organizational Innovation Management Frameworks

Adams et al. (2006) conducted a structured review of existing literature on innovation management measurements (Adams et al., 2006). In an attempt to extend measurement theory and practice beyond a focus on output performance, they reviewed the literature as it relates to the measurement of innovation management in the context of a conceptual framework. They brought together disparate suggestions for innovation management measurement made in various parts of the literature and summarized commonly used dimensions and measures. In their review they present six frameworks which they consider as the most relevant organizational innovation management frameworks; they are presented in Figure 47.

Dimension	Cooper and Kleinschmidt (1995)	Chiesa et al. (1996)	Cormican and O'Sullivan (2004)	Goffin and Pfeiffer (1999)	Burgelman et al. (2004)	Verhaeghe and Kfir (2002)
Inputs				Creativity and human resources	Resource availability	Idea generation Technology acquisition
Knowledge management		Resource provision			Understand relevant technological developments and competitor strategies	Networking
Strategy	NPD strategy		Strategy and leadership	Innovation strategy	Strategic management	
Organization and organizational culture	Organizational culture management commitment	Leadership	Culture and climate		Structural and cultural context of the organization	
Portfolio management	NPD process	Systems and tools	Planning and selection	Portfolio management		
Project management			Communication and collaboration	Project management		Development
Commercialization			Structure and performance			Commercializa-tion

Figure 47: Classification of Frameworks of Organizational Innovation Management (Adams et al., 2006)

12.7 Investigation of Assumptions of Regression Models

In the following chapters, results of investigations of assumptions are presented.

12.7.1 Assumptions of OLS regressions

In the following chapters, excerpts of results from testing the assumptions of OLS regressions are presented. They depict results of the tests with regards to multicollinearity, heteroskedasticity, linearity, and normal distribution of assumptions.

Table 30: Assumptions OLS Regressions: Multicollinearity

Model 3		
Multicollinearity		
Variable	VIF	1/VIF
Size_ln	1.79	0.5591
Machinery /Equipment	1.62	0.6183
Scope of networking	1.58	0.6333
IPR experts	1.58	0.6337
Universities/Research	1.57	0.6378
Age_ln	1.55	0.6449
ICT/Electrical/Optical	1.44	0.6945
Network partners	1.41	0.7090
Biotechnology/Pharmaceuticals/ Chemicals	1.34	0.7486
Suppliers	1.31	0.7625
Direct customers	1.29	0.7757
Number of co-development ties	1.27	0.7888
Space/Aeronautics	1.23	0.8137
Indirect customers	1.20	0.8310
Food and beverages	1.20	0.8315
Efficiency of network	1.13	0.8873
Textile	1.11	0.8977
Mean VIF	1.39	

Model 6		
Multicollinearity		
Variable	VIF	1/VIF
Size_ln	1.92	0.5210
Machinery /Equipment	1.62	0.6172
Universities/Research	1.61	0.6205
Scope of networking	1.60	0.6234
Age_ln	1.60	0.6268
IPR experts	1.59	0.6275
ICT/Electrical/Optical	1.44	0.6927
Network partners	1.44	0.6931
Suppliers	1.35	0.7418
Direct customers	1.34	0.7469
Number of co-development ties	1.34	0.7486
Biotechnology/Pharmaceuticals/ Chemicals	1.33	0.7517
Indirect customers	1.26	0.7923
Space/Aeronautics	1.24	0.8087
Innovation development	1.23	0.8110
Food and beverages	1.22	0.8201
Innovation strategy & ideation	1.17	0.8520
Culture for innovation	1.16	0.8641
Efficiency of network	1.15	0.8715
Investment into internal knowledge base	1.14	0.8738
Innovation controlling	1.13	0.8875
Textile	1.12	0.8930
Mean VIF	1.36	

Table 31: Assumptions of OLS Regressions: Heteroskedasticity

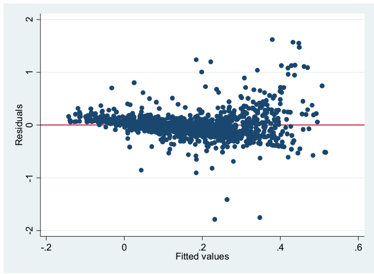
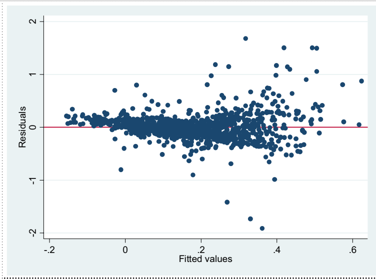
Model 3	Model 6
Heteroskedasticity	Heteroskedasticity
	

Table 32: Assumptions o f OLS Regressions: Linearity

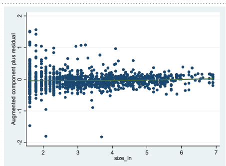
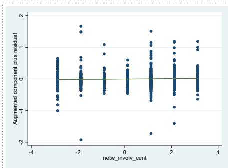
Model 3	Model 6
Linearity	Linearity
Example	Example
	
Size_ln	Network involvement

Table 33: Assumptions o f OLS Regressions: Normality of Residuals

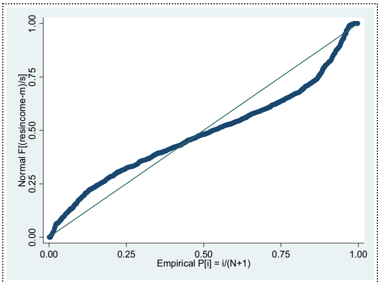
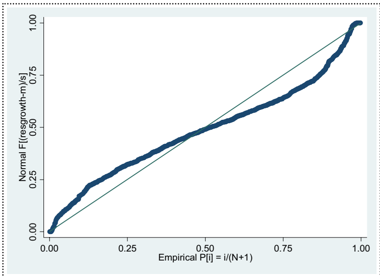
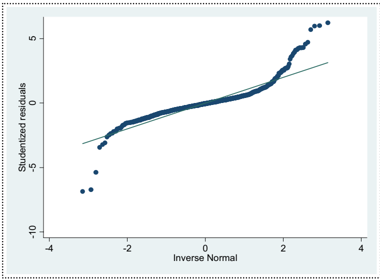
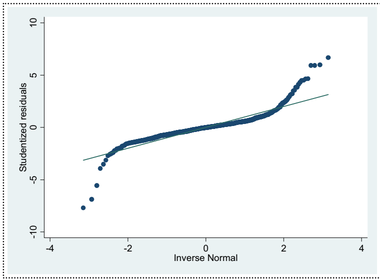
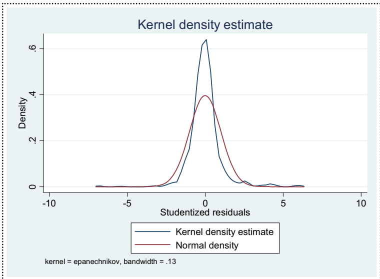
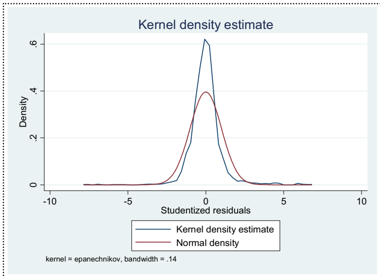
Model 3	Model 6
Normal Distribution of Residuals	Normal Distribution of Residuals
	

Table 34: Assumptions of OLS Regressions: Normality of Residuals (Continued)

Model 3	Model 6
Normal Distribution of Residuals	Normal Distribution of Residuals
	
	

12.7.2 Assumptions of Tobit Regressions: Income from Innovation

In the following chapters, excerpts of test of the assumptions of tobit regressions for the dependent variable income from innovation are presented. Assumptions of multicollinearity, heteroskedasticity and normal distribution of residuals are shown.

Table 35: Assumptions of Tobit Regressions: Multicollinearity – Model 3

Model 3

Multicollinearity

Correlation matrix of coefficients of tobit model

e(V)	model age_ln	size_ln	biotec~m	food_dum	ict_dum	mach_dum	space_~m	textil~m	cust_i..	cust_i..	suppl_~w	netw_i~w	ipr_in~w	uni_in~w	networ~w	degree~w	inno_p~w	_cons	sigma _cons
model																			
age_ln	1.0000																		
size_ln	-0.4009	1.0000																	
biotech_dum	-0.1516	-0.0292	1.0000																
food_dum	-0.0169	-0.1315	0.2296	1.0000															
ict_dum	-0.0721	-0.0343	0.3653	0.2739	1.0000														
mach_dum	-0.2057	-0.0835	0.3973	0.3091	0.4628	1.0000													
space_dum	-0.0968	-0.0786	0.2606	0.2083	0.3011	0.3424	1.0000												
textile_dum	-0.1033	-0.0242	0.1970	0.1489	0.2294	0.2584	0.1659	1.0000											
cust_invol..	0.0519	0.0407	0.0144	0.0779	-0.0199	-0.0169	-0.0550	-0.0124	1.0000										
cust_invol..	-0.0051	-0.0156	0.0107	-0.0107	-0.0140	0.0319	0.0159	-0.0071	-0.1704	1.0000									
suppl_invo~w	-0.0564	-0.0303	-0.0022	-0.1038	-0.0180	-0.1017	-0.0233	-0.0664	-0.2694	-0.1620	1.0000								
netw_invol~w	0.0152	0.0093	0.0046	0.0478	0.0786	0.1071	0.0741	0.0567	-0.1277	-0.0850	-0.0914	1.0000							
ipr_involv~w	0.1004	-0.0685	-0.1211	-0.0010	-0.0345	-0.0713	-0.0726	-0.0197	-0.0151	-0.0902	-0.1026	-0.1408	1.0000						
uni_involv~w	-0.0276	-0.0778	-0.0648	-0.0195	-0.1167	-0.0431	0.0104	-0.0478	-0.0925	-0.0105	0.0337	-0.1387	-0.4490	1.0000					
network_in~w	0.0201	-0.0784	0.0104	-0.0790	-0.0171	-0.0161	-0.0678	0.0242	-0.0217	-0.0022	-0.0365	-0.0496	0.0109	0.0686	1.0000				
degree_col~w	0.0227	-0.0543	-0.0111	-0.0086	0.0262	0.0062	-0.0013	0.0098	0.0003	-0.0735	-0.0814	-0.2327	0.0194	-0.1051	-0.1522	1.0000			
inno_partn~w	0.1096	0.4048	0.0577	0.0428	0.0014	0.0149	0.0681	0.0223	0.0072	0.0330	-0.0513	-0.0749	0.0186	-0.0584	-0.2028	-0.1442	1.0000		
_cons	-0.3826	-0.5491	-0.1338	-0.0827	-0.2539	-0.1212	-0.0875	-0.0744	-0.0785	0.0011	0.1062	-0.0861	0.0235	0.1100	0.0039	0.0606	-0.4888	1.0000	
sigma																			
_cons	0.0124	0.0007	-0.0014	0.0034	0.0113	0.0033	-0.0043	0.0051	0.0073	0.0048	0.0091	0.0033	0.0038	0.0081	0.0025	-0.0038	0.0048	-0.0317	1.0000

Table 36: Assumptions of Tobit Regressions: Multicollinearity – Model 6

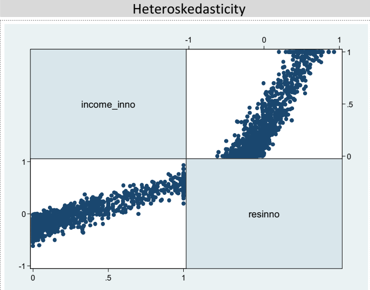
Model 6

Multicollinearity

e(V)	age_ln	size_ln	biotec~m	food_dum	ict_dum	mach_dum	space_~m	textil~m	cust_i..	cust_i..	suppl_~w	netw_i~w	ipr_in~w	uni_in~w	networ~w	degree~w	inno_p~w	FAC1_2	FAC2_2	FAC3_2	FAC4_2	FAC5_2
model																						
age_ln	1																					
size_ln	-0.3900	1																				
biotech_dum	-0.1467	-0.0402	1																			
food_dum	-0.0120	-0.1249	0.2281	1																		
ict_dum	-0.0765	-0.0354	0.3595	0.2670	1																	
mach_dum	-0.2022	-0.0815	0.3924	0.3125	0.4598	1																
space_dum	-0.0980	-0.0721	0.2565	0.2138	0.2976	0.3456	1															
textile_dum	-0.0855	-0.0371	0.1910	0.1511	0.2194	0.2546	0.1643	1														
cust_invol..	0.0466	0.0612	0.0160	0.0765	-0.0147	-0.0186	-0.0544	-0.0229	1													
cust_invol..	-0.0095	0.0174	0.0029	-0.0133	-0.0201	0.0310	0.0132	-0.0171	-0.1605	1												
suppl_invo~w	-0.0538	-0.0003	-0.0058	-0.1002	-0.0193	-0.0997	-0.0186	-0.0754	-0.2561	-0.1540	1											
netw_invol~w	0.0151	0.0309	0.0013	0.0448	0.0750	0.1000	0.0687	0.0549	-0.0970	-0.0630	-0.0848	1										
ipr_involv~w	0.0824	-0.0428	-0.1168	-0.0024	-0.0254	-0.0732	-0.0747	-0.0142	-0.0019	-0.0889	-0.0957	-0.1351	1									
uni_involv~w	-0.0490	-0.0457	-0.0716	-0.0269	-0.1044	-0.0439	0.0078	-0.0569	-0.0797	-0.0175	0.0434	-0.1408	-0.4105	1								
network_in~w	0.0177	-0.0697	0.0201	-0.0738	-0.0193	-0.0148	-0.0575	0.0337	-0.0219	0.0059	-0.0237	-0.0397	0.0066	0.0558	1							
degree_col~w	0.0024	-0.0278	-0.0160	-0.0174	0.0242	-0.0010	-0.0134	0.0139	0.0250	-0.0431	-0.0928	-0.2041	0.0458	-0.0889	-0.1505	1						
inno_partn~w	0.0943	0.4042	0.0496	0.0514	0.0068	0.0104	0.0643	0.0132	0.0333	0.0292	-0.0366	-0.0572	0.0338	-0.0390	-0.1940	-0.1216	1					
FAC1_2	0.0208	-0.1398	0.0296	-0.0295	0.0230	-0.0140	-0.0484	0.0056	-0.0644	-0.0534	-0.1026	-0.1093	0.0008	0.0012	-0.1030	-0.0179	-0.0746	1				
FAC2_2	-0.0134	-0.1249	0.0560	0.0611	-0.0325	0.0451	0.0445	0.0460	-0.1372	0.0503	-0.0677	-0.0462	-0.1021	-0.1194	0.0360	-0.0608	-0.1034	0.1290	1			
FAC3_2	0.0394	-0.2087	-0.0002	-0.0177	-0.0121	-0.0184	-0.0195	-0.0344	-0.0302	-0.1576	-0.0503	-0.0406	-0.0989	-0.0581	-0.0091	-0.1070	-0.0345	0.1511	0.1296	1		
FAC4_2	0.0325	-0.0089	-0.0101	0.0231	0.0150	0.0399	0.0461	0.0148	-0.1213	-0.0968	0.0315	-0.1142	-0.0169	0.0466	-0.0309	-0.1494	-0.0834	0.0998	0.1118	0.0777	1	
FAC5_2	0.1749	-0.0246	-0.0075	0.0321	-0.0689	-0.0024	-0.0057	0.0345	-0.0275	0.0104	0.0354	-0.0067	-0.0744	-0.1208	0.0105	-0.0957	-0.0617	0.0408	0.0894	0.0684	0.0911	1
cons	-0.3862	-0.5623	-0.1189	-0.0868	-0.2385	-0.1174	-0.0858	-0.0689	-0.0899	-0.0221	0.0798	-0.0981	0.0170	0.1008	0.0022	0.0574	-0.4711	0.0868	0.0936	0.1546	-0.0404	-0.123

Table 37: Assumptions of Tobit Regressions: Heteroskedasticity

Model 3	Model 6
Heteroskedasticity	Heteroskedasticity



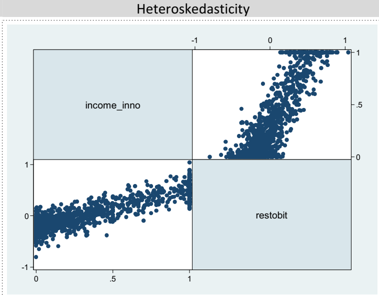
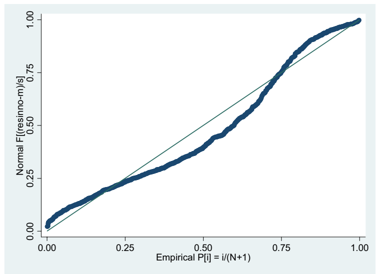
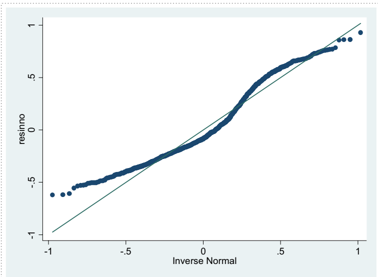
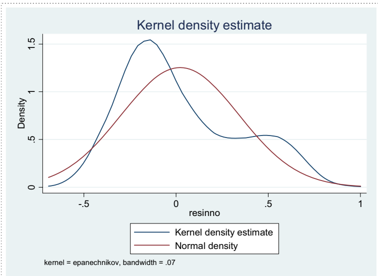


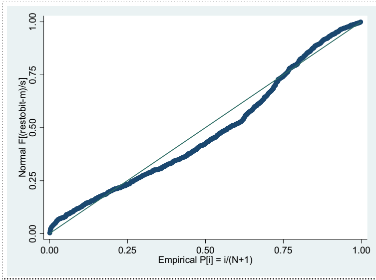
Table 38: Assumptions of Tobit Regressions: Normality of Residuals

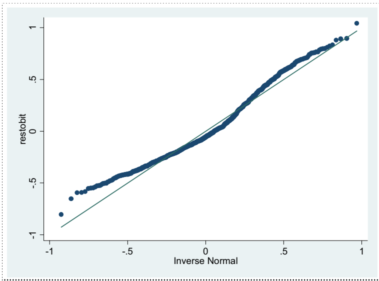
Model 3	Model 6
Normal Distribution of Residuals	Normal Distribution of Residuals

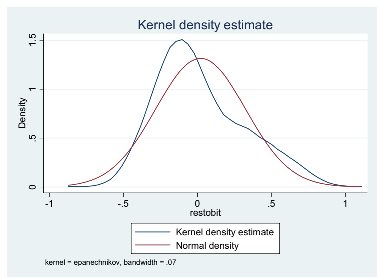












12.7.3 Assumptions of Tobit Regressions: Income from Major Innovation

Below, excerpts of test of the assumptions of tobit regressions for the dependent variable income from major innovation are presented. Assumptions of multicollinearity, heteroskedasticity and normal distribution of residuals are presented.

Table 39: Assumptions of Tobit Regressions 2: Multicollinearity – Model 3

Model 3

Multicollinearity

Correlation matrix of coefficients **tobit** model

e(V)	model age_ln	size_ln	biotec~m	food_dum	ict_dum	mach_dum	space_~m	textil~m	cust_i..	cust_i..	suppl_~w	netw_i~w	ipr_in~w	uni_in~w	networ~w	degree~w	inno_p~w	_cons	sigma _cons
model																			
age_ln	1.0000																		
size_ln	-0.4038	1.0000																	
biotech_dum	-0.1462	-0.0423	1.0000																
food_dum	-0.0067	-0.1301	0.2276	1.0000															
ict_dum	-0.0633	-0.0503	0.3645	0.2732	1.0000														
mach_dum	-0.2042	-0.0969	0.3971	0.3064	0.4640	1.0000													
space_dum	-0.0812	-0.0914	0.2610	0.2097	0.3043	0.3453	1.0000												
textile_dum	-0.0915	-0.0321	0.1951	0.1462	0.2284	0.2567	0.1668	1.0000											
cust_invol..	0.0561	0.0399	0.0098	0.0765	-0.0220	-0.0163	-0.0495	-0.0187	1.0000										
cust_invol..	-0.0042	-0.0085	0.0151	-0.0043	-0.0219	0.0286	0.0173	0.0034	-0.1702	1.0000									
suppl_invo~w	-0.0658	-0.0291	-0.0055	-0.1051	-0.0192	-0.1093	-0.0351	-0.0671	-0.2740	-0.1548	1.0000								
netw_invol~w	0.0081	-0.0098	0.0108	0.0404	0.0808	0.1131	0.0675	0.0542	-0.1295	-0.0838	-0.0906	1.0000							
ipr_involv~w	0.1060	-0.0508	-0.1170	-0.0013	-0.0316	-0.0702	-0.0596	-0.0261	-0.0092	-0.0895	-0.1088	-0.1343	1.0000						
uni_involv~w	-0.0298	-0.0852	-0.0599	-0.0210	-0.1125	-0.0368	0.0120	-0.0391	-0.1082	-0.0116	0.0364	-0.1429	-0.4546	1.0000					
network_in~w	0.0233	-0.0749	0.0096	-0.0856	-0.0141	-0.0177	-0.0652	0.0172	-0.0136	-0.0072	-0.0480	-0.0403	0.0187	0.0731	1.0000				
degree_col~w	0.0186	-0.0549	-0.0162	-0.0072	0.0212	0.0026	0.0057	0.0090	0.0051	-0.0858	-0.0889	-0.2185	0.0229	-0.0971	-0.1551	1.0000			
inno_partn~w	0.1107	0.4014	0.0550	0.0482	-0.0054	0.0091	0.0717	0.0245	0.0025	0.0440	-0.0529	-0.0910	0.0318	-0.0676	-0.1943	-0.1467	1.0000		
_cons	-0.3848	-0.5392	-0.1257	-0.0914	-0.2495	-0.1134	-0.0925	-0.0770	-0.0810	-0.0098	0.1215	-0.0663	-0.0057	0.1149	-0.0087	0.0606	-0.4892	1.0000	
sigma																			
_cons	0.0054	-0.0114	0.0050	0.0086	0.0211	0.0219	0.0104	0.0102	0.0064	0.0154	-0.0108	0.0095	0.0219	0.0146	0.0294	0.0237	0.0073	-0.0860	1.0000

Table 40: Assumptions of Tobit Regressions 2: Multicollinearity – Model 6

Model 6

Multicollinearity

orrelation matrix of coefficients of tobit model

e(V)	age_ln	model size_ln	biotec~m	food_dum	ict_dum	mach_dum	space_~m	textil~m	cust_i..	cust_i..	suppl_~w	netw_i~w	ipr_in~w	uni_in~w	networ~w	degree~w	inno_p~w	FAC1_2	FAC2_2	FAC3_2	FAC4_2
		model																			
	age_ln	1.0000																			
size_ln	-0.3923	1.0000																			
biotech_dum	-0.1400	-0.0508	1																		
food_dum	-0.0002	-0.1251	0.2264	1																	
ict_dum	-0.0648	-0.0482	0.3570	0.2665	1																
mach_dum	-0.1990	-0.0954	0.3919	0.3114	0.4605	1															
space_dum	-0.0821	-0.0842	0.2569	0.2156	0.2997	0.3483	1														
textile_dum	-0.0684	-0.0454	0.1867	0.1484	0.2166	0.2513	0.1644	1													
cust_invol..	0.0521	0.0654	0.0090	0.0745	-0.0135	-0.0201	-0.0476	-0.0271	1												
cust_invol..	-0.0100	0.0251	0.0099	-0.0105	-0.0249	0.0249	0.0146	-0.0094	-0.1575	1											
suppl_invo~w	-0.0630	0.0054	-0.0086	-0.1028	-0.0233	-0.1089	-0.0335	-0.0747	-0.2610	-0.1463	1										
netw_invol~w	0.0068	0.0109	0.0093	0.0357	0.0812	0.1049	0.0613	0.0532	-0.0975	-0.0585	-0.0886	1									
ipr_involv~w	0.0918	-0.0282	-0.1179	-0.0022	-0.0231	-0.0729	-0.0608	-0.0231	0.0034	-0.0919	-0.1013	-0.1294	1								
uni_involv~w	-0.0509	-0.0531	-0.0656	-0.0288	-0.0998	-0.0373	0.0097	-0.0445	-0.0975	-0.0190	0.0502	-0.1440	-0.4188	1							
network_in~w	0.0232	-0.0662	0.0218	-0.0773	-0.0168	-0.0148	-0.0533	0.0269	-0.0150	0.0030	-0.0354	-0.0359	0.0131	0.0588	1						
degree_col~w	-0.0028	-0.0284	-0.0242	-0.0211	0.0199	-0.0082	-0.0077	0.0145	0.0275	-0.0544	-0.0986	-0.1901	0.0466	-0.0821	-0.1572	1					
inno_partn~w	0.0951	0.4028	0.0476	0.0558	0.0013	0.0026	0.0681	0.0160	0.0284	0.0429	-0.0378	-0.0722	0.0445	-0.0494	-0.1869	-0.1222	1				
FAC1_2	0.0233	-0.1514	0.0225	-0.0207	0.0158	-0.0079	-0.0421	-0.0000	-0.0783	-0.0617	-0.0911	-0.1035	0.0071	-0.0018	-0.0975	-0.0175	-0.0749	1			
FAC2_2	-0.0122	-0.1280	0.0612	0.0643	-0.0390	0.0486	0.0496	0.0396	-0.1389	0.0483	-0.0755	-0.0527	-0.0902	-0.1176	0.0503	-0.0589	-0.0980	0.1393	1		
FAC3_2	0.0256	-0.2145	0.0040	-0.0100	-0.0180	-0.0110	-0.0199	-0.0371	-0.0396	-0.1544	-0.0517	-0.0417	-0.0934	-0.0586	-0.0074	-0.1056	-0.0474	0.1536	0.1386	1	
FAC4_2	0.0359	-0.0116	-0.0084	0.0332	0.0036	0.0503	0.0424	0.0133	-0.1068	-0.1116	0.0329	-0.1261	-0.0059	0.0458	-0.0121	-0.1509	-0.0883	0.1085	0.1278	0.0966	1
FAC5_2	0.1697	-0.0273	-0.0040	0.0453	-0.0626	0.0065	-0.0061	0.0412	-0.0283	0.0074	0.0359	-0.0170	-0.0689	-0.1211	0.0176	-0.1068	-0.0619	0.0479	0.0992	0.0806	0.1103
_cons	-0.3895	-0.5522	-0.1137	-0.0971	-0.2364	-0.1111	-0.0912	-0.0735	-0.0940	-0.0297	0.0898	-0.0733	-0.0109	0.1071	-0.0136	0.0644	-0.4699	0.0893	0.0836	0.1632	-0.0586

Table 41: Assumptions of Tobit Regressions 2: Heteroscedasticity

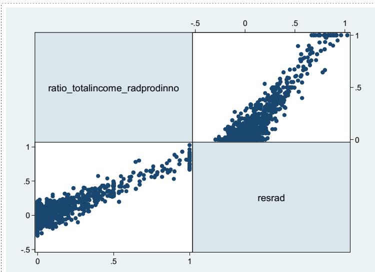
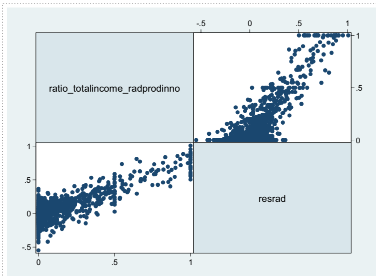
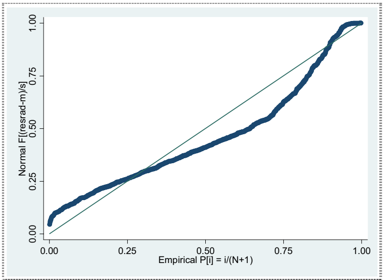
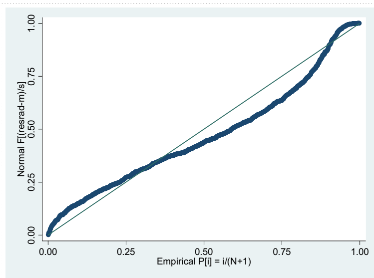
Model 3	Model 6
Heteroscedasticity	
	

Table 42: Assumptions of Tobit Regressions 2: Normality of Residuals

<table>
<tr><th>Model 3</th><th>Model 6</th></tr>
<tr><td>Normal Distribution of Residuals</td><td></td></tr>
<tr><td>
</td><td>
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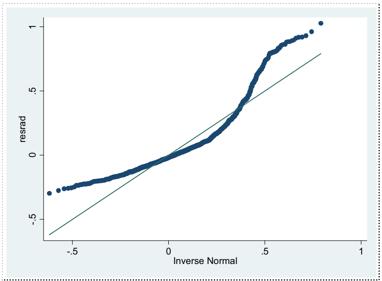
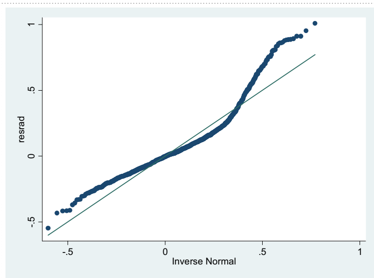
<tr><td>
</td><td>
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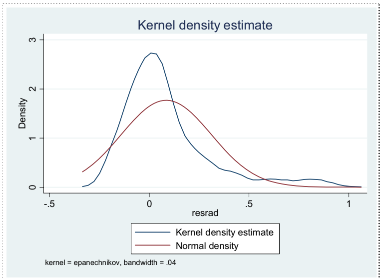
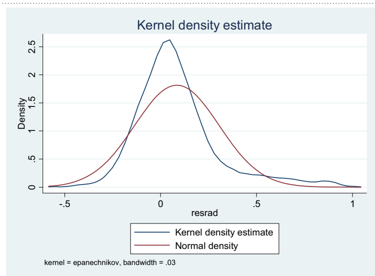
<tr><td>
</td><td>
</td></tr>
</table>

12.7.4 Assumptions of Ordered Logit Regressions

Below, excerpts of test of the assumptions of ordered logit regressions for the dependent variable innovation success are presented. Test results on multicollinearity and parallel slopes are presented.

Table 43: Assumptions of Ordered Logit Regressions: Multicollinearity

Model 3			Model 6		
Multicollinearity			Multicollinearity		
Variable	VIF	1/VIF	Variable	VIF	1/VIF
Size_ln	1.92	0.5206	Size_ln	2.04	0.4906
Age_ln	1.64	0.6115	Age_ln	1.68	0.5943
Scope of networking	1.61	0.6220	Universities/Research	1.65	0.6072
IPR experts	1.60	0.6249	Scope of networking	1.64	0.6108
Machinery /Equipment	1.59	0.6286	IPR experts	1.63	0.6134
Universities/Research	1.59	0.6307	Machinery /Equipment	1.61	0.6210
ICT/Electrical/Optical	1.42	0.7056	ICT/Electrical/Optical	1.43	0.7017
Network partners	1.35	0.7416	Network partners	1.41	0.7093
Biotechnology/Pharmaceuticals/ Chemicals	1.32	0.7575	Number of co-development ties	1.35	0.7387
			Direct customers	1.34	0.7442
Suppliers	1.29	0.7722	Biotechnology/Pharmaceuticals/ Chemicals	1.32	0.7555
Direct customers	1.29	0.7734			
Number of co-development ties	1.28	0.7806	Suppliers	1.32	0.7588
Space/Aeronautics	1.24	0.8093	Innovation development	1.28	0.7836
Food and beverages	1.22	0.8198	Indirect customers	1.26	0.7964
Indirect customers	1.20	0.8363	Space/Aeronautics	1.25	0.8008
Efficiency of network	1.14	0.8799	Food and beverages	1.24	0.8080
Textile	1.11	0.9014	Innovation strategy & ideation	1.22	0.8200
Mean VIF	1.40		Culture for innovation	1.17	0.8529
			Efficiency of network	1.16	0.8618
			Investment into internal knowledge base	1.15	0.8715
			Innovation controlling	1.14	0.8737
			Textile	1.12	0.8960
			Mean VIF		

Table 44: Assumptions o f Ordered Logit Regressions: Parallel Slopes

Model 3	Model 6
Testing the Assumption of Parallel Slopes	Testing the Assumption of Parallel Slopes
POM: AIC=4358 BIC=4489 (df=27)	POM: AIC=4049 BIC=4204 (df=32)
PPOM: not calculable	PPOM: AIC=3946 BIC=4971 (df=212)
GOLOGIT: AIC=4307 BIC=5183 (df=180)	GOLOGIT: AIC=3916 BIC=5024 (df=229)

12.8 Investigation of Non-linear Effects in Networking Strategies

The following chapters present the estimates of regression models testing the inverted U-shaped relationships between the *number of co-development ties* and *innovation-based value creation.*

Table 45 presents results of ordered logit regressions of the model 3² for the dependent variable *innovation success*. No significant effect of both the direct effect and the squared term was identified.

Table 45: Ordered Logit Regressions Explaining Success of Launch (Squared Terms)

Independent & interaction variables	**Model 0**	**Model 1**	**Model 3²**
	Odds ratio (s.e.)	Odds ratio (s.e.)	Odds ratio (s.e.)
External innovation search			
Direct customers		1.0367 (0.0352)	1.0259 (0.0343)
Indirect customers		**1.0884*** (0.0325)**	**1.0830*** (0.0319)**
Suppliers		**1.0563* (0.0333)**	**1.0762** (0.0335)**
Network partners		**1.1565*** (0.0365)**	**1.1330*** (0.0363)**
IPR experts		**0.8492*** (0.0361)**	**0.9050*** (0.0316)**
Universities/research		**0.9303** (0.0317)**	0.9491 (0.0307)
Non-linear effects of co-development ties			
Number of co-development ties			1.5485 (0.4432)
Squared co-develop. ties			0.7969 (0.1551)
Control variables			
Age_ln	1.0467 (0.0633)	1.0077 (0.0640)	1.0393 (0.0663)
Size_ln	0.9934 (0.0472)	1.0503 (0.0522)	1.0579 (0.0605)
Industry_dummies [ref KIS]		**Space 1.5608* (0.3623)**	**Space 1.5326* (0.3523)**
		Mach 1.3074* (0.2039)	
No. of observations	1153	1098	1077
Chi Square	6.67	**93.00*** **	**59.89*** **
Loglikelihood	-2626.5344	-2461.6378	-2428.3689
Pseudo R² (Nagelkerke)	0.006	**0.056*** **	**0.055*** **

*p<0.1, **p<0.05, ***p<0.01

Table 46 presents results of tobit regressions of the model 3² for the dependent variable *income from innovation*. Results support the hypothesis that there is inverted U-shaped relationship between the size of a firm's co-development network and income from innovation.

Table 46: Tobit Regressions Explaining Income from Innovations (Squared Terms)

Independent & interaction variables	**Model 0**	**Model 1**	**Model 3²**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.5745*** (0.0308)**	**0.5878*** (0.0328)**	**0.4442*** (0.0366)**
External innovation search			
Direct customers		**0.0137** (0.0061)**	**0.0107* (0.0058)**
Indirect customers		-0.0029 (0.0053)	-0.0018 (0.0052)
Suppliers		0.0020 (0.0056)	-0.0000 (0.0056)
Network partners		**0.0214*** (0.0057)**	**0.0168*** (0.0056)**
IPR experts		**0.0148** (0.0073)**	**0.0115* (0.0065)**
Universities/research		-0.0052 (0.0061)	-0.0093 (0.0059)
Non-linear effects of co-development ties			
Number of co-development ties			**0.2672*** (0.0504)**
Squared co-develop. ties			**-0.0941*** (0.0338)**
Control variables			
Age_ln	**-0.0795*** (0.0111)**	**-0.0638*** (0.0111)**	**-0.0573*** (0.0113)**
Size_ln	**-0.0189** (0.0090)**	**-0.0281*** (0.0091)**	0.0046 (0.0102)
Industry_dummies [ref KIS]	**ICT 0.0567** (0.0279)**	**ICT 0.0462* (0.0281)**	**ICT 0.0597** (0.0281)**
	Bio -0.0632 (0.0368)**	**Bio -0.0834** (0.0372)**	
No. of observations	1442	1365	1341
No. of left censored data	187	175	175
No. of non censored data	1255	1190	1166
No of right censored data	0	0	0
Chi Square	132.53	216.09	197.78
Pseudo R^2 (Nagelkerke)	**0.134*** **	**0.177*** **	**0.211*** **

*p<0.1, **p<0.05, ***p<0.01

Table 47 presents results of tobit regressions of the model 3² for the dependent variable *income from major innovation*. Results support the hypothesis that there is inverted U-shaped relationship between the number of co-development partners and income from major innovation.

Table 47: Tobit Regressions Explaining Income from Major Innovations (Squared Terms)

Independent & interaction variables	**Model 0**	**Model 1**	**Model 3²**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.2595*** (0.0291)**	**0.2692*** (0.0309)**	**0.1861*** (0.0348)**
External innovation search			
Direct customers		0.0059 (0.0058)	0.0006 (0.0055)
Indirect customers		0.0041 (0.0050)	0.0068 (0.0049)
Suppliers		-0.0015 (0.0053)	-0.0031 (0.0053)
Universities/research		0.0002 (0.0058)	-0.0004 (0.0056)
IPR experts		**0.0171** (0.0069)**	**0.0153** (0.0061)**
Network partners		**0.0119** (0.0054)**	0.0070 (0.0054)
Non-linear effects of co-development ties			
Number of co-development ties			**0.1706*** (0.0474)**
Squared co-develop. ties			**-0.0698** (0.0313)**
Control variables			
Age_ln	**-0.0669*** (0.0106)**	**-0.0541*** (0.0106)**	**-0.0480*** (0.0108)**
Size_ln	**-0.0148* (0.0086)**	**-0.0224** (0.0087)**	-0.0040 (0.0098)
Industry_dummies [ref KIS]			**Textile 0.0995* (0.0578)**
No. of observations	1458	1381	1355
No. of left censored data	564	529	523
No. of non censored data	894	852	832
No of right censored data	0	0	0
Chi Square	**84.55*** **	**133.86*** **	**115.27*** **
Pseudo R^2 (Nagelkerke)	**0.089*** **	**0.119*** **	**0.131*** **

*p<0.1, **p<0.05, ***p<0.01

Table 48 presents results of OLS regressions of the model 3² for the dependent variable income from major innovation. Results support the hypothesis that there is inverted U-shaped relationship between the size of a firm's co-development network and income growth.

Table 48: OLS Regressions Explaining Income Growth (Squared Terms)

Independent & interaction variables	**Model 0**	**Model 1**	**Model 3²**
	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	**0.5047*** (0.0229)**	**0.5106*** (0.0256)**	**0.4391*** (0.0281)**
External innovation search			
Direct customers		-0.0024 (0.0046)	-0.0038 (0.0043)
Indirect customers		-0.0057 (0.0040)	-0.0049 (0.0039)
Suppliers		0.0057 (0.0043)	0.0056 (0.0042)
Universities/research		**-0.0093** (0.0046)**	**-0.0111** (0.0044)**
IPR experts		**0.0148*** (0.0056)**	**0.0114** (0.0049)**
Network partners		0.0036 (0.0043)	0.0001 (0.0043)
Non-linear effects of co-development ties			
Number of co-development ties			**0.1640*** (0.0381)**
Squared co-develop. ties			**-0.0776*** (0.0252)**
Control variables			
Age_ln	**-0.1314*** (0.0082)**	**-0.1290*** (0.0087)**	**-0.1232*** (0.0087)**
Size_ln	0.0093 (0.0066)	0.0077 (0.0070)	**0.0253*** (0.0077)**
Industry_dummies [ref KIS]	**Space -0.0582* (0.0317)**	**Space -0.0664** (0.0334)**	
No. of observations	1441	1364	1339
R^2	**0.1979***	**0.2127***	**0.2085***
Adjusted R^2	**0.1934***	**0.1956***	**0.1989***

*p<0.1, **p<0.05, ***p<0.01

12.9 Examination of Conditions of Mediating Regressions

The following chapters provide the evidence required for performing mediating regression analyses (see chapter 6.3.2). As discussed in chapter 4.4 and chapter 6.3.1, three assumptions need to hold. Two assumptions are addressed below (The third assumption is discussed in the main part of the document). First, it is investigated whether there is a significant relationship between the independent variable and the mediating variable (see chapter 12.9.1). Second, significant relationships between the mediating and dependent variable should be identified (see chapter 12.9.2).

12.9.1 Influence of Independent Variables on Mediating Variables

Below, results of the regression models of type i are presented. They estimate the effects of the independent variable on each component of organizational practices for innovation. Model i1 includes the search variables only whilst model i3 includes both external innovation search and relationship variables. OLS regressions were estimated.

12.9.1.1 Dependent Variable: Factor 1 (Innovation Controlling)

Table 49: OLS Regressions Explaining Factor 1

Independent variables	**Model i0**	**Model i1**	**Model i3**
	coef (s.e.)	coef (s.e.)	Coef (s.e.)
Intercept	-0.0674 (0.0909)	**-0.6552*** (0.1288)**	**-0.8822*** (0.1528)**
External innovation search			
Direct customers		0.0279 (0.0171)	0.0268 (0.0169)
Indirect customers		0.0179 (0.0151)	0.0176 (0.0151)
Suppliers		**0.0543*** (0.0161)**	**0.0497*** (0.0161)**
Universities/research		-0.0109 (0.0165)	-0.0098 (0.0165)
IPR experts		-0.0206 (0.0181)	-0.0179 (0.0180)
Network partners		**0.0559*** (0.0160)**	**0.0481*** (0.0166)**
Relationships			
Number of co-development ties			-0.0153 (0.0217)
Scope of networking			**0.2978*** (0.0869)**
Efficiency of networking			**0.1270* (0.0766)**
Control variables			
Age_ln	-0.0298 (0.0328)	-0.0222 (0.0324)	-0.0117 (0.0325)
Size_ln	**0.0753*** (0.0264)**	**0.0793*** (0.0262)**	**0.0988*** (0.0284)**
Industry_dummies [ref KIS]			
No. of observations	1124	1124	1124
R^2	**0.0187*****	**0.0628*****	**0.0774*****
Adjusted R^2	**0.0116*****	**0.0510*****	**0.0632*****

*p<0.1, **p<0.05, ***p<0.01

Table 49 presents the results of regressions the mediating variable *innovation controlling* on the independent variable. First, the control model (model i0) is estimated. Model i1 and model i3 make a significant contribution over and above model i0. Both models reveal significant relationships between the independent variables and the mediating variable. The magnitude and the direction of the effect are not in focus when examining the preconditions of mediating regressions. Interestingly, the involvement of suppliers and network partners influences a firm's discipline in managing innovation. In addition, a firm's relational ties also propel a firm's innovation controlling.

12.9.1.2 Dependent Variable Factor 2 (Innovation Planning)

Table 50 presents the results of OLS regressions estimating the causal relationship between openness and a firm's *innovation planning* routines. Just like in the previous chapter, the control model was estimated first. Model i1 and model i3 make a significant contribution over and above model i0. This suggests that a firm's open and collaborative innovation strategies are shaping a firm's internal planning routines.

Table 50: OLS Regressions Explaining Factor 2

Independent variables	**Model i0**	**Model i1**	**Model i3**
	coef (s.e.)	coef (s.e.)	Coef (s.e.)
Intercept	**-0.1855** (0.0920)**	**-0.8383*** (0.1272)**	**-0.9495*** (0.1516)**
External innovation search			
Direct customers		**0.0679*** (0.0168)**	**0.0690*** (0.0168)**
Indirect customers		**-0.0433*** (0.0150)**	**-0.0431*** (0.0150)**
Suppliers		**0.0320** (0.0159)**	**0.0291* (0.0160)**
Universities/research		**0.0675*** (0.0163)**	**0.0624*** (0.0164)**
IPR experts		**0.0497*** (0.0178)**	**0.0512*** (0.0178)**
Network partners		0.0178 (0.0158)	0.0117 (0.0164)
Relationships			
Number of co-development ties			0.0147 (0.0215)
Scope of networking			-0.1388 (0.0862)
Efficiency of networking			**0.1919** (0.0760)**
Control variables			
Age_ln	-0.0084 (0.0332)	0.0200 (0.0320)	0.0281 (0.0322)
Size_ln	**0.0765*** (0.0268)**	**0.0579** (0.0258)**	**0.0862*** (0.0281)**
Industry_dummies [ref KIS]	**ICT 0.1737 ** (0.0825)**	**Bio -0.2066* (0.1064)**	**Bio -0.1948* (0.1063)**
	Food -0.3379 (0.1413)**	**Food -0.3202* (0.1362)**	**Food -0.2915** (0.1365)**
No. of observations	1124	1124	1124
R^2	**0.0205*****	**0.1097*****	**0.1165*****
Adjusted R^2	**0.0135*****	**0.0985*****	**0.1029*****
*p<0.1, **p<0.05, ***p<0.01			

Both models reveal significant relationships between the independent variables and this mediating variable. Interestingly, all external search activities show a significant for effect on a firm's organizational practices for innovation except for network partner involvement. In addition, a firm's relational ties also propel a firm's innovation planning. The efficiency of networking strategies influences a firm's discipline in innovation planning.

12.9.1.3 Dependent Variable: Factor 3 (Innovation Development Processes)

Table 51 presents the results of OLS regressions estimating the causal relationship between the independent variables and the mediating variables *innovation development processes*.

Table 51: OLS Regressions Explaining Factor 3

Independent variables	**Model i0**	**Model i1**	**Model i3**
	coef (s.e.)	coef (s.e.)	Coef (s.e.)
Intercept	**-0.5400*** (0.0934)**	**-1.2715*** (0,1294)**	**-1.5075*** (0.1540)**
External innovation search			
Direct customers		0.0039 (0.0171)	0.0041 (0.0171)
Indirect customers		**0.0819*** (0.0152)**	**0.0786*** (0.0152)**
Suppliers		0.0256 (0.0162)	0.0190 (0.0162)
Universities/research		**0.0312* (0.0166)**	0.0249 (0.0167)
IPR experts		**0.0465** (0.0182)**	**0.0489*** (0.0181)**
Network partners		**0.0284* (0.0161)**	0.0133 (0.0167)
Relationships			
Number of co-development ties			**0.0656*** (0.0219)**
Scope of networking			-0.0062 (0.0876)
Efficiency of networking			0.0526 (0.0772)
Control variables			
Age_ln	**-0.0644* (0.0337)**	-0.0375 (0.0326)	-0.0304 (0.0327)
Size_ln	**0.1967*** (0.0272)**	**0.1747*** (0.0263)**	**0.1827*** (0.0286)**
Industry_dummies [ref KIS]	**Bio 0.1845* (0.1111)**		
	Textile 0.3861 (0.1884)**		
No. of observations	1124	1124	1124
R^2	**0.0649*****	**0.1461*****	**0.1544*****
Adjusted R^2	**0.0582*****	**0.1353*****	**0.1414*****

*p<0.1, **p<0.05, ***p<0.01

Model i1 and model i3 make a significant contribution over and above the control model. There are several independent variables that show a significant effect on a firm's innovation performance and income growth. Involvement of customers and IPR experts influence a firm's development processes the most. As one may have expected, the number of co-development ties significantly affects a firm's development processes.

12.9.1.4 Dependent Variable: Factor 4 (Culture for Innovation)

Table 52 presents the results of OLS regressions estimating the causal relationship between the independent variables and the mediating factor *culture for innovation*. Both models - model i1 and model i3 - make a significant contribution over and above model i0. There are several parameters that shape a firm's culture for innovation. If firms involve market related actors or network partners, they may show a stronger culture for innovation. In addition, a large network of co-development partners and a high efficiency of networking strategies (that is, a combination of operational and innovation ties) significantly shape a firm's innovation performance and growth.

Table 52: OLS Regressions Explaining Factor 4

Independent variables	**Model i0**	**Model i1**	**Model i3**
	coef (s.e.)	coef (s.e.)	Coef (s.e.)
Intercept	**0.4212*** (0.0892)**	**-0.3258*** (0.1249)**	**-0.7971*** (0.1470)**
External innovation search			
Direct customers		**0.0532*** (0.0165)**	**0.0533*** (0.0163)**
Indirect customers		**0.0549*** (0.0147)**	**0.0498*** (0.0145)**
Suppliers		-0.0104 (0.0156)	-0.0229 (0.0155)
Universities/research		-0.0231 (0.0160)	**-0.0331** (0.0159)**
IPR Experts		-0.0065 (0.0175)	-0.0015 (0.0173)
Network partners		**0.0795*** (0.0155)**	**0.0525*** (0.0159)**
Relationships			
Number of co-development ties			**0.0956*** (0.0209)**
Scope of networking			0.0882 (0.0836)
Efficiency of networking			**0.1674** (0.0737)**
Control variables			
Age_ln	**-0.0568* (0.0322)**	-0.0361 (0.0315)	-0.0196 (0.0312)
Size_ln	**-0.0508* (0.0259)**	**-0.0468* (0.0254)**	-0.0214 (0.0273)
Industry_dummies [ref KIS]	**Space -0.2250* (0.1253)** **Mach -0.1459* (0.0825)**	**Space -0.2159* (0.1220)**	**Space -0.2000* (0.1207)**
No. of observations	1124	1124	1124
R^2	**0.0251*** **	**0.0906*** **	**0.1197*** **
Adjusted R^2	**0.0181*** **	**0.0791*** **	**0.1062*** **
*p<0.1, **p<0.05, ***p<0.01			

12.9.1.5 Dependent Variable: Factor 5 (Investment into Knowledge Base)

Table 53 presents the results of OLS regressions estimating the causal relationship between the independent variables and the mediating factor *investment into knowledge base*. There are significant effects in model i1 and model i3. Two parameters of external innovation search shape a firm's investment into its knowledge base: IPR experts and universities. In addition, a firm's co-development activities and efficiency of network strategies are also associated with a stronger investment into the knowledge base.

Table 53: OLS Regressions Explaining Factor 5

Independent variables	**Model i0**	**Model i1**	**Model i3**
	coef (s.e.)	coef (s.e.)	Coef (s.e.)
Intercept	**0.5926*** (0.0960)**	**0.3879*** (0.1366)**	**0.1630 (0.1626)**
External innovation search			
Direct customers		0.0010 (0.0181)	0.0017 (0.0180)
Indirect customers		-0.0132 (0.0161)	-0.0155 (0.0161)
Suppliers		-0.0152 (0.0170)	-0.0215 (0.0171)
Universities/research		**0.0742*** (0.0175)**	**0.0671*** (0.0176)**
IPR Experts		**0.0371* (0.0192)**	**0.0396** (0.0191)**
Network partners		0.0074 (0.0170)	-0.0064 (0.0176)
Relationships			
Number of co-development ties			**0.0538** (0.0231)**
Scope of networking			-0.0720 (0.0925)
Efficiency of networking			**0.1350* (0.0815)**
Control variables			
Age_ln	**-0.2289*** (0.0346)**	**-0.2101*** (0.0344)**	**-0.2010*** (0.0345)**
Size_ln	-0.0012 (0.0279)	-0.0209 (0.0277)	-0.0008 (0.0302)
Industry_dummies	**ICT 0.2433*** (0.0861)**	**ICT 0.1681* (0.0859)**	**ICT 0.1729** (0.0857)**
No. of observations	1124	1124	1124
R^2	**0.0685*** **	**0.1039*** **	**0.1116*** **
Adjusted R^2	**0.0618*** **	**0.0926*** **	**0.0979*** **
*p<0.1, **p<0.05, ***p<0.01			

12.9.2 Direct Effects of Mediating Variables on Dependent Variables

Table 54 presents the results of regressions estimating the causal relationship between the mediating variables and the independent variables. As reported in chapter 6.3.1, models of type ii include all mediating variables that were composed via factor analysis. The regression modelling took into account the specifics of the dependent variable, just like in previous chapters. All models are significant suggesting that organizational practices are important determinants of a firm's innovation-based value creation.

Table 54: Regressions on Relationships between Mediating and Dependent Variables

	Successful Launch Ordered Logit	**Income Inno Tobit**	**Major Income Tobit**	**Growth Income OLS**
Independent & interaction variables	**Model ii**	**Model ii**	**Model ii**	**Model ii**
	Odds ratio (s.e.)	coef (s.e.)	coef (s.e.)	coef (s.e.)
Intercept	-	**0.5419*** (0.0297)**	**0.2372*** (0.0287)**	**0.4848*** (0.0232)**
Innovation practices				
Innovation planning	1.0774 (0.0594)	**0.0529*** (0.0091)**	**0.0452*** (0.0089)**	**0.0122* (0.0069)**
Innovation development process	**1.2563*** (0.0712)**	0.0014 (0.0093)	0.0122 (0.0089)	-0.0114 (0.0071)
Innovation controlling	**3.2929*** (0.2537)**	**0.0961*** (0.0092)**	**0.0624*** (0.0090)**	-0.0009 (0.0069)
Culture for innovation	**1.4926*** (0.0878)**	**0.0788*** (0.0094)**	**0.0627*** (0.0092)**	**0.0157** (0.0071)**
Investment into knowledge base	0.9931 (0.0538)	**0.0641*** (0.0093)**	**0.0684*** (0.0088)**	**0.0282*** (0.0072)**
Control variables				
Age_ln	1.0175 (0.0636)	**-0.0542*** (0.0105)**	**-0.0437*** (0.0102)**	**-0.1288*** (0.0082)**
Size_ln	0.9421 (0.0464)	**-0.0290*** (0.0086)**	**-0.0251*** (0.0084)**	**0.0132** (0.0066)**
Industry dummies		**Bio -0.0732****		
No. of observations	1122	1419	1435	1403
No. of left censored data		182	551	
No. of non censored data		1237	884	
No of right censored data		0	0	
Chi Square	313.24	371.10	257.86	
Loglikelihood	-2401.6005			
Pseudo R^2 (Nagelkerke)	**0.246*****	**0.354*****	**0.260*****	
Significance	0.0000	0.0000	0.0000	
R^2				**0.2311*****
Adjusted R^2				**0.2239*****
*p<0.1, **p<0.05, ***p<0.01				

In the first column of Table 54, estimates of the ordered logit regression for the dependent variable *innovation success* are reported. There are three factors that show a significant and positive effect: Innovation development processes (odds ratio =1.2563, p<0.01), innovation controlling (odds ratio = 3.2929, p<0.01) and culture for innovation (odds ratio= 1.4926, p<0.01). It is worth pointing out that the effect of innovation controlling is very strong. Strategic and cultural factors are shaping a firm's innovation success in launching an innovation.

In the second column, results of the tobit regression for the dependent variable *income from innovation* are reported. Four out of five factors show a significant effect: Innovation planning (c.= 0.0529, p<0.01), innovation controlling (c.= 0.0961, p<0.01), culture for innovation (c.= 0.0788, p<0.01), and investment into knowledge base (c= 0.0641, p<0.01).

The third column presents the results of the tobit regression for the dependent variable *income from major innovation*. The overall model is significant suggesting that organizational practices for innovation constitute critical capabilities when aiming for breakthrough innovations. Results reveal that that same practices matter to affect a firm's financial income from major innovation as for income from innovation (see column 3).

The final column contains the results of the OLS regression for the dependent variable *income growth*. The model is significant. Innovation planning, culture for innovation and investment into the knowledge base shape a firm's income growth. Interestingly, operational practices and routines do not matter.

Overall, results suggest that the pre-conditions of mediating regression analyses hold.