Intra-Firm Knowledge Integration and Innovation Performance: The Role of Departmental Absorptive Capacities and Firm Environment

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AC	Absorptive Capacity
AIC	Akaike's Information Criterion
ASV	Average Shared Variance
ATECO	ATtività ECOnomiche (economic activities), Italian translation of the European Community's NACE framework, comparable to the US' Standard Industrial Classification (SIC)
AVE	Average Variance Explained
B2C	Share of sales from business-to-consumers products/services
BS	Bollen-Stine bootstrap
CFA	Confirmatory Factor Analysis
CFAC	Cross-functional Absorptive Capacity
CFI	Cross-functional Integration (or in the context of model fit: Comparative Fit Index)
CLF	Common latent factor
CMB	Common method bias
CMIN	Chi-square MINimum (minimum discrepancy)
CNTR	Centralization
c.r.	critical ratio
CR	Composite Reliability
d.f.	degrees of freedom
DV	Dependent Variable
EBIT(DA)	Earnings Before Interest Tax (Depreciation and Amortization)
EFA	Exploratory Factor Analysis
ENV	Environmental turbulence
FAC	Functional Absorptive Capacity
FIM	Formal Intra-organizational integration Mechanisms
FXM	Formal Cross-functional integration Mechanisms
IIM	Informal Intra-organizational integration Mechanisms
IND2ROS	INDustry's 2-digit ATECO sectors' average Return On Investment
IOI	Internal Open Innovation
IPO	Innovation Performance relative to Objectives
IXM	Informal Cross-functional integration Mechanisms
KBV	Knowledge-Based View (of the firm)
KI	Knowledge Integration

M&S	Marketing and Sales
MAR	Missing At Random
MCAR	Missing Completely At Random
ML	Maximum Likelihood
MNC	Multinational Corporation
MSV	Maximum Shared Variance
NFI	Normed Fit Index
NMAR	Not Missing At Random
NPD	New Product Development
OLS	Ordinary Least Squares
PAC	Potential Absorptive Capacity
PCA	Principal Component Analysis
R&D	Research and Development
RAC	Realized Absorptive Capacity
RBV	Resource-Based View (of the firm)
REW	Market oriented Rewards
RMSEA	Root Mean Square Error of Approximation
ROA	Return on Assets
ROE	Return on Equity
ROS	Return on Sales
SE	Standardized Estimate
SEM	Structural Equation Model
Sig.	Significance level
SMC	Squared Multiple Correlations
(S)RMR	(Standardized) Root Mean Square Residual
Std. Dev.	Standard Deviation
TLI	Tucker-Lewis Index

I. General Introduction

I.1. Intra-Firm Knowledge Integration in the Innovation Process and their growing Relevance

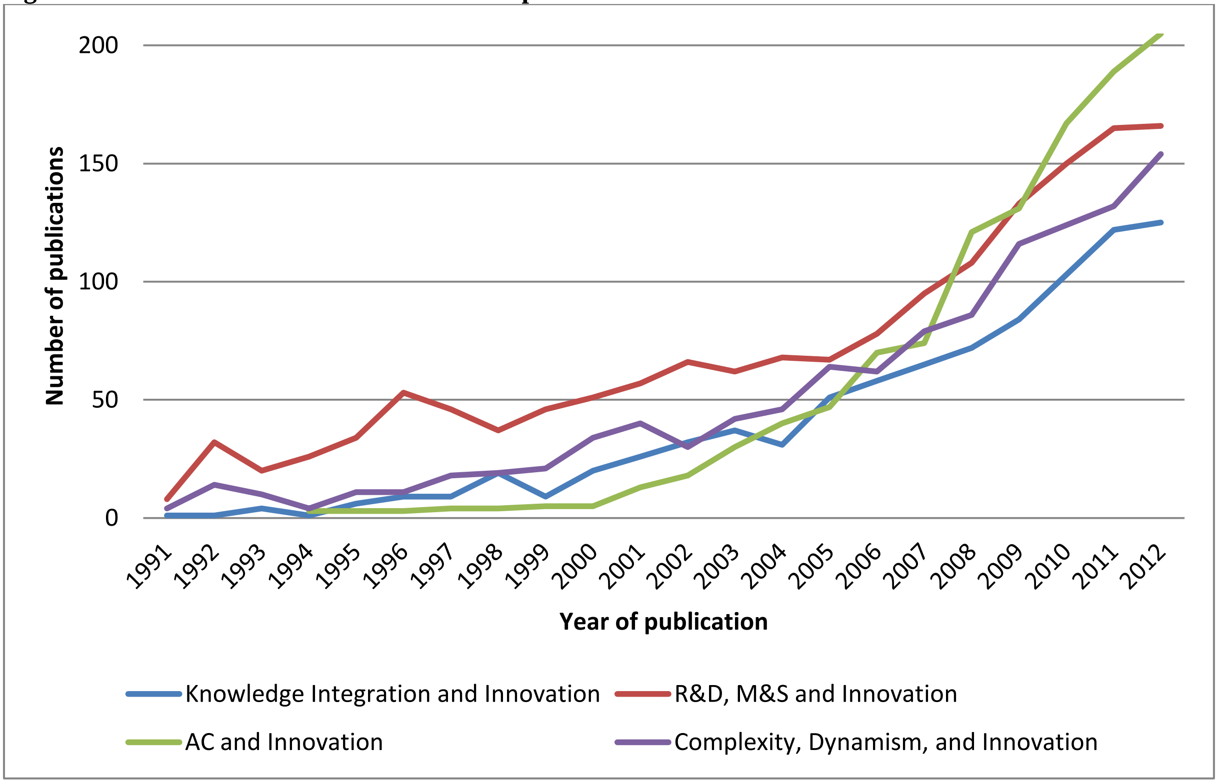
Since the rise of the knowledge-based view of the firm (Grant, 1996a; Teece, Pisano, & Shuen, 1997) as an elaboration of the resource-based view (Barney, 1991; Wernerfelt, 1984), the crucial importance of valuable knowledge for long term survival and sustainable competitive advantage appear largely unchallenged. However, the definition of what constitutes "valuable" knowledge appears difficult and early attempts have been found to be grounded on tautological reasoning (Priem & Butler, 2001). Knowledge, as such, escapes any simple definition (Spender, 1996). It is generally accepted in management literature to regard it as "justified true belief" (Nonaka, 1994). This belief refers to an assumed objective reality and hence knowledge is always tied to feedback from experience and its repositories (Walsh & Ungson, 1991). Its value constantly changes as the environment changes to which it relates. Therefore knowledge is not a single monolithic entity nor is it a homogeneous good. Rather, it is one of the most complex resources of an organization. Knowledge exists in fact in a myriad of types and domains exhibiting in each of its expressions a specific combination of characteristics, one of the most important of these characteristics being its degree of tacitness (Polanyi, 1966).

The environment of organizations is not necessarily simple but exhibits at times immense degrees of complexity to which firms have to adapt (Levinthal, 1997; Nelson & Winter, 1982). The various knowledge stocks that refer to the interdependent environmental realities are interdependent. This complementarity can only be valorized if these distinct knowledge stocks are integrated. This ability to integrate knowledge is regarded as the fundamental raison-d'être of firms as opposed to markets (Kogut & Zander, 1993). In fact, it is claimed that "(..) the primary role of the firm, and the essence of organizational capability, is the *integration of knowledge*" (Grant, 1996b:375). This ability to integrate knowledge, whether it is called "architectural knowledge" (Henderson & Clark, 1990) or "combinative capability" (Kogut & Zander, 1992) or "internal integration" (Iansiti & Clark, 1994) enables companies at least in principle to innovate and to adapt continuously and thus can be one of the main drivers of sustainable competitive advantage.

It can be concluded thus that both complementarities between functions as well as fundamental environmental characteristics are closely related to the potential of knowledge integration for innovation performance. The literature on Absorptive Capacity (AC) recognizes the importance of environment in the need of firms to absorb new external knowledge (Cohen & Levinthal, 1990). AC becomes thus a fundamental requirement of innovation. As all organizational behaviors, knowledge integration can be regarded as an emergent phenomenon, i.e. as carried out by individual organizational members, but with distinct organization level properties that result from their direct and indirect interactions. While it might be an efficient shortcut to investigate the relationship between macro-level variables, an in-depth understanding of the emergence of the effects observed at that level can be developed only through consideration of lower levels. While this has been done for several levels more or less extensively, there is a lacuna in research regarding the level of functional departments.

On the other hand, it is exactly through the consideration of the functional level that the relevance of AC for intra-firm knowledge integration becomes obvious. In fact, the intra-firm integration of complementary knowledge from different functions is an integral part of innovation and in particular as regards the integration of technological and market knowledge accumulated through both acquiring from firm-external sources as well as internal generation (Griffin & Hauser, 1996; Iansiti & Clark, 1994).

Figure 1: Publications in related research topics over time



Data source: ISI Web of Science[1]

These aspects—the complexity and dynamism of the firm environment, Absorptive Capacity, and the R&D-M&S interface—relate fundamentally to innovation performance as can be observed in their development in terms of number of scholarly publications that develop in close relationship with that of knowledge integration and innovativeness as illustrated in Figure 1. In fact, all three research streams grow apparently more than linearly pinpointing likewise to the growing relevance of these related research streams for innovation management.

Therefore, these three aspects are in focus in the three main chapters regarding their role for the innovation performance impact of intra-firm knowledge integration. In the following

[1] The following search algorithms have been used: For the series *Knowledge Integration and Innovation* (TS=(innovation or innovativeness or "innovation performance") and TS=(knowledge and integration)); for *AC and Innovation* (TS=("absorptive capacity" and ("innovation" or "innovativeness" or "innovation performance")); for *R&D, M&S and Innovation* (TS=(R&D) and TS=(marketing or sales) and TS=(innovation or innovativeness or "innovation performance")); and for *Complexity, Dynamism, and Innovation* (TS=(complex and dynamic and innovation) or TS=(complexity and dynamism and innovation) or TS=(complexity and change and innovation) or TS=(complexity and turbulence and innovation); all followed by: and Language=(English).

section, a brief overview of the three following chapters of this thesis is provided by explaining the related research questions and goals of each of them out of an identification of the respective research gaps.

The goals are summarized as:

- the conceptualization of Absorptive Capacity for functionally specialized departments and the development of propositions regarding its antecedents in terms of different types of prior related knowledge and consequences in terms of innovation outcome;
- providing empirical evidence of the role of Departmental ACs for the relationship between intra-firm knowledge integration and innovation performance;
- disentangling the roles of environmental complexity and dynamism for the optimal degree of intra-MNC knowledge integration.

I.2. Research questions and contributions

I.2.1. How can the influence of intra-firm Knowledge Integration on Innovation Performance be explained by means of Absorptive Capacity (AC) of Functional Departments?

In chapter II, I aim at contributing to the two research areas that have been identified as crucially important for innovation management, viz. Absorptive Capacity (AC) and Knowledge Integration (KI). The relevance of knowledge to innovation and performance is well recognized in the therefore burgeoning research strand on knowledge transfer (Van Wijk, Jansen, & Lyles, 2008) as occurring both between and within firms. The research strand evolving around AC, however, is geared almost exclusively towards technological knowledge (Volberda, Foss, & Lyles, 2010). This research gap is very surprising given the immense relevance for innovation and performance that is attributed to internal integration of complementary knowledge (Henderson & Clark, 1990; Iansiti & Clark, 1994; Jansen, Tempelaar, Van Den Bosch, & Volberda, 2009). Moreover, treating AC only on firm, business unit, subsidiary, or individual level, without recognition of the peculiarities that distinguish corporate functions and consequently their knowledge domains, this research stream inevitably remains ignorant of the important contribution that its application of this concept could make on this level of analysis to the understanding of intra- and cross-functional knowledge integration, the two aspects of intra-firm knowledge integration.

The research question in chapter II of this dissertation therefore is: How can the influence of intra-firm knowledge integration on innovation performance be explained by means of AC of functional departments? I argue that it is important to distinguish between the capacity to absorb knowledge from other departments of the own functional domain—i.e. Functional AC (FAC)—and the capacity to absorb knowledge from other departments of other functional domains—i.e. Cross-Functional AC (CFAC). I furthermore develop a model around these two concepts in that I make concrete propositions how different types of prior related knowledge might differently impact the two capacities FAC and CFAC as well as how these latter two impact innovation performance in different ways in terms of, on the one hand, either separate technology-push or market pull innovations and, on the other hand, integrated innovations.

This has very relevant implications for theory and practice. It is useful because it shows potentially different dynamics through which different knowledge integration efforts impact innovation performance. Moreover, it might reveal as a useful perspective on how internal AC develops. Practitioners might find these reflections useful in order to create greater awareness of different requirements as regards different boundaries within the firm.

A further related goal of the chapter is to show how the influence of prior related knowledge as an antecedent of AC has to be rethought in order to apply it appropriately to this level of analysis.

I.2.2. How are the effects of different Knowledge Integration Mechanisms on Innovation Performance mediated by Departmental Absorptive Capacities at the R&D-M&S Interface?

One of the most important cases of cross-functional knowledge integration takes place at the interface between Research and Development (R&D) and Marketing and Sales (M&S) (Brettel, Heinemann, Engelen, & Neubauer, 2011; Calantone, Di Benedetto, & Divine, 1993; Griffin & Hauser, 1996; Olson, Walker, Ruekert, & Bonner, 2001). The high complementarity of technological and market knowledge derives from the simple fact that any kind of invention—no matter whether in terms of product or services—has value only in so far as it is demanded by customers. This simple truism has long been studied only at the periphery of innovation management research and has largely been left to marketing research where the role of market orientation for innovation and business performance has been widely recognized (e.g. Jaworski & Kohli, 1993; Verhoef & Leeflang, 2009). Nonetheless, it has long been debated in innovation management literature that innovations can be achieved by means of technology-push or a market-pull (Kline & Rosenberg, 1986; Rothwell, 1994) and might at the moment regain terrain in strategic and innovation management (Priem, S. Li, & Carr, 2012; Priem, 2007).

Thus, in the third chapter of this dissertation, the previously conceptualized departmental ACs will be operationalized and it is aimed to provide empirical evidence for their mediating role in the relationship between integration mechanisms—distinguished as formal and informal, intra-functional and cross-functional ones—and innovation performance. Different mediating effects of FAC and CFAC across these types of integration mechanisms and innovation performance as well as different effects for R&D as for M&S departments might explain previously contrasting results regarding the performance impact of functional integration (Troy, Hirunyawipada, & Paswan, 2008).

The results pinpoint the fundamental role of AC for innovation performance also at this level of analysis and show clearly that the implementation of knowledge integration mechanisms per se might not have any effect at all on innovation performance, if the department cannot recognize the value, assimilate, or use the complementary knowledge that is required for innovation and aimed at by the implementation of these mechanisms. The discussion in this chapter ultimately proposes a new perspective on integration in general and the R&D-M&S interface in particular.

The results are highly relevant because this new understanding could help practitioners to fine-tune integration efforts and adapt mechanisms both to the departments' heterogeneous needs and adapt the departments' learning behavior to their heterogeneous capacities.

I.2.3. Is more Intra-Firm Knowledge Integration always better considering environmental complexity and dynamism and the heterogeneous market contexts to which most big firms, like MNCs, are exposed?

In the first two papers of this thesis, focus is on how intra-firm knowledge integration depends on different types of capacities required as a results of the heterogeneous knowledge domains to which all firms are exposed, like the technological vis-à-vis the market knowledge domain. Nowadays however, the environment to that firms are exposed is potentially very heterogeneous regarding both uncertainty and market contexts. For Multi-National Corporations (MNCs), which are by definition exposed to various markets that are potentially very heterogeneous in terms of customers' demands, the internal integration of complementary knowledge like technological and market knowledge is both amplified in relevance and difficulty (Foss & Pedersen, 2002; Gupta & Govindarajan, 2000; Kogut & Zander, 1993). Moreover, industries that are characterized as exhibiting a high degree of heterogeneity across the different country markets, i.e. such that are rather international instead of global (Ghoshal & Bartlett, 1995), might still exhibit a globally homogeneous technological environment. Furthermore, not all industries provide equally dynamic environments, as regards both technology and market. Both complexity and dynamism as the main sources of environmental uncertainty are highly relevant for long-term term survival (S. L. Brown & Eisenhardt, 1997; Duncan, 1972; Eisenhardt & Tabrizi, 1995). The case of MNCs thus underlines the importance of environment's complexity and dynamism to intra-firm knowledge integration. The role of these two elements can be disentangled by means of agent-based simulations, particularly nk-models as introduced to management by Levinthal (1997). Previous simulation studies on organizational search behavior in complex environments focused on several, very different aspects like the trade-off between explorative and exploitative search heuristics (Fang, J. Lee, & Schilling, 2010; March, 1991), whether search behavior that actually is rational maximizing might be falsely diagnosed as satisficing (Sakhartov & Folta, 2012), or alternative organizational designs like centralized vis-à-vis decentralized or decomposing institutional arrangements in response to environmental dynamism and complexity (Marengo & Dosi, 2005; Siggelkow & Levinthal, 2003). However, it is less clear whether intra-organizational knowledge integration is always positive in the described case of MNCs and which are the precise roles of complexity and dynamism individually. Particularly in organizations where subunits are exposed to heterogeneous market contexts, as is the case for MNCs, we may expect non-linear or even negative relation between intra-firm knowledge integration and innovation performance. Chapter IV provides a simulation model that can be used to determine the optimal degree of openness of MNC subsidiaries in terms of willingness to integrate knowledge from peers of similar market contexts.

II.
Departmental Absorptive Capacity: Its Conceptualization and Role For Cross-Functional Integration[2]

Abstract – Although both Absorptive Capacity (AC) and Knowledge Integration (KI) are largely seen as critically important for competitive advantage, their interplay seems to be understudied. Moreover, AC has never been defined on the level of functionally specialized departments, while these sub-units might be the key to a better understanding of a successful balance between exploitative and explorative activities. In this chapter, a framework for AC on the level of departments is developed that takes into account the importance of the functional nature of knowledge.
Therefore, departmental ACs are theoretically conceptualized based on a more fine-grained definition of prior related knowledge. The theory discussed ultimately leads to propositions regarding the particular role of prior related knowledge for the development of departmental ACs as well as the consequences of these ACs regarding innovation performance in terms of generation of technology-push, market-pull and integrated innovations. It is argued that firms' functional departments do have not only the traditional AC in form of Functional AC (FAC), i.e. AC regarding knowledge that they have to absorb from other departments of the same corporate function, but also have a "Cross-Functional" AC (CFAC) regarding the knowledge that they have to absorb from departments of their corporate group that exercise different functions. Finally, it is suggested that FAC permits to increase the performance in output of function-specific innovations, like either technology-push or market-pull innovations through realizing complementarities within corporate functions. Only CFAC, however, allows for more integrated innovations that can contemporaneously appropriate value from several complementary functions.

Keywords: Absorptive Capacity; Cross-Functional Integration; Intra-organizational Knowledge Transfer; Organizational Capabilities; Innovation

JEL Codes: M10, O32, O31

[2] This chapter is based on Hausberg (2012), Departmental Absorptive Capacity. *Paper presented at the DRUID Annual Summer Conference 2012*.

II.1. Introduction

Knowledge is not only becoming inevitably one of the most important drivers of sustained competitive advantage (e.g. Ambrosini & Bowman, 2001; Grant, 1996), but it also becomes always more complex in character and ephemeral in value. A common response of organizations to environmental complexity is an increase in specialization over time (Lawrence & Lorsch, 1967). This specialization resulting from knowledge complexity does potentially happen inside the firm, but also the firm itself specializes and cannot claim to possess or generate all necessary knowledge itself. Hence, external knowledge has to be recognized, assimilated, and exploited, i.e. absorbed (Cohen & Levinthal, 1990).

At the same time, the speed with which various markets offer new products has increased tremendously, which makes time-to-market crucial for product innovation success (Calantone & Di Benedetto, 2012; Eisenhardt & Tabrizi, 1995; Lieberman & Montgomery, 1988). Since this implies also a rapid depreciation of knowledge, the consequence of the speed of innovation is an increased need to re-integrate the specialist functions (Olson et al., 2001). Moreover, in many technological markets today network effects can be observed, which even further augment the importance of time-to-market, because the first mover advantage can consist in reaching as the first player the critical network size.

Pressure on firms arrives thus from technological development and increasing complexity as well as fast changing and heterogeneous demand. In fact, in innovation management, these two principal pressures to innovate have not only spawned the terms “technology push” and “demand pull” as two fundamental types of innovations (Kline & Rosenberg, 1986; Rothwell, 1994), but also the notion of parallel development to address the need to innovate timely. Parallel development refers to the organization of the new product development (NPD) process as happening mostly parallel as opposed to the sequential push and pull innovation models and is suggested to be most appropriate in dynamic environments at least since the

90ies (Rothwell, 1994). However, the parallel development process per se does not provide for high impact innovations, because the key for many radical innovations seems to lie in the valorization of the complementarity of technological and market knowledge. This is the key insight of much and literature on cross-functional integration (CFI) at the R&D-Marketing interface (Brettel et al., 2011; Olson et al., 2001).

Two fundamental approaches to address the dual pressure coming from supply and demand side can be identified, i.e. external knowledge absorption and speeding up the innovation process through internally combining the absorbed knowledge. For the realization of these two important requirements of successful innovation, two organizational characteristics have been found crucial: Absorptive Capacity (AC) (Cohen & Levinthal, 1989, 1990, 1994) and Cross-Functional Integration (CFI) (e.g. Iansiti & Clark, 1994; Song, Montoya-Weiss, & Schmidt, 1997). AC refers to "the ability to recognize the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen & Levinthal, 1990:128). Cross-functional integration can be defined as "the capacity for extensive coordination between different specialized subunits within an organization, and explicitly targets the implementation of a given project concept." (Iansiti & Clark, 1994:569).

These two concepts, AC and CFI, are both fundamental to innovation management. Both research streams received much attention in terms of their impact on innovation performance (Griffin & Hauser, 1996; Lane, Koka, & Pathak, 2006; Olson et al., 2001; Volberda et al., 2010). It has been noted, however, that notwithstanding a plethora of factors, constraints, and contingencies have been studied as potential positive or negative antecedents and consequences of AC, the "lack of research regarding intra-organizational antecedents is surprising" (Volberda et al., 2010). In fact, Volberda et al. (2010) identify several related relevant gaps that are addressed herein:

- "*Research on AC should be explicit about what kind of knowledge is being absorbed*" (p. 943),

- "(..) *address the varying nature of knowledge, the knowledge stock, and the flow of knowledge*" (p. 943), and
- "(..) *clarify how ACs existing on different levels of analysis (individual, organizational, dyadic, etc.) are related*." (p. 945)

Some very insightful steps into this direction have been undertaken (Jansen, Van den Bosch, & Volberda, 2005; Lewin, Massini, & Peeters, 2011). However, research falls short so far to provide an understanding of how AC has to be understood at functional interfaces. There is indeed not much research on how AC could explain the success of CFI efforts in terms of innovation performance, nor vice-versa how successful CFI could explain AC.

It is implicitly assumed that knowledge absorption of organizational sub-units follows the same logic across and within functional knowledge domains as diverse as R&D and M&S and that functionally specialized units are homogeneous regarding the level of their AC. On the other hand, when the distinction of technological and market search for innovativeness has been pointed out as important for the investigation of the relationship between search and innovation (Sidhu, Commandeur, & Volberda, 2007), the internal integration has been neglected; the complementarity of the different knowledge domains has been implicitly assumed to be zero.

Regarding the research on knowledge integration, a rich literature builds on seminal contributions analyzing differentiation and integration of corporate functions and the impact on performance and innovation (Galbraith, 1974; Lawrence & Lorsch, 1967), but similarly does not consider the organizational ability to absorb knowledge across functional interfaces. In fact, although it is well known that technological and market knowledge are highly complementary (Iansiti & Clark, 1994), and that integration mechanisms can help to capitalize on this complementarity (De Luca & Atuahene-Gima, 2007), surprisingly little is known on how departmental abilities to manage and leverage integration mechanisms develop and consequently impact innovativeness.

These research gaps have not only major theoretical implications as pointed to by Volberda et al. (2010), but are also highly important to managers involved in the innovation process and strategic decision making on middle and top-levels alike. For middle managers of functionally specialized departments it is important to know whether they (1) can focus their limited time and resources on the implementation of integration activities that they will have difficulties because they know that their department masters them or whether they (2) should invest part of their resources and attention on the development and improvement on skills to use integration mechanisms and understand external knowledge even if it is from totally different areas. For top managers it is important to know whether departmental ACs play a role in internal integration, because then they could benchmark departments on this and/or adapt integration process to the strengths of the departments.

In this chapter I aim at answering the question of how AC can be defined and understood at the level of functionally specialized departments. More specifically I will concentrate on the major example of the R&D-M&S interface, the way departmental AC, particularly at this interface, might be relevant for the innovation process, and how it impacts the innovation output in terms of push, pull, or integrated innovations. I argue thus that it is necessary to open the black box of firms' AC and to shift analytical focus to the levels of the specialized corporate functions in order to understand the dynamics of internal knowledge integration. In particular, it has never been theorized whether there might be a difference between organizational unit's ability to absorb external knowledge that falls into their functional area and the ability to absorb such that does not belong to their functional area. This might be particularly relevant for the R&D-M&S interface.

This chapter is structured as follows. In the next section, the literature on AC is reconsidered in the light of a clear definition of knowledge. In the subsequent section, the theoretical background of integration in terms of both Intra-functional and Cross-Functional Integration is briefly reviewed with particular attention to the potential positive and negative effects of CFI under various contingencies. Based on these literature reviews, the departmental ACs, Functional and Cross-Functional AC (FAC and CFAC), are defined and conceptualized and a model is developed that positions these new concepts in the context of CFI in the innovation process.

II.2. Literature Review

II.2.1. Absorptive Capacity

II.2.1.1. The development in extant literature

Absorptive Capacity (AC) was originally defined as “the ability to recognize the value of new, external information, assimilate it, and apply it to commercial ends” (Cohen & Levinthal, 1990:128). Cohen & Levinthal (1989, 1990, 1994) seminally contributed to innovation management literature by advocating for R&D as a means to keep up with external knowledge developments and become or remain able to understand and hence absorb that new external knowledge. The authors hence claimed a dual nature of internal R&D, in that the maintenance or creation of the ability to observe external developments and absorb them whenever convenient would constitute a “second face” or collateral effect besides the main motivation behind R&D to generate new knowledge internally. They compare the organizational process of knowledge absorption mainly to that of individuals, identify and corroborate empirically the relevance of “prior related knowledge” for their concept, measuring AC, however, by means of R&D intensity (R&D investment/sales).

In the following literature on firm level AC, it has been suggested that AC constitutes of three or four distinct sub-dimensions. In the literature strand that developed thereupon, this has been refined and reconceptualized several times (cf. Lane, Koka, & Pathak, 2006; Volberda et al., 2010). Most importantly, it has been argued that it might be distinguished between Potential and Realized AC, where the former (PAC) is constituted by the ability (1) to acquire and (2) assimilate external knowledge and the latter (RAC) by the ability to (3) transform and (4) exploit it (Zahra & George, 2002).

In both conceptualizations of firm level AC, the question necessarily arises of how intra-organizational antecedents determine these different abilities. While a large body of literature developed around AC, there has been still identified a substantial research gap in this regard (Volberda, Foss, & Lyles, 2010). In fact, in an attempt to tackle this issue, most recently Lewin, Peeters, & Massini (2011) identified several meta-routines that constitute such organizational antecedents of what they call “internal AC”. The distinction between external and internal AC practices/mechanisms (Lewin et al., 2011) can be compared to previous distinctions between inward- and outward-looking AC (Cohen & Levinthal, 1990). Moreover, this view is in fact similar to the distinction between external and internal knowledge integration abilities in the literature on functional integration (Iansiti & Clark, 1994). All these distinctions, however, between external and internal AC or inward- and outward-looking, can be applied to all levels of AC. That means, “internal” and “external” is always relative to the chosen boundary and organizational level. Therefore, choosing the level of analysis has important implications to the research question, design and results.

The fact that AC does not need to be limited in its application only to the firm level but can also be applied to sub-unit levels down to even single individuals is clear since the concept has been coined originally. In fact, Cohen & Levinthal (1990) state outright that while their focus is particularly on the firm level, “outside sources of knowledge are often critical to the innovation process, whatever the organizational level at which the innovating unit is defined” (p. 128). However, as a matter of fact, most empirical studies apply AC to the business units / divisions (M. T. Hansen, 2002; Tsai, 2001), subsidiaries (Gupta & Govindarajan, 2000), and undefined or unspecialized sub-unit (Szulanski, 1996) – often branches, or production sites.

However, AC of functionally specialized departments regarding other more or less related specialist disciplines of their own functional knowledge domain might well differ from AC of the same department regarding knowledge from an entirely different domain; a distinction that would not make sense on the firm level. This could explain why extant AC literature largely ignored the issue of the knowledge's different nature across corporate functions; it was simply out of sight. In the next paragraph, it is sought to broaden thus the horizon and argue for the importance to differentiate between knowledge disciplines, e.g. physics vis-à-vis mechanics, and knowledge domains, e.g. technological vis-à-vis market.

II.2.1.2. Broadening the scope of knowledge to be absorbed

Cohen & Levinthal (1990:133) already distinguished between knowledge structures and "sort of knowledge". Therewith they referred to the fact that each particular sort of knowledge might require knowledge from a complementary sort in order to build valuable knowledge structures: "Critical knowledge does not simply include substantive, technical knowledge; it also includes awareness of where useful complementary expertise resides within and outside the organization" (idem, p. 133). This sort of knowledge, i.e. such on who knows what, is sometimes termed "transactive memory" (Wegner, 1987) and constitutes a precondition to simply leverage external knowledge without bearing the cost of completely integrating it (Grant & Baden-Fuller, 2004).

Notwithstanding this upfront recognition that different sorts of complementary knowledge are important for each single sort's absorption, AC literature considers organizational knowledge stock and prior related knowledge almost exclusively in form of scientific and technological knowledge. This is most evident from the way in that the overwhelming majority of AC literature measures the concept, i.e. by means of R&D intensity (cf. Flatten, Engelen, Zahra, & Brettel, 2011).

There are, however, many definitions and classifications of knowledge (Nonaka, 1994; Spender, 1996). The most commonly cited one is probably the distinction between explicit and tacit knowledge (Polanyi, 1966). These different kinds of knowledge categorizations, as above all those based on the related characteristics tacitness, appropriability and stickiness, have been recognized as crucial for the governance of knowledge transfer and hence also its absorption (e.g. Grant, 1996; Szulanski, 1996; Von Hippel, 1994).

While several further and likewise important taxonomies of knowledge exist (Foss, Husted, & Michailova, 2010; Nonaka & Peltokorpi, 2006), which might also overlap and are not necessarily mutually exclusive since many categorize knowledge by its characteristics, it appears to be fundamental to a correct understanding of AC to consider that there are different knowledge domains.

The distinction of the functional nature of knowledge can reasonably be assumed to rank amongst the most important ones for innovativeness and hence performance, above all regarding the distinction between scientific and technological knowledge on the one hand and market knowledge on the other. These two domains are fundamentally different in nature, i.e. different across several important characteristics, rather than merely different knowledge fields or disciplines that may exist within each domain and are simply more or less related in terms of content but similar in terms of their important characteristics.

Most salient is that they relate closely to the complementary knowledge sets of “facts” and “values” (cf. Spender, 1996). Offering a new product or service in itself is not sufficient to add value; recognizing the consumers’ utility attributed to realizable products and services is. There is indeed little doubt that market knowledge is crucial for commercialization success of new products and firm performance (Jaworski & Kohli, 1993; Verhoef & Leeflang, 2009) as indicated by the large body of literature in which the R&D-Marketing-Interface has been investigated (cf. Griffin & Hauser, 1996). And AC can with similar certainty be applied to market knowledge, as suggests for example the explorative-exploitative search literature (e.g.

Li, Vanhaverbeke, & Schoenmakers, 2008; Sidhu, Commandeur, & Volberda, 2007) and has been claimed in a recent review of the AC research (Volberda et al., 2010), but has not found sound consideration in this literature stream yet.

The literature distinguishing potential and realized AC points well to the importance of social integration mechanisms for the efficiency of converting PAC to RAC (Zahra & George, 2002), and more recently the view of external and internal AC concluded likewise that internal knowledge integration is one of the processes that underlies internal AC (Lewin et al., 2011). But social integration mechanisms themselves have to be learned to be applied by the individuals involved and the departments collectively and so do integration mechanisms in general. Moreover, social integration mechanisms which are well suited for intra-functional, cross-discipline integration might fail to integrate cross-functionally. Finally, departments' AC can be assumed to be as path dependent as firm-level AC due to reliance of prior related knowledge and thus there might be considerable heterogeneity across departments of a single firm that has to be accounted for by both, the top management fostering particular integration mechanisms and the middle management applying them with other departments of more or less adequate AC.

The literature stream regarding CFI can thus contribute to AC research in several ways. In order to provide a theoretical background for the CFI aspect, in particular as regards the R&D-marketing interface, in the following section the most relevant extant literature on the consequences and contingencies of CFI success are briefly reviewed before the model for Functional and Cross-Functional Absorptive Capacity is developed.

II.2.2. Cross-functional Integration

II.2.2.1. Definitions, understanding, and related concepts

Cross-functional integration (CFI) could be defined as "the degree of interaction, communication, information sharing, or coordination across functions" (Troy, Hirunyawipada, & Pasawan, 2008:132). But extant literature distinguishes between several other closely related and by times competing constructs like cross-functional collaboration, cross-functional coordination, cross-function cooperation, joint involvement, internal integration, etc. As Troy et al. (2008) note that the confusion that exists in the relevant literature is not limited to construct definitions but extends to measurement, sampling, research design, and analysis as well. This might also be due to the issue being also one of level and perspective. Studies that investigate cross-functional integration on the project level necessarily face different requirements than studies choosing the firm level, business unit level or multiple levels for their research design.

Notwithstanding the broad extant research, until today no satisfying general definition seems to have emerged (Brettel et al., 2011). Some of the commonly referred to related constructs are summarized in Table 1. Two predominant types of views have been distinguished, the behavioral and the attitudinal (Ernst, Hoyer, & Rübsaamen, 2010). From a behavioral point of view, functional integration consists in the observable cross-functional interactions, whereas the attitudinal point of view adds the opinions and motivation of the involved personnel as the decisive element. Kahn (1996) claimed that the aspect along which the definitions can be distinguished is the duration of the relationship, i.e. whether it is a one-shot interaction or a long-term collaboration. However, from the overview of exemplary definitions it is clear that the picture is more complex than that and that several concepts might be overlapping, but are not competing. Definitions can be classified into (1) processes, (2) systems, (3) abilities, (4) outcomes. Further possible distinction is between those where

(1) partners have a common goal or collective set of tasks vis-à-vis those where (2) they follow individual tasks which are interdependent. Another worthwhile distinction is between those concepts that focus on (1) activities that are performed jointly vis-à-vis those that focus on (2) exchange between partners required for them to carry out activities individually. Finally, it can be distinguished between (1) specialized definitions that address the issue of integration at a precise type of organizational boundary vis-à-vis (2) general definitions that are not constrained to a particular boundary.

The common aspect of all definitions can be found in that two or more specialized organizational units depend on each other in the achievement of their goals or tasks and therefore establish some kind of relationship, independently of whether their goals or tasks are the same, similar, or completely different. This interdependence derives from their specialization and the organizational structure that follow the environmental pressures to which the organization at large adapts. In fact, integration cannot be thought of without the differentiation that necessarily precedes it. Differentiation refers to “state of segmentation of the organizational system into subsystems, each of which tends to develop particular attributes in relation to the requirements posed by its relevant external environment” (Lawrence & Lorsch, 1967:3f).

Now, this relationship can simply serve to exchange commodities, but as long as these are easy to transfer or leverage, integration will not be an issue. It becomes crucial, however, where the transfer or leverage is difficult, as in case of resources, like complex or tacit knowledge or where knowledge on what is worth to be transferred or leveraged has yet to be established between the parties.

Table 1: Definitions of concepts underlying, overlapping and/or competing with CFI

Concepts:	Definitions:	Authors:
Inter-departmental Interaction	• "represents the structural nature of cross-departmental activities" (p. 139); emphasis on temporary nature	Kahn (1996)
Coordination	• "integrating or linking together different parts of an organization to accomplish a collective set of tasks" (p. 322)	Van De Ven, Delbecq, & Koenig (1976)
Cooperation	• "quality of task and interpersonal relations when different functional areas work together to accomplish organizational tasks." (p. 203)	Pinto & Pinto (1990)
	• "presence of deliberate relations between otherwise autonomous organizations for the joint accomplishment of individual operating goals." (p. 847)	Schermerhorn (1975)
R&D-marketing Interface	• "the process in which marketing and R&D functions communicate and cooperate with each other" (p. 14)	Li & Calantone (1998)
Inter-functional Interaction	• "particular form of open social system (..) [that] consists of a group of two or more individuals or organizational entities (..) that interact and exchange things of value on a regular basis" (p. 2) transforming inputs from the intra- and extra-firm environment via transactions, communication, and coordination into functional and psycho-social outputs	Ruekert & Walker, (1987)
Collaboration	• "affective, volitional, mutual/shared process where two or more departments work together, have mutual understanding, have a common vision, share resources, and achieve collective goals" (p. 139) continuously	Kahn (1996)
Integration	• "process of achieving unity of effort among the various subsystems in the accomplishment of the organization's task." (p. 4)	Lawrence & Lorsch (1967)
Joint involvement	• "the process of achieving effective unity of efforts in accomplishment of NPD success" (p. 303) • Measured as the level of information sharing, degree of coordination and collaboration at various stages	Song, Thieme, & Xie (1998)
Internal Integration	• "the capacity for extensive coordination between different specialized subunits within an organization, and explicitly targets the implementation of a given project concept." (p. 569)	Iansiti & Clark (1994)
R&D-Marketing Integration	• "the information that is communicated and used, which transactions occur across boundaries (tasks completed and decisions made), and how much coordination is achieved (processes are followed and conflicts resolved)" (p. 201)	Griffin & Hauser (1996)

Concepts:	Definitions:	Authors:
Knowledge integration	• "Integration of specialist knowledge to perform a discrete productive task is the essence of *organizational capability*, defined as a firm's ability to perform repeatedly a productive task which relates either directly or indirectly to a firm's capacity for creating value through effecting the transformation of inputs into outpus." (p. 377)	Grant (1996b)
Internal Integrative capabilities	• "Once the required technological and market knowledge has been both produced and absorbed, *internal integrative capabilities* organize its use." (p. 137)	Verona (1999)
Architectural competence	• "both 'architectural knowledge' (..)—the communication channels, information filters and problem-solving strategies that develop between groups within a problem-solving organization—as well as the other organizational characteristics that structure problem-solving within the firm and that shape the development of new competencies: the control systems and the 'culture' or dominant values of the organization." (p. 66)	Henderson & Cockburn (1994)
Combinative capabilities	• "generate new combinations of existing knowledge (..) exploit its knowledge of the unexplored potential of the technology" (p. 391)	Kogut & Zander (1992)
Combinative capabilities	• "*three types of combinative capabilities*": "*System capabilities* (..) reflect the degree to which rules, procedures, instructions, and communications are laid down in written documents or formal systems", "*coordination capabilities* (..) refer to lateral ways of coordination", "*socialization capabilities* (..) refer to the ability of the firm to produce a shared ideology that offers members an attractive identity as well as a collective interpretations of reality." (p. 556f)	Van Den Bosch, Volberda, & De Boer (1999)

(Continuation of Table 1 from previous page)

As a conclusion of this brief overview, the following definitions are suggested for functional integration in general as well as intra- and cross-functional integration in particular:

Definition: Functional Integration (FI) *shall be defined as the level to which two or more organizational sub-units succeed in exchanging or leveraging resources of each other that contribute the successful completion of their individual tasks.*

Definition: Intra-Functional Integration (IFI) *shall be defined as the Functional Integration of to two or more organizational sub-units that belong to the same corporate function.*

Definition: Cross-Functional Integration (CFI) *shall be defined as the Functional Integration of to two or more organizational sub-units that belong to different corporate functions.*

It can be noted that these definitions are outcome-oriented and do hence not specify underlying processes like interaction, communication, etc., since the antecedents should not enter the definition. Furthermore, it is supposed that successful integration allows integrating units to access complementary resources to fulfill their individual goals, which leaves the question of agency problems and goal incongruity out of the issue of integration so that it can be addressed separately. This, together with the outcome orientation, does permit to separate integration of sub-units from the performance effect on higher organizational levels.

Griffin & Hauser (1996) found broad consensus in literature that cross-functional integration, although differently defined across studies, by and large positively impacts the innovation process. In contrast, Troy, Hirunyawipada, & Paswan (2008) find that the relationship between cross-functional integration and innovation performance is still not sufficiently understood and several authors find even a negative influence of false or exaggerated integration onto performance. Amongst the reasons of negative impact is not only the extensive devotion of resources to organize and control the collaboration effort that might offset potential gains, but also misunderstandings resulting from inadequate communication or insufficient background knowledge.

There might hence be considerable heterogeneity across firms and across departments within firms regarding departments' ability to absorb knowledge from complementary functions. In order to establish thus the context of our framework in form of potential contingency factors of successful CFI, in the next paragraph, opportunities and threads are reviewed.

II.2.2.2. Opportunities and threats of CFI

Organizational integration can become manifest in several forms. In their seminal early article on organizational differentiation and integration, Lawrence & Lorsch (1967) show in a comparative case study not only several factors which are important for integration success, but also first hints for a positive influence of contemporaneous differentiation and integration, a difficult goal as the author's describe these two to be inherently antagonistic constructs.

Research of cross-functional integration empirically is particularly focused on the impact on new product development (NPD) success in terms of product quality, development time, met objectives and general project success (e.g. Griffin & Hauser, 1996; Perks, Kahn, & Zhang, 2010; Song et al., 1997) as well as product innovation (cf. Song & Thieme, 2006). The success in terms of impact of integration of organizational units from different functional areas in the context of new product development projects has been shown to depend highly on the phase of the project (e.g. Olson, Walker, Ruekert, & Bonner, 2001) as well as on the degree of innovativeness of the projects (Brettel et al., 2011).

Also in the knowledge integration literature, integration mechanisms have been noted above all as positive, e.g. as drivers of product development or ambidexterity. Iansiti & Clark (1994) present the examples of two industries to show the modes of and benefits from knowledge integration. They claim that dynamic capability is the capacity to build new relevant capabilities in response to continuously changing contingencies, both internal as external, through a process of problem solving that integrates diverse knowledge types. According to their framework, the presence of such a dynamic capability could be deducted from the presence of dynamic performance, i.e. the consistent positive performance of the organization.

Moreover, functional differentiation has been found a major driver behind efficient organization of complex technologies and services through increasing the firm's ambidexterity (e.g. Jansen et al., 2009). In a related study, the authors find furthermore also functional integration interacting with the said relationship between ambidexterity and performance (Burgers, Jansen, Van Den Bosch, & Volberda, 2009). This might be because considerable costs can accrue from coordination requirements due to this very specialization (Gupta, Raj, & Wilemon, 1986; Ruekert & Walker, 1987).

Instead, Raisch, Birkinshaw, Probst, & Tushman (2009) see in differentiation and integration two distinct approaches to organizational ambidexterity. However, from mere differentiation might result separated knowledge silos that hamper innovation because R&D might produce inventions without latent needs on side of the costumers or the marketing might not find existing latent needs and opportunities due to a lack of understanding of the potential of NPD project proposals or already completed inventions coming from R&D. (e.g. Nerkar & Roberts, 2004:783).

The term “Silo Busting” tackles exactly this issue, as it has been coined to refer to the strategic endeavor of some corporations to change their either explicit or implicit but de facto product-centric approach towards an actual customer-centric one. As Gulati (2007) claims, some companies might exhibit difficulties to address customer needs notwithstanding all knowledge and capabilities required are generally present somewhere in the corporation, but stored in separated silos that hinder their cross-fertilization. In consequence, Gulati explains, successful companies show some common features related to customer- and solution-oriented approaches of value creation. These are coordination, cooperation, capability development, and connection to external partners. The first two behaviors – the establishment of structural mechanisms and processes to harmonize information and activities and the encouragement of cooperation – are particularly relevant also for the proposed concept of cross-functional AC.

Cross-functional collaboration is however far from being viewed as only beneficial, with the issue being merely how to achieve it. Not only do the different integration mechanisms come at varying costs (Smulders, H. Boer, & P. H. K. Hansen, 2002), each one potentially comes in a range of different variants that can be more or less appropriate and hence more or less beneficial in particular contexts, like for example cross-functional teams, which are per se regarded as a media-rich and hence powerful integration mechanism (Daft & Lengel, 1986). There are, for example, several different forms of cross-functional teams, as e.g. leightweight, autonomous, and heavyweight teams (Clark & Wheelwright, 1992), that moreover can exhibit different degrees of structural diversity (Cummings, 2004). A broad literature shows that cross-functional teams in themselves are a complex issue for organizations to deal with. This is another example of the need of refinement of analysis, since cross-functional teams are widely claimed to exhibit a positive effect on innovation output, but also significantly negative outcomes have been found (Henderson & Clark, 1990).

Moreover, integration can become even more costly if conflicts of interest and battles for resources, development paths, and the dominant design emerge (Cyert & March, 1963). Further conflicts might arise in general due to the different mindsets and cultures of members from different functions, as principally between engineers and marketers (Shaw & Shaw, 1998), as well as due to an exceedingly high degree of competition resulting in an arduous relationship between source and recipient in intra-organizational knowledge transfer (Szulanski, 1996). This can impede the bridging of boundaries between departments of different corporate functions, particularly in case of tacit or otherwise sticky knowledge (e.g. Sorenson, Rivkin, & Fleming (2006). However, competition has been shown to be also a complement to the cooperative nature of relationships, resulting in “cross-functional coopetition” (Luo, Slotegraaf, & Pan, 2006).

Various other factors can result in a likewise negative impact of cross-functional integration on different performance measures. Related to the arguments above regarding conflict and competition across functions, Carlile (2004) suggests how the learning in one domain can have negative consequences in another when interests are in conflict. With that he describes one of the arguments that also underlies the skunk works model of innovation.

Table 2: Contingency factors of CFI success

Factors related to KI:	**Effects:**	**Examples in literature:**
Knowledge networks	A small-world knowledge network provides short paths to business unit with related task knowledge and enables to balance explorative and exploitative search	Fang, Lee, & Schilling, (2009); Hansen (2002); Tsai, (2001a), Nahapiet & Ghoshal (1998)
Organizational structure; centralization, autonomy, formalization	Centralization of organization and the closely related autonomy of departments have been regarded both as alternatives and antecedents to integration mechanisms. E.g. centralization can substitute for lateral integration and be positive for innovation within the R&D function and negative across functions, increasing thus the relevance of integration.	Argyres & Silverman (2004), Calantone, Di Benedetto, & Divine (1993), Cyert & March (1963), Gulati (2007), Nahapiet & Ghoshal (1998), Tushman & Nadler (1978), Jansen et al. (2009)
Goal incongruity/ incompatibility	Incompatible goals and interests of interdependent units can hamper the necessary integration, but if well managed this conflict of interests can be leveraged to increase motivation	Carlile (2004), Fosfuri & Rønde (2009), Ashok K. Gupta, Raj, & Wilemon (1985)
Motivation / Incentive system	Lack of motivation can be a major hurdle to integration, while over-motivation to source knowledge can create a bias towards external knowledge	Hansen & Nohria (2004), Henderson & Cockburn (1994)
Ambiguous or uncertain cost-benefit ratio	Wrong estimation of the potential return on investment of integration measures	Hansen (2009)
Group identity and group think	Shared identity can help to create communities-of-practice across organizational boundaries, but also spawn pathologies as the not-invented-here syndrome and intra-organizational provincialism	Burcharth & Fosfuri (2012), Katz & Allen (1982), Reitzig & Sorenson (2010), Brown & Duguid (1991)
Cultural differences, thought-worlds, or mental models, languages, norms	Common languages, norms, and thought-worlds permit interpretation and sense-making, while perspective taking permits the integration from groups with differences in these elements	Dougherty (1992), Mohammed & Dumville (2001), Boland & Tenkasi (1995), Daft & Weick (1984)
Opposing personalities, stereotypes	Conflicts detrimental to performance, particularly between R&D and marketing personnel	Saxberg & Slocum (1968), Shaw & Shaw (1998)
Geographical distance and physical environment and hurdles	Greater geographical distance and spatial separation reduces spontaneous communication and renders conflict resolution more difficult, which impacts mostly informal integration mechanisms	Li et al. (2008), Hinds & Mortensen (2005)

The skunk works model, originally introduced in the 1940s by military equipment manufacturer, holds that the isolation of innovative activities are key to radical projects' success (Rosenau, 1988). Innovation striven for by one department might be opposed by another, because it implies sometimes a heavy burden to them, e.g. in form of arduous change processes, reorganization and learning costs with the introduction of a radically new product resulting in an effort to influence the other department towards a bias for incremental innovation. In consequence, literature from this stream usually suggests the total separation and also physical dislocation of radical innovation projects.

However, this phenomenon might prove to be quite useful as well. Fosfuri & Rønde (2009) propose that such a resistance can be leveraged by an intelligent innovation management if the costs to change and the expected gains from the innovation are sufficiently explicit. Another downside of intensifying cross-functional collaboration is averted by Hansen & Nohria (2004) in exaggerating collaboration and losing a clear focus on concrete results and performance. Too intense knowledge exchange can also reduce performance due to time constraints which leads again to a loss of focus (Haas & M. T. Hansen, 2005) which might equally hold for any other resource constraints. Moreover, Hansen (2009) warns that integration can turn out not even to fall short of expectations but as detrimental for the company. He identifies three major errors of which managers can fall victim, which are to overestimate the return, to underestimate the costs of collaboration and to ignore the costs of forgone opportunities of non-collaborative activities.

An exemplary overview is given in Table 2. In conclusion it can thus be summarized that several basic factors are important to integration and either foster or hamper successful or efficient integration between functions according to their concrete expression and context. The literature regarding the transfer of knowledge across functional areas points principally to a positive effect on innovation performance, but doubts persist as to whether tight integration of functional knowledge and functionally differentiated departments is beneficial at all and if so under what circumstances.

In the following sections, the concept of departmental Absorptive Capacities are therefore conceptualized, followed by the elaboration of the model that explains their path dependent nature deriving from prior related knowledge and relates them to different types of innovation outcomes considering in particular the R&D-M&S interface.

II.3. Conceptualizing departmental Absorptive Capacities

II.3.1. Functional AC as an organizational ability

Building on the previous literature review of Absorptive Capacity and Cross-functional Integration, I propose the following definition:

> ***Definition: Functional AC (FAC)*** *shall be defined as the ability of functionally specialized departments to absorb, i.e. to recognize and evaluate, acquire and assimilate as well as transform and use, knowledge from other organizational units that possess knowledge of the SAME functional specialization, both outside and inside their business unit and corporate group.*

This definition adopts the framework of Zahra & George (2002) in terms of the fundamental sub-processes that co-determine an organizational units absorptive capacity. This is particularly justified also in light of the above discussed empiric evidence of this understanding (Jansen et al., 2005). Moreover, the distinction between potential and realized absorptive capacity appears very appropriate also on the level of functional departments since it is at this level that concepts as the Not-invented-here-syndrome emerged (Katz & Allen, 1982).

However, I explicitly depart from the conceptualization of AC as a dynamic capability. It has been claimed that defining AC as a dynamic capability would make it “possible to analyze the stocks and flows of a firm’s knowledge and relate these variables to the creation and sustainability of competitive advantage." (Zahra & George, 2002:188). Capabilities are usually understood as high-level routines or sets of routines that permit to achieve certain outcomes under certain inputs and constraints given, while dynamic capabilities are viewed as those supplementary processes or routines that challenge continuously the former and change them if needed, allowing thus organizations to adapt dynamically to changing environment (Teece et al., 1997; Winter, 2000, 2003; Zollo & Winter, 2002). In fact, as Winter emphasizes, "brilliant improvisation is not a routine" (Winter, 2003:991) and hence not included in the common definition of capabilities, neither common nor dynamic ones. Winter thus explicitly distinguishes capabilities from ad-hoc problem solving, as for example discussed in literature on collective sense-making (Priem & Nystrom, 2011; Weick & Roberts, 1993; Weick, 1993).

Although this view of dynamic capabilities has been widely adopted in strategic management from evolutionary economics, the changing environmental conditions and contingencies put in question whether such meta-routines can be eventually found or are equally subject to continuous change. Continuing such a line of reasoning would lead to an infinite regress on always higher meta-capabilities and no such thing as a general-purpose routine can be claimed to exist (Winter, 2003). But more importantly, it is difficult to imagine how the definition of dynamic capabilities as high-level routines or patterned behavior can be reconciled with the claim that they can be applied in dynamic environments. Particularly in dynamic environments patterned behavior—even such that adjusts the routines of "making a living" or core competences—has to be adjusted continuously to problems that arise from their application, hence potentially not patterned, non-routine behavior.

For common capabilities intuition suggests that ad-hoc problem solving allows for the necessary small adjustments to the patterned behavior that allows it to better fit the idiosyncratic nature of a situation that will never repeat exactly in this same way and that could not be anticipated by any recipe-like patterned behavior, even if it coordinates individual skills. Capabilities and ad-hoc problem solving are thus complements and their interdependence ought to increase with environmental complexity. In fact, particularly in innovation processes this is crucial as described for example by Dougherty (1992): “Successful developers violated all three routines, and created a new social order for their collaborative efforts.” (p. 192).

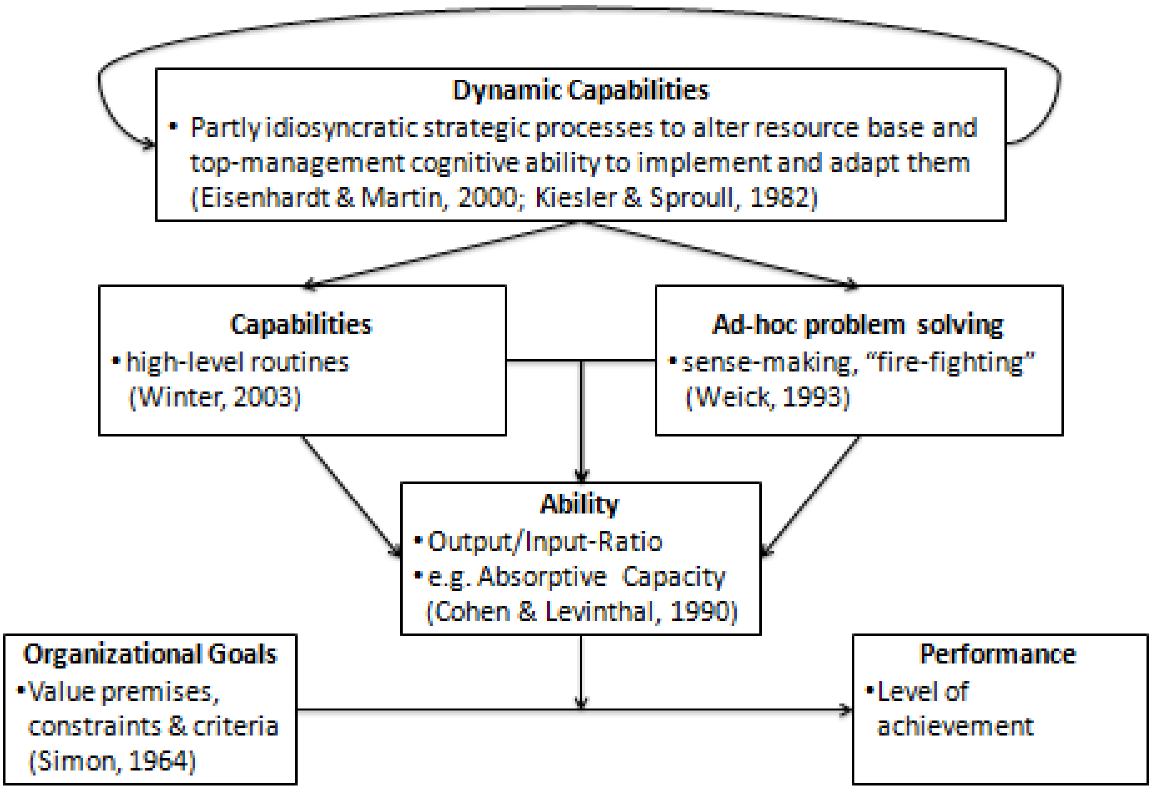
For the more strategic dynamic capabilities the individuals’ cognitive abilities and sense-making is even more important, to a point that the routine behavior of the strategizing top-management cannot separate in its effect from the individual top-managers cognitive abilities and problem sensing behavior (Kiesler & Sproull, 1982). This can thus supplement the definition of dynamic capabilities by Eisenhardt & Martin (2000) as partly idiosyncratic strategic processes to alter the resource base.

I suggest thus to separate the organizational ability from specific sets of processes and to understand it rather as the efficiency—the output-input-ratio—of a transforming social system to achieve intermediate goals required for the realization of higher-level organizational goals. In fact, we say a person is “able” to do something, if she can intentionally realize particular outcomes. Organizational abilities derive thus from both kind of heuristics with which organizational goals are addressed: capabilities and ad-hoc problem solving. The thus delineated concepts are illustrated with their respective relationships in Figure 2.

Departmental ACs, as AC in general, are thus particular abilities, i.e. the efficiency with which the resources like organizational knowledge in various repositories of different departments are absorbed by a focal department. It can thus potentially influence the achievement of various goals, like innovativeness as well as business performance. Defining FAC as such an ability requires therefore its measurement with socio-metric measures of ability self-assessment since no objective measures of valuable externally available knowledge—which could be set into relation with performance outcome, i.e. the actually absorbed knowledge—are readily available. This ratio would be the perfect measure, but is not realistically achievable. Nonetheless, the definition in terms of ability has a fundamental advantage. Although being more intangible, at the same moment it allows for a more in-depth analysis of the related effects. At the same time they permit to separate higher-level outcomes from antecedent routines and problem solving behaviors.

While a study of AC in form of processes and routines would connect these processes directly to outcomes, a study of AC as ability would treat these processes and routines as antecedents and be analyzed thus in its role as a mediating variable. This allows for the possibility to distinguish between various different kinds of other mediating abilities influenced by these routines which could potentially reveal that routines previously thought not having any effects on performance exhibit contrasting effects on different mediating abilities.

Figure 2: General framework of organizational abilities in context of goals, behavior, and performance



Moreover, it is important to note that FAC, although defined at a different level of analysis is generally most congruent with the traditional understanding of AC, particularly in case of R&D departments, since traditionally AC is focused on the absorption on new, external knowledge from more or less related disciplines, but at the same time – at least implicitly – confined to the scientific and technological domain. It should be underlined that other characteristics of the intra-functional boundary are not constrained by this definition. This means that FAC refers to the absorption of new knowledge of other organizational units that belong to their own or other business units, divisions, or corporate groups or to universities, institutes or other entities, as long as these units posses relevant scientific or technological knowledge.

II.3.2. Divergent integration boundaries and Cross-Functional AC

While FAC is thus a department-level adaptation of the firm-level AC as discussed commonly so far, it appears useful to conceptualize departmental AC related to absorption across functional domains separately, due to the different pattern of boundaries that divide departments within a domain and those that divide departments across domains. This second departmental AC shall be thus defined as follows:

> ***Definition: Cross-Functional AC (CFAC)*** *shall be defined as the ability of functionally specialized departments to absorb, i.e. to recognize, assimilate as well as transform and use, knowledge from organizational units that possess knowledge of a DIFFERENT functional specialization, both outside and inside their business unit and corporate group.*

As has been discussed before, the existence of substantial complementarities between specialized corporate functions exist notwithstanding the different environments that require differentiation in the first place. However, the realization of these complementarities requires not only the possession of relevant knowledge from potentially complementary knowledge categories, but also the ability to internally integrate them (Iansiti & Clark, 1994). It is not sufficient for complementary knowledge to be contemporaneously present in the same firm, since they might be in quite remote parts, both geographically as well as socio-cognitively (Y. Li et al., 2008). This holds thus for knowledge of different domains just as it does so for knowledge of complementary disciplines of the same domain. However, the boundaries separating them differ, which requires thus respective distinction between departmental ACs.

Building on a classical triad of the information-processing literature, Carlile (2004) suggests the syntactic, the semantic, and the pragmatic boundaries as the three principal boundaries that have to be faced in order to integrate knowledge. The syntactic boundary refers to the differences in lexica and to the difficulty to process and thus transfer knowledge between organizational units. The semantic boundary refers to changes in dependencies and arising ambiguities that make the interpretation of the knowledge that needs to be integrated difficult. Carlile (2004) argues that the organizational unit needs to be able to translate the knowledge in order to overcome this boundary, which might be supplemented by the ability of the absorbing unit as a knowledge community to take the perspective of the other knowledge community from which to absorb, which is why knowledge communities have also been considered as interpretive communities (Boland & Tenkasi, 1995). In analogy, also cross-functional interfaces in NPD processes have been described as problematic due to different thought worlds that impede correct interpretation of decontextualized information (Dougherty, 1992). Hence, the semantic boundary cannot be assumed to be particularly different across interface types. Finally, the pragmatic boundary refers to cases where knowledge integration depreciates part of the knowledge stock of one of the parties and thus requires the transformation of this knowledge. This would inflict costs and hence reduces the willingness to integrate.

Each boundary can be managed either through traversing it based on a minimum common ground or boundary objects regarding an underlying requirement related to the particular barrier (Bechky, 2003; Carlile, 2002; Priem & Nystrom, 2011), which might be also non-material artifacts (Rullani & Haefliger, 2013). Alternatively, a boundary can be also "transcended" by analyzing the issue from a higher level (Majchrzak, More, & Faraj, 2011). Carlile (2004) argues that these boundaries rise with novelty of the knowledge to be integrated. However, he focused on integration between technicians in the development of a collaborative engineering tool, thus disregarding the demand-side aspect and other functions in general. This might not impair the effect of novelty on the semantic boundary, which arises due to shifts in interdependencies and causalities that are more profound in cases of highly novel knowledge both at the inter- and the intra-functional interface.

However, considering that there are other fundamental differences across functions that have to be integrated besides their knowledge's novelty, it becomes obvious that the relationship novelty-boundary is not that linear anymore across all boundaries. In fact, lexica of different, complementary corporate functions are usually quite different *a priori*, independently of knowledge's novelty. Moreover, at least two further boundaries ought to be included in the analysis of integration and are especially important when considering cross-functional / intra-functional differences in general and the demand-side aspect in particular: the sympathetic and the teleological boundary.

The sympathetic boundary refers to the differences across units that relate to the emotional aspects of their relationship and hence principally impact the motivation to integrate. This has to be included due to the finding that shared identity is an important but ambiguous contingency of functional integration success in that it can have both positive and negative effects on integration and innovation (J. S. Brown & Duguid, 1991; Burcharth & Fosfuri, 2012). However, the positive effects of shared identity appear to be prevalent, and also on the level of teams it has been found that for example team identity apparently increases performance of diverse, multidisciplinary teams (Van der Vegt & Bunderson, 2005). Another theme besides shared identity is the empathy that can overcome the identity barrier.

For example, the insensitivity of the other's view point has been found to be the second most important barrier to integration between R&D and M&S functions (Gupta et al., 1985) and cooperativeness has been linked to social perspective taking (Johnson, 1975). If there is no ground for a harmonious relationship or groups even dislike the idea of interaction with each other, every other their abilities is of very limited importance to integration. Thus to overcome in one way or another the sympathetic boundary can be thought to be a precondition for successful integration across any other of boundary. It is however neither independent from the other boundaries in that tensions and can rise if misunderstandings or conflict along one of the other boundaries cannot be resolved.

The teleological boundary, on the other hand, refers to the differences in goals that the involved units aim at when engaging in the relationship. It has been found that a principal impediment of fruitful knowledge integration lies in divergent opinions of what the necessary or optimal scope of integration is (Gupta et al., 1985). Members of the R&D and Marketing departments had substantially different ideas on the optimal scope of integration. This might derive more generally from the tasks causal ambiguity (Lippman & Rumelt, 1982) and would hence rather be a case of semantic boundary. But while Carlile (2004) argues that the differences that constitute the semantic and the pragmatic boundary arise from novelty of the involved knowledge, I suggest that the differences in goals are due to the different goal orientation inherent in the functional specialization of the involved units and independent from the knowledge itself.

For example, two R&D departments that engage in integrating their knowledge might struggle due to the novelty of the involved knowledge and the ensuing differences in interpretation of potential outcomes or potential devaluation of the knowledge stock of at least one off the units. These would be examples of semantic (interpretative) and pragmatic (political) boundaries. But once the differences in views on the causal relationships are settled and it is resolved how the knowledge stock can be transformed so that also divergent interests due to the sunk costs are reconciled, the potential for conflicting goals that remains is low. The different goals that might obstacle integration of an R&D and a marketing department, on the other hand, are potentially inherent in their goal orientation, e.g. monetary rewards vs. recognition as inventor. That is, it might be equally settled how the market knowledge relates to the scientific and technological knowledge to increase potential value of an R&D project and it might be equally possible for the R&D department to transform the knowledge to adapt it to the new development path, but it might be less technologically appealing and reduce the potential for peer recognition. However, since interpretative differences (semantic boundary) between separate thought worlds are more fundamental (Dougherty, 1992) that their resolution is a precondition for a successful negotiate conflicting goals.

On the other hand, the difference between pragmatic and teleological boundary becomes even clearer when comparing the capability that allows transcending the teleological boundary vis-à-vis that which is required to transcend the pragmatic one. While the pragmatic boundary can be transcended by knowledge transformation as described by Carlile (2004), the teleological boundary requires the ability to mentalize. Individuals are more or less able to estimate others' "intentions, beliefs, and desires, referred to as 'theory of mind' or 'mentalizing,'" (Singer & Fehr, 2005:340). This mentalizing capacity can help individuals to recognize otherwise only latent misalignment in integration scope between the involved partners which can trigger a process of joint resolution of conflicting goals.

Moreover, while the pragmatic boundary at the intra-functional interface increases with the novelty of knowledge, because it requires increased transformation of the old knowledge stock, higher novelty of knowledge integrated at cross-functional interfaces ought to imply only a limited pragmatic boundary the more the corporate functions are complementary, because the own knowledge domain's knowledge does not need to be transformed. For example, novel market knowledge that was developed to search new markets for the technological competences of the firm increases the value of the R&D department's knowledge stock. Therefore, the effect of novelty at the inter-functional interface either low or even reversed.

It can be concluded that the types of boundaries found between departments are at least five and that boundaries at the inter-functional interface generally are constantly high, while those at intra-functional interfaces increase with the novelty of the involved specialist knowledge (Table 3). Therefore, these five boundaries between departments belonging to different knowledge domains differ substantially from those between departments belonging to different disciplines, specialist fields, or specialized tasks within a functional domain above all regarding the most fundamental boundaries.

Table 3: Different levels of difficulty to integrate across various barriers within and across functions

Boundaries (misfit, resolving ability)	**Difficulty at Intra-Functional Interface**	**Difficulty at Cross-Functional Interface**
Sympathetic boundary (identity, empathizing)	low	high
Syntactic boundary (lexica, information processing)	low	high
Teleological boundary (goals, mentalizing)	medium	high
Semantic boundary (mental models, perspective-taking)	medium	medium
Pragmatic boundary (knowledge stock, transformation)	high	low

These fundamental differences of requirements for Intra-Functional Integration vis-à-vis Cross-Functional Integration constitute an important justification of the distinction between FAC and CFAC. The above examples moreover show that the reasons for conflicts during the processes to integrate different departments might relate to several boundaries contemporaneously which makes it even more difficult to identify and address them. Without a clear distinction between the underlying constructs actual effects will be even more blurred.

After discussing in the next paragraph how these two concepts are related, the model will be further developed to highlight the implications of these boundaries for the prior related knowledge as antecedent of departmental ACs.

II.3.3. Functional complementarity and the relation between FAC and CFAC

The defined departmental ACs, FAC and CFAC, cannot be assumed to be independent of each other. Although the differences between inter- and intra-functional integration are substantial, as described in the precedent paragraph, to some degree CFAC builds on FAC. Since FAC provides improved knowledge and since valuable external knowledge from the own functional domain can be faster integrated, the knowledge stock that informs the department in absorbing knowledge from other functional domains is of higher value. An R&D department, for example, that is able to absorb knowledge from a broad range of other scientific and technological disciplines, can promptly get informed on technological feasibilities during the cross-functional knowledge absorption process. Whether this is true also in the opposite direction depends on the type of task interdependence and complementarity between the functions involved.

Take for example an R&D department involved mainly in explorative, basic research activities. For these activities it does not need feedback from the marketing or manufacturing functions. Actually, as the skunkworks literature reported above suggests, in activities in this fuzzy front end of the innovation funnel such knowledge can detrimentally narrow down search focus (Bommer, Delaporte, & Higgins, 2002). Intra-functional knowledge instead can be very helpful for these departments and integration of scientific and technological knowledge between business units has been observed as leading to creative new combinations (Martin & Eisenhardt, 2010; Miller, Fern, & Cardinal, 2007). Hence, intra-functional knowledge has to be absorbed while cross-functional knowledge absorption is irrelevant at best. On the other hand, an R&D department that is involved in new product development has to absorb knowledge from other functions at various stages of the NPD process (Song et al., 1998). However, it remains vital to be able to absorb knowledge from other R&D departments in case it is discovered during the NPD process that features have to be added to the new product about which other departments already posses cutting-edge knowledge.

> ***Proposition 1:*** *FAC positively impacts CFAC. The higher are the complementarities between the focal function and other functions, the stronger is this relationship.*

II.4. A model of departmental Absorptive Capacities

II.4.1. A broader perspective on prior related knowledge

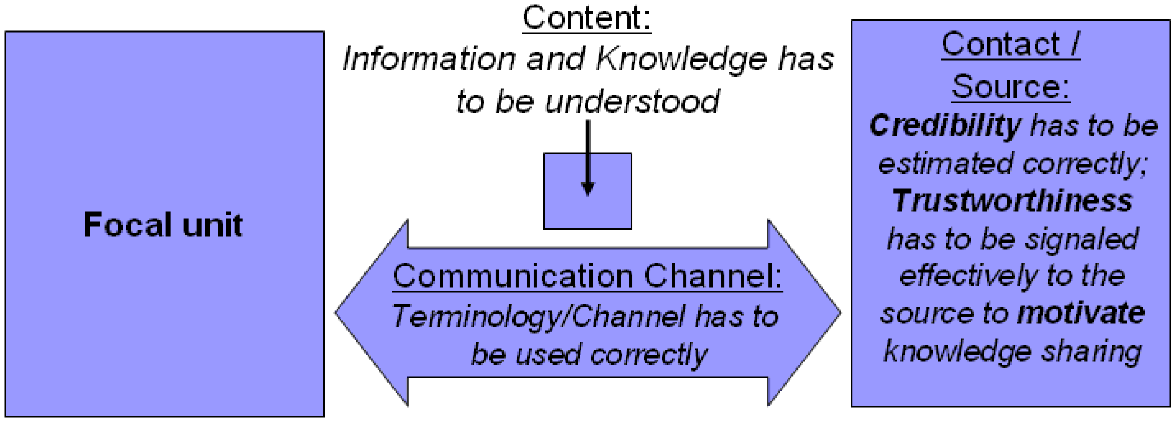
If the same antecedents impacted in the same way on FAC as on CFAC, there would be no reason to distinguish them. In case of firm level AC, for example, the principal antecedent has often been seen in prior related knowledge (Cohen & Levinthal, 1990) and thus there was no need to distinguish for example between bio-technological AC or nano-technological AC or other special forms of it. The dynamics of AC are assumed to be equal across scientific and technological disciplines since they were derived from basic cognitive characteristics of the individuals and the organizational level phenomena emerging from them. More prior bio-technological knowledge permits to absorb further knowledge of this discipline and more prior nano-technological knowledge permits to absorb further knowledge that discipline; therefore it can be generalized to prior related knowledge augmenting AC.

Prior related knowledge is important also for cross-functional knowledge absorption and leads to path-dependency; but different types of prior related knowledge play a role and in substantially different ways. As discussed above, from the consideration of the different pattern of boundaries at intra- and cross-functional interfaces it could be concluded that different abilities are required to traverse or transcend them. While for example for intra-functional integration those abilities related to the pragmatic boundaries are most important and the more so the more novel the knowledge is, abilities related to the sympathetic and semantic boundary are most important to CFI. Therefore the underlying, lower-level abilities constituting FAC differ from those constituting CFAC. Each one can be learned by the organizational sub-units through the accumulation of related knowledge—in the moment of knowledge absorption referred to as 'prior related knowledge'—, but the type of knowledge constituting different abilities is obviously different.

Therefore, I suggest a revision of the traditional understanding of prior related knowledge in order to distinguish three kinds of prior related knowledge: (1) prior related specialist knowledge, (2) prior related channel knowledge, and (3) prior related relational knowledge. Elements of all three thus distinguished types of prior related knowledge are also included by elaborations of the original concept of AC, most notably in the two seminal papers of the AC research stream that applied the concept of AC as partly idiosyncratic to the dyad level (Dyer & Singh, 1998; Lane & Lubatkin, 1998). This so-called Relational View claims that AC also grows out of the experience with each partner that permits better understanding, communication, and mutual trust. This is also in line with empirical findings on individual information seeking behavior that pinpointed the importance of valuing a source's knowledge and being able to get timely access to that (Borgatti & Cross, 2003).

The first type prior related knowledge refers to technical expertise with a specific *content* to be absorbed and is more or less congruent to the previous conceptualization of prior related knowledge as an antecedent of firm-level AC. The second accumulates through learning to implement and use specific *channels* of knowledge transfer and absorption, like meetings, liaison officers, task forces, job rotation, or cross-functional project teams etc. The third type of prior related knowledge accumulates through experience with specific type of *contact/source* from which knowledge has to be absorbed. In the following three paragraphs, it is described how these three types of prior related knowledge—the content-channel-contact model as illustrated in Figure 3—impact differently FAC and CFAC via the above elaborated intra- and inter-functional boundaries.

Figure 3: Communication-based framework for AC relevant prior related knowledge



Source: Based on communication models, above all by Gupta & Govindarajan (2000), Moenart & Souder (1996), and Szulanski (1996).

II.4.2. Antecedents of departmental ACs

II.4.2.1. Prior related specialist knowledge: A knowledge-based view

Cohen & Levinthal (1990) argue based on insights from research on individual learning and psychology that the accumulation of knowledge in a certain field reduces the cost of acquiring additional knowledge. In particular, it is suggested that the possession of experience in a related field helps to grasp quicker how new knowledge is to be understood, principally because important notions and concepts are already defined and understood and hence can be built upon. So far that it has even been observed that firms might decide to hold more knowledge than what is directly required for production in order to maintain the common ground that permits to integrate modules and parts on which their core product still depends but the production of which is outsourced (Brusoni, Prencipe, & Pavitt, 2001). In line with the above boundaries, it could be argued that in this way prior related knowledge permits the correct interpretation and transformation of knowledge, hence to tackle the semantic and pragmatic boundaries arising in integration processes.

However, differences between the intra-functional and cross-functional interface in the knowledge absorption requirements might influence the degree to which that impacts FAC and CFAC. As far as regards CFI, it is mostly out of scope to acquire in-depth specialist knowledge, because the nature of that knowledge exploitation is fundamentally different than in cases of intra-functional integration. It seems more to be a department-level analogy to the knowledge accessing theory of alliances (Grant & Baden-Fuller, 2004). In case of R&D marketing integration, for example, it is rather sought to guide and provide orientation for research activity to increase customer and market orientation (Jaworski & Kohli, 1993), accelerate product development (Eisenhardt & Tabrizi, 1995), or business performance (Verhoef & Leeflang, 2009).

In the case of functionally specialized organizational units, these units hold qua definition only limited related knowledge regarding specific disciplines or issues within the other functional knowledge area. They are not supposed to, it would have little sense to distinguish between functions if they do not differ fundamentally in their tasks and hence required knowledge base. In-depth knowledge would put in question the sense of the functional structure. The raison d'être of functional differentiation would be lost, which lies precisely in the ideal that division of labor according to specialization allows to speed up processes and hence efficiency with which organizational units respond to their particular environment (Jansen et al., 2009; Lawrence & Lorsch, 1967). In fact, recently it has been found that cross-functional teams can achieve knowledge integration through transcending the specialty boundary, rather than traverse it (Majchrzak et al., 2011).

While for intra-functional knowledge absorption it might be helpful and even required to understand for example the causalities that led to scientific findings and technological developments, the knowledge in question in case of cross-functional knowledge absorption is not the knowledge that permits the other function to do its work, but the knowledge which results from this work and is complementary to the own knowledge base. In this case, therefore, it would be highly inefficient to develop a similar profound understanding and background as the other functional department which would permit to repeat the work done by the other function, potentially even reducing performance and the ability to absorb efficiently. In consequence, a functional department can lack in-depth prior related specialist knowledge from other functional domains commonly required and fundamental for intra-functional knowledge absorption, but still have relatively high CFAC. Thus, although the semantic boundary can be of similar importance at intra- and cross-functional interfaces, prior related specialist knowledge is less important to CFAC than for FAC, because knowledge absorption follows different dynamics and finalities at intra-functional interfaces vis-à-vis cross-functional ones. Based on this argumentation, the following proposition can thus be put forth:

> ***Definition: Prior related specialist knowledge*** *is such from the specialist knowledge domain itself.*

> ***Proposition 2:*** *Prior related specialist knowledge of an absorbing organizational unit positively impacts its abilities to overcome the semantic and pragmatic boundaries relative to that specific specialist knowledge. Since these boundaries are much higher in case of intra-functional interfaces vis-à-vis cross-functional interfaces the positive impact of this prior related knowledge type is much higher on FAC than on CFAC, for which it could even turn out to impair performance.*

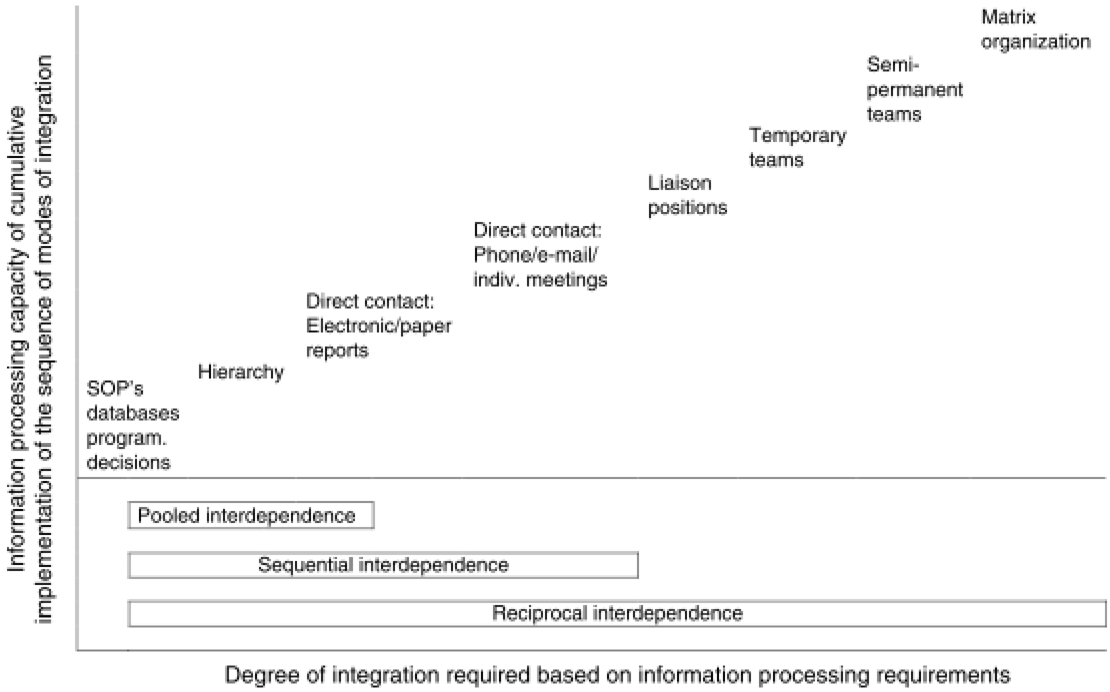
II.4.2.2. Prior related channel knowledge: An information processing view

The exchange or flow of knowledge within and between organizational units has been described in differing terms, as e.g. knowledge sharing, diffusion, or transfer (Foss et al., 2010; Van Wijk et al., 2008), and many different more or less formal integration mechanisms have been discussed (Galbraith, 1974; Sherman & Keller, 2011). Many of these mechanisms, like job rotation for example, are frequently discussed in innovation and AC literature. For example, Cohen & Levinthal (1990) argue that the practice of some Japanese companies to assign technical personnel in some cases up to several years to other functions as marketing and manufacturing would suggest that “breadth of knowledge cannot be superficial to be effective” (p. 135). This stands in no contrast to the argument previously put forth, however, that departments do not need in-depth understanding of how the knowledge was generated or obtained, because the gatekeepers that bridge cross-functional boundaries have to develop necessarily some more profound background and be accustomed to both worlds (Tushman & Katz, 1980; Tushman, 1977). In this way they serve as translators and become a kind of personified repository of common ground, shared knowledge that the involved parties know they share (Cramton, 1996), the lack of which can constitute a major problem for successful collaboration. Another example are cross-functional teams, which are among the most valued integration mechanisms in the innovation process and can take various concrete expressions depending on the degree of integration required (Clark & Wheelwright, 1992). Most of these mechanisms can also be described as boundary objects (Carlile, 2002), which can also be tools like CAD, clay models or other ways of illustrating and communicating non-verbally (Carlile, 2004).

However, important for integration of whatever kind is the correct choice of integration mechanisms, since each type is more or less apt according to the particular context to which it is applied (Galbraith, 1974; Grant, 1996a). Indeed, the literature that considers integration mechanisms from an information processing perspective, it has been argued that integration mechanisms are most usefully distinguished regarding their different potential to convey more or less rich information (Daft & Lengel, 1986; Galbraith, 1974) and that they might usefully implemented cumulatively according the degree of integration required as shown in Figure 4 (Sherman & Keller, 2011).

In some cases of the most intense formal integration mechanisms, it is decided centrally on their implementation, many other lateral mechanisms of integration are often at the discretion of the departments’ heads or members. However, in all cases their effective use by departments can be more or less successful. The more different integration mechanisms are disposable and the more frequently these are used , the more department members have the chance to accumulated knowledge on not only how to correctly implement them and profit from them, but also in which situation what type of integration mechanism is the most appropriate. This accumulated experience constitutes the ‘prior related channel knowledge’—whether these channels are simple information transfer mechanisms, boundary objects or complex socialization routines. Which kind of boundary this type of prior knowledge serves depends however on the kind of integration mechanism to that it relates, that is whether it relates to more or less information rich integration mechanisms.

Figure 4: Information Processing Capacity of Cumulative Implementation of the Sequence of Modes of Integration



Source: Sherman & Keller (2011:247)

Simple integration mechanisms like such that simply transfer information or codified knowledge standardize communication and therefore if prior knowledge allows their correct implementation and use they help to transcend differences in idioms and languages that pertain to a particular party involved in the integration process. Hence, accumulated prior knowledge related to simple ‘channels’ permits to bridge the syntactic boundary, which is much higher at inter-functional interfaces than at intra-functional ones. This kind of prior knowledge can therefore be expected to increase CFAC.

On the other hand, a correct use of information rich integration mechanisms can serve to establish common ground (Carlile, 2004; Cramton, 1996) and thus also permits to jointly refine understanding and transform the own knowledge stock. Thus with increasing information richness of the integration mechanism to that the prior knowledge relates it permits to transcend first the semantic and finally the pragmatic boundary. The former is equally relevant to both types of interfaces while the latter is much more important at intra-functional interfaces as discussed above. Therefore, increased experience in the right use of integration mechanisms can be expected to positively impact FAC.

Hence, it can be concluded that since the syntactic boundary is higher at the inter-functional boundary, prior knowledge related to simple transfer channels will positively impact CFAC and since the pragmatic boundary is higher at intra-functional interfaces, prior knowledge related to complex mechanisms will positively impact FAC. Thus, although for different underlying dynamics, prior related transfer knowledge in general impacts both FAC and CFAC:

Definition: Prior related transfer knowledge *is such that is related to the knowledge transfer mechanism, i.e. channel, to be used.*

Proposition 3: *The effect of prior related transfer knowledge of an absorbing organizational unit depends on the complexity and richness of the specific channel. It potentially impacts positively both FAC and CFAC.*

II.4.2.3. Prior related relational knowledge: A relational view

The characteristics on which another department has to be assessed in order to succeed in integration can be manifold. It has been observed in extant literature that important elements that permit the absorption of knowledge are relational aspects between source and receiver, teacher and learner, or participants in mutual exchange are a likewise integral part of knowledge transfer success. Nahapiet & Ghoshal (1998) include into this part of social capital trust, norms, obligations, and identification. Among the most salient relational aspects are trust (Gupta & Govindarajan, 2000; Minbaeva, Mäkelä, & Rabbiosi, 2010; Schulz, 2001; Van Wijk et al., 2008) as well as credibility (Gupta & Wilemon, 1988; Moenaert, Souder, De Meyer, & Deschoolmeester, 1994; Moenaert & Souder, 1996; Song, Xie, & Di Benedetto, 2001).

The importance of trust in interpersonal relationships has been highlighted also in various studies on socialization and intra-organizational networks (Gupta & Govindarajan, 2000; Minbaeva et al., 2010; Schulz, 2001). Trust in form of a harmonious perception of marketers has been shown particularly relevant for the perception of marketers' information quality by R&D managers (Gupta & Wilemon, 1988; Maltz, Souder, & Kumar, 2001). Within functional domains communities-of-practice (J. S. Brown & Duguid, 1991), and across them cohesive socialization mechanisms (Burcharth & Fosfuri, 2012), create a common identity and trust, showing how important the impact of such informal networks can be for an organization's innovativeness and performance; although being potentially both positive and negative for performance.

Trust works in two ways, however. Even if in a particular integration process knowledge was exchanged only in one direction, it would still be necessary for both parties to trust each other at least to some degree, because the receiving party runs potentially the risk to acquire "faulty" knowledge or that collaboration is rendered costly by errors or sabotage of the other party, while the sender runs potentially the risk for example to lose status through revealing too much. So the trustworthiness of the trustee has to be assessed correctly, which includes estimation of ability, benevolence, and integrity (Mayer, Davis, & Schoorman, 1995). Therefore the knowledge on how trustworthiness can be signaled to a particular integration partner or knowledge source is a fundamental part prior related relational knowledge.

One example how an organizational unit could signal trustworthiness is through network position (Granovetter, 1985). Network closure permits the establishment of norms and the possibility of sanctioning which reduces the probability harmful behavior and hence the necessity of trust (Coleman, 1988). Moreover, Uzzi (1997) argued that part of the positive effect of strong interpersonal relationships on the ease of knowledge transfer might be explained by transfer capabilities that develop through continuous, intense interaction and are partly idiosyncratic to the particular dyad. This argument is the individual level version of the firm-level Relational View (Dyer & Singh, 1998). Finally, is has been found that these network effects can be created through structural diversity of teams (Cummings, 2004). This also implies that organizational units can potentially learn how to pro-actively manage their networks through team participations and staffing.

It has been argued however that relationships are quite idiosyncratic. In their seminal paper on Relative AC, Dyer & Singh (1998) define that "*partner-specific absorptive capacity* refers to the idea that a firm has developed the ability to recognize and assimilate valuable knowledge *from a particular alliance partner*" (p. 665, italics in original). According to Dyer & Singh (1998), this ability depends on the overlap of the partners' knowledge bases, interaction routines that maximize frequency and intensity of socio-technical interactions, as well as the degree of incentive alignment between the two partners. Lane & Lubatkin (1998) proposed the same antecedents as proposed by Dyer and Singh and added as a further one the dominant logics prevalent in the exchanging partners. Therefore, the wider recognized contribution of the Relational View is that AC is at least partly idiosyncratic to that individual relationship. In Dyer and Singh's framework, Absorptive Capacity is interpreted as an asset that derives from specific investments in a relationship.

However, it can be deducted that the relative and the absolute views of AC are not mutually exclusive; i.e. that AC has both a specific and a general component. Moreover, experience with a set of similar types of sources can be aggregated by an organizational unit and help increase AC, in particular regarding the sympathetic and the teleological boundary. This does not mean that the idiosyncratic part of AC approaches zero with increasing number of similar contacts, because certain aspects will always remain partly tied to the particular relationship just as underlined in the relational view literature. Nonetheless, if an organization sources knowledge, for example, from several suppliers and clients, but only from one university research institute, the idiosyncratic part of AC will be relatively limited for relations with suppliers and clients and much more important to the relationship with the university since little to no transfer of experience from comparable relationships is possible. With an increasing number of different university institutes to source from, however, commonalities throughout this category of interlocutor can be identified and with an increasing history of collaboration the inferences become more reliable.

This suggests that a general AC regarding particular groups of external organizational units can be developed and is associated to prior related knowledge sourcing experience. However, more similar is the other group, the less useful is learning even more on their relational characteristics and for example too much trust can also reduce the ability to absorb knowledge, because it is 'trusted' that the other knows curtain contexts that are necessary for a correct interpretation of the actually conveyed information; it is thus decontextualized (Bechky, 2003). If the other knowledge receiver is from a different functional domain, this creates a upper boundary for trust in the others understanding reducing thus the possibility of overconfidence.

It can be concluded that relational aspects can help to transcend the sympathetic boundary, which is much higher at cross-functional interfaces, while it has limited potential to impact the other boundaries, although signaling too much trustworthiness in terms of ability to understand might lead to reduced interpretability and reduced knowledge absorption. Therefore, it can be expected that prior related relational knowledge impacts positively only, or at least significantly higher, on CFAC than on FAC.

Definition: Prior related relational knowledge *is such related to the type of knowledge source from which knowledge is to be absorbed.*

Proposition 4: *Prior related relational knowledge of an absorbing organizational unit positively impacts its abilities to overcome the syntactic and sympathetic boundaries to that source type to which it relates. Since these boundaries are much higher in case of cross-functional interfaces vis-à-vis intra-functional interfaces the positive impact of this prior related knowledge type is much higher on CFAC than on FAC.*

II.4.3. Impact of departmental ACs

II.4.3.1. FAC and “push” & “pull” innovations

Innovations have been distinguished *inter alia* into “technology push” and “market pull” innovations (Kline & Rosenberg, 1986), considered to represent the first- and second-generation innovation models (Rothwell, 1994). Both are described as basically sequential processes of innovation; the former starting out from basic research, the latter from market research. Both models do not require particular levels of knowledge integration between functions since the results are passed from function to function and are hence a mere issue of information processing, not knowledge absorption.

However, even in these sequential innovation processes, knowledge can still be profitably integrated within functions across differently specialized departments. For example, knowledge from diverse divisions has been found to positively influence the impact of innovations (e.g. Miller et al., 2007). Moreover, intra-firm networks of organizational sub-units and the weak ties among them have been found an important factor for inter-divisional knowledge sharing (M. T. Hansen, 1999).

And as has been already reviewed in more detail above, the literature that applies empirically the concept of AC following Cohen & Levinthal (1990) clearly suggests the importance of AC also to these intra-organizational knowledge absorption, like between subsidiaries of multinationals (e.g. Gupta & Govindarajan, 2000). Likewise, absorptive capacity has been found to interact with network centrality in enhancing innovativeness (e.g. Tsai, 2001), which can partly be explained by the shorter paths to diverse knowledge together with this knowledge's tacit character. Thus, AC of functionally specialized departments plays an important role also in these sequential innovation processes, but since all departments involved come from the same function, the departmental AC that really impacts innovation success can be assumed to be FAC.

However, although this intra-functional knowledge integration might be a very creative and successful process, particularly when complementarities exist between the heterogeneous areas that are integrated within a function, it can be supposed to be related principally to "push" or "pull" innovations. For example, in case of R&D integration across divisions breakthrough scientific and technological advances can be made, while in case of M&S integration across similar boundaries, new creative solutions for emerging markets can be discovered that would have been out of sight if focus was kept on the extant division's markets. Moreover, just as firm-level AC has been found to interact with external knowledge (Escribano, Fosfuri, & Tribó, 2009), this should apply also to FAC, in this case however for both extra- and intra-organizational knowledge from the own functional domain.

Moreover, Cohen & Levinthal (1990) averted that an increase in shared language and symbols across sub-units of the same organization could decrease this overlap in shared coding schemes vis-à-vis external knowledge sources, describing this phenomenon as the trade-off between inward- and outward-looking absorptive capacities, which is underpinned by the findings of Burcharth & Fosfuri (2012) that cohesive socialization mechanisms might spawn the not-invented-here syndrome. This relates to a possible trade-off between increased perspective-making versus perspective-taking. On the other hand, the knowledge-based view of the firm regards precisely the superior knowledge transfer capacity of firms as the very reason of their existence (Kogut & Zander, 1993). However, said trade-off between inward- and outward-looking ACs can be deemed to be alleviated by the possibility of firms to leverage external knowledge without complete absorption (Grant & Baden-Fuller, 2004). Therefore, we can put forth the following proposition:

> ***Proposition 5:*** *The higher FAC of functionally specialized departments, the better they can absorb both extra- and intra-organizational knowledge of the own functional domain, which results in innovations related to sequential innovation processes, e.g. "technology push" in case of R&D departments or "market pull" in case of M&S departments.*

II.4.3.2. CFAC and "integrated" innovations

In contrast to the sequential innovation models, Rothwell (1994) describes the third- and fourth-generation innovation models as departing from the "push" and "pull" models in that increased attention is paid to augment market orientation in the NPD process. It is also pointed out that the third-generation model of innovation, dubbed "coupling" model, remains basically a sequential process, although with feedback loops. On the other hand, the fourth-generation model focuses on integration of the involved functions in a parallel process of innovation, hence dubbed "parallel and integrated" innovation model.

Integration mechanisms are at the heart of the third and even more so of the fourth generation innovation model. Both of these more complex and dynamic innovation models can thus be claimed to foster "integrated" innovations. The higher success of these more dynamic models of innovation can be regarded to lie in a higher degree of market orientation and the realization of the complementarities related to this in combination with faster time-to-market. Faster time-to-market permits the realization of first-mover advantages, which are increasingly important in industries with growing relevance of network effects and battles for standard setting. In fact, Rothwell (1994) argues that these integrated innovation models permit to shift the curve that describes the trade-off between development time and development cost. Higher market orientation aims at realizing the above discussed advantages of combining scientific and technological creativity with market insight to create products that are at the same time technologically cutting-edge and strongly demanded by current or new customers. Therefore, innovations resulting from successfully integrated innovation process have much higher performance than either push or pull innovations. Push and pull innovations can be radical in the sense that they open radically new technological or market niches, but value appropriation will be difficult and very limited if the other side has not been optimally integrated.

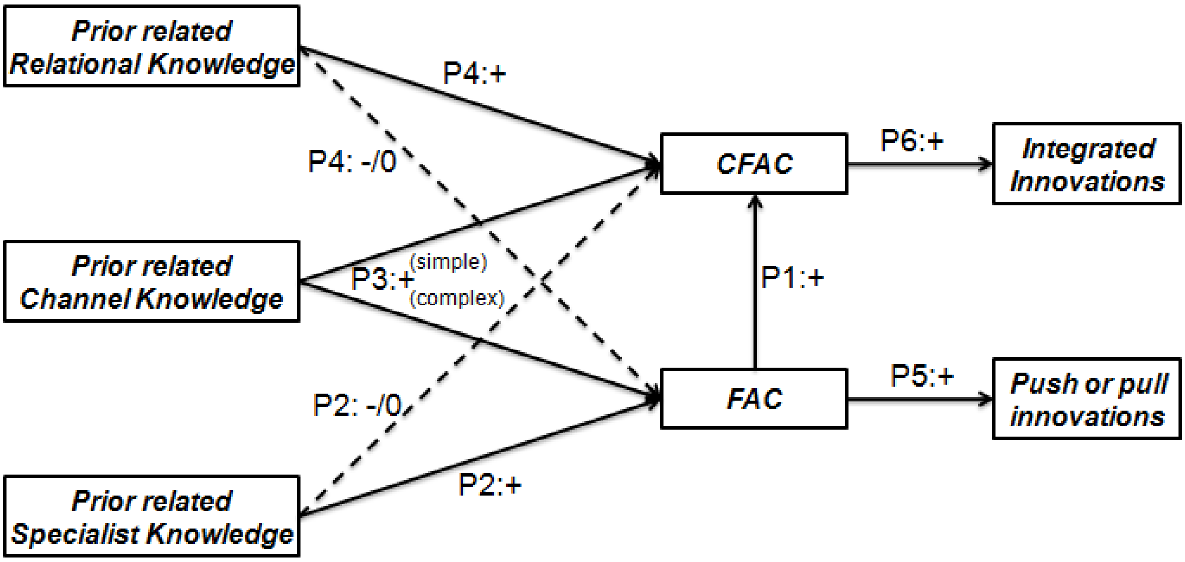
Moreover, the knowledge integration of functionally differentiated departments has been regarded as a major driver behind ambidexterity (Jansen et al., 2009). Ambidexterity refers to the ability to exploit technological fields or markets for which a considerable stock of knowledge exists while contemporaneously generating and/or acquiring new knowledge to explore new fields promising fields (March, 1991) and is found a major driver of long term firm performance and survival (O'Reilly & Tushman, 2004, 2008). Whether success CFI is impacted in any way by departmental AC is very relevant also for new product development success and firm performance in general, since both have been found to be impacted by CFI (Gemser & Leenders, 2011; Troy et al., 2008).

However, as reviewed in the above paragraph II.2.2.2 on the opportunities and threats of CFI, the implementation of integration mechanisms and hence of the more complex third- and fourth-generation innovation models comes at a cost and with the risk of failure. As has been claimed, CFAC is the result of a process of learning to implement the very integration process that is so fundamental to these high-performing innovation models. Hence the following proposition is made:

> ***Proposition 6:*** *The higher CFAC of functionally specialized departments, i.e. the better they can absorb both extra- and intra-organizational knowledge of other, complementary functional domains, the more innovations related to parallel and integrated innovation processes, i.e. "integrated" innovations, will be achieved.*

Figure 5 illustrates the overall model of departmental Absorptive Capacities.

Figure 5: A Model of Departmental Absorptive Capacities



Source: Author's own.

II.5. Conclusion

In this chapter, a new perspective on Absorptive Capacity and Cross-Functional Integration is proposed, precisely by merging elements of both of these very broad and mature research streams. This is done by changing the perspective in two ways: Firstly, the level of analysis is changed to that of functionally specialized departments, which is unprecedented in the extant literature on Absorptive Capacity. Secondly, the knowledge scope is broadened to include knowledge from outside the own knowledge domain, which is a likewise underdeveloped aspect of AC.

In this way, contributions are made to the literature of Absorptive Capacity, Cross-Functional Integration, and Innovation Management. Most fundamentally, revisiting the theory on intra- and cross-functional integration, a framework is developed that supplements Carlile's (2004) three boundaries between organizational sub-units – syntactic, semantic, and pragmatic – with two further boundaries, i.e. the sympathetic and the teleological boundary. This permits to distinguish major differences in the pattern of the different boundaries' relevance at intra- and cross-functional interfaces. This has implications for management theory and practice. Theory can take this as point of departure for revisiting extant findings that have been assumed to apply for organizational sub-units in general investigating whether conclusions have to be refined. The need to do so is even more evident considering the implication for practice. The identified five boundaries that have to be crossed for successful knowledge absorption between organizational sub-units are not fully independent from each other, but awareness of their different nature and their disentanglement can help managers to adapt their processes, routines, and problem solving behaviors.

Building on this development, two distinct departmental ACs are conceptualized, Functional AC (FAC) and Cross-Functional AC (CFAC). Moreover, the concept of prior related knowledge is differentiated into prior related specialist knowledge, prior related channel knowledge, and prior related relational knowledge. This allows to devise a model that suggests that FAC and CFAC depend to different degrees on the various categories of prior related knowledge. This has implications for organizational learning theory and for practitioners, because the distinction between FAC and CFAC permits to identify potential for improvement of knowledge absorption and consequentially reorient learning attention on the specific type of relevant knowledge.

Finally, it is argued that the distinct nature of FAC and CFAC will permit different kinds of innovations; the former either push or pull innovations and the latter integrated innovations. These have substantially different effects on innovation performance, because the value appropriation potential of integrated innovations is much higher than that of innovations that result from sequential innovation process in which the value potential of their complementarities is not leveraged.

High potential can be assumed to lie above all in the differential impact that the antecedents of Cross-Functional Absorptive Capacity might have regarding the classic Functional AC, that is the above suggested limited trade off. If actually opposing effects of the antecedent factors on the various sub-dimensions could be shown empirically, this might explain why there are contrasting results regarding the impact of cross-functional integration on innovation and/or performance. It could also show practitioners how the negative consequences of an otherwise useful integration approach could be balanced out by the simultaneous implementation of counter-measures. Beyond that, there are several related issues that would be worthwhile to be addressed by future research. Two examples of relevant future empirical research questions are: Can CFAC actually be learned during internal cross-functional integration processes and applied to absorb also external cross-functional knowledge? How do departments' FAC and CFAC translate to overall divisional or firm-level AC? How does CFAC work across national and divisional boundaries?

III.
The Role of Departmental Absorptive Capacities at the R&D-Marketing Interface for Innovation Performance: Evidence from the Italian Manufacturing Industry[3]

Abstract:
Based on a unique data set from Italian manufacturing industries, we provide empirical evidence of the influence of Departmental Absorptive Capacities on Innovation Performance at the R&D-M&S interface and its mediating role in the relationship between (Cross-) Functional Integration Mechanisms and Innovation Performance. We measure the abilities of research and development (R&D) as well as marketing and sales (M&S) departments to absorb knowledge from their peer departments and from departments belonging to the respective other, complementary function; herein Functional (FAC) and Cross-Functional Absorptive Capacity (CFAC), respectively.
We find that there are significant differences between the two functions in terms of effect sizes and significances. In particular, we find that R&D departments build CFAC via formal CFI mechanisms, while they build FAC by means of informal coordination, which appears to be true vice-versa for M&S departments. However, only for R&D departments has CFAC a significant and substantial effect on innovation performance. This corroborates also previous findings regarding the relevance of market knowledge in the NPD process.
This study provides two major contributions to the literature streams of Functional Integration (FI) and Absorptive Capacity (AC). Firstly, the concept of CFAC is operationalized and empirically investigated. Secondly, a better understanding of the relationship between FI and Innovation Performance is allowed for by introducing departments' ACs as mediating variables, which sheds some light on previously contrasting findings in CFI literature. Implications for theory and practice are discussed.

Keywords: Absorptive Capacity; Cross-Functional Integration; R&D-Marketing Interface; Innovation

JEL Codes: O32, O31, M10.

[3] This chapter is based on Hausberg (2013), The Role of Departmental Absorptive Capacities at the R&D-Marketing Interface for Innovation Performance. *Paper to be presented at the DRUID Anniversary Conference 2013, Barcelona*.

> "(..) any business enterprise has two—and only two—basic functions: marketing and innovation. They are the entrepreneurial functions."
>
> Peter F. Drucker
> *The Practice of Management*
> *1954/2006, p. 37*

III.1. Introduction

Although several studies find that innovation and performance are positively affected by Absorptive Capacity (AC) (e.g. Rothaermel & Alexandre, 2009), AC literature lacks explicit consideration of the knowledge type in focus (Volberda et al., 2010) as well as a consideration of the construct on the level of functionally specialized departments. Indeed, rooted in the reasoning of the seminal articles by Cohen & Levinthal (1989, 1990), AC has almost always at least implicitly on the firm level referred to technological knowledge. However, in order to direct search activities and render them more efficient, technological knowledge has to be complemented at least by market knowledge.

This necessity of cross-functional integration (CFI) of technological and market knowledge is recognized in strategic management since decades (e.g. Iansiti & Clark, 1994), but found only marginal consideration in an AC literature focused on R&D. Zahra & George (2002), however, see social integration mechanisms in a key position of their framework. In their model, social integration mechanisms impact the efficiency of transformation of potential into realized AC. Another exception is the empirical study by Jansen et al. (2005), in which the authors operationalize a multi-item scale for AC on the sub-unit level and explicitly focus on intra-organizational antecedents and combinative capabilities as its antecedents. However, the sub-units analyzed by Jansen and colleagues are not functionally specialized, but appear to be rather full process integrated units, as their data is based on branches of a single financial services provider. So the issue remains open whether departmental AC can contribute to explain differentials in the success in implementation of integration mechanisms in the innovation process.

In fact, an Absorptive Capacity (AC) perspective at functional interfaces on the level of functionally specialized departments has never been applied so far to the best of my knowledge, but could shed light on an essential part of the underlying dynamics. This is a surprising research gap in that it could be shown that the explicit consideration of the nature of the absorbed knowledge (e.g. market vs. technology knowledge) as well as the analysis of lower levels of analysis are two important persisting research gaps in AC literature (Volberda et al., 2010). In particular, Volberda and colleagues (2010:937) claim that "AC is a multilevel construct and should be studied at the individual, unit, firm, and interfirm level of analysis", but find that extant empirical studies are largely limited to the analysis at the business unit or subsidiary level.

When analyzing AC at this level of analysis, however, the distinction between two types of AC is fundamental (see chapter II above). Just as AC might be specific to a dyadic relationship (Dyer & Singh, 1998) it might be specific to the functional type. Moreover, different integration mechanisms might have contrasting, partly off-setting influences on the distinct types of departmental AC and these distinct types of AC might differently mediate or not the relationship between integration mechanisms and innovation performance. A distinction between AC specific to peer knowledge – Functional AC (FAC) – and AC regarding non-peer knowledge – Cross-Functional AC (CFAC) – is hence crucial for a sound understanding of the actual mechanisms behind the overall impact of integration mechanisms on innovation performance.

As emerged clearly from the long research tradition investigating departmentalization and integration, the particularly high complementarity of market and technological knowledge can be regarded as the principal cause of a largely positive effect of integration at the R&D-marketing interface on innovation performance (e.g. Galbraith, 1974; Griffin & Hauser, 1996; Gupta, Raj, & Wilemon, 1986; Lawrence & Lorsch, 1967; Ruekert & Walker, 1987). Similarly, findings from literature on market orientation underline an influential role of the marketing function that can significantly increase business performance (Jaworski & Kohli, 1993; Verhoef & Leeflang, 2009). On the other hand, however, several examples of negatives outcomes of cross-functional integration have continuously been put forth (e.g. Bommer, Delaporte, & Higgins, 2002; Hansen, 2009). Hence substantial divergence in findings persist regarding the relation between cross-functional integration (CFI) and new product success and hence ultimately innovation performance (cf. Troy, Hirunyawipada, & Paswan, 2008). The fundamental relevance of department-level ACs is that these might mediate the relationship between integration mechanisms and innovation performance.

The research question is whether ACs of functionally specialized departments, in particular the complementary Research & Development (R&D) and Marketing & Sales (M&S) departments, mediate the relationship between different types of integration and innovation performance and whether these effects differ across the two types of departments. I show in this way the relevance of two distinct particular capabilities of functional departments for integration and innovation performance. It is important to know whether one or both of the departmental ACs mediates the innovation impact of integration mechanisms. Secondly, we investigate whether there are differences between formal and informal integration mechanisms regarding this mediation. Thirdly, the direction of knowledge flow shall be evidenced by showing significant differences across the two department types regarding the relevance of cross-functional AC. Finally, we aim to provide a measurement instrument for future research into departmental Absorptive Capacities.

The context of our study is the manufacturing industry in Italy. Due to the high complementarity reported in literature regarding technological and market knowledge and the related functions, we focus on the integration of R&D and Marketing. The level of analysis is that of functionally specialized departments. Hence, we collected data via an online survey of both Research & Development and Marketing & Sales professionals from manufacturing firms selected from the AIDA database, an almost comprehensive database of Italian firms.

We find that there are significant differences between the two functions for various effects. In particular, we find that R&D departments build CFAC via formal CFI mechanisms and CFAC in turn strongly impacts innovation performance. Consequently, we find that CFAC allows for a significantly positive indirect effect of CFI mechanisms on innovation performance, while there can be found no direct effect from formal CFI mechanisms on innovation performance nor an indirect effect of informal CFI. For M&S departments, on the other hand, only the direct effect between formal CFI mechanisms and innovation performance is significant. This corroborates also previous findings regarding the relevance of market knowledge in the NPD process (Drechsler, Natter, & Leeflang, 2013; Song et al., 2001; Verhoef & Leeflang, 2009). Marketing departments' influence on innovation performance without the need of capacity to absorb R&D knowledge underlines their role as knowledge deliverers.

In the following section we will discuss briefly the theoretical background and core concepts. Subsequently the hypotheses of our conceptual model are developed after which we describe our data and analyses and discuss the results. In the concluding section, implications for theory and practice are presented along with the limitations of this study.

III.2. Theoretical Background

III.2.1. Departmental ACs

In extant literature on firm level AC, it has been suggested that it is composed by three or four distinct sub-dimensions. Initially it was argued that AC is a combination of the ability to recognize the value of external knowledge, assimilate it, and exploit it to commercial ends (Cohen & Levinthal, 1990). This has been refined and reconceptualized several times in the relevant literature. Most importantly, it has been argued that it might be distinguished between Potential and Realized AC, where the former is constituted by the ability to acquire and assimilate external knowledge and the latter by the ability to transform and exploit it (Zahra & George, 2002). In both conceptualizations of firm level AC the question inevitably arises how organizational antecedents determine these different abilities (Berger & Leeflang, 2013), and while a large body of literature developed around AC, there has been still identified a substantial research gap (Volberda, Foss, & Lyles, 2010).

In fact, most recently Lewin, Peeters, & Massini (2011) identified several meta-routines that constitute such organizational antecedents of what they call internal AC. As in the vast majority of literature on AC, however, the issue of the knowledge's different nature across corporate functions and the contribution of their integration to firm level AC has been largely marginalized. Although Cohen & Levinthal (1990) clearly defined their construct originally with regard to technological knowledge, it is surprising how little the AC literature investigated whether an enlargement of the understanding of AC might be fruitful in general or whether AC can help to explain when market knowledge has a positive impact on innovation and general business performance. The literature stream regarding cross-functional integration can cross-fertilize hence the research strand of AC in this regard.

In chapter II, a framework has been developed that suggests that the pattern of levels of different boundaries that exists between departments specialized within the same corporate function is fundamentally different from the pattern of the levels of these boundaries in case these departments exercise complementary corporate functions. The identified boundaries—syntactic, sympathetic, teleological, semantic, and pragmatic—relate to three broader categories of prior related knowledge that enable departments to overcome those boundaries. However, since the levels of the boundaries are different according to whether knowledge integration takes place in an inter- or intra-functional context, different types of prior related knowledge are relevant.

III.2.2. Functional Integration Mechanisms and Formalization of Integration

Functional and Cross-Functional AC – in the remainder FAC and CFAC respectively – have been argued to depend on prior related knowledge (see chapter II), as the traditional concept of AC on the firm-level (Cohen & Levinthal, 1990). These specific abilities of functional departments has to be build and is subject to depreciation, i.e. is forgotten or unlearned automatically if not used with a minimum of regularity. In fact, for AC on higher levels it is claimed that its application and use maintains or even increases this very capacity (Cohen & Levinthal, 1994; Helfat & Peteraf, 2003; Zahra & George, 2002). Similarly, on the individual level, it has been found that learning orientation of individuals can generally improve learning outcomes of knowledge sourcing activities as has been found in an international context (Gray & Meister, 2004). In consequence, higher degrees of use of these mechanisms provides greater acquaintance with them and allows thus for higher reliability and accuracy in integration with other functional departments. This increases the probability that the most apt ways of implementation are chosen. Indeed, as already noted by Cohen & Levinthal (1990), AC cannot develop based on brief exposure to the relevant knowledge, be it AC in general or problem-solving skills in particular.

However, higher degrees of formalization of inter-departmental relations might increase the probability that the most apt ways of implementation are chosen. Formalization can be regarded as the result of a process of routinization and learning, in this case regarding the integration mechanisms and knowledge transfer channels. Hence, it can be reasonably considered an expression of deliberate learning efforts (Zollo & Winter, 2002). It is the explicit manifestation of the dominant conviction within the competent management team about which processes are most beneficial to the operative and strategic goals of the organizational unit in question, here the single functional department. This is because formalization allows for an augmentation of the efficiency of well known processes. In the case of cross-functional relations it allows the harmonization of knowledge transfer in that it establishes and assigns explicit roles and responsibilities to the involved staff, which reduces redundant search, communication and coordination. Consequently, it should be one of the major causes of CFAC.

III.3. Hypotheses and Model

III.3.1. Functional Integration Mechanisms and departmental ACs

In the extant literature, a broad range of integration mechanisms, both formal and informal (e.g. Moenaert et al., 1994) as well as both intra- (e.g. Hoegl, Weinkauf, & Gemuenden, 2004) and cross-functional (e.g. Gupta et al., 1986; Olson et al., 2001), have been related directly to innovation and/or performance. As can be deducted from Daft & Lengel's (1987) discussion of knowledge transfer channels, certain processes are inherently formal while others informal. Moreover, the cumulative implementation of integration mechanisms with increasing degrees of media richness is claimed to permit significant increases in information processing capacity of organizational units (Sherman & Keller, 2011).

On the other hand, formalization is far from being considered only as positive for performance. As March (1991) showed that due to short term benefits firms might tend to overemphasize rather formalized, exploitative search, while neglecting less formalized and hence more uncertain explorative search, which becomes detrimental for the ability to produce radical innovations and for the survival in the long run.

Moreover, formalization can also hamper "good learning". Firstly, organizational learning theory suggests that several kinds of detrimental learning can occur in organizations, such as superstitious learning (Argyris & Schön, 1996). Secondly, organizations can also find themselves in a learning trap or competency trap (Levitt & March, 1988) or work based on routines that have become core-rigidities (Leonard-Barton, 1992). If the department's overall approach to cross-functional integration becomes more and more rigid, it is less able to react to substantial changes occurring eventually in the organization and its various departments. Thus, a balance between formalized integration and spontaneous exchange and collaboration has to be strived for. Both formal and informal integration mechanisms offer particular opportunities for integration so that neither one can substitute the other.

> ***Hypotheses 1:*** *The more a department uses* ***formal*** *intra-functional integration mechanisms* ***(FIM)****, the more FAC it develops.*

> ***Hypotheses 2:*** *The more a department uses* ***informal*** *intra-functional integration mechanisms* ***(IIM)****, the more FAC it develops.*

This is different for cross-functional integration mechanisms, however. As argued in chapter II, the order of relevance of the different types of prior related knowledge is inverted at the cross-functional interface. It is argued, that prior related relational knowledge is more important in this case in order to bridge the sympathetic and teleological boundaries that are present to higher degrees at this interface.

Hence, different types of departments might develop relational knowledge in different ways and might benefit from the various available integration mechanisms to different degrees. Informal integration mechanisms can be expected to build relational knowledge also at cross-functional interfaces. For example, Pinto & Pinto (1990) find particularly informal integration mechanisms to have a significant influence on cross-functional project team cooperation which in turn is found to impact significantly psychosocial outcomes, which can be considered to be closely related to relational knowledge.

> ***Hypothesis 3a:*** *The more informal CFI mechanisms are used by M&S departments (IXM), the more CFAC they develop.*

> ***Hypothesis 3b:*** *The more informal CFI mechanisms are used by R&D departments (IXM), the less CFAC they develop.*

Pinto & Pinto (1990) could not find similar effect for formal integration mechanisms on cross-functional project team collaboration, however. Moreover, in the particular context at the R&D-M&S interface, it can be reminded that formal integration mechanisms are used most successfully at particular stages of new product development and in order to make market knowledge available to the R&D function (Ernst et al., 2010; Song et al., 1998). Since it is only the R&D unit, that receives knowledge in this context, it is only R&D that is incentivized to learn to integrate with the M&S departments and thus build relational knowledge.

> ***Hypothesis 4a:*** *The more formal CFI mechanisms (FXM) are used by R&D departments, the more CFAC they develop.*

> ***Hypothesis 4b:*** *The use of formal CFI mechanisms (FXM) by M&S departments has no effect on their CFAC.*

Another particularity of cross-functional interfaces vis-à-vis functional ones is the impact of informal integration mechanisms at these former interfaces on the ability to integrate at the latter ones. As suggested in chapter II (cf. in particular Table 3), the most salient boundaries impeding integration at intra-functional interfaces, are the semantic and pragmatic boundaries. As argued in favor of hypotheses 2 and 3, intra-functional informal integration mechanisms increase FAC and informal CFI mechanisms increase CFAC. However, informal CFI mechanisms bear the potential to get fast, spontaneous feedback on ideas previously out of search scope that might help to reconcile conflicting interests.

For example, two R&D departments might disagree about the potential to integrate their findings. If members of one of these departments have the possibility to use informal channels to get spontaneous feedback from a complementary function a solution might be found that either appears promising to both departments or gives a decisive weight to one of the two conflicting views. This is crucial to bridge the pragmatic boundary that is potentially high between departments of the same function. Thus, while informal CFI mechanisms positively impact CFAC through decreasing principally the syntactic boundary (H3), they positively impact FAC through decreasing the pragmatic boundary at the intra-functional interface:

Hypothesis 5: *The more a department uses informal CFI mechanisms (IXM), the more FAC it develops.*

As argued in chapter II above (cf. Figure 5), FAC and CFAC are closely related. This overlap is due the conceptualization of FAC as kind of fundamental AC of the department. FAC provides a general ability of knowledge integration from other departments, while CFAC is a specialized supplement ability. Therefore, the more FAC is developed the higher also CFAC.

Hypothesis 6: *The higher a department's FAC, the higher its CFAC.*

III.3.2. Direct and Indirect effects on Innovation Performance

Effects of AC have not been observed among departments of different functional specializations, however, but only within one functional setting or on higher levels, like the transfer of more or less sticky practices among operational units (e.g. Szulanski, 1996) or across subsidiaries of MNCs (e.g. Gupta & Govindarajan, 1991, 2000). In fact, the construct of CFAC itself has not been studied before. This might be very important, however, if the benefit from cross-functional integration actually derives from knowledge integration. In this case, the direction of knowledge flow in integration is crucial for whether a direct effect on innovation performance might be observed or not. In intra-functional integration, there is no specific direction and departments need to be able to integrate the knowledge in question. In case of CFI, however, there might be one function that depends more fundamentally on insights from the other function. This is particularly the case at the R&D-Marketing interface.

Correlations have been found between knowledge flows from R&D to Marketing and NPD performance (Moenaert et al., 1994) but other studies analyzing in-depth the effect at various stages suggest the role of R&D-Marketing information to lie principally in the provision of market feedback to the R&D department according to specific stages of the NPD process (Brettel et al., 2011; Drechsler et al., 2013; Olson et al., 2001), e.g. in the stages of market opportunity analysis, development and pretesting (Song et al., 1998), in the creation of market orientation (Jaworski & Kohli, 1993) or customer connection (Moorman & Rust, 1999).

Because we can hence conclude that the knowledge that is most important to innovation performance flows from M&S to R&D and not vice-versa, R&D cannot simply implement formal CFI mechanisms and benefit from them without being able to absorb the knowledge in question. M&S on the other hand can—ceteris paribus—directly improve innovation performance through participation in formal CFI mechanisms, because it delivers its knowledge without being required to absorb itself.

Hypothesis 7a: *The use of formal CFI mechanisms (FXM) by R&D departments has no effect on innovation performance (IPO).*

Hypothesis 7b: *The use of formal CFI mechanisms (FXM) by M&S departments positively affects innovation performance (IPO).*

However, the implementation of knowledge integration mechanisms might be problematic and hence the outcomes are not always positive for several reasons (cf. Troy et al., 2008). As Sherman & Keller (2011) show, managers might well misperceive the task interdependence of their own unit with other functional units and in consequence choose wrong degrees of integration which lowers performance. Moreover, as has been discussed and implied by various authors (e.g. Nadler & Tushman, 1978:618), the richness of transmission channels is closely connected to their complexity, which imposes in turn a cost on the management and transfer of knowledge. Managers might furthermore also misperceive the degree of inherent complexity and tacitness of the knowledge. This knowledge that thus withstands transfer efforts to a considerable degree has been termed “sticky” (Von Hippel, 1994) and requires different ways and degrees of integration than simple, easy-to-transfer knowledge.

The potential capacity of specific knowledge integration mechanisms to convey more or less rich information might not be completely valorized due to a lack of ability to use those mechanisms. Just as everything people do, integration can be carried out with more or less mastery and success. Thus the implementation of the processes in itself should not have significant direct effects on innovation performance. This can be assumed to be the case equally across functions for intra-functional integration.

Hypothesis 8: *The use of* ***formal*** *intra-functional integration mechanisms* ***(FIM)*** *has no direct effect on innovation performance.*

Hypothesis 9: *The use of* ***informal*** *intra-functional integration mechanisms* ***(IIM)*** *has no direct effect on innovation performance.*

Hypothesis 10: *The use of* ***informal CFI*** *mechanisms* ***(IXM)*** *has no direct effect on innovation performance.*

On the other hand, if this circumstance is recognized by the focal organizational unit, a learning process might take place as suggested by the previous hypotheses linking the implementation of integration mechanisms at the different interfaces to departmental ACs. In fact, the experience with different types of integration mechanisms should enhance an organizational unit's understanding of when and how to select, implement and use them. So departments as collectives with the necessary decision autonomy have to learn to integrate with other departments in two important and complementary ways. They have to learn which is the set of integration mechanisms that allows the most efficient integration with particular other units and how to apply each mechanism most effectively.

This knowledge absorption is crucially important in the innovation process where more fundamental and explorative discoveries can be made by means of recombination of knowledge stuck in separated knowledge silos (cf. chapter II). It can be concluded thus, that FAC positively impacts innovation performance:

Hypothesis 11: *FAC of R&D and M&S departments exhibits a positive direct effect on innovation performance (IPO).*

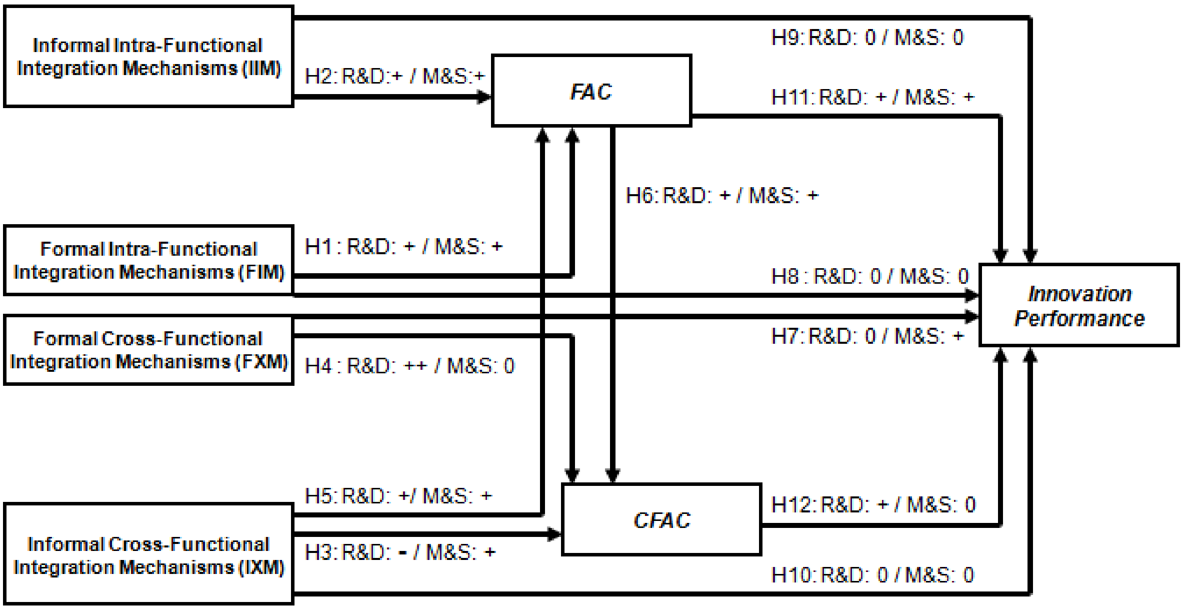
Once the departments developed thus FAC, they can valorize potential synergies and complementarities that exist between them and other departments of their corporate function by absorbing their knowledge. In fact, in studies of firms' sub-unit's absorptive capacity, the recipient's AC has been found also empirically to be a major determinant of the success or failure of intra-organizational knowledge transfer (cf. Van Wijk et al., 2008). As regards the department level, Luo et al. (2006) find that interdepartmental "cooperative ability"—defined by the authors actually by means of absorptive capacity—among departments regarding market knowledge positively impacts both customer and financial performance.

Hypothesis 12: *CFAC of R&D departments exhibits a positive direct effect on innovation performance (IPO).*

Hypothesis 12: *CFAC of M&S departments exhibits no direct effect on innovation performance (IPO).*

The entire set of hypotheses of the conceptual model can thus be summarized as illustrated in Figure 6.

Figure 6: Conceptual model



Control variables not illustrated in the figure.

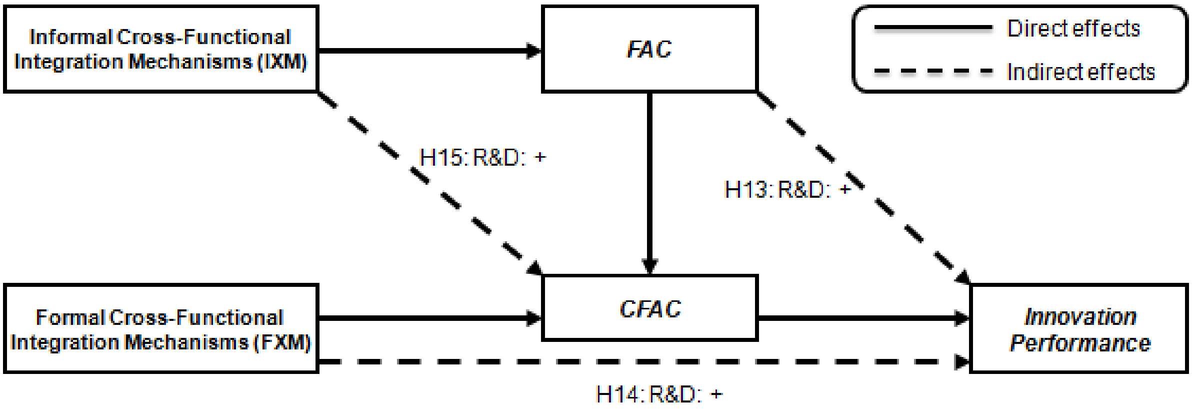
From the above discussion, several indirect effects are implied for R&D departments. One indirect effect indicates that FAC positively mediates the effect of informal CFI mechanisms. This means that it counterbalances the negative direct effect. The other two indicate that CFAC mediates both FAC and formal CFI mechanisms (FXM) for R&D departments, thus evidencing the role of CFAC. CFI aims at providing the necessary knowledge directly through lateral relations to those who need it in other functions due to task interdependence. Hence, in order to valorize formal CFI mechanisms, knowledge has to be absorbed successfully. The mere collaboration without understanding is not sufficient for a receiving unit, as was stated in hypothesis 7a. In this case, the receiving unit is hypothesized to be the R&D unit, which heavily relies on market information from M&S departments to direct and orient its work towards current and future market demand. The M&S departments as information providers, on the other hand, do not have to understand technological knowledge to the same degree. Thus, if the data confirms a direct effect of integration mechanisms as hypothesized above for M&S departments and not for R&D departments, while it supports the hypothesis of an indirect effect through CFAC, it clearly would support the intuition of the direction of knowledge flow from marketing and sales towards R&D (summarized as illustrated in Figure 7).

Hypothesis 13: *FAC exhibits a positive indirect effect on innovation performance (IPO) via CFAC.*

Hypothesis 14: *For R&D departments, there is a positive indirect effect from the intensity of use of formal CFI mechanisms (FXM) via CFAC on Innovation Performance (IPO).*

Hypothesis 15: *For R&D departments, there is a positive indirect effect from the use of informal cross-functional integration mechanisms (IXM) via FAC on CFAC.*

Figure 7: Indirect effects of conceptual model



III.4. Methodology

III.4.1. Research design and Operationalization

III.4.1.1. General survey design, pretest, and construct validity

With the exception of the newly established construct of departmental ACs, all variables have been measured based on items previously validated and used in management literature (see Appendix B: Questionnaire). However, also the measurements for the new concepts FAC and CFAC have been constructed based on items established in the literature measuring AC on the organizational or sub-unit level, adapting them slightly to fit the context of the functionally specialized departments chosen, i.e. Research & Development and Marketing & Sales. These and all the other established scales can be found in Appendix B together with their respective items and reliability statistics. In order to avoid any biases related to the sequence of items in a battery, all item batteries used have been presented in a random order.

Particular care was taken to avoid the creation of an overly lengthy questionnaire that could have increased the number of interruptions of compilation and thus incomplete responses. The survey software automatically records response times, but cannot recognize whether the window is active or just open in the background, which is why there are quite a few very high values and thus the mean does not make sense here. The median response time, though, is more informative and was approximately 15 minutes.

Moreover, construct validity was assessed in two steps. In a first step, the questionnaire was discussed with senior researchers from both innovation management and marketing. In a second step, a pretest with several professionals was made who where afterwards interviewed on comprehensibility and validity of the constructs. Both, researchers and professionals have been Italian mother tongue with excellent comprehension of English and asked also to confirm the validity of the translation. However, the questionnaire language could be chosen and changed online by the respondents. Good construct validity can thus be assumed.

III.4.1.2. Dependent Variables: Innovation Performance

Innovation Performance and new product performance have been measured with a range of different single- and multi-item scales (Moorman & Rust, 1999; Song, Kawakami, & Stringfellow, 2010; Song et al., 1998). Herein, a set of items has been chosen to measure innovation performance based on instruments used in both marketing and management literature (Atuahene-Gima, Slater, & Olson, 2005; De Luca & Atuahene-Gima, 2007; Foss, Laursen, & Pedersen, 2011). Innovation Performance was measured relative to the stated objectives regarding the innovation process on the following four dimensions: market share (IPO1), sales (IPO2), return on investment (IPO3), and product performance (IPO4).

III.4.1.3. Mediating Variables: Departmental FAC and CFAC

In order to measure FAC and CFAC at the level of functional departments, items from literature on Absorptive Capacity and knowledge integration (Flatten et al., 2011; M. T. Hansen & Nitin Nohria, 2004; Jansen et al., 2005; Szulanski, 1996). A study that comes particularly close to the measure of departmental AC is that of Luo et al. (2006). Although the authors name their concept “cross-functional cooperative ability”, they measure it with variables indicating it as a type of “absorptive capacity” at the department level, rather than “cooperative ability”. However, their measure does not actually distinguish between the knowledge domain and hence remains ignorant of the potential distinct natures of FAC and CFAC. Herein, instead, this distinction is at focus and it was aimed to measure these concepts as distinct, underlined as discussed below by their good discriminant validity and distinct effects.

Particular care was taken to select from previous literature only reflective items and that these were coherent with the theoretic conceptualization of the construct as ability, rather than a capability or a set of processes and routines; that is, those that do not ask “how extensively do you apply process X (a process that aims at knowledge absorption)?”, but instead “how successful are you with Y (an aspect of knowledge absorption)?”. Furthermore, items have been chosen to represent the four distinct sub-dimensions theorized for both higher level AC (Zahra & George, 2002) as well as department level ACs (cf. chapter II), which have recently been validated in several studies.

III.4.1.4. Exogenous variables: Formal and informal integration mechanisms

Formal and informal integration mechanisms each at both types of interfaces, thus obtaining four variables; i.e. Formal (FIM) and Informal (IIM) Intra-functional integration Mechanisms as well as Formal (FXM) and Informal (IXM) Cross-functional integration Mechanisms. Informal integration was measured with four items from previous literature (Zahra & Nielsen, 2002) as a reflective scale, thus indicating the degree of a latent informal integration. While functional integration has been measured also uni-dimensional in the past, for example by means of extensiveness of use of cross-disciplinary teams within the R&D function (Henderson & Clark, 1990), formal integration mechanisms have been adopted from previous literature treating this as a formative, multi-dimensional scale (Gupta & Govindarajan, 2000; Jansen, Van den Bosch, & Volberda, 2005). The formative scale of formal integration mechanisms was also measured with an additional item in order to have a more complete construct, which is particularly important for formative constructs (Edwards & Bagozzi, 2000).

III.4.1.5. Control variables

III.4.1.5.1. Industry

For *industry* was controlled because several studies have shown significant differences in both innovation approaches as well as innovation outcomes across industries which might consequentially lead to spurious results (Pavitt, 1984). Such effects have to be expected in particular for such industries as different as automotive suppliers, on the one hand, and food and beverage, on the other. It is controlled for this in form of variable IND2ROS that is the industry average Return on Sales (ROS) as calculated based on the 2 digit ATECO code (e.g. Coombs & Bierly, 2006). Alternatively, common industry dummies based on 2 digit ATECO codes have been used in OLS regression analysis as a further robustness check (e.g. Cassiman & Veugelers, 2006) (cf. section **Fehler! Verweisquelle konnte nicht gefunden werden.**).

III.4.1.5.2. Firm size

Firm size was included as a further control variable, since it has turned out frequently that firm size effects innovation performance as well as business performance. Mostly, a positive or insignificant effect has been found, but also negative relations have been reported (Fosfuri & Tribó, 2008). A broad variety of factors has been found as contributing to the relationship between firm size and innovation performance, as there are for example slack resources and less exposure to environmental shocks. Particularly the availability of slack resources might be associated to the possibility to pursue more uncertain but also potentially more rewarding explorative innovation projects which is associated with higher long-term innovation performance vis-à-vis exclusively exploitative innovation strategies (March, 1991).

On the other hand large corporations tend to be more focused on short term results, in particular publicly listed corporations that have to report quarterly financial statements which might have the opposite effect and decrease explorative activities. A further reason for a negative effect might be that large monolithic organizations can be also associated to considerable degrees of bureaucracy and consequential inflexibility in adapting organizational routines. We apply here the most common measure of firm size, i.e. the logarithm of the number of full-time equivalent employees.

III.4.1.5.3. Centralization

This argument is closely connected to another variable that we want to control for, that is the degree of *centralization*, which has been found an important factor in market orientation (Jaworski & Kohli, 1993). On the one hand, Argyres & Silverman (2004) find that centralization in R&D decision-making authority improves the impact of innovations, arguing that this might derive for example from a better integration of spillovers across business units. Therefore, a positive impact of centralization can be expected on innovation performance.

On the other hand, Song & Thieme (2006) find that in some countries centralization augments the need to integrate the marketing function in the NPD process, while in others the need to integrate stronger the R&D function, while they could find no impact at all on the market information gap, which is in line with the argument that centralization of authority reduces spontaneous communication and collaboration across units. Since between differently specialized functional departments the absolute difference is greater qua definition, the impact should be relatively more important and particularly pronounced in form of a negative effect of centralization on FAC.

III.4.1.5.4. B2C/B2B

An important control variable to include is the degree to which the firm or business unit directly serves end consumers (business-to-consumer, B2C) rather than other businesses (business-to-business, B2B). As argued for example by Homburg, Workman, & Krohmer (1999), a higher degree of sales to other business rather than directly to end consumers could increase the interaction of units from functions other than marketing with customers and hence decrease the power of the marketing function that derives from its exclusive provision of market knowledge. This implies, however, that at the R&D-Marketing interface, the functions are even less acquainted with the other function's knowledge and integration will be more difficult, thus reducing ceteris paribus the level of CFAC. No effect between the level of B2C sales and FAC is expected.

However, in sectors that serve products to businesses, taste and fashion play much less a role than in sectors that serve products to consumers. Thus, in the latter markets more incremental innovations can be successfully placed and hence innovation targets easier be reached. We expect thus that the higher the degree of business-to-consumer (B2C) sales, the higher innovation performance.

III.4.1.5.5. Environmental turbulence

Several studies find that *environmental turbulence* impacts the innovation behavior and outcomes of integration activities (Lawrence & Lorsch, 1967; Olson et al., 2001). Most importantly, environmental turbulence creates higher levels of uncertainty which in turn might increase need but also the difficulty of lateral communication (Fry & Slocum, 1984). It can however also more directly impact innovation performance as it has been found that such environmental characteristics might impact the efficiency of particular product innovation strategies (Eisenhardt & Tabrizi, 1995). Innovativeness is the most fundamental way in which firms can assure their survival in more dynamic environments with higher competitive pressure. Therefore we expect a positive impact on innovation performance. Environmental turbulence is measured by means of a formative item battery used in previous literature (Verhoef & Leeflang, 2009).

III.4.1.5.6. Market oriented reward mechanisms

The *market oriented reward mechanisms* in place have been found to impact significantly on market orientation (Jaworski & Kohli, 1993), which is closely related to functional integration success, as well as on NPD performance (Song et al., 1997), which in turn is closely related to innovation performance. Moreover, rewards might even interact with market orientation on innovation performance (Wei & Atuahene-Gima, 2009). This shows that rewards as performance pay might inflate spuriously the relationship between CFAC and Innovation Performance impacting both positively. They might generally incentivize to try to improve results wherever possible, i.e. to search harder for knowledge in every direction (FAC and CFAC) as well as to augment directly innovation performance through increased engagement. Items previously developed in literature for this purpose have been used (Jaworski & Kohli, 1993), but not as a reflective scale, but as formative. This specification appears more appropriate since single measures implemented by the firm do not have to come necessarily together and reflect a latent reward orientation. At the most it could be argued that it reflects a latent propensity of top management to implement market oriented reward schemes. It seems more appropriate thus to assume that each reward mechanism does what it is implemented for at least to some degree and that they thus cumulatively explain the latent variable. This choice is justified by empirical observation of inter-item correlations (see discussion below in results section).

III.4.2. Analysis techniques

III.4.2.1. Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) has been chosen as approach to analyze the cross-sectional data with SPSS and its add-on AMOS. The SEM approach is a multivariate, covariance-based modeling approach and can be thought of as a generalization of the simpler and more commonly used multiple OLS regression models (Byrne, 2010). The SEM approach as a generic term comprises what Bagozzi & Yi (2012) call "first-generation statistical methods", like canonical correlation analysis or multiple regression analysis, while it moreover allows some analysis that are not possible with these, most importantly the estimation of latent variables explicitly modeling random and measurement errors. Often SEM is referred to, however, as one of its specific variants that allows for the simultaneous estimation of the measurement model for latent variables and the structural model (Leeflang, Wittink, Wedel, & Naert, 2000). Particularly important for this study is that SEM provides of "more straightforward tests of mediation, methods to assess construct validity in broader and deeper ways than possible with traditional correlation analyses, and ways to correct for systematic bias in tests of substantive hypotheses." (Bagozzi & Yi, 2012:12). Since at focus here is the mediating effect of AC between integration mechanisms and innovation performance, SEM is a very appropriate choice to analyze our data.

As regards the conclusions that can be drawn it should be noted that the set of related equations that will be specified in the following reflects causality, but as Bagozzi and Yi (2012) avert, this cannot be taken as a "proof of causality", but be better interpreted as evidence of functional relationships or "weak" causal evidence. This is however not a peculiarity of the SEM approach, but due to the cross-sectional nature of the survey data. Given this kind of data, SEM remains one of the soundest ways of testing causal relationships.

III.4.2.2. Sample Size

Even though SEM models have found to possibly perform well even with sample sizes as low as 50 (Iacobucci, 2010), adequacy of sample size depends on the number of observed variables and for better convergence and reduction of bias it should be aimed at sample sizes above 100 cases, preferably even above 200 (Bagozzi & Yi, 2012). The sample here includes 126 subjects and thus is an adequate size, though towards the lower bound.

Although the two models of an SEM, i.e. the measurement model and the structural model, are often estimated in one-step simultaneously, also two-step approaches testing first the measurement model alone followed by the estimation of both simultaneously have been suggested in order to isolate the goodness of fit of each of the two models (J. C. Anderson & Gerbing, 1988). However, since the adequacy of a sample's size might be connected to the distinct parameters to be estimated by a model, it might be indicated to reduce eventual problems by estimating the two models comprised by a full SEM separately. In fact, it could be shown in Monte Carlo simulation studies that the bias in structural path estimates that arises from parceling items of a latent variable into a single measure is negligible while fit estimates are meliorated (Bandalos, 2002). However, to further check robustness to sample size in terms of stable parameter estimates both models, the measurement and the pure structural model, have been estimated with the first 100 cases and with the final set of 126 cases with no indication of any substantial changes.

III.4.2.3. Treatment of missing data

Missing data can have serious effects on data quality and hence the conclusions that can be drawn from empirical data. Missing data is commonly distinguished as missing completely at random (MCAR), missing at random (MAR), and not missing at random (NMAR) (Byrne, 2010; Schafer & Graham, 2002). MCAR indicates a situation where the missingness of a value depends neither on other variables nor on the variable for which it is missing, MAR indicates that the missing values might depend on the underlying variable, but not on others, while for NMAR data neither of these two conditions hold. There is no way to test whether the MAR condition is met, which is why it is commonly simply assumed that it is met. Therefore, it appears good practice not to delete listwise if not absolutely necessary but to impute missing observations and to check for robustness of results applying different imputation techniques. In this study some cases had to be deleted listwise since in some cases far more than half of the answers were missing while for the rest of cases with missing data this could be imputed (see detailed description below in the section about data).

The two most common imputation techniques have been chosen and imputation has been performed twice, once based on variable means and once based on ML estimation as available in AMOS. All analyses of the measurement and structural models have been executed based on both kinds of imputation techniques. Both results are reported and do not differ substantially, which allows for higher confidence with the assumption that the missing data meets the MAR condition. In fact, simulation studies on imputation techniques claiming imputation based on ML being more efficient are confirmed in that standard errors of parameter estimates of the analyses with ML imputed data are smaller. Hence, and because generally ML estimation of missing observations is regarded as robust even in cases where the MAR condition is not exactly met (Byrne, 2010), we report in the text principally the results based on this imputation technique[4]. It is referred also to the alternative analyses only for robustness checks that are not possible with ML estimation of missing observations (like checking SRMR values or examining standardized residual covariance matrixes).

[4] The results from analysis based on data with missing observations imputed from variable means are reported in the appendix.

III.4.2.4. Assessing Model Fit

The assessment of model specification and fit differs slightly between measurement model and structural model. For both model estimations the fit between observed and implied covariance matrixes has to be assessed. In addition to that, for the measurement model the reliability and validity of the used scales has to be estimated as well. Reliable and valid measurement scales are fundamental to any further analysis. To assess thus the measurement model, several ways have been proposed to conduct a purification of item batteries (Gerbing & J. C. Anderson, 1988). It has been suggested to assess the factor loading and SMC of the items to judge whether to include them or not. Furthermore, it has been proposed to judge a scale reliable if construct reliability (CR) is at least .7 (Bagozzi & Yi, 1988). Several measures have been developed to estimate validity. Convergent validity is achieved if average variance extracted (AVE) is smaller than CR and discriminant validity if AVE is greater than both maximum shared squared variance (MSV) and average shared squared variance (ASV) (Hair, Black, Babin, & R. Anderson, 2010).

To assess fit of the entire model, a broad range of fit indices has been developed (Leeflang et al., 2000). This derives principally from the fact that each measure has particular advantages and disadvantages and depending on for example sample size, to which various fit indices are sensitive (Iacobucci, 2010). The various fit indexes are commonly categorized as absolute, incremental, and parsimonious fit indexes, since this expresses their principal strength, that often have some drawbacks, however. It is hence quite common to report several indexes from different covering all the three categories. Usually at least chi-square values (and corresponding p-values), chi-square/d.f., CFI, TLI, RMSEA, and SRMR are reported. For a detailed discussion of all fit indexes, the reader might be referred for example to Hooper, Coughlan, & Mullen (2008) or Byrne (2010:73ff). In the remainder of this section, only those most appropriate to report in the context of this study shall be briefly presented.

The chi-square value is actually the most basic fit statistic as it measures the discrepancy between the observed and the implied covariance matrixes. Since it is aimed to reduce the discrepancy, the logic of the significance test is reversed and p-values should be at least above .05 so that the null hypothesis that the two matrixes are equal needs not to be rejected. Due to its high sensitivity to sample size, however, often it is reported in relation to the degrees of freedom.

The TLI, also known as Non-Normed Fit Index (as also the NFI on which it is based) is an incremental fit index, but sensitive to sample size, particularly under 200 cases (Kline, 2005) with cut off values ranging between .8 and .95 (Hooper et al., 2008). A common alternative is the CFI, which is likewise an incremental fit index. For CFI the suggested cut off value is .90 (Hu & Bentler, 1999). Both criteria are considered incremental fit indexes because they compare the hypothesized model with the null model, i.e. the model not assuming any paths—the opposite of the saturated model assuming all variables to be related to each other.

For RMSEA, values from .1 downwards are judged as moderate fit and good fit from .08 or more conservatively .05 downwards (Hooper et al., 2008). This fit index is lately increasingly claimed to be the most informative fit index as it allows the estimation of a confidence interval (Hooper et al., 2008:54).

The SRMR is the standardized variant of the root mean square residual, and is—as the name hints to—a measure of the average residuals resulting from the fitting attempt. Therefore, also this criterion should be as low as possible. Usually .05 and lower is suggested (Byrne, 2010:77).

III.4.2.5. Violation of the multivariate normality assumption, potential consequences and remedies

One assumption of the SEM approach is multivariate normality. Consequences of nonnormal are (1) an inflated chi-square value, even for small sample sizes, (2) failure of convergence or improper solutions, (3) modestly underestimated CFI values, and/or (4) spuriously low standard errors, which might lead to apparently significant path coefficients (Byrne, 2010:330). Bollen & Stine (1992) introduced the bootstrapping approach as an approach to deal with nonnormality in SEM, which is now commonly used in management research (e.g. Wei & Atuahene-Gima, 2009) to correct an inflated chi-square value. Moreover, bootstrapping provides a possibility to estimate bias-corrected standard errors (Byrne, 2010:330). Therefore, all results have been corrected based on 2000 randomly generated bootstrap samples providing more robust estimates.

III.4.2.6. Model Specification

The measurement and the structural model are estimated separately, as indicated above. First, the pure measurement model of the reflective scales is estimated. This allows to estimate not only composite reliability, but also convergent and discriminant validities, from which then composite variables are imputed via regression. These are used subsequently for the estimation of the pure structural model in a path analysis. The measurement model can thus be formulated in the following general form for the endogenous and all exogenous latent variables (cf. Leeflang, et al., 2000:443f):

“ $y = \Lambda_y \eta + \varepsilon$ $\qquad\qquad$ $x = \Lambda_x \xi + \delta$

where:

y	=	a (p x 1) vector of manifest endogenous variables,
η	=	a (m x 1) vector containing the latent endogenous variables (i.e. the variables that are explained within the model),
Λ_y	=	the (p x m) matrix of loadings, showing which manifest variable loads on which latent exogenous variable,
ε	=	a vector of error terms with expectation zero, and uncorrelated with η,
x	=	a (q x 1) vector of manifest exogenous variables,
ξ	=	a (n x 1) vector of latent exogenous variables (i.e. variables that explain the model),
Λ_x	=	the (q x n) matrix of loadings, showing which manifest variable loads on which latent exogenous variable, and
δ	=	a vector of error terms uncorrelated with ξ and expectation zero.”

The structural model can be generally stated as following (Iacobucci, 2009:676):

“$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta$,

with items defined as follows:

η	=	is a of endogenous (“dependent”) factors
B	=	is a matrix of coefficients of the η’s on other η’s (part of the structural relationships)
Γ	=	is a matrix of coefficients of the ξ’s on the η’s (also part of the structural relationships)
ξ	=	is a vector of the independent latent variables, exogenous constructs (i.e., predictor factors)
ζ	=	is a vector of equation errors (random disturbances) trying to predict the endogenous constructs η (prediction inaccuracies).”

Further matrices estimated in an SEM but not noted in the equations are the factor intercorrelation matrix Φ (between the ξ’s), the covariance matrixes with the measurement error terms of the endogenous variables, θ_{ε}, those of the exogenous variables, θ_{δ}, and the equation error terms, ψ. This general form can be decomposed into the following equations that represent the measurement model for reflective scales and as well as the overall structural model including the item parcels from formative scales (Table 4).

Table 4: Model specifications

	Measurement model:		
(1) IPO:	$y_1 = \lambda_{y,1}\eta_1 + \varepsilon_1$	(4) IXM:	$x_1 = \lambda_{x,1}\xi_1 + \delta_1$
(2) CFAC:	$y_2 = \lambda_{y,2}\eta_2 + \varepsilon_2$	(5) IIM:	$x_2 = \lambda_{x,2}\xi_2 + \delta_2$
(3) FAC:	$y_3 = \lambda_{y,3}\eta_3 + \varepsilon_3$	(6) CNTR:	$x_3 = \lambda_{x,3}\xi_3 + \delta_3$

	Structural Model:
(7) IPO:	$\eta_1 = \beta_{1,2}\eta_2 + \beta_{1,3}\eta_3 + \gamma_{1,4}\xi_4 + \gamma_{1,6}\xi_6 + \gamma_{1,7}\xi_7 + \gamma_{1,8}\xi_8 + \gamma_{1,9}\xi_9 + \gamma_{1,10}\xi_{10} + \zeta_1$
(8) CFAC:	$\eta_2 = \beta_{1,3}\eta_3 + \gamma_{1,2}\xi_2 + \gamma_{1,5}\xi_5 + \gamma_{1,6}\xi_6 + \zeta_2$
(9) FAC:	$\eta_3 = \gamma_{1,1}\xi_1 + \gamma_{1,2}\xi_2 + \gamma_{1,3}\xi_3 + \gamma_{1,4}\xi_4 + \gamma_{1,6}\xi_6 + \gamma_{1,10}\xi_{10} + \zeta_3$

		Symbols:		
y_i / x_j	=	are respectively the (n_i x 1) and (n_j x 1) vector of the manifest items indicating the first endogenous latent variable *i* and *j*, that is the first n_i and n_j elements of the concatenated vector **y** and **x** of the general form,		
$\lambda_{y,i} / \lambda_{x,j}$	=	are respectively the (n_i x 1) and (n_j x 1) vector of the factor loadings of the n_i and n_j items on the latent construct *i* and *j* for each of its n_i and n_j items, i.e. the first block in the block-diagonal matrix $\mathbf{\Lambda_y}$ and $\mathbf{\Lambda_x}$ above,		
η_i	=	the scalar for the *i*-th endogenous latent construct		
ξ_j	=	the scalar for the *i*-th exogenous latent construct		
ε_i	=	the (n_i x 1) vector of error terms of the equations estimating each of the n_i items indicating endogenous, latent construct *i*,		
δ_j	=	the (n_j x 1) vector of error terms of the equations estimating each of the n_j items indicating exogenous, latent construct *j*,		
$\beta_{i,l} / \gamma_{i,j}$	=	are respectively the coefficients for the path from another endogenous latent factor *l* and an exogenous latent factor *j* to the *i*-th endogenous latent factor, thus part of matrixes Β and Γ, resepectively,		
ζ_i	=	the error term of the equation estimating latent construct *i*,		
i	=	1	IPO:	Innovation Performance relative to Objectives (IPO)
		2	CFAC:	Cross-Functional Absorptive Capacity
		3	FAC:	Functional Absorptive Capacity
j	=	1	IIM:	Informal Intra-functional integration Mechanisms
		2	IXM:	Informal Cross-functional integration Mechanisms
		3	CNTR:	Centralization
		4	FIM:	Formal Intra-functional integration Mechanisms
		5	FXM:	Formal Cross-functional integration Mechanisms
		6	REW:	Market oriented REWards
		7	SIZE:	Firm size
		8	ENV:	Environmental turbulence
		9	B2C:	Share of business-to-consumers products/services
		10	IND2ROS:	INDustry's 2-digit ATECO sectors' mean Return On Investment

III.5. Results and Discussion

III.5.1. Data

We collected data from the Italian manufacturing industry. In a first step we selected all Italian manufacturing firms from the AIDA database of Italian public and private firms. This database has been used in many previous studies and has been described as almost exhaustive, including not only publicly listed companies but also privately held SMEs. The list includes 3769 firms with at least 200 employees. From this list, several firms had to be dropped because they were no longer active. In a second step an online pool of potential survey participants was accessed that permits to select professionals by firm and department so that only individuals were selected that worked since at least one year in either an R&D or M&S department of a firm from the remaining set of firms.

Thus 541 individual professionals could be matched to R&D and M&S departments and firms in that they worked at least one year. Matches of professionals that worked less than one year in a firm of the sample have been excluded because their responses cannot be assumed to be sufficiently reliable because the process of socialization might take some time. The thus matched professionals were then contacted with the request to complete an online questionnaire. As shown in Figure 11, the distribution of experience of survey participants is inclined towards less than what can be expected as the mean experience, which is due to an overrepresentation of younger professionals in the database itself. The figure shows likewise, however, that the effect is rather limited. Industry sector experience does not bias hence the results of this particular research question.

The questionnaire was hosted on a dedicated server under the official university domain and password protected in order to further signal careful and confidential use of the participants' data. Moreover, in the contact e-mail all participants were assured not only the confidentiality of their answers, but incentivized also with a personalized benchmark report. There have been two rounds with reminder e-mails.

The received responses amounted to 140 of which 126 were sufficiently complete not to be entirely deleted. Although it is preferable to impute missing data (see discussion above), the cases in question were so early interrupted or so incomplete that less than half of answers were filled in so that deleting them altogether was the only viable option. From the remaining 126, a small amount of missing item values has been imputed by ML estimation as provided for in AMOS as well as by group variable means as a robustness check (cf. Byrne, 2010). Although the missing values are largely distributed arbitrarily across cases and variables which is indicated by the high number of cases per variable (mostly about 124 out of 126) but low number of listwise valid cases (85), two variables, FXM and IXM, exhibit a higher number of missing values for all their items (descriptive statistics are reported Table 12). However, these missing values appear together casewise which indicates a problem of comprehension of the questionnaire design where the two scales appeared in two columns next to each other. In fact, individual feedback from practitioners reviewing again the questionnaire confirmed that the fact that the scales where juxtaposed could be interpreted as asking to respond only in one column instead of both, i.e. only in that with the headline mentioning the own corporate function, which would result in answering only for FIM and IXM, which are in fact as complete as the other variables. Since this problem of understanding can be assumed to appear randomly, this allows for application of either one of the imputation techniques, variable mean imputation as well as ML estimation. However, even in these cases, less than 10% of cases are missing, which would still sufficiently limit potential bias (Schafer & Graham, 2002).

Thus overall we achieved a response rate of almost 24%, which is a good rate for online surveys of managers. These 126 complete questionnaires came from 51 marketing or sales professionals while 75 came from employees of research and/or development departments.

The sectors present in our final sample are automotive and suppliers, food and beverage, consumer electronics and home appliances, telecommunications equipment, instruments and industrial machinery, chemicals, etc. As indicated in Figure 10, the difference in sectoral composition is not too different between the respondents and non-respondents. However, it was tested for non-response bias using the financial data from the AIDA database. Since this was available for both groups it was possible to test for significant differences in key variables potentially related to the issue, above all performance indicators, but also indicators of differences between sectors. This was done by means of a paired-sample t-test on mean differences for each of the selected key variables for the overall groups as well as for the two sub-samples of respondents from R&D and M&S departments. At no point significant differences could be found thus indicating that it can be confidently assumed that there is no non-response bias (cf. Table 11).

Common method bias (CMB) was checked for by means of Harman's single factor test (Harman, 1967) that is commonly applied in cross-sectional studies (e.g. Verhoef & Leeflang, 2009). Thus, a principal component analysis (PCA) on all items of the survey extracting factors with eigenvalues above 1, which resulted in many factors explaining about 75% of total variance and another PCA constraining the extraction of one single factor of the unrotated solution. This single factor could explain only about 23.8% of total variance (cf. Table 14). We found thus no indication that common method bias is a major problem. Although this method is the most commonly used test, it can only potentially confirm that common method bias might be a major problem, not proof the absence of less strong common method variance (cf. Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Therefore, to avoid potential biases related to the survey method several further measures were taken. To reduce the potential of social desirability bias, particular care was taken signaling absolute anonymity of both individuals and firms. In order to avoid biases due to the order of items, the items of all multi-item scales have been presented in random order each time the site was accessed.

III.5.2. Measurement model

III.5.2.1. Reflective scales

A first check applied to every scale was that for sufficiently high inter-item correlations (cf. Table 15 through Table 18). All have been found correlated at least above .45 and significant, mostly at the 1%-level, with exception of some of the reversed coded items of the FAC and CFAC scales. This is in line with the pattern of factor loadings identified by the exploratory factor analysis (cf. Table 13), where all items of the reflective scales load together on their respective factors with the exception of a few items of the FAC and CFAC scales.

Finally, the confirmatory factor analysis (CFA) for the entire measurement model was run. An item purification process led to the elimination of several items from the original scales because of too low factor loadings (< .55). The final model specification is illustrated in Figure 8. This figure includes the factor loadings and inter-construct correlations. The model results in terms of standardized estimates of factor loadings, item r-squares, as well as reliability and validity measures of scales are reported in Table 5.

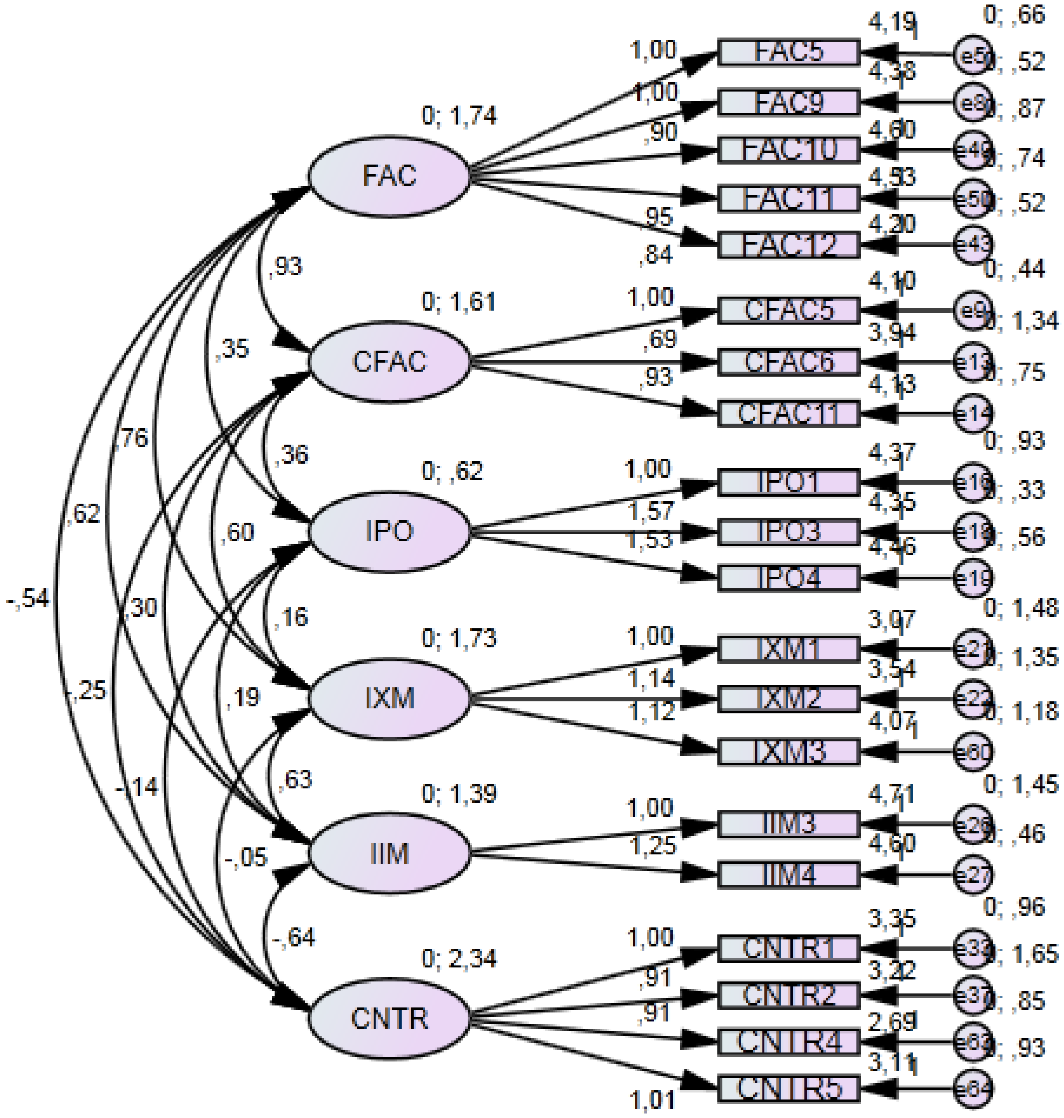
The model fit can be judged as fairly good notwithstanding a relatively high chi-square value, because this value begins to be inflated from hundred cases upwards and all other indicators show a good fit. Both the Tucker-Lewis-Index (TLI) and the comparative fit index (CFI) are over .9 with values of .921 and .941, respectively, the root mean square error of approximation (RMSEA) is with .063 in a well acceptable range (<.1 moderate; <.05 good), and chi-square/d.f. is far below the conservative threshold of 2 with a value of 1.491. Model fit is at least as good also for the solution with variable means imputed data for which also the estimate of SRMR was well below the threshold of .08 (Hu & Bentler, 1999) [5]. Moreover, no indication of problems with model fit could be found based on a check of the matrix of the

[5] SRMR is not reported by AMOS for data with missing values that are imputed by ML estimation.

standardized residual covariances available for the analysis with mean imputed variable means[6] (cf. Table 21 and Table 22), since no value is larger than 2.58 (cf. Byrne, 1999:86).

The values for composite reliability (CR) of all scales were largely above the .7 threshold (Bagozzi & Yi, 1988). Moreover, for all variables convergent and discriminant validity is achieved with average variance extracted (AVE) always smaller than CR and always greater than both maximum shared squared variance (MSV) and average shared squared variance (ASV).

Figure 8: Measurement model for reflective scales



[6] Residual moments are not available in AMOS for data with missing values since different sample moments are possible and residual moments are defined as the difference between implied and sample moments.

Table 5: Measurement model results (ML estimation of missing data)

Construct	Path			R^2	Estimate	Standardized Estimate	Construct Reliability	AVE	MSV	ASV
IPO							.844	.648	.131	.064
	IPO1	<---	IPO	.402	1.00 (n.a.)	.634				
	IPO3	<---	IPO	.820	1.57***	.906				
	IPO4	<---	IPO	.722	1.53***	.850				
CFAC							.814	.599	.310	.125
	CFAC5	<---	CFAC	.786	1.00 (n.a.)	.887				
	CFAC6	<---	CFAC	.360	.69***	.600				
	CFAC11	<---	CFAC	.649	.93***	.806				
FAC							.921	.699	.310	.170
	FAC5	<---	FAC	.725	1.00 (n.a.)	.852				
	FAC9	<---	FAC	.771	1.00***	.878				
	FAC10	<---	FAC	.616	.90***	.785				
	FAC11	<---	FAC	.680	.95***	.824				
	FAC12	<---	FAC	.704	.84***	.839				
IXM							.820	.604	.194	.103
	IXM1	<---	IXM	.538	1.00 (n.a.)	.734				
	IXM2	<---	IXM	.625	1.14***	.790				
	IXM3	<---	IXM	.648	1.12***	.805				
IIM							.789	.656	.168	.107
	IIM3	<---	IIM	.489	1.00 (n.a.)	.699				
	IIM4	<---	IIM	.823	1.25***	.907				
CNTR							.888	.665	.128	.046
	CNTR1	<---	CNTR	.709	1.00 (n.a.)	.842				
	CNTR2	<---	CNTR	.539	.91***	.734				
	CNTR4	<---	CNTR	.693	.91***	.833				
	CNTR5	<---	CNTR	.719	1.01***	.848				

Notes: n = 126; *** < .001, (n.a.) = significance level not applicable to fixed parameters; $\chi^2(174) = 259.379$; p = .000; χ^2/d.f. = 1.491; TLI = .921; CFI = .941; RMSEA = .063 (90% confidence interval: .046 → .078); SRMR = not defined for data with missing values.

Finally, the measurement model was tested for configural and metric invariance between the two sub-groups R&D and M&S departments (cf. Byrne, 2010:197-230). Configural invariance was confirmed by finding a good fit for both subgroups estimated separately with the same model configuration as well as for both groups estimated in the same model simultaneously. Metric invariance was judged by means of a chi-square difference test between this configural, unconstrained model and a fully cross-group invariance constrained model, i.e. all factor loadings constrained to be equal across groups (cf. Table 19). Since the model exhibits a good fit, all constructs are indicated as highly reliable and valid and measurement invariance has been confirmed, values for all latent construct could be imputed to be used in the subsequent separate estimation of the structural model.

At this point it should be mentioned that AMOS does not report the estimate for multivariate normality for data with missing values. It has to be assumed, however, that the multivariate normality assumption was violated. This can be deduced from the multivariate kurtosis statistic for the data with missing values imputed based on variable means. Mardia's coefficient (for multivariate kurtosis) is with a value of 29.810 much too high (< 3) and with a critical ratio of 4.351 also significantly so. Mahalanobis' d-squared distance does not reveal any particular outliers. This could also explain the relatively high chi-square. To correct for a bias in the chi-square estimate a Bollen-Stine bootstrap with 2000 random samples has been performed on the mean imputed data. Only three random samples failed to yield a solution and had to be redrawn. The adjusted p-value was .640 (>.05) and suggests that we cannot reject the null that the model is correct.

III.5.2.2. Formative Scales

For all formative scales, it is arguable whether to treat these indicators as reflective or as formative (Edwards & Bagozzi, 2000). In fact, one of the scales argued to be formative has been previously treated as reflective (see discussion above in the corresponding section on the specific scales). An important criterion is the logic of causal direction theorized, which should be confirmed by high the inter-item correlations in case of reflective scales (Edwards & Bagozzi, 2000), because if there is a common latent factor influencing the items they have to be correlated to some degree, while there is no such constraint if the indicators "form" the latent variable. That means, in turn, that low inter-item correlations are good indicators for formative measures, while high inter-item correlations are not per se indicative of either direction. Indeed, for all scales herein argued to be formative the correlations, although quite significant, are not as high as one should expect if they were reflective scales as can be seen in Table 6 and Table 7.

Table 6: Inter-item correlations: Formal Intra- and CFI Mechanisms scales (FIM & FXM)

		FIM1	FIM2	FIM3	FIM4		FXM1	FXM2	FXM3	FXM4
Pearson	**FIM1**	1	,345(**)	,276(**)	,328(**)	**FXM1**	1	,418(**)	,372(**)	,282(**)
Sig.			,000	,002	,000			,000	,000	,002
N		124	124	124	124		114	114	114	114
Pearson	**FIM2**		1	,219(*)	,281(**)	**FXM2**		1	,366(**)	,290(**)
Sig.				,015	,001				,000	,002
N			125	124	125			115	115	115
Pearson	**FIM3**			1	,395(**)	**FXM3**			1	,385(**)
Sig.					,000					,000
N				124	124				115	115
N	**FIM4**				126	**FXM4**				117

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

Table 7: Inter-item correlations: Rewards and Environmental turbulence scaeles (REW and ENV)

		REW1	REW2	REW3		ENV1	ENV2	ENV3	ENV4	ENV5
Pearson	**REW1**	1	,290(**)	,397(**)	**ENV1**	1	,491(**)	,461(**)	,305(**)	,402(**)
Sig.			,002	,000			,000	,000	,001	,000
N		118	116	118		121	121	121	120	118
Pearson	**REW2**		1	,529(**)	**ENV2**		1	,661(**)	,382(**)	,388(**)
Sig.				,000				,000	,000	,000
N			117	117			121	121	120	118
Pearson	**REW3**			1	**ENV3**			1	,378(**)	,408(**)
Sig.									,000	,000
N				120				121	120	118
Pearson					**ENV4**				1	,711(**)
Sig.										,000
N									120	118
N					**ENV5**					118

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

While commonly formative scales are simple, i.e. non-weighted averages of the equally scaled items, formal integration mechanisms have been differently summed in extant literature. In previous studies using the same items to measure cross-functional integration or interfaces, these have been combined into a weighted average in previous studies, with weights 1 for liaison personnel, 2 for temporary task forces and 3 for permanent teams (e.g. Gupta & Govindarajan, 2000; Jansen et al., 2005). The same weights have been applied herein, while the additional indicator, job rotation, is weighted with one, because it is closest in nature to liaison personnel, since it involves only single individuals.

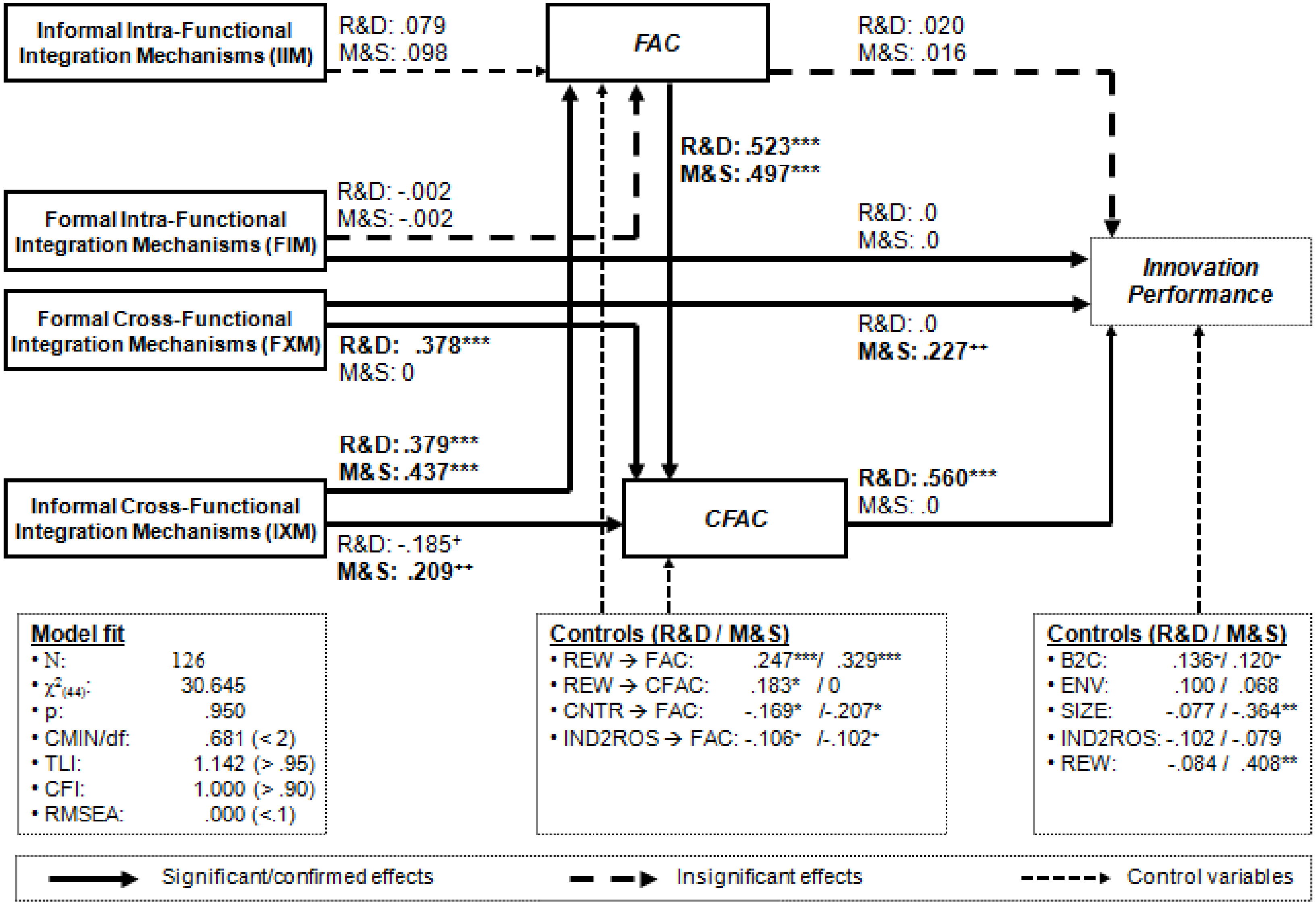
III.5.3. Structural model

The structural model is based on the specified hypotheses and includes the specified control variables. As can be seen from the estimation based on the variable mean imputed data, multivariate normality remains an issue for the R&D sub-sample, for which Mardia's coefficient was with a value of 13.750 (< 3) not acceptable (c.r. = 3.015). There was no such indication for the M&S sub-sample (kurtosis: 1.970, c.r.: .356). However, chi-square statistic appears not to be downward biased too much by this since it is still exceptionally good (.910) just as is the chi-square/d.f. value (.731). The overall results based on data with missing values replaced by variable means are summarized in the Appendix in Table 24. The analysis that follows is based on the more efficient ML estimation of missing values.

Examining the estimates (Table 8 and Figure 9) we could confirm several of our hypotheses. First of all it can be stated that a good part of variance is explained by the model for all three endogenous variables as R-squares for all three are between .35 and .59. Most of the control variables load as predicted, with the exception of market oriented incentives and firm size on innovation performance in case of R&D departments. Industry sectors as measured by average return on sales of the sector has no effect, which is confirmed by mostly not significant industry dummies in OLS regressions (see paragraph on further robustness checks below).

To begin with, it can be highlight that CFAC significantly positively impacts innovation performance as expected. This effect is robust across diverse model specifications and all models that specify a direct effect of integration mechanisms onto innovation performance had to be rejected due to bad model fit. On the other hand, however, I cannot find evidence for the hypothesized direct effect of FAC on innovation performance. Nonetheless, the hypothesized indirect effects through CFAC on innovation performance are highly significant.

Figure 9: Pure structural model results overview based on data with missing values imputed via ML estimation



Estimates for indirect effects in Table 8.

Table 8: Structural model results (ML estimation of missing data)

DV	Hypo-thesis	Path			R&D R²	R&D SE	M&S R²	M&S SE	Expected sign	Result
FAC					**.357**		**.590**			
	H1:	FAC	<---	FIM		-.002		-.002	+	not confirmed
	H2:	FAC	<---	IIM		.079		.098	+	not confirmed
	H5:	FAC	<---	IXM		.379***		.437***	+	confirmed
	C:	FAC	<---	CNTR		-.169*		-.207*	-	confirmed
	C:	FAC	<---	IND2ROS		-.106+		-.102+	-	borderline
	C:	FAC	<---	REW		.247***		.329***	+	confirmed
CFAC					**.529**		**.407**			
	H3a:	CFAC	<---	IXM(R&D)		-.185+			-	borderline
	H3b:	CFAC	<---	IXM(M&S)				.209++	+	borderline
	H4a:	CFAC	<---	FXM(R&D)		.378***			++	confirmed
	H4b:	CFAC	<---	FXM(M&S)				0	0	confirmed
	H6:	CFAC	<---	FAC		.523***		.497***	++	confirmed
	C:	CFAC	<---	REW(R&D)		.183*			+	confirmed
	C:	CFAC	<---	REW(M&S)				0	0	confirmed
IPO					**.372**		**.356**			
	H7a:	IPO	<---	FXM(R&D)		0			0	confirmed
	H7b:	IPO	<---	FXM(M&S)				.227++	+	borderline
	H8:	IPO	<---	FIM		0		0	0	confirmed
	H9:	IPO	<---	IIM		0		0	0	confirmed
	H10:	IPO	<---	IXM		0		0	0	confirmed
	H11:	IPO	<---	FAC		.020		.016	+	not confirmed
	H12a:	IPO	<---	CFAC(R&D)		.560***			++	confirmed
	H12b:	IPO	<---	CFAC(M&S)				0	0	confirmed
	C:	IPO	<---	B2C		.136+		.120+	+	borderline
	C:	IPO	<---	ENV		.100		.068	+	not confirmed
	C:	IPO	<---	SIZE(R&D)		-.077			-	not confirmed
	C:	IPO	<---	SIZE(M&S)				-.364**	-	confirmed
	C:	IPO	<---	IND2ROS		-.102		-.079	-	not confirmed
	C:	IPO	<---	REW(R&D)		-.084			+	not confirmed
	C:	IPO	<---	REW(M&S)				.408**	+	confirmed
Indirect Effects:										
	H13	IPO	<---	CFAC <--- FAC		.283***			+	confirmed
	H14	IPO	<---	CFAC <--- FXM		.204**			+	confirmed
	H15	CFAC	<---	FAC <--- IXM		.198***			+	confirmed

Notes: n = 126; $^{+}$< .11, $^{++}$< .07, * < .05, ** < .01 *** < .001; $\chi^2(45) = 30.645$; p = .950; χ^2/d.f. = .681; TLI = 1.142; CFI = 1.00; RMSEA = .000 (90% confidence interval .000 → .003); SRMR = not defined for data with missing values. Significance levels of indirect effects based on two-tailed Sobel-test. Hypotheses regarding zero effects have been tested by constraining the parameters in question to zero and calculate the chi-square difference test statistic to compare it with the unconstrained model. Acceptance based on chi-square difference test always coincided with decision if based on Akaike's Information Criterion (AIC).

For R&D departments it can be confirmed that formal CFI mechanisms (FXM) highly significantly, positively impact CFAC, while informal CFI mechanisms (IXM) have a slightly significant, negative effect on CFAC. Neither one impacts innovation performance directly.

This and all other zero-effect hypotheses were tested by chi-square difference tests of the nested models.

Moreover, I find evidence that these effects of formal and informal CFI mechanisms (FXM / IXM) are as predicted partly inversed when considering M&S departments. Constraining the path of formal CFI mechanisms (FXM) on CFAC to zero for M&S departments significantly improves model fit and the effect of informal mechanisms has a positive rather than negative effect that is significant at 7%. Furthermore, I find support also for the interrelation of FAC and CFAC in that FAC impacts significantly and highly positively on CFAC.

However, neither formal nor informal intra-functional integration mechanisms, FIM and IIM respectively, could be confirmed as positive antecedents of FAC. Since there is thus no direct nor an indirect effect of intra-functional integration mechanisms on innovation performance, this contrasts with previous findings of positive as well as with those finding negative effects. An explanation could be that within functional areas vertical information flows are more important as well as that within functional areas complementarities are realized directly and exclusively in projects and not on the level of departments.

On the other hand, the positive effect of informal integration across functional domains (IXM) is found highly significant for both R&D and M&S departments. In case of the R&D department, the fact that the indirect effect from IXM through FAC on CFAC is highly significant and positive compensates for the negative direct effect of IXM on CFAC, making for an total effect close to zero. Together with the confirmation that the hypothesis of zero effects cannot be rejected for direct paths of IXM onto innovation performance, this might explain previous contrasting results that do find negative, no, or positive effects of integration on innovation performance.

Finally, and maybe most importantly, I can confirm that formal CFI mechanisms (FXM) have the expected significant, positive direct effect on innovation performance for M&S

departments while they do not exhibit such an effect for R&D departments, where as described above, the direct effect is zero but the indirect one is highly significant and positive. This is evidence for the direction of knowledge flow between departments, i.e. that M&S departments do not need CFAC to increase innovation performance because they deliver the required knowledge without the necessity to absorb in turn R&D knowledge. R&D departments on the other hand can use all formal integration mechanisms as much as possible, but without learning how to use them to foster knowledge absorption the effect on innovation performance will remain zero.

III.5.4. Further robustness checks

III.5.4.1. Competing models: More or less paths and Reverse Causality

The doubt that is commonly raised against SEM models concerns the fact that myriads of different model specifications are possible. This is also why the theoretical underpinning of the causal effects is so crucial. However, this is not less the case for OLS regressions, in which implicitly the strong assumption is always made that the various exogenous variables do not cause each other.

We describe some competing models that have been tested and compared to the base model. Since at least one of the two competing models discussed in the remainder of this section is not nested, a comparison by means of a chi-square difference test seems little appropriate. Instead, the Akaike's Information Criterion (AIC) can be used that compares model fit statistics of competing non-nested models based on model parsimony (Schermelleh-Engel, Moosbrugger, & Müller, 2003). The model with the lowest AIC value should be preferred. Three competing models are compared to the original model. All models are based on data with missing values imputed via ML estimation.

In the first model I assume that FAC is not a prerequisite causing CFAC as argued above, but that both variables independently cause innovation performance. This model has been tested and model fit is worse as compared to the base model: The value for AIC is 391.685 (AIC of independence model 643.729; equal for any of the competing models), compared to an AIC value of the base model of 356.645.

In the second model I assume that not only informal (IXM) but also formal (FXM) CFI mechanisms impact FAC, because it is less the informal spontaneous exchange that creates a general culture of knowledge absorption positive also for FAC, but that the more extensively a department seeks to integrate external knowledge also from beyond their functional domain the more they generally know how to integrate. Knowledge about the use of formal integration mechanisms used across domain boundaries could be transferred also to improve the implementation of these same integration mechanisms with the own function and thus improving FAC. Interestingly this model performs slightly better on some fit indexes. However, not only is the effect itself insignificant (p-level .253), but also the chi-square difference test—that is possible in this case since the models are nested—does not indicate a significant difference (p-level .269). Moreover, the AIC is lower in case of the base model as compared to model 2. Taken all findings regarding model 2 together, the base model should be preferred for reasons of parsimony.

Table 9: Competing models compared

Model	χ^2	d.f.	$p(\chi^2)$	χ^2/d.f.	CFI	TLI	RMSEA	AIC
(0) Base model	30.645	45	.950	.681	1.000	1.142	.000	356.645
(1) no FAC→CFAC	67.685	46	.020	1.471	.947	.791	.062	391.685
(2) FXM→FAC	29.425	44	.955	.669	1.000	1.147	.000	357.425
(3) Reverse causality	32.210	44	.906	.732	1.000	1.119	.000	360.210

Finally, I calibrate a model that accounts for reversed causality. In this model I assume that higher innovation performance increases the perception of managers of how able their department is in absorbing new external knowledge. While this model performs better than model 1, it performs worse than the base model, not only based on comparison of the AIC (360.210) but also base on all other model fit indicators except for CFI, which is equally maximized. Table 9 shows an overview of the fit of the different competing models presented juxtaposed to the fit of the main model.

III.5.4.2. Multiple Ordinary Least Squares (OLS) regression

Finally, OLS regression has been applied to confirm the principal hypotheses above. This permits to check for robustness not only in terms of model configuration, but also in terms of an alternative and more common way for industry effects, i.e. by means of the usual industry dummies. All other controls and composite variables are those used in the structural model. Contemporaneously, OLS permits also to check for multicollinearity issues by means of inspection of the variance inflation factors (VIF). Here, all have been found between 1 and 2 (only in the case of IIX in model 4 a VIF of up to 3 has been observed), and thus all are far below the upper threshold value of 10 (Leeflang, et al., 2000). Finally, visual inspection for heteroskedasticity does not suggest such an issue for any of the discussed OLS models (see Figure 14 through Figure 18).

A first important observation is that formal CFI mechanisms (FXM) have generally a positive effect on innovation performance if apart from the controls none of the other main variables are included (cf. model 1 in Table 10). On the other hand, including only FAC and CFAC the previous results are confirmed that only CFAC exhibits a highly significant positive effect on innovation performance (model 2). However, regression on cross-functional integration mechanisms (FXM and IXM) and departmental ACs (FAC and CFAC) contemporaneously crowds out the positive direct effect of FXM as expected and is also shown in the structural base model. Testing more in-depth for difference between the two sub-groups, the overall model becomes insignificant in case of the M&S subgroup (therefore not reported), while for the R&D subgroup the negative effect of IXM on innovation performance is slightly significant. On the other hand, the negative effect of IXM on CFAC could not be confirmed. This is the only noteworthy contradiction to the structural model above, in which no net effect of informal CFI mechanisms has been found. This pinpoints the importance to study the issue by means of panel data in order to better capture the underlying dynamics.

Table 10: Multiple OLS Regression models for core hypotheses

Model nr.: Dependent Variable:	(0) IPO	(1) IPO	(2) IPO	(3) IPO	(4) IPO (R&D)a	(5) CFAC (R&D)
Intercept	(n.s.)	(n.s.)	(n.s.)	(n.s.)	(n.s.)	(n.s.)
(industry dummies)	1 sig. at 5%	2 sig. at 5%	0 sig. at 5%	0 sig. at 5%	0 sig. at 5%	0 sig. at 5%
SIZE	-.116 (.213)	-.110 (.228)	-.098 (.283)	-.095 (.29)	.052 (.679)	-.126 (.250).
REW	.199 (.045)	.172† (.077)	.134 (.182)	.128 (.20)	.014 (.923)	.130 (.285)
ENV	.134 (.160)	.094 (.347)	.064 (.507)	.066 (.50)	.103 (.440)	-.033 (.778)
CNTR	-.064 (.48)	-.078 (.380)	-.047 (.602)	-.057 (.520)	-.014 (.899)	.000 (.998)
B2C	.039 (.674)	.023 (.803)	.054 (.545)	.040 (.654)	.105 (.361)	-.089 (.377)
FXM		.266* (.019)		.228 (.040)	.180 (.237)	.273* (.036)
IXM		-.036 (.757)		-.114 (.359)	-.294† (.091)	-.030 (.841)
FAC			.007 (.958)	.013 (.921)	-.018 (.910)	.526*** (.000)
CFAC			.299** (.008)	.262* (.020)	.573** (.001)	
R^2	,543	,586	.602	,623	.541	,636
Adj. R^2	,295	,343	.362	,389	.333	,482
F Chng.	2, 192** (,006)	2, 449** (,001)	2,658*** (,000)	2,674*** (,000)	2.610** (.002)	4,135*** (,000)

Table shows standardized coefficients with p-values in parentheses.
*Significance levels: †10% * 5%; ** 1%; *** 0.1%*
[a] The F-statistic for this model is not significant for the M&S subgroup.

Another major hypothesis is supported in the last model with CFAC as dependent variable (model 5), which shows that the significantly positive effect of formal cross-functional integration on CFAC is significant. A two-tailed Sobel-test on the indirect effect shows that it is slightly significantly different from zero at 6.5%. Following established practice in testing for mediation effects (Baron & Kenny, 1986; Judd & Kenny, 1981), it can be concluded in conjunction with the finding that the initially direct positive effect of FXM on innovation performance is crowded out in model 3 by CFAC it can be concluded that this is not a simple indirect effect, but completely mediates the relation between FXM and innovation performance.

III.6. Conclusion, Limitations and Future Research

I now summarize the most important outcomes of this study. Firstly, I succeeded to establish a valid and reliable empirical measurement instrument for the previously only theorized (see chapter II) constructs of Functional and Cross-functional Absorptive Capacity (FAC and CFAC respectively). A refinement would be still desirable since it does not yet reflect the theorized multi-dimensionality, but it is an important first step showing the value for future research of conducting a full-fledged scale development, which has to be the next step.

Already now, however, these simpler scales could be used for further inquiries while practitioners might already be able to benchmark their departments based on this scale in order to judge the need to align CFAC with FAC and learn how to learn. This is important since resources are always scarce and if CFAC is already sufficiently high, focus can be put on other likewise important issues. On the other hand, if the R&D department costly developed a high degree of FAC and integration mechanisms are in place to direct research activities but CFAC is low, a good part of potential innovativeness from cross-functional integration is lost. Hence, the second important contribution of this empirical research is that the significant positive mediation of the effect from formal cross-functional integration mechanisms on innovation performance by departmental CFAC could be supported for R&D departments.

A third important contribution is to put forth evidence of a contrasting effect of informal cross-functional integration on CFAC. In fact, it is important to note that informal cross-functional integration mechanisms have a highly significant positive effect on FAC, which is most congruent to a department-level version of higher level AC, while it has contemporaneously a negative effect on CFAC. That is, it improves generally the ability to understand what types of external knowledge from within the own functional domain are most valuable due to the complementarity with other functional domains, but it likewise adds confusion and too much potentially contradictory information that hinders integration from these other functional domains. Since the indirect effect of informal cross-functional integration via FAC on CFAC is highly significant and positive while the direct effect is significantly negative, the total effect on CFAC and hence innovation performance is close to zero. For innovation management theory this is an important deeper understanding of the integration process in that it might explain previously contrasting results in the literature on cross-functional integration and innovation performance. For management practice this shows that informal, spontaneously communication might have serious pitfalls for R&D departments that might be however avoided if managers are aware of them.

This study suffers also several limitations. Firstly, while the relatively limited sample size appears not be a major issue as discussed above, results are limited so far to the Italian context and a cross-national replication would add to the reliability of the generalization of the results. Secondly, the fact that the data is cross-sectional data makes the causal directions hinge fundamentally on the developed theory. It would add to the strength of the causal inference to survey a follow up in one or two years time in order to actually observe the evolution of departmental FAC and CFAC and their impact on innovation performance.

Besides the proposed remedies to the limitations of this study, future research could fruitfully address the issue of intra-firm heterogeneity in the development of these abilities and what that means for example in the context of multinational corporations and globally dispersed innovation activities. On close examination, the application of AC in form of FAC and CFAC on the department level might thus open an important future research stream.

III.7. Appendix A: Figures & Tables

Figure 10: Manufacturing industry sectors in final sample by 2-digit ATECO code

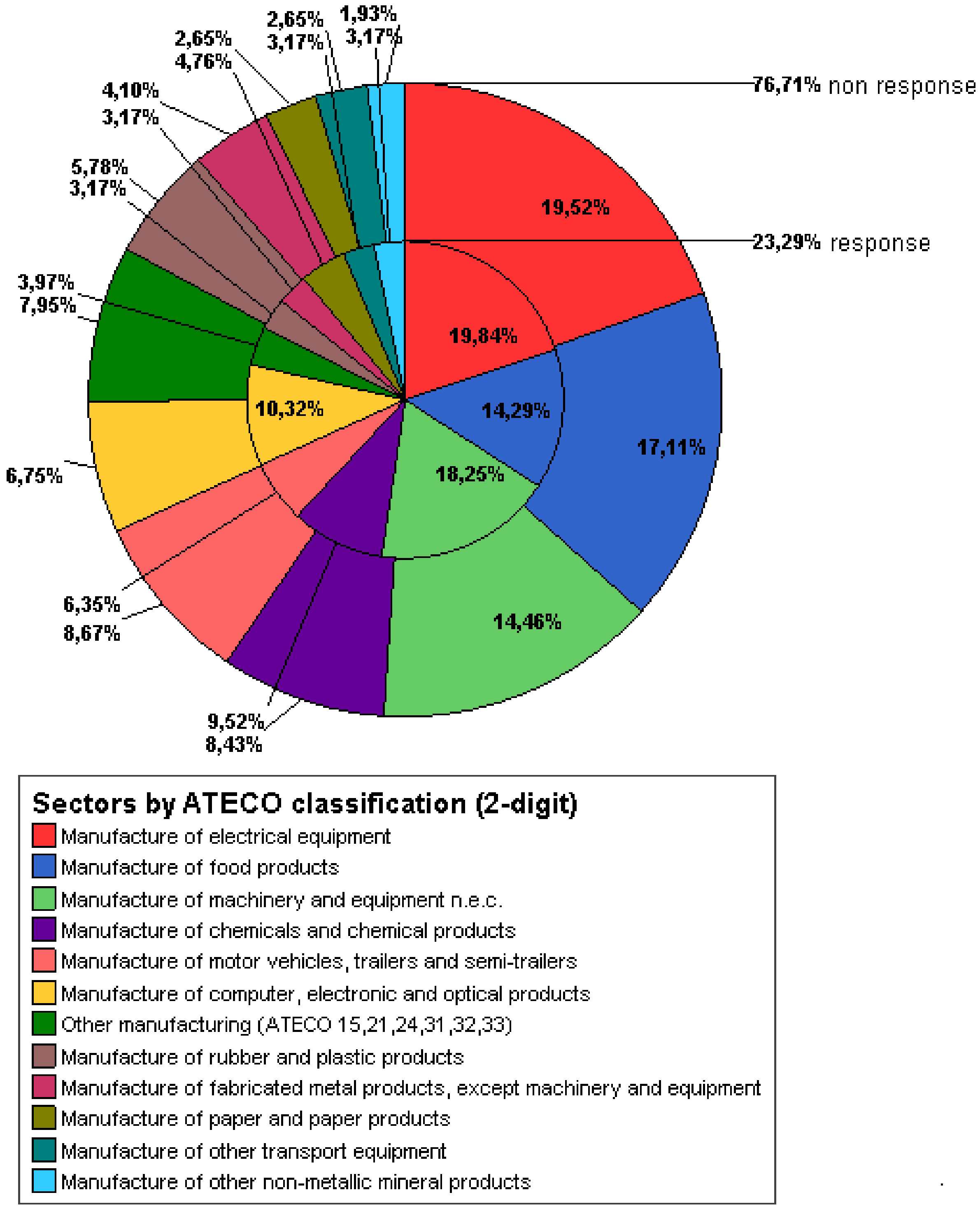


Table 11: Respondents / Non-respondents mean comparison

	Levene's Test		t-test for Equality of Means				
Complete	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
EMPL	.514	.474	.252	521	.801	97.85511	388.23186
PROD	.357	.550	.374	539	.708	100690.69	268887.90
SALES	.331	.565	.374	539	.708	96954.092	258991.85
EBITDA	1.910	.168	.478	539	.633	3563.706	7458.189
EBIT	.972	.325	.565	539	.572	4091.443	7241.009
ROA	.045	.832	-.340	539	.734	-.23984	.70566
ROS	.419	.518	-.319	539	.750	-.22604	.70834
ROE	.526	.469	.822	531	.411	1.53287	1.86488
M&S	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	S.E. Difference
EMPL	.212	.645	-0.316	242	.752	-204.785	647.494
PROD	.041	.840	-0.050	254	.960	-22871.306	453840.910
SALES	.056	.813	-0.058	254	.954	-25189.424	437401.639
EBITDA	.067	.795	-0.683	254	.495	-7399.570	10836.520
EBIT	.000	.998	-0.045	254	.964	-528.504	11757.723
ROA	.096	.757	-0.769	254	.443	-0.860	1.118
ROS	1.904	.169	-1.240	254	.216	-1.349	1.087
ROE	.398	.529	0.417	251	.677	1.260	3.022
R&D	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
EMPL	2.006	.158	0.668	277	.504	320.724	479.779
PROD	1.217	.271	0.637	283	.524	209110.043	328091.088
SALES	1.238	.267	0.645	283	.519	203734.573	315783.477
EBITDA	3.094	.080	1.043	283	.298	10817.585	10374.436
EBIT	1.791	.182	0.815	283	.416	7511.080	9215.089
ROA	.001	.980	0.297	283	.767	.272	.918
ROS	.031	.861	0.624	283	.533	.590	.945
ROE	.132	.716	0.777	278	.438	1.852	2.384

EMPL = number of employees; PROD = total value of production; SALES = turnover from sales;
EBIT(DA) = Earnings before interests tax (depreciation and amortization);
ROA = Return on assets; ROS = Return on sales; ROE = Return on equity

Figure 11: Histogram: Industry Experience (EXPI)

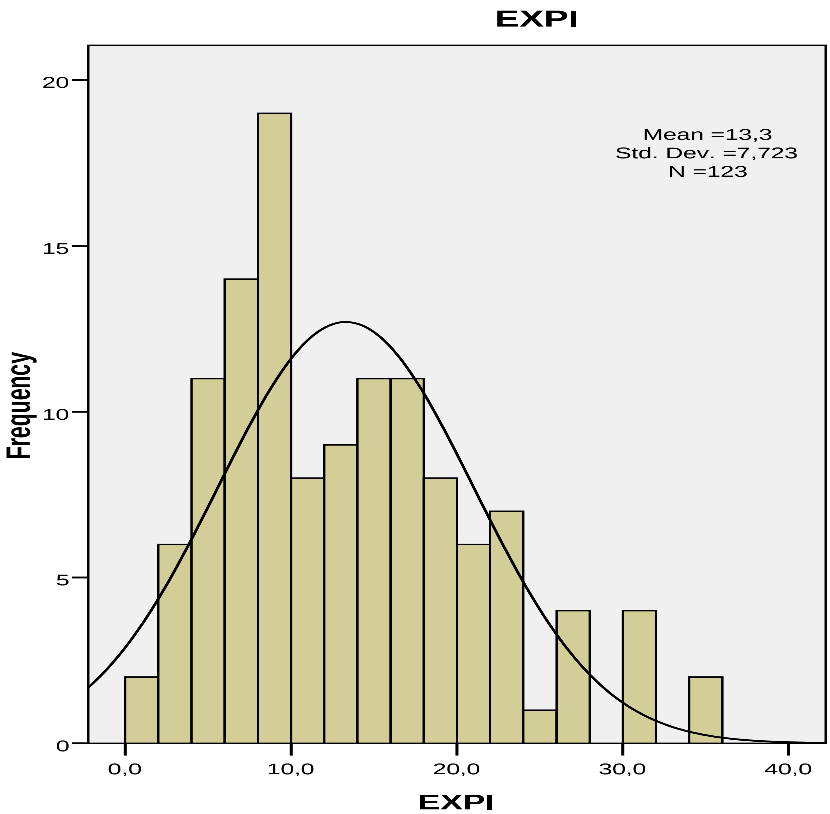


Figure 12: Histogram: Return on Sales (ROS)

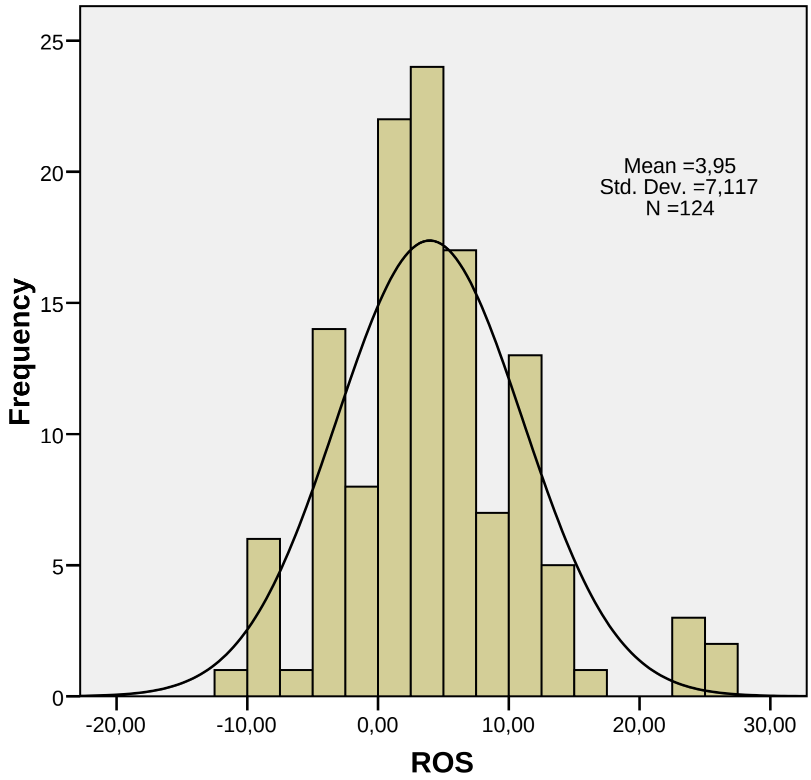


Table 12: Descriptives

	N	Min.	Max.	Mean	Std. Dev.	Skewness		Kurtosis	
	126					Statistic	Std. Error	Statistic	Std. Error
FAC1	125	1,00	7,00	4,3120	1,59847	,005	,217	-,839	,430
FAC2	124	1,00	7,00	3,1694	1,49101	,333	,217	-,637	,431
FAC3	124	1,00	7,00	3,6694	1,61155	,174	,217	-1,102	,431
FAC4	124	1,00	7,00	3,6532	1,74395	,164	,217	-,960	,431
FAC5	124	1,00	7,00	4,1694	1,54983	-,048	,217	-,697	,431
FAC6	124	1,00	7,00	4,2903	1,44140	-,126	,217	-,613	,431
FAC7	124	1,00	7,00	4,1532	1,59799	,073	,217	-,877	,431
FAC8	124	1,00	7,00	3,8790	1,67037	,120	,217	-,917	,431
FAC9	123	1,00	7,00	4,3740	1,50626	-,236	,218	-,586	,433
FAC10	124	1,00	7,00	4,5887	1,50885	-,166	,217	-,710	,431
FAC11	124	1,00	7,00	4,5161	1,52744	-,045	,217	-,815	,431
FAC12	124	1,00	7,00	4,1855	1,32129	,081	,217	-,549	,431
CFAC1	125	1,00	7,00	3,9040	1,49420	-,025	,217	-,495	,430
CFAC2	124	1,00	7,00	3,6855	1,59454	,151	,217	-,567	,431
CFAC3	125	1,00	7,00	3,5120	1,66373	,374	,217	-,863	,430
CFAC4	126	1,00	7,00	3,5238	1,60855	,132	,216	-1,044	,428
CFAC5	126	1,00	7,00	4,1032	1,43571	,212	,216	-,476	,428
CFAC6	124	1,00	7,00	3,9435	1,45559	-,077	,217	-,569	,431
CFAC7	126	1,00	7,00	4,1032	1,44681	-,167	,216	-,691	,428
CFAC8	125	1,00	7,00	4,0400	1,58318	-,129	,217	-,722	,430
CFAC9	126	2,00	7,00	4,1508	1,36860	,142	,216	-,810	,428
CFAC10	126	1,00	7,00	4,2698	1,50950	-,244	,216	-,642	,428
CFAC11	126	1,00	7,00	4,1270	1,46415	,165	,216	-,824	,428
CFAC12	124	1,00	7,00	3,9597	1,34587	,013	,217	-,781	,431
FIM1	124	1,00	7,00	3,9435	1,77747	-,116	,217	-,927	,431
FIM2	125	1,00	7,00	4,0080	1,86000	,011	,217	-,997	,430
FIM3	124	1,00	7,00	4,3226	1,85905	-,282	,217	-,897	,431
FIM4	126	1,00	7,00	2,9762	1,88240	,591	,216	-,790	,428
IIM1	124	1,00	7,00	3,7177	1,85910	,159	,217	-1,026	,431
IIM2	124	1,00	7,00	4,4274	1,79961	-,237	,217	-1,002	,431
IIM3	126	1,00	7,00	4,7143	1,69166	-,498	,216	-,530	,428
IIM4	122	1,00	7,00	4,6148	1,62850	-,243	,219	-,881	,435
FXM1	114	1,00	7,00	3,5175	1,98326	,251	,226	-1,156	,449
FXM2	115	1,00	7,00	3,2783	1,94010	,405	,226	-1,020	,447
FXM3	115	1,00	7,00	3,6609	2,03861	,124	,226	-1,285	,447
FXM4	117	1,00	7,00	2,0171	1,37077	1,542	,224	2,060	,444
IXM1	116	1,00	7,00	3,0603	1,79995	,673	,225	-,509	,446
IXM2	116	1,00	7,00	3,5259	1,90405	,267	,225	-1,144	,446
IXM3	114	1,00	7,00	4,0526	1,84267	,008	,226	-,950	,449
IXM4	114	1,00	7,00	4,0175	1,83372	-,096	,226	-1,100	,449
IPO1	121	1,00	7,00	4,3719	1,25255	-,118	,220	-,290	,437
IPO2	121	1,00	7,00	4,3388	1,22851	,037	,220	-,455	,437
IPO3	122	1,00	7,00	4,3525	1,37223	-,095	,219	-,478	,435
IPO4	121	1,00	7,00	4,4711	1,42638	-,230	,220	-,629	,437
B2C	118	0	9	3,70	3,779	,373	,223	-1,607	,442
ENV1	121	1	7	4,01	1,739	,151	,220	-1,066	,437
ENV2	121	2	7	4,89	1,347	-,238	,220	-,790	,437
ENV3	121	1	7	4,76	1,571	-,277	,220	-,717	,437
ENV4	120	2	7	5,27	1,430	-,692	,221	-,205	,438
ENV5	118	1	7	4,65	1,458	-,165	,223	-,811	,442
REW1	118	1	7	3,70	1,878	,086	,223	-1,078	,442
REW2	117	1	7	3,18	1,878	,482	,224	-,978	,444
REW3	120	1	7	2,87	1,768	,781	,221	-,315	,438
CNTR1	119	1	7	3,35	1,825	,457	,222	-,915	,440
CNTR2	119	1	7	3,23	1,902	,585	,222	-,889	,440
CNTR3	120	1	7	2,97	2,021	,742	,221	-,773	,438
CNTR4	120	1	7	2,69	1,674	,708	,221	-,678	,438
CNTR5	120	1	7	3,11	1,828	,568	,221	-,880	,438
lgEMPL	123	2,33	4,40	3,0771	,41531	,955	,218	1,064	,433
IND2ROS	126	-,96	6,78	3,4077	1,49751	-,990	,216	,948	,428
Valid N (listwise)	85								

Table 13: Pattern Matrix of Rotated Factor Solution of all surveyed variables

	Component														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
FAC9	,814														
FAC10	,807														
FAC11	,801														
FAC7	,794														
FAC12	,758														
FAC5	,745														
FAC6	,721														
FAC1	,667														
FAC4	-,594														
FAC2	-,494						,353								,387
CFAC5		,792													
CFAC11		,766													
CFAC9		,725													
CFAC10		,686													
CFAC12		,608													
CFAC6		,597							,365						
CFAC7	,351	,573													-,342
CFAC1		,539		,329											
CNTR4			,856												
CNTR5			,855												
CNTR1			,823												
CNTR3			,793												
CNTR2			,757												
IXM3				,805											
IXM4				,800											
IXM1				,793											
IXM2				,743											
FXM2				,576										,570	
IPO3					,840										
IPO4					,818										
IPO2					,778										
IPO1					,747										
IIM1						,751									
IIM4						,724									
IIM3						,617								,398	
IIM2						,528					-,417			,406	
FAC3							,730								
CFAC3							,703								
CFAC2							,696								
CFAC4	-,336	-,404					,491								
ENV2								,687							
ENV3								,666							
ENV1								,595		,316					
B2C								-,564				,341			
REW3									,755						
REW2									,694						
REW1									,541						
ENV5										,807					
ENV4										,799					
FIM1						,444					,643				
FXM1				,425							,635				
FXM3				,422								,715			
FIM3						,432						,711			
FXM4													,728		
FIM4						,478							,670		
FIM2														,741	
CFAC8		-,332													,682
FAC8	-,370											-,306			,649

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a Rotation converged in 47 iterations.

Figure 13: Scree Plot of unrotated solution of EFA (PCA) for surveyed variables

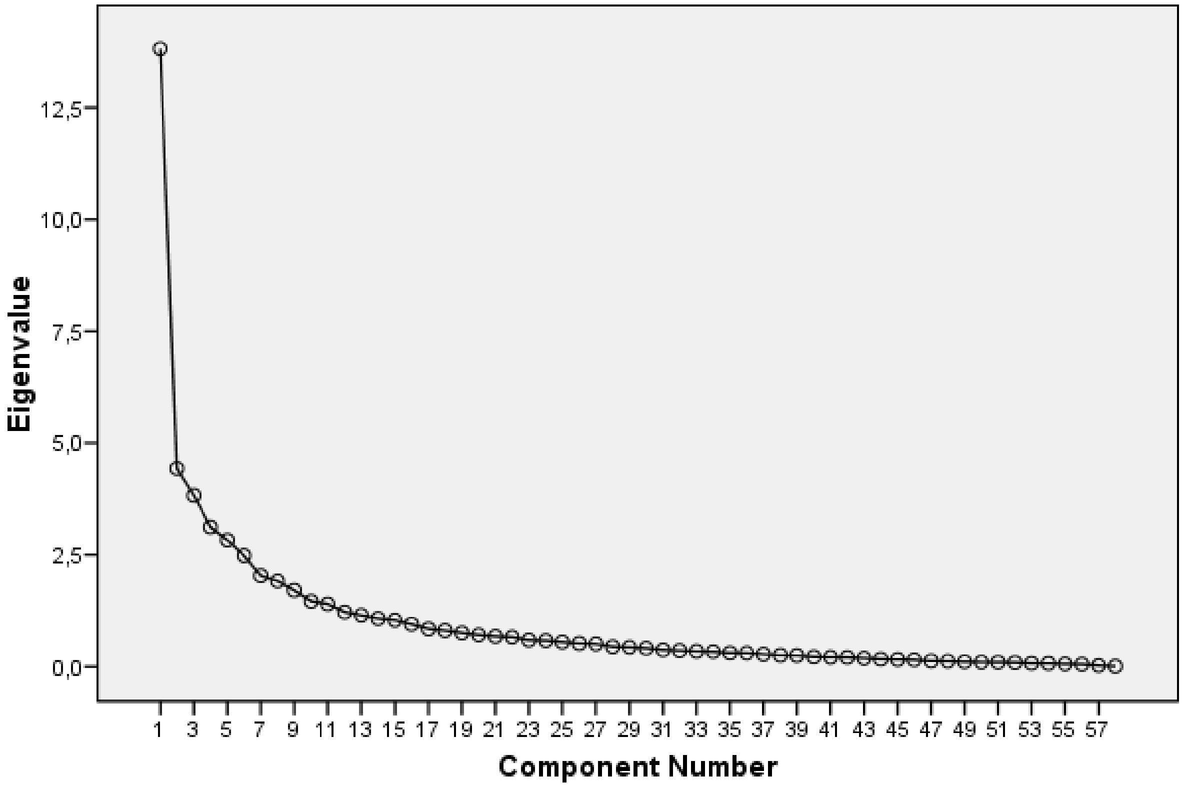


Table 14: Total Variance Explained by PCA for entire measurement model

Com-ponent	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**13,815**	**23,819**	**23,819**	**13,815**	**23,819**	**23,819**	6,949	11,981	11,981
2	4,428	7,634	31,453	4,428	7,634	31,453	4,773	8,230	20,211
3	3,831	6,606	38,059	3,831	6,606	38,059	3,988	6,876	27,087
4	3,120	5,380	43,439	3,120	5,380	43,439	3,980	6,862	33,949
5	2,827	4,874	48,313	2,827	4,874	48,313	3,092	5,331	39,280
6	2,483	4,281	52,595	2,483	4,281	52,595	2,922	5,038	44,318
7	2,037	3,513	56,107	2,037	3,513	56,107	2,589	4,464	48,782
8	1,915	3,302	59,409	1,915	3,302	59,409	2,330	4,018	52,799
9	1,706	2,941	62,350	1,706	2,941	62,350	2,199	3,791	56,590
10	1,461	2,518	64,868	1,461	2,518	64,868	2,014	3,472	60,063
11	1,399	2,412	67,280	1,399	2,412	67,280	1,768	3,048	63,111
12	1,219	2,102	69,382	1,219	2,102	69,382	1,753	3,022	66,133
13	1,149	1,980	71,363	1,149	1,980	71,363	1,738	2,996	69,129
14	1,074	1,852	73,214	1,074	1,852	73,214	1,710	2,948	72,077
15	1,039	1,791	75,005	1,039	1,791	75,005	1,698	2,928	75,005
16	,948	1,634	76,639						
..	..	..	..						
58	,008	,013	100,000						

Extraction Method: Principal Component Analysis.

Table 15: Inter-Item Correlations FAC and CFAC

	FAC1	FAC2	FAC3	FAC4	FAC5	FAC6	FAC7	FAC8	FAC9	FAC10	FAC11	FAC12	CFAC1	CFAC2	CFAC3	CFAC4	CFAC5	CFAC6	CFAC7	CFAC8	CFAC9	CFAC10	CFAC11	CFAC12
FAC1	1	-,388(**)	-,138	-,436(**)	,595(**)	,675(**)	,583(**)	-,256(**)	,579(**)	,637(**)	,612(**)	,559(**)	,402(**)	-,082	-,084	-,300(**)	,259(**)	,429(**)	,488(**)	-,158	,236(**)	,202(*)	,219(*)	,301(**)
		,000	,127	,000	,000	,000	,000	,004	,000	,000	,000	,000	,000	,367	,355	,001	,003	,000	,000	,079	,008	,024	,014	,001
	125	124	124	124	124	124	124	124	123	124	124	124	124	123	124	125	125	123	125	124	125	125	125	123
FAC2	-,388(**)	1	,358(**)	,432(**)	-,382(**)	-,360(**)	-,386(**)	,449(**)	-,380(**)	-,439(**)	-,417(**)	-,350(**)	-,227(*)	,230(*)	,208(*)	,420(**)	-,180(*)	-,235(**)	-,255(**)	,329(**)	-,216(*)	-,171	-,155	-,120
	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,012	,011	,021	,000	,045	,009	,004	,000	,016	,057	,085	,190
	124	124	124	124	124	124	124	124	123	124	124	124	123	122	123	124	124	122	124	123	124	124	124	122
FAC3	-,138	,358(**)	1	,361(**)	-,179(*)	-,154	-,160	,329(**)	-,305(**)	-,307(**)	-,211(*)	-,231(**)	-,254(**)	,362(**)	,448(**)	,467(**)	-,219(*)	-,181(*)	-,069	,362(**)	-,219(*)	-,051	-,182(*)	-,129
	,127	,000		,000	,046	,087	,076	,000	,001	,001	,019	,010	,005	,000	,000	,000	,015	,046	,448	,000	,015	,576	,042	,156
	124	124	124	124	124	124	124	124	123	124	124	124	123	122	123	124	124	122	124	123	124	124	124	122
FAC4	-,436(**)	,432(**)	,361(**)	1	-,474(**)	-,484(**)	-,401(**)	,424(**)	-,513(**)	-,472(**)	-,466(**)	-,561(**)	-,337(**)	,329(**)	,116	,487(**)	-,315(**)	-,357(**)	-,353(**)	,359(**)	-,371(**)	-,297(**)	-,227(*)	-,389(**)
	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,200	,000	,000	,000	,000	,000	,000	,001	,011	,000
	124	124	124	124	124	124	124	124	123	124	124	124	123	122	123	124	124	122	124	123	124	124	124	122
FAC5	,595(**)	-,382(**)	-,179(*)	-,474(**)	1	,695(**)	,597(**)	-,341(**)	,760(**)	,666(**)	,674(**)	,703(**)	,374(**)	-,083	,031	-,358(**)	,438(**)	,446(**)	,465(**)	-,163	,326(**)	,433(**)	,387(**)	,366(**)
	,000	,000	,046	,000		,000	,000	,000	,000	,000	,000	,000	,000	,364	,735	,000	,000	,000	,000	,072	,000	,000	,000	,000
	124	124	124	124	124	124	124	124	123	124	124	124	123	122	123	124	124	122	124	123	124	124	124	122
FAC6	,675(**)	-,360(**)	-,154	-,484(**)	,695(**)	1	,626(**)	-,218(*)	,755(**)	,627(**)	,655(**)	,706(**)	,480(**)	-,024	,031	-,347(**)	,464(**)	,563(**)	,507(**)	-,241(**)	,360(**)	,388(**)	,371(**)	,375(**)
	,000	,000	,087	,000	,000		,000	,015	,000	,000	,000	,000	,000	,792	,737	,000	,000	,000	,000	,007	,000	,000	,000	,000
	124	124	124	124	124	124	124	124	123	124	124	124	123	122	123	124	124	122	124	123	124	124	124	122
FAC7	,583(**)	-,386(**)	-,160	-,401(**)	,597(**)	,626(**)	1	-,243(**)	,678(**)	,667(**)	,710(**)	,579(**)	,280(**)	,037	,027	-,277(**)	,342(**)	,316(**)	,456(**)	-,041	,332(**)	,296(**)	,233(**)	,283(**)
	,000	,000	,076	,000	,000	,000		,007	,000	,000	,000	,000	,002	,690	,770	,002	,000	,000	,000	,649	,000	,001	,009	,002
	124	124	124	124	124	124	124	124	123	124	124	124	123	122	123	124	124	122	124	123	124	124	124	122
FAC8	-,256(**)	,449(**)	,329(**)	,424(**)	-,341(**)	-,218(*)	-,243(**)	1	-,314(**)	-,262(**)	-,297(**)	-,277(**)	-,235(**)	,249(**)	,157	,331(**)	-,028	-,090	-,258(**)	,328(**)	-,110	-,102	-,078	-,136
	,004	,000	,000	,000	,000	,015	,007		,000	,003	,001	,002	,009	,006	,083	,000	,754	,324	,004	,000	,225	,261	,392	,135
	124	124	124	124	124	124	124	124	123	124	124	124	123	122	123	124	124	122	124	123	124	124	124	122
FAC9	,579(**)	-,380(**)	-,305(**)	-,513(**)	,760(**)	,755(**)	,678(**)	-,314(**)	1	,665(**)	,731(**)	,744(**)	,349(**)	-,066	-,040	-,404(**)	,342(**)	,440(**)	,435(**)	-,173	,381(**)	,309(**)	,311(**)	,349(**)
	,000	,000	,001	,000	,000	,000	,000	,000		,000	,000	,000	,000	,469	,663	,000	,000	,000	,000	,056	,000	,000	,000	,000
	123	123	123	123	123	123	123	123	123	123	123	123	122	121	122	123	123	121	123	122	123	123	123	121
FAC10	,637(**)	-,439(**)	-,307(**)	-,472(**)	,666(**)	,627(**)	,667(**)	-,262(**)	,665(**)	1	,689(**)	,650(**)	,208(*)	-,131	,004	-,470(**)	,381(**)	,378(**)	,421(**)	-,213(*)	,308(**)	,310(**)	,253(**)	,288(**)
	,000	,000	,001	,000	,000	,000	,000	,003	,000		,000	,000	,021	,152	,962	,000	,000	,000	,000	,018	,001	,000	,005	,001
	124	124	124	124	124	124	124	124	123	124	124	124	123	122	123	124	124	122	124	123	124	124	124	122
FAC11	,612(**)	-,417(**)	-,211(*)	-,466(**)	,674(**)	,655(**)	,710(**)	-,297(**)	,731(**)	,689(**)	1	,685(**)	,394(**)	-,047	-,022	-,375(**)	,401(**)	,440(**)	,500(**)	-,162	,427(**)	,374(**)	,383(**)	,373(**)
	,000	,000	,019	,000	,000	,000	,000	,001	,000	,000		,000	,000	,605	,810	,000	,000	,000	,000	,074	,000	,000	,000	,000
	124	124	124	124	124	124	124	124	123	124	124	124	123	122	123	124	124	122	124	123	124	124	124	122
FAC12	,559(**)	-,350(**)	-,231(**)	-,561(**)	,703(**)	,706(**)	,579(**)	-,277(**)	,744(**)	,650(**)	,685(**)	1	,411(**)	-,058	,002	-,378(**)	,447(**)	,412(**)	,405(**)	-,195(*)	,345(**)	,420(**)	,328(**)	,407(**)
	,000	,000	,010	,000	,000	,000	,000	,002	,000	,000	,000		,000	,526	,982	,000	,000	,000	,000	,030	,000	,000	,000	,000
	124	124	124	124	124	124	124	124	123	124	124	124	123	122	123	124	124	122	124	123	124	124	124	122
CFAC1	,402(**)	-,227(*)	-,254(**)	-,337(**)	,374(**)	,480(**)	,280(**)	-,235(**)	,349(**)	,208(*)	,394(**)	,411(**)	1	-,269(**)	-,262(**)	-,384(**)	,496(**)	,594(**)	,391(**)	-,264(**)	,432(**)	,425(**)	,535(**)	,509(**)
	,000	,012	,005	,000	,000	,000	,002	,009	,000	,021	,000	,000		,002	,003	,000	,000	,000	,000	,003	,000	,000	,000	,000
	124	123	123	123	123	123	123	123	122	123	123	123	125	124	125	125	125	124	125	125	125	125	125	124
CFAC2	-,082	,230(*)	,362(**)	,329(**)	-,083	-,024	,037	,249(**)	-,066	-,131	-,047	-,058	-,269(**)	1	,406(**)	,334(**)	-,111	-,176	-,043	,149	-,197(*)	-,122	,019	-,188(*)
	,367	,011	,000	,000	,364	,792	,690	,006	,469	,152	,605	,526	,002		,000	,000	,218	,051	,637	,100	,028	,176	,837	,037
	123	122	122	122	122	122	122	122	121	122	122	122	124	124	124	124	124	123	124	124	124	124	124	123
CFAC3	-,084	,208(*)	,448(**)	,116	,031	,031	,027	,157	-,040	,004	-,022	,002	-,262(**)	,406(**)	1	,243(**)	-,112	-,098	-,127	,200(*)	-,209(*)	-,016	-,167	-,096
	,355	,021	,000	,200	,735	,737	,770	,083	,663	,962	,810	,982	,003	,000		,006	,215	,277	,157	,025	,019	,862	,062	,290
	124	123	123	123	123	123	123	123	122	123	123	123	125	124	125	125	125	124	125	125	125	125	125	124
CFAC4	-,300(**)	,420(**)	,467(**)	,487(**)	-,358(**)	-,347(**)	-,277(**)	,331(**)	-,404(**)	-,470(**)	-,375(**)	-,378(**)	-,384(**)	,334(**)	,243(**)	1	-,425(**)	-,487(**)	-,367(**)	,520(**)	-,530(**)	-,362(**)	-,341(**)	-,375(**)
	,001	,000	,000	,000	,000	,000	,002	,000	,000	,000	,000	,000	,000	,000	,006		,000	,000	,000	,000	,000	,000	,000	,000
	125	124	124	124	124	124	124	124	123	124	124	124	125	124	125	126	126	124	126	125	126	126	126	124
CFAC5	,259(**)	-,180(*)	-,219(*)	-,315(**)	,438(**)	,464(**)	,342(**)	-,028	,342(**)	,381(**)	,401(**)	,447(**)	,496(**)	-,111	-,112	-,425(**)	1	,518(**)	,576(**)	-,331(**)	,574(**)	,570(**)	,728(**)	,441(**)
	,003	,045	,015	,000	,000	,000	,000	,754	,000	,000	,000	,000	,000	,218	,215	,000		,000	,000	,000	,000	,000	,000	,000
	125	124	124	124	124	124	124	124	123	124	124	124	125	124	125	126	126	124	126	125	126	126	126	124
CFAC6	,429(**)	-,235(**)	-,181(*)	-,357(**)	,446(**)	,563(**)	,316(**)	-,090	,440(**)	,378(**)	,440(**)	,412(**)	,594(**)	-,176	-,098	-,487(**)	,518(**)	1	,456(**)	-,279(**)	,541(**)	,451(**)	,452(**)	,614(**)
	,000	,009	,046	,000	,000	,000	,000	,324	,000	,000	,000	,000	,000	,051	,277	,000	,000		,000	,002	,000	,000	,000	,000
	123	122	122	122	122	122	122	122	121	122	122	122	124	123	124	124	124	124	124	124	124	124	124	123
CFAC7	,488(**)	-,255(**)	-,069	-,353(**)	,465(**)	,507(**)	,456(**)	-,258(**)	,435(**)	,421(**)	,500(**)	,405(**)	,391(**)	-,043	-,127	-,367(**)	,576(**)	,456(**)	1	-,360(**)	,469(**)	,430(**)	,556(**)	,500(**)
	,000	,004	,448	,000	,000	,000	,000	,004	,000	,000	,000	,000	,000	,637	,157	,000	,000	,000		,000	,000	,000	,000	,000
	125	124	124	124	124	124	124	124	123	124	124	124	125	124	125	126	126	124	126	125	126	126	126	124
CFAC8	-,158	,329(**)	,362(**)	,359(**)	-,163	-,241(**)	-,041	,328(**)	-,173	-,213(*)	-,162	-,195(*)	-,264(**)	,149	,200(*)	,520(**)	-,331(**)	-,279(**)	-,360(**)	1	-,222(*)	-,159	-,328(**)	-,125
	,079	,000	,000	,000	,072	,007	,649	,000	,056	,018	,074	,030	,003	,100	,025	,000	,000	,002	,000		,013	,076	,000	,167
	124	123	123	123	123	123	123	123	122	123	123	123	125	124	125	125	125	124	125	125	125	125	125	124
CFAC9	,236(**)	-,216(*)	-,219(*)	-,371(**)	,326(**)	,360(**)	,332(**)	-,110	,381(**)	,308(**)	,427(**)	,345(**)	,432(**)	-,197(*)	-,209(*)	-,530(**)	,574(**)	,541(**)	,469(**)	-,222(*)	1	,611(**)	,533(**)	,521(**)
	,008	,016	,015	,000	,000	,000	,000	,225	,000	,001	,000	,000	,000	,028	,019	,000	,000	,000	,000	,013		,000	,000	,000
	125	124	124	124	124	124	124	124	123	124	124	124	125	124	125	126	126	124	126	125	126	126	126	124
CFAC10	,202(*)	-,171	-,051	-,297(**)	,433(**)	,388(**)	,296(**)	-,102	,309(**)	,310(**)	,374(**)	,420(**)	,425(**)	-,122	-,016	-,362(**)	,570(**)	,451(**)	,430(**)	-,159	,611(**)	1	,509(**)	,443(**)
	,024	,057	,576	,001	,000	,000	,001	,261	,000	,000	,000	,000	,000	,176	,862	,000	,000	,000	,000	,076	,000		,000	,000
	125	124	124	124	124	124	124	124	123	124	124	124	125	124	125	126	126	124	126	125	126	126	126	124
CFAC11	,219(*)	-,155	-,182(*)	-,227(*)	,387(**)	,371(**)	,233(**)	-,078	,311(**)	,253(**)	,383(**)	,328(**)	,535(**)	,019	-,167	-,341(**)	,728(**)	,452(**)	,556(**)	-,328(**)	,533(**)	,509(**)	1	,384(**)
	,014	,085	,042	,011	,000	,000	,009	,392	,000	,005	,000	,000	,000	,837	,062	,000	,000	,000	,000	,000	,000	,000		,000
	125	124	124	124	124	124	124	124	123	124	124	124	125	124	125	126	126	124	126	125	126	126	126	124

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

Table 16: Inter-Item Correlations IIM & IXM scales

		IIM1	IIM2	IIM3	IIM4	IXM1	IXM2	IXM3	IXM4
IIM1	Pearson's	1	,371(**)	,412(**)	,550(**)	,522(**)	,239(*)	,202(*)	,273(**)
	Sig.		,000	,000	,000	,000	,010	,032	,004
	N	124	123	124	121	114	114	114	112
IIM2	Pearson's		1	,559(**)	,509(**)	,309(**)	,471(**)	,213(*)	,271(**)
	Sig.			,000	,000	,001	,000	,023	,004
	N		124	124	121	115	115	114	113
IIM3	Pearson's			1	,634(**)	,203(*)	,192(*)	,420(**)	,250(**)
	Sig.				,000	,029	,039	,000	,007
	N			126	122	116	116	114	114
IIM4	Pearson's				1	,303(**)	,283(**)	,325(**)	,476(**)
	Sig.					,001	,002	,000	,000
	N				122	112	112	111	112
IXM1	Pearson's					1	,582(**)	,592(**)	,615(**)
	Sig.						,000	,000	,000
	N					116	116	114	114
IXM2	Pearson's						1	,644(**)	,691(**)
	Sig.							,000	,000
	N						116	114	114
IXM3	Pearson's							1	,729(**)
	Sig.								,000
	N							114	112
IXM4	Pearson's								1
	N								114

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

Table 17: Inter-Item Correlations ENV, REW, and CNTR scales

	ENV1	ENV2	ENV3	ENV4	ENV5	REW1	REW2	REW3	CNTR1	CNTR2	CNTR3	CNTR4	CNTR5
ENV1	1	,491(**)	,461(**)	,305(**)	,402(**)	,201(*)	,124	,164	-,043	-,113	,122	-,005	,026
		,000	,000	,001	,000	,029	,183	,074	,639	,222	,185	,958	,778
	121	121	121	120	118	118	116	119	119	119	119	119	119
ENV2		1	,661(**)	,382(**)	,388(**)	,146	,202(*)	,214(*)	-,007	-,112	,134	,034	,016
			,000	,000	,000	,115	,030	,020	,939	,224	,147	,717	,863
		121	121	120	118	118	116	119	119	119	119	119	119
ENV3			1	,378(**)	,408(**)	,237(**)	,336(**)	,251(**)	-,204(*)	-,306(**)	-,068	-,148	-,153
				,000	,000	,010	,000	,006	,026	,001	,460	,109	,097
			121	120	118	118	116	119	119	119	119	119	119
ENV4				1	,711(**)	,254(**)	,131	,202(*)	-,138	-,152	-,062	-,202(*)	-,124
					,000	,006	,162	,028	,136	,101	,505	,029	,181
				120	118	117	116	118	118	118	118	118	118
ENV5					1	,168	,233(*)	,234(*)	-,065	-,078	,059	-,049	-,009
						,073	,013	,012	,487	,404	,527	,599	,926
					118	115	114	116	116	116	116	116	116
REW1						1	,290(**)	,397(**)	-,349(**)	-,387(**)	-,247(**)	-,243(**)	-,221(*)
							,002	,000	,000	,000	,007	,008	,016
						118	116	118	118	118	118	118	118
REW2							1	,529(**)	-,250(**)	-,262(**)	-,106	-,057	-,047
								,000	,007	,005	,255	,541	,612
							117	117	116	116	117	117	117
REW3								1	-,191(*)	-,274(**)	-,088	-,105	-,097
									,037	,003	,338	,254	,292
								120	119	119	120	120	120
CNTR1									1	,648(**)	,528(**)	,692(**)	,707(**)
										,000	,000	,000	,000
									119	119	119	119	119
CNTR2										1	,621(**)	,607(**)	,593(**)
											,000	,000	,000
										119	119	119	119
CNTR3											1	,605(**)	,615(**)
												,000	,000
											120	120	120
CNTR4												1	,728(**)
													,000
												120	120
CNTR5													1
													120

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

Table 18: Inter-item correlations Innovation Performance Objectives Scale

		IPO1	IPO2	IPO3	IPO4
IPO1	Pearson Correlation	1	,591(**)	,584(**)	,521(**)
	Sig. (2-tailed)		,000	,000	,000
	N	121	120	121	120
IPO2	Pearson Correlation		1	,549(**)	,557(**)
	Sig. (2-tailed)			,000	,000
	N		121	121	120
IPO3	Pearson Correlation			1	,772(**)
	Sig. (2-tailed)				,000
	N			122	
IPO4	Pearson Correlation				1
	N				121

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

Table 19: Configural and metric invariance tests

Models		χ^2	*df*	$p(\chi^2)$	*AIC*	*CMIN/df*	*CFI*	*RMSEA*	*SRMR*	*p(BS)*
ML imputation										
Conf	R&D	205.248	155	.004		1.324	.934	.066	-	-
Conf	M&S	208.029	155	.003		1.342	.908	.083	-	-
A	Uncon-strained	413.541	310	.000	713	1.334	.923	.052	-	-
B	Full metric invariance	422.681	324	.000	694	1.305	.926	.050	-	-
	A vs. B	9.139	14	.822						
Mean imputation										
Conf	R&D	196.878	155	.013		1.270	.948	.060	.0721	.452
Conf	M&S	204.055	155	.005		1.316	.919	.080	.0875	.639
A	Uncon-strained	401.203	310	.000	621	1.294	.935	.049	.0721	.604
B	Full metric invariance	410.081	324	.001	602	1.266	.939	.046	.0747	.640
	A vs. B	8.878	14	.839						

Table 20: Correlation Matrix of Composite Constructs (based on data with missing values imputed via ML estimation) and Parcels

		IPO	CFAC	FAC	IIM	IXM	CNTR	FIM	FXM	ENV	REW	SIZE	IND2ROS	B2C
IPO	Pearson	1												
	N	126												
CFAC	Pearson	,411(**)	1											
	Sig.	,000												
	N	126	126											
FAC	Pearson	,371(**)	,615(**)	1										
	Sig.	,000	,000											
	N	126	126	126										
IIM	Pearson	,230(**)	,233(**)	,451(**)	1									
	Sig.	,010	,009	,000										
	N	126	126	126	126									
IXM	Pearson	,190(*)	,425(**)	,510(**)	,482(**)	1								
	Sig.	,034	,000	,000	,000									
	N	126	126	126	126	126								
CNTR	Pearson	-,130	-,147	-,296(**)	-,408(**)	-,039	1							
	Sig.	,146	,101	,001	,000	,666								
	N	126	126	126	126	126	126							
FIM	Pearson	,286(**)	,222(*)	,285(**)	,583(**)	,304(**)	-,196(*)	1						
	Sig.	,001	,013	,001	,000	,001	,029							
	N	124	124	124	124	124	124	124						
FXM	Pearson	,274(**)	,398(**)	,358(**)	,233(*)	,631(**)	-,052	,499(**)	1					
	Sig.	,003	,000	,000	,013	,000	,582	,000						
	N	114	114	114	114	114	114	113	114					
ENV	Pearson	,235(*)	,360(**)	,402(**)	,334(**)	,362(**)	-,136	,331(**)	,248(**)	1				
	Sig.	,011	,000	,000	,000	,000	,143	,000	,010					
	N	118	118	118	118	118	118	117	107	118				
REW	Pearson	,311(**)	,336(**)	,456(**)	,353(**)	,240(**)	-,298(**)	,293(**)	,223(*)	,360(**)	1			
	Sig.	,001	,000	,000	,000	,009	,001	,001	,022	,000				
	N	116	116	116	116	116	116	115	105	114	116			
SIZE	Pearson	-,181(*)	-,017	,059	,042	,065	,003	,036	,028	,071	-,073	1		
	Sig.	,046	,855	,516	,647	,476	,976	,692	,771	,447	,443			
	N	123	123	123	123	123	123	121	111	116	113	123		
IND2	Pearson	-,114	,019	-,093	,028	,031	-,059	,057	,074	,095	,063	-,036	1	
ROS	Sig.	,205	,834	,300	,758	,732	,513	,529	,434	,306	,499	,692		
	N	126	126	126	126	126	126	124	114	118	116	123	126	
B2C	Pearson	,076	-,068	,085	,031	,020	,054	,072	,009	-,142	,063	-,001	-,120	1
	Sig.	,416	,466	,358	,737	,827	,558	,441	,927	,131	,508	,993	,195	
	N	118	118	118	118	118	118	116	107	114	112	115	118	118

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

Table 21: Standardized Residual Covariances for Metric Invariant Measurement Model (R&D)

	CNTR2	CNTR4	IXM3	FAC11	FAC10	FAC5	CFAC11	CNTR5	CNTR1	IIM4	IIM3	IXM2	IXM1	IPO4	IPO3	IPO1	CFAC6	CFAC5	FAC12	FAC9
CNTR2	,158																			
CNTR4	,206	,073																		
IXM3	-,824	,334	,065																	
FAC11	-,557	1,611	-,339	,026																
FAC10	-1,557	,352	,128	,075	-,591															
FAC5	-1,876	,377	,228	-,181	-,453	-,006														
CFAC11	-,448	,241	,875	,446	-,699	,397	,317													
CNTR5	-,166	,048	-,616	,861	-,126	-,412	,930	-,111												
CNTR1	,316	-,048	,310	,263	-,433	-,681	-,202	-,216	-,083											
IIM4	-,268	,501	,063	,663	1,059	,541	1,407	-,816	-,015	,221										
IIM3	,111	,507	,724	-1,628	-,758	-1,061	-,772	-1,083	,812	-,063	-,273									
IXM2	-,704	,302	,111	-,609	,382	,107	,497	,333	1,111	,157	-,857	,073								
IXM1	-,777	-,074	-,177	-,413	,146	,034	1,253	-,898	,100	,095	-,706	-,028	-,186							
IPO4	-,958	,039	,690	,200	,228	,237	,590	-,172	-,693	1,187	,235	,196	,152	-,384						
IPO3	-,330	,364	-,408	,128	-,480	-,299	-,088	,813	-,221	-,469	-,303	-,578	-,340	-,204	,140					
IPO1	-,967	-1,253	1,364	-,264	,304	,499	,312	,171	,272	-,182	,591	1,774	1,344	,066	,373	,235				
CFAC6	-2,040	-,370	,193	1,224	1,217	1,917	,320	-,066	-,079	,437	,040	,817	,851	-,580	-,460	2,066	,299			
CFAC5	-,594	,037	-1,050	-,791	-,708	-,269	,065	,568	-,434	-,479	-,262	-,526	-,303	-,709	,286	-,100	,082	-,345		
FAC12	-1,000	,482	,017	,047	-,314	,123	-,163	-,520	-,499	,485	-,347	,692	,372	-,240	-,143	,088	1,597	,187	,191	
FAC9	-1,225	1,293	-,341	,201	-,579	,138	,135	-,039	-,091	,664	-,780	-,172	-,190	,299	,044	,875	1,701	-,840	,189	,118

Table 22: Standardized Residual Covariances for Metric Invariant Measurement Model (M&S)

	CNTR2	CNTR4	IXM3	FAC11	FAC10	FAC5	CFAC11	CNTR5	CNTR1	IIM4	IIM3	IXM2	IXM1	IPO4	IPO3	IPO1	CFAC6	CFAC5	FAC12	FAC9
CNTR2	-,158																			
CNTR4	-,357	-,137																		
IXM3	-,416	,562	-,074																	
FAC11	,243	1,249	,476	-,035																
FAC10	-,885	-,152	-,942	,716	,836															
FAC5	-,129	-,691	-,738	-,284	,650	,015														
CFAC11	,106	-1,164	-,594	-,263	-,568	-,175	-,338													
CNTR5	-,198	,224	,892	1,311	-,315	-,241	,001	,102												
CNTR1	,048	-,192	,532	-,071	-,407	-,928	-,728	,093	,071											
IIM4	-,214	-,179	-,013	-,782	-,037	,727	-1,203	-,059	,501	-,092										
IIM3	-,457	-,250	,920	,282	,164	,106	-1,077	-,347	,091	,077	,196									
IXM2	-,164	-,175	-,169	,256	-,597	-,424	-,527	,084	,648	-,485	-,422	-,078								
IXM1	-1,439	-,862	,038	,767	,301	,149	-,306	-,967	-1,254	,323	-,070	,324	,212							
IPO4	-,470	-,454	-,221	1,038	1,009	1,259	-,521	-,312	-,691	,572	,262	,263	,500	,394						
IPO3	,291	,158	,172	-,267	-,967	,325	-,591	,364	-,071	-,061	-,242	-,433	,044	,220	-,082					
IPO1	-,338	-,994	,192	-,166	,384	1,074	,731	-,376	,026	-,035	-,302	,916	-,393	-,005	-,254	-,228				
CFAC6	-1,277	-,695	,346	1,235	,367	,079	-,346	-,611	-,666	,449	,239	2,164	1,228	1,800	1,182	1,608	-,323			
CFAC5	-,101	-,598	,090	,629	,573	,267	-,270	,633	-,459	-,157	,043	-,235	,169	,654	-,207	,381	-,307	-,063		
FAC12	-,156	,179	,482	-,274	,356	-,459	-,851	,818	,243	-,642	,103	,225	,885	,497	-,871	,672	-,047	-,543	-,417	
FAC9	-1,072	,693	-,276	-,207	,545	-,104	-1,577	-,047	-,380	,141	,713	-,278	,317	1,279	-,080	,569	,139	-,968	-,321	-,249

Table 23: Measurement model results (missing data imputed by variable means)

Construct	Path			R^2	Standardized Estimate	Construct Reliability	AVE	MSV	ASV
CFAC						.866	.692	.360	.116
	CFAC5	<---	CFAC	1.042[a]	1.021**				
	CFAC6	<---	CFAC	.375	.612**				
	CFAC11	<---	CFAC	.659	.812**				
FAC						.892	.623	.360	.242
	FAC5	<---	FAC	.616	.785**				
	FAC9	<---	FAC	.679	.824**				
	FAC10	<---	FAC	.558	.747**				
	FAC11	<---	FAC	.656	.810**				
	FAC12	<---	FAC	.606	.778**				
IPO						.873	.701	.112	.070
	IPO1	<---	IPO	.471	.686**				
	IPO3	<---	IPO	.915	.956**				
	IPO4	<---	IPO	.717	.847**				
IXM						.830	.620	.262	.117
	IXM1	<---	IXM	.533	.730**				
	IXM2	<---	IXM	.637	.798**				
	IXM3	<---	IXM	.690	.831**				
IIM						.868	.768	.245	.128
	IIM3	<---	IIM	.684	.827**				
	IIM4	<---	IIM	.852	.923**				
CNTR						.896	.684	.298	.134
	CNTR1	<---	CNTR	.770	.877**				
	CNTR2	<---	CNTR	.586	.765**				
	CNTR4	<---	CNTR	.618	.786**				
	CNTR5	<---	CNTR	.763	.874**				

Notes: n = 126; ** < .01 (significance levels based on bias-corrected estimates from 2000 bootstrap samples; therefore also available for fixed parameters); $\chi^2(174) = 241.260$; p(Bollen-Stine) = .159; χ^2/d.f. = 1.387; TLI = .946; CFI = .955; RMSEA = .056 (90%: .038 → .072); SRMR = .0604.
[a] This overshoot is due to a Heywood-case, a negative variance in this item's error term, which is however not significantly different from 0 (a considerable part of the confidence interval is above 0) and can be thus ignored.

Table 24: Structural model results (missing data imputed by variable means)

DV	Hypo-thesis	Path			R^2	Standardized Estimates R&D	M&S	Expected	Result
CFAC (R&D)					.567**				
CFAC (M&S)					.441**				
	H3a:	CFAC	<---	FXM(R&D)		.289*	/	++	confirmed
	H3b:	CFAC	<---	FXM(M&S)		/	0	0	confirmed
	H5a:	CFAC	<---	IXM(R&D)		-.138	/	-	not confirmed
	H5b:	CFAC	<---	IXM(M&S)		/	.212++	+	Borderline
	H8:	CFAC	<---	FAC		.592**	.522**	+	confirmed
	C:	CFAC	<---	REW(R&D)		.18++	/	+	not confirmed
	C:	CFAC	<---	REW(M&S)		/	0	0	confirmed
FAC (R&D)					.338**				
FAC (M&S)					.600*				
	H1:	FAC	<---	IIM		.073	.098	+	not confirmed
	H2:	FAC	<---	FIM		.015	.018	+	not confirmed
	H4:	FAC	<---	IXM		.380**	.447***	+	confirmed
	C:	FAC	<---	CNTR		-.148*	-.187*	-	confirmed
	C:	FAC	<---	IND2ROS		-.079	-.075	+	confirmed
	C:	FAC	<---	REW		.243**	.348**	+	confirmed
IPO (R&D)					.325*				
IPO (M&S)					.361*				
	H6:	IPO	<---	FIFN		0	0	0	confirmed
	H7a:	IPO	<---	FXM(R&D)		0	/	0	confirmed
	H7b:	IPO	<---	FXM(M&S)		/	.243*	+	confirmed
	H9:	IPO	<---	FAC		.057	.044	+	not confirmed
	H10a:	IPO	<---	CFAC(R&D)		.493**	/	++	confirmed
	H10b:	IPO	<---	CFAC(M&S)		/	0	0	confirmed
	C:	IPO	<---	B2C		.126+	.116+	+	borderline
	C:	IPO	<---	ENV		.128	.112	+	not confirmed
	C:	IPO	<---	SIZE(R&D)		-.041	/	-	not confirmed
	C:	IPO	<---	SIZE(M&S)		/	-.369*	-	confirmed
	C:	IPO	<---	IND2ROS		-.061	-.045	+	confirmed
	C:	IPO	<---	REW(R&D)		-.080	/	+	not confirmed
	C:	IPO	<---	REW(M&S)		/	.361*	+	confirmed
Indirect Effects:									
		IPO	<---	FXM		.141*	-	+	confirmed
		IPO	<---	FAC		.293**	-	+	confirmed

Notes: n = 126; $^{+}$ < .11, $^{++}$ < .7; * < .05, ** < .01 *** < .001 (all significance levels, including indirect effects, based on bias-corrected estimates from 2000 bootstrap samples); $\chi^2(45)$ = 38.158; p(Bollen-Stine) = .913; χ^2/d.f. = .848; TLI = 1.053; CFI = 1.00; RMSEA = .000 (90%: .000 → .044); SRMR = .0378.

Table 25: Models based on differently imputed data compared

Model with data imputed via	χ^2	d.f.	$p(\chi^2)$	χ^2/d.f.	CFI	TLI	RMSEA	AIC
(0) ML estimation	30.191	44	.944	.686	1.000	1.137	.000	358.191
(1) variable mean	38.158	44	.913*	.848	1.000	1.053	.000	312.158

* p-value for model (1) based on Bollen-Stine-bootstrap corrected chi-square.

Figure 14: Scatter plot for visiual inspection of homoskedasticity for OLS model 1

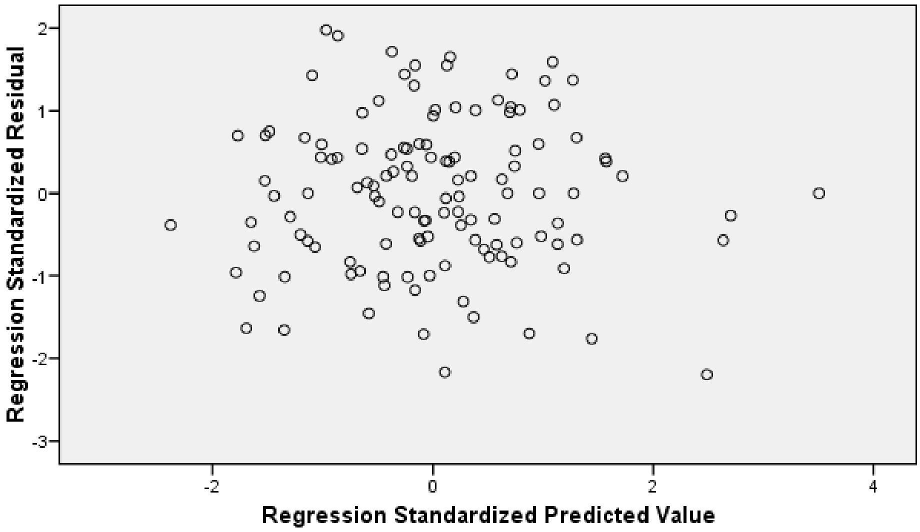


Figure 15: Scatter plot for visiual inspection of homoskedasticity for OLS model 2

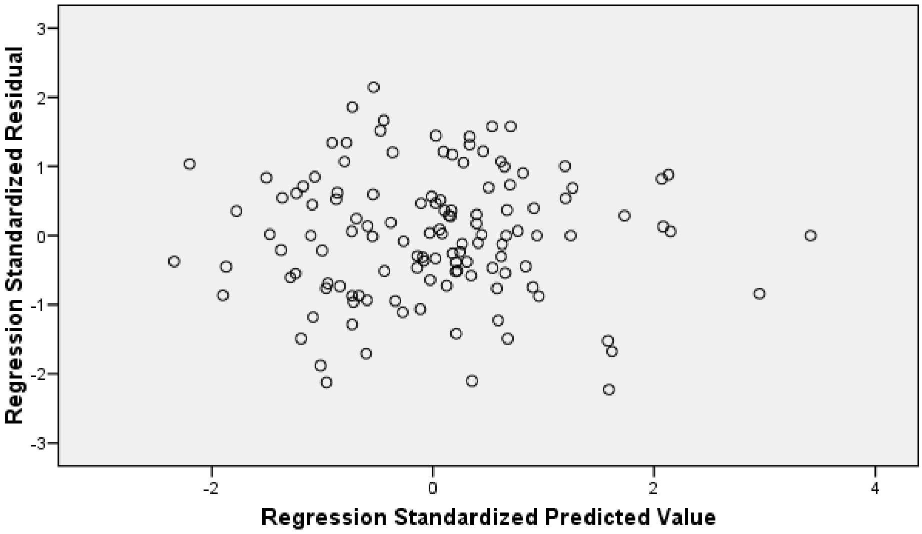


Figure 16: Scatter plot for visiual inspection of homoskedasticity for OLS model 3

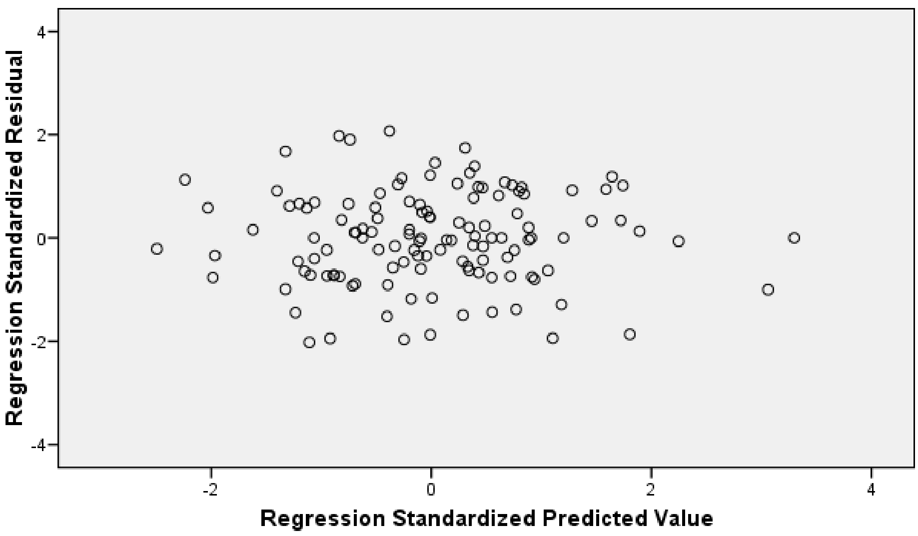


Figure 17: Scatter plot for visiual inspection of homoskedasticity for OLS model 4 (R&D subgroup)

Figure 18: Scatter plot for visiual inspection of homoskedasticity for OLS model 5 (CFAC)

III.8. Appendix B: Questionnaire

Table 26: Informal and Formal, Intra- and Cross-Functional Integration Mechanisms Scales

Coding:	Items:	Item-total correlations:	
Informal Integration (IIM & IXM Scales) (*reflective*) (Zahra & Nielsen, 2002)			
	To what extent does your department use …	**IIM**	**IXM**
IIM1/ IXM1	*(a) free exchange of operating and financial information, with other departments of the (*own/other function+*)*	†	.662
IIM2/ IXM2	*(b) bypassing of formal communication channels, as needed, with other departments of the (*own/other function+*)*	†	.684
IIM3/ IXM3	*(c) informal relationships for getting things done, with other departments of the (*own/other function+*)*	.673	.726
IIM4 / IXM4	*(d) maintains open communication channels in its operations with other departments of the (*own/other function+*).*	.673	†
	Cronbach's Alpha:	.804	.831
	Composite reliability:	.810	.832
		Weights	
Formal Integration (FIM & FXM Scales) (*formative*) (Gupta & Govindarajan, 2000; Jansen, Van den Bosch, & Volberda, 2005)	*To what extent does your department use:*	**Extant scale**	**Extended scale (FIM/ FXM)**
FIM)1 / FXM1	*(e) liaison personnel with other departments of the (*own/other function+*)*	1	1
FIM2 / FXM2	*(f) temporary task forces with other departments of the (*own/other function+*)*	2	2
FIM3 / FXM3	*(g) permanent teams with other departments of the (*own/other function+*)*	3	3
FIM4 / FXM4	*(h) job rotation with other departments of the (*own/other function+*)*	N.A.	1

(1) "No or very little extent" … (7) "Very large extent"
† Item deleted.
+ (own function) replaced with "R&D function" for R&D departments and "M&S function" for M&S departments (IIF); (other function) replaced with "M&S function" for R&D departments and "R&D function" for M&S departments (IIX).

Table 27: Innovation Performance

Coding	Items (Atuahene-Gima et al., 2005; De Luca & Atuahene-Gima, 2007; Foss et al., 2011) *(reflective)*	Cronbach's Alpha if item deleted	Item-Total corr.:
	Rate how your business unit is performing on the following new product development objectives relative to your firm's stated objectives:		
IPO1	- *Market share*	.870	.601
IPO2	- *Sales*	†	†
IPO3	- *ROI*	.695	.785
IPO4	- *Profitability*	.745	.737
	Cronbach's Alpha:	.840	
	Composite Reliability:	.848	

Items measure on the following scale: 1 – "much worse" … 7 – "much better".

Table 28: Intra- and Cross-Functional Absorptive Capacity Scales

Coding:	**Item:** *Members of our department…***	**Based on:**	**Cronbach's Alpha if item deleted: FAC**	**Cronbach's Alpha if item deleted: CFAC**	**Item-Total correlations: FAC**	**Item-Total correlations: CFAC**
FAC1/ CFAC1	*... find and access without problems useful information and expertise of other departments.*	Hansen & Nohria (2004)	†	†	†	†
FAC2 / CFAC2	*... experts with useful knowledge are difficult to locate in the other departments. (r)*	Hansen & Nohria (2004)	†	†	†	†
FAC3 / CFAC3	*... have difficulties to find useful documents and information in the company's databases and knowledge-management systems. (r)*	Hansen & Nohria (2004)	†	†	†	†
FAC4 / CFAC4	*... are slow to recognize shifts in our «technological»/«market» environment (e.g. recent discoveries, emerging «technologies»/«markets», new trends). (r)*	Jansen, et al. (2005)	†	†	†	†
FAC5 / CFAC5	*... quickly analyze and interpret changing opportunities of «technologies»/«markets».*	Jansen, et al. (2005)	.916	.676	.808	.704
FAC6 / CFAC6	*... structure and integrate new external knowledge with ease.*	Jansen, et al. (2005)	.918	.811	.791	.573
FAC7 / CFAC7	*... quickly recognize the usefulness of new external knowledge even if this contests existing convictions and ways of thinking.*		†	†	†	†
FAC8 / CFAC8	*... laboriously grasp the opportunities from the kind of new external knowledge that requires a fundamental change in our way of working. (r)*	Jansen, et al. (2005)	†	†	†	†
FAC9 / CFAC9	*... recognize timely the consequences of new external knowledge to our mode of operation.*	Flatten, Engelen, Zahra, & Brettel, (2011)	.912	†	.841	†
FAC10 / CFAC10	*... are able to apply new external knowledge in their practical work.*	Flatten, et al. (2011)	.922	†	.763	†
FAC11 / CFAC11	*... regularly reconsider their knowledge and adapt it according to new external knowledge.*	Jansen, et al. (2005)	.920	.702	.778	.680
FAC12 / CFAC12	*... know to share and apply new external knowledge with those in our department who is most apt.*	Szulanski (1996)	.917	†	.804	†
		Cronbach's Alpha:	.93	.804		
		Composite Reliability:	.931	.811		

** Items measure on the following scale: 1 – "No or very little extent" … 7 – "Very large extent".
* *The first value indicates the individual item SMCs for the R&D sub-group, the second value those for the M&S sub-group.*
(r) Reversed item.
† Item deleted.

Table 29: Control Variables

	Items	Cronbach's Alpha if item deleted	Item-Total corr.:
Centralization (CNTR) Javorski & Kohli (1993) *(reflective)*			
	Please indicate how much you agree or disagree with the following statements: *(1= No or very little extent … 7= Very large extent)*		
CNTR1	- *There can be little action taken here until a supervisor approves it.*	.839	.780
CNTR2	- *A person who wants to make his own decision would be quickly discouraged here.*	.877	.684
CNTR3	- *Even small matters have to be referred to someone higher up for a final answer.*	†	†
CNTR4	- *I have to ask my boss before I do almost anything.*	.846	.768
CNTR5	- *Any decision I make has to have my boss' approval.*	.844	.768
	Cronbach's Alpha:	.884	
	Composite Reliability:	.887	
Rewards and Incentives (REW) Javorski & Kohli (1993) *(formative)*			
	To what extent do you agree or disagree with the following statements:		
REW1	- *No matter which department they are in, people in this business unit get recognized for being sensitive to competitive moves.*		
REW2	- *Customer satisfaction assessments influence senior managers' pay in this business unit.*		
REW3	- *Formal rewards (i.e. pay raise, promotion) are forthcoming to anyone who consistently provides good market intelligence.*		
Environmental turbulence (ENV) Verhoef & Leeflang (2009) *(formative)*			
	Can you indicate the level of change in the last three years in the most important market where your firm was active on the following elements		
ENV1	- *production/process technology*		
ENV2	- *introduction of new products/services*		
ENV3	- *R&D activities*		
ENV4	- *Competitive intensity*		
ENV5	- *Customer preferences*		
	(1=no change … 7= very frequent changes)		
Business-to-Consumer-Scale (B2C) Verhoef & Leeflang (2009)			
	Please indicate the percentage of your turnover that arise from B2B or B2C markets: B2C … (10) B2B		

IV.
How much Knowledge Integration in MNCs? An Agent-based Model to find the Optimal Degree of Knowledge Integration Considering Environmental Complexity and Turbulence[7]

Abstract In today's knowledge economy, it is vital for MNCs (Multi-National Corporations) to leverage all their globally dispersed knowledge resources. Extant literature argues that MNCs can be viewed as knowledge sharing networks and that knowledge exchange within the group enhances performance. But mere knowledge transfer differs from intra-MNC collaboration on innovative projects. However, literature on Open Innovation is largely focused on the external boundary of the firm, so that little can be said on whether openness towards corporate group internal knowledge sources is either or both, beneficial and detrimental, and how this depends on the difference of national industries and on the correct communication of these before the final transfer of knowledge.
The principal research question thus is: To what degree should MNC subsidiaries be open to their intra-MNC peers given a common, evolving technological environment but different local market contexts?
In this chapter, we make a first attempt to theorize this issue by means of proposing an agent-based model that is analyzed through computer simulation. We explore the degree of openness of MNC subsidiaries together with their communication competence in different organizational structures and environments, based on previous developments in theory of knowledge transfer and complexity as well as international business.

Keywords. Knowledge Integration, MNC, Intra-Firm Knowledge Transfer, Agent-Based Model, Computer Simulation

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[7] This chapter is based on Hausberg, Sabini, & Valentino (2013), How much Internal Open Innovation in MNCs? An Agent-based Model to find the Optimal Degree of Knowledge Integration Considering Environmental Complexity and Turbulence under bounded rationality. *Forthcoming in the International Journal of E-Services management and Mobile Applications (IJESMA)*.

IV.1. Introduction

The concept of knowledge transfer within the MNC and its impediments have received increasing attention in the international business literature since the seminal work of Dunning (1981). In fact, the MNC can be considered as a “knowledge based entity”, where different units seek to transmit, transfer, integrate and leverage knowledge across national boundaries (Foss & Pedersen, 2004) and its raison-d’être has been claimed to lie exactly in its superior capacity to transfer knowledge across national boundaries (Kogut & Zander, 1993). It has been suggested that knowledge transfers within the MNC take place within the context of an inter-organizational “network” of differentiated units (subsidiaries) (Bartlett & Ghoshal, 1990; Gupta & Govindarajan, 2000; Hendlund, 1986). MNC subsidiaries have been recognized not only as mere exploiters of knowledge that is centrally held by the MNC, but also as generators of knowledge in their own right and a way to tap locally the internationally distributed knowledge (Kuemmerle, 1997). Increasingly, also the lateral knowledge exchange, i.e. that directly among the subsidiaries, is focus of studies of intra-MNC knowledge transfer (e.g. Gupta & Govindarajan, 2000). This follows in analogy to the development of the concept of Open Innovation on the overall firm level (Chesbrough, 2003). Chesbrough – and large part of the literature following him – argues that knowledge has become too complex and the environment to turbulent as to continue to manage the innovation process in a closed, stand-alone manner.

We assume that the increased attention to intra-MNC knowledge transfer is due to the fact that subsidiaries that aim at knowledge and innovation generation but contemporaneously compete with their peer subsidiaries in the MNC network on resources, charter amplification, and headquarters’ attention have to open their search process to the expertise of the very peers with which they compete. MNCs that incentivize or else foster the opening of the innovation process of their subsidiaries in this direction, i.e. towards their intra-MNC peers, can be thus said to apply "internal open innovation" (IOI). But necessarily the question arises whether this IOI is always beneficial for the MNC, that is what factors could constitute important contingencies.

As far as regards innovation as an adaptive process, environmental uncertainty has been found a major contingency co-determining the efficacy of various approaches to innovation (Eisenhardt & Tabrizi, 1995). Environmental uncertainty is usually regarded as determined mainly by the two factors "environmental complexity" and "environmental dynamism" (Duncan, 1972). This impact of environmental uncertainty on innovation is in large part the result of the potential for erosion or depreciation of the value of existing knowledge in that becomes outdated. In so far, environmental uncertainty, or concretely its dynamism and complexity, can be deemed to be major contingencies of the effectiveness of IOI as well.

On the one extreme, there are low complexity, low dynamic industries and on the other one, there are highly dynamic high-tech industries. In between there are industries that are very dynamic but not very complex, as for example a large part of the so-called "fast moving consumer goods", which exhibit a large amount of fast fading trends without being actually high-tech products in most cases, while other industries present a considerable degree of complexity, but exhibit – at least periodically – little dynamism, as is the case for example for some electronics industries. However, while environmental uncertainty has been studied broadly with regard to its impact on both innovation and firm performance, it remains unclear how its two major constituencies – complexity and dynamism – do individually affect the appropriateness of intra-MNC IOI in terms of innovativeness, particularly considering that subsidiaries of an MNC might be exposed to different market contexts even if the technological environment with which they deal is the same.

This casts doubt on a simple linear relationship between knowledge integration and innovation performance in the sense "the more the better". We recognize in this a major research gap that is gaining relevance due to the fact that today's knowledge economies increasingly augment in both complexity and dynamism in a large variety of industries. This leads inevitable to the question of what is the optimal degree to which MNC subsidiaries should openly exchange knowledge with their intra-MNC peers given a common, evolving technological environment but different local market contexts.

We approach this research question by means of an agent-based computer simulation model. This model permits us to get a clear picture of the relations between IOI and the two environmental contingencies, complexity and dynamisms. We test furthermore whether our findings are altered by the degree to which the local country market actually is important to the MNCs, that is whether the MNC is innovating in an international industry that is characterized by very different demands in different countries or in a global industry that is characterized by rather homogeneous demand worldwide. Finally, we check whether findings are robust for different degrees of interdependence between knowledge areas.

We find that environmental complexity substantially alters the effect that exhibits environmental dynamism on the broadly positive effect of IOI. While in the case of low complexity environments, we find an inverse u-shaped effect of dynamism on IOI effectiveness, this effect is largely linear in complex environments. That means that highly dynamic environments are most impacted by the degree of complexity. While in low complexity environments, we do not find a significant effect of IOI on innovation performance, in high complexity environment is not only highly significant but exhibits also the highest impact on innovation performance.

In the following section we discuss the theoretical background of the concepts on which we build our model that we describe in detail in the subsequent section. Following the model description we analyze the results and present our propositions based thereupon before we finally discuss in the conclusion implications for future research and management practice.

IV.2. Theoretical Background

IV.2.1. Innovation in the MNC

Innovation has been defined at all possible levels of analysis from the individual to transnational organizations (Scott & Bruce, 1994; Wolfe, 1994). What is common to the vast majority of the relevant literature though is that innovation is understood not as a mere invention, but rather as the commercially successful application of an invention, be it in form of products, production processes, services, or organizational procedures, structures, governance mechanisms or else.

Firms are increasingly driven to internationalize both from the supply side as well as the demand side, in that pressure to internationalize their innovative activities comes from the fact that knowledge has to be sought globally in an increasing number of industries and pressure to internationalize sales activities comes from increasing competition maturing home-markets and/or increasing growth opportunities in emerging market countries. However, the technology underlying inventions—be it products, processes, or services—might be universally the same, but the value that is attributed to them is defined by the market demand which can be rather heterogeneous across national markets. In fact, the principal difference between international industries vis-à-vis global industries is that the former exhibit considerable demand-side heterogeneity across country markets, whereas truly global industries do not (Ghoshal & N Nohria, 1993). Firms that compete worldwide in international industries respond to this circumstance by investing more in local subsidiaries in order to be closer to the market and adapt their overall knowledge base to the local requirements. Since the underlying technology might however still be globally the same, an essential part of knowledge can potentially be very valuable to peers.

In fact, in line with social capital theory, which holds that the ties held by members of a network permit them to exchange social resources and thus create value (Bourdieu, 1986), extant literature in international business claims that the MNC as a whole can be understood in terms of a network in which various organizational sub-units (the subsidiaries) can be more or less inclined to share knowledge among each other (Bartlett & Ghoshal, 1990). The exchange of knowledge between organizational units has indeed become a main focus of the resource based view in form of the Knowledge Based View of the firm (Spender & Grant, 1996; Grant, 1996). In fact, the higher ability of firms vis-à-vis markets to transfer knowledge is seen as one if not the raison-d'être of the MNC (Kogut & Zander, 1993).

According to early theories on how knowledge, or more generally firms' intangible assets, can influence the internationalization process, knowledge is spawned at the home base and subsequently diffused among the firm's international business units as new products or processes (Almeida & Phene, 2004). On basis of a large number of case studies it was found that the organization of international innovation can exhibit further schemes. Bartlett & Ghoshal (1990), proposed four organizational approaches to international innovation: (1) the classical 'centre-for-global', (2) its extreme counterpart 'local-for-local', where internationally dispersed R&D sites work on new products and processes for their respective location, (3) 'locally-leveraged', where local R&D-resources are used to develop innovations for the global market, thus rather 'local-for-global', and (4) 'globally-linked', where resources and capabilities of internationally dispersed R&D sites are pooled to jointly innovate. Each organizational form has its specific advantages and disadvantages.

Therefore, it has been noted that both, the degree of innovation and internationalization, can differ sensibly between different corporate functions. It has been found, for example, that commonly the R&D function is less internationalized than production and sales (e.g. Zedtwitz & Gassmann, 2002). Moreover, also in divisionally structured MNCs the charters of the various subsidiaries might have clear foci on either competence exploration or competence exploitation. This has also been termed 'home-base augmenting' or 'home-base exploiting' (Kuemmerle, 1997) and is closely related to the resulting predominant innovation behavior of subsidiaries, which has been classified for example into local market, internal market, and global market initiatives (J. Birkinshaw & Hood, 1998).

To be able to manage a portfolio of subsidiaries with different objectives means to have the opportunity to balance exploration and exploitation (March, 1991) at the international corporate group level. To achieve ambidexterity, i.e. equal ability to explore and exploit knowledge, by means of leveraging the hence globally dispersed knowledge of subsidiaries requires intra-organizational knowledge integration across national boundaries (e.g. Gupta & Govindarajan, 2000).

In comparison to the literature on open innovation, which is characterized by very high degrees of collaboration and/or integration with firm-external environment in the innovation process, in this work we focus on the "internal" open innovation, in the sense that the openness of the subsidiaries refers to the degree to which subsidiaries seek knowledge from their peer subsidiaries within the MNC to which they belong in order to enhance their innovation performance. Therefore, we develop our model as considering the MNC as a network of knowledge based entities, where these different units seek the most appropriate knowledge across national boundaries (Foss & Pedersen, 2004). MNCs are complex multi-dimensional entities, in which knowledge flows occur not only along multiple directions but also across multiple dimensions (Gupta & Govindarajan, 2000).

IV.2.2. Internal Open Innovation

Openness is generally understood as the willingness to share knowledge (Albino, Garavelli, & Schiuma, 1998; Chesbrough, 2004; Hamel, 1991). Wathne, Roos, & Von Krogh (1996) argue that "openness can be understood in terms of overall perceived openness of dialogue, the degree to which the partner representatives work closely together on a common task, and the degree to which the partner representatives perceive that the others withhold their knowledge"

(Wathne et al., 1996). Research in Open Innovation is increasingly considering different levels of openness. Gassmann & Enkel (2004), underline the need to transform "a company's solid boundaries into a more semi-permeable membrane to enable innovation to move more easily between the external environment and the company's internal innovation process", thus underlining the bi-directionality of the concept. Furthermore, Chesbrough (2002, 2003), describes the need for a shift of organizational innovation strategy into a more flexible open innovation approach at different levels, thus eventually pointing also to the consideration of openness of subsidiaries.

In line with Jerez-Gómez, Céspedes-Lorente, & Valle-Cabrera (2005), who consider individual level openness, it can be argued that also MNCs have to commit to a culture of knowledge exchange—or even explicitly incentivizing it—in order to build a climate of openness and avoid the rejection of outside knowledge without consideration of its actual value, i.e. avoid forms of the not-invented-here syndrome (Katz & Allen, 1982). This can be achieved by countering the formation of "egocentric attitude", that is a potentially detrimental inclination of considering the value of the centrally developed knowledge, strategies or culture as better than that of the rest of the group (McGill, Slocum, & Lei, 1992). A similar negative consequences of sticking too firmly to the once developed own knowledge is the possibility that this previously valuable knowledge changes its character from a core-competence to a core-rigidity due to environmental dynamism (Leonard-Barton, 1992).

We focus on the subsidiary level in the context of internal MNC-networks, arguing that differences across industries regarding the heterogeneity of their various national markets, i.e. the degree to which a certain industry is rather global or rather international, determines how the internal openness of subsidiaries in an MNC-network structure impacts innovation performance.

In particular, we define Internal Open Innovation (IOI) as the behavior of subsidiaries to actively search for innovation partners amongst their peer subsidiaries in other divisions and countries throughout the entire MNCs and providing the entire knowledge stock to their intra-MNC peers if asked for[8]. Since subsidiaries in MNCs compete with each other on resources, power, autonomy and/or headquarters' attention (Mudambi & Navarra, 2004), reasons similar to those theorized for firms in general might thus drive them to apply innovation strategies that are rather closed with respect to the MNC or even prefer knowledge from their local environment over that from their MNC-internal peer subsidiaries as a particular variation of the classic not-invented-here syndrome (Katz & Allen, 1982).

IV.2.3. Environmental dynamism and complexity

Superior knowledge can constitute a resource advantage, which has been recognized long since in strategic management as a way to successfully cope with hypercompetition although this kind of advantage is also claimed to be not sustainable (D'Aveni, 1994). Therefore, this fundamental assumption of the RBV (Barney, 1991) might not apply to very dynamic and complex environments, while at the same time – seemingly paradoxically – it might account as the reason for the development of the KBV (Grant, 1996) since it is in this environments that cutting-edge knowledge can appropriate enormous value in the short period before it depreciates.

To some degree, complexity and dynamism are interwoven (Aldrich, 1979). Given that in complex environments the different dimensions depend in their effects on the states of a relatively high number of other dimensions, a particular degree of change in dimensions in complex environments will evoke higher performance landscape changes than the same degree of change causes ceteris paribus in less complex environments. This might also explain why they are often investigated together in form of environmental uncertainty.

[8] In the following, we refer to IOI when we intend the parameter of individual MNC subsidiaries and to knowledge integration (KI) when referring to this parameter on the MNC level relating it to overall MNC performance.

Eisenhardt & Tabrizi (1995) for example find a moderating effect of environmental uncertainty on the effectiveness of two opposed product innovation strategies. However, it is not further investigated how the two principal components of uncertainty, i.e. dynamism and complexity, interact to produce such an effect nor whether this effect holds true also for knowledge transfer across countries. Moreover, it has been contested recently that more knowledge transfer is always better, arguing that it varies across firms and their respective environmental contexts (Reus, Ranft, Lamont, & Adams, 2009). Indeed, this intuition has been long since theorized in form of the "interpretive systems view" or sense-making (Daft & Weick, 1984). Consequently, Reus and colleagues theorize, that firms might well over- and under-invest into knowledge acquisition and transfer.

IV.2.4. Knowledge integration in MNCs

In international business literature, scholars have given substantial attention to the knowledge transfer process among different units (Bartlett & Ghoshal, 1990; Gupta & Govindarajan, 2000; Kogut & Zander, 1992; Mudambi & Navarra, 2004). Knowledge transfer can be understood as the "process through which one unit exerts influence on other units" (Argote & Ingram, 2000). Szulanski (1996, 2000) argues that transfer of knowledge is best understood by identifying and defining its various sub-processes or stages. This process is divided in his framework into four parts: initiation, implementation, ramp-up, and integration. While acknowledging the merits of this framework, we apply a somewhat more basic one herein. In particular, we distinguish two steps, the source evaluation stage and the knowledge transfer stage. Both together taking place at the level of subsidiary lead to knowledge integration at the level of the MNC. In both stages knowledge is transferred, but different one.

In the evaluation phase, organizational units have to search among their contacts within (and as possible beyond) their ego-network—which herein are subsidiaries that search among the entire set of their peer subsidiaries within the MNC group—those partners that are most probably able to contribute to the searcher's innovative activities. Therefore, they the knowledge that has to be transferred is such that permits the searching subsidiary to evaluate whether the source's technological knowledge might be fruitfully applied in the own market context. Hence, market contexts have to be compared and to this end knowledge has to be transferred regarding each potential source's market context.

In the second, the transfer stage, the four stages initiation, implementation, ramp-up, and integration can be collocated and requires a good fit between the partners. In fact, Szulanski (1996) finds that the degree of performance in sharing the knowledge between two entities depends on how the distance between these two entities (communicative gap) is bridged. According to the knowledge based view, several further very different reasons might inhibit successful knowledge exchange, such as geographical distance—particularly relevant in international settings—and stickiness—particularly relevant in knowledge intensive industries. These points have been raised in RBV literature (J. S. Brown & Duguid, 1991), in knowledge transfer literature (Szulanski, 2000) and in MNC literature (Bartlett & Ghoshal, 1990; M. T. Hansen, 1999; Kogut & Zander, 1992, 1993). For example, the way in which knowledge is transferred most successfully might vary from case to case according to the repository in which the knowledge is embedded. Several classes have been theoretically distinguished in that knowledge can be embedded. Walsh & Ungson (1991), for example, distinguish organizational members, physical and functional design, routines, and culture, whereas (Argote & Ingram, 2000) categorize more generally members, tools, and tasks. However, it could be argued that the principal difference is the degree of tacitness across these categories. This might be justified by the fact that in all instances organizational members have to mediate the transfer of the knowledge, be it the skills that are embedded within themselves or the tools they use and the tasks they execute. In all instances someone has to be aware of or evaluate the performance characteristics of the knowledge however embedded.

Hence, in both stages of knowledge integration complexity might well influence the success of knowledge transfer efforts. However, we want to establish herein the utility of knowledge integration in relation to the environment independently from issues of the ability to transfer knowledge or absorptive capacity, because the question herein is not how absorptive capacity influences innovation performance, but whether it should be aimed at absorption in the first place[9]. To this end we have to abstract from these issues assuming perfect absorptive capacity in both stages of knowledge integration.

IV.3. Model

IV.3.1. The NK-model in management research

In recent years, an increasing amount of research in management sciences could be witnessed that was built on agent-based computer simulations (e.g. Gavetti & Levinthal, 2000; Levinthal, 1997; Marengo & Dosi, 2005; Rivkin & Siggelkow, 2003; Sakhartov & Folta, 2012; Siggelkow & Rivkin, 2005). Herein, we explore the issue using the classical NK model (Kauffman, 1993), which builds the backbone of this research stream. This model is useful to describe in a simple, intuitive way an environment composed of several interacting dimensions, where each dimension can be in one of several possible states. The parameter N indicates the number of dimensions that impact performance. The parameter K indicates the 'degree' of interaction between these dimensions. Concretely, K determines the number of other dimensions that impact its performance contribution. For each of the N dimensions, it is randomly determined which exactly are these K other dimensions that influence its

[9] This does not mean that the influence of absorptive capacity was not important or should be disregarded. To the contrary, and in fact it has found already a lot of consideration in the context of intra-organizational knowledge transfer (cf. van Wijk et al., 2008). However, this model could easily be modified to investigate this issue in a future study.

performance contribution. Consequently, for each configuration of any single of the dimensions n = 1,…, N and its respective K dimensions that co-determine its impact, a performance contribution is randomly drawn from the uniform distribution (0,1). Since all dimensions can take the two states 0 and 1, for each single dimension n there are 2^{K+1} distinct potential performance contributions.

The great value of Kauffman's (1993) model lies in the possibility to easily tune both the overall size of the landscape and the number of its local "hills and valleys", that is its complexity, via changes to its two parameters N and K. When the parameter K is high, landscapes are called "rugged", which refers to their characteristic of exhibiting many local optima and "valleys of attraction" that lead to them (see Figure 1 for examples of NK-fitness landscapes). The latter term already indicates that the performance of local searchers in this setting depends crucially on their point of departure. This is because the searching subjects are assumed to be boundedly rational, or more generally resource constrained, and therefore cannot explore all possible combinations and take an informed decision to move to the global optimum.

In our model, subsidiaries are likewise resource constraint in that they search the landscape according to a simple hill-climbing heuristic. That is, in each period, subsidiaries choose randomly one variable for which they analyze whether a change in its state would have a positive effect on performance or not. Thus we assume the subsidiaries are boundedly rational in terms of analyzing capacity and without memory, but they nonetheless possess perfect information on the underlying relations of the environment, i.e. their analysis is limited, but within these limits flawless.

IV.3.2. Environment: Complexity and Dynamism

We base our model principally on the NK-model elaborated by Gavetti, Levinthal, & Rivkin (2005) (henceforth GLR). GLR build a very effective model to analyze analogical reasoning. The GLR-model permits to analyze in a still relatively simple way relatedness of different optimization landscapes. We will build on this for the modeling of different country markets and hence the degree to which the industry exposes the MNC to different local conditions in the varying markets. This shall be the context in which we propose to explore the impact of varying degrees of openness of subsidiaries on organizational innovation performance.

Each single landscape draws from a contribution matrix that determines the interrelatedness of the various dimensions of the industry, just as in the classic NK-model. However, in order to test for how robust the conclusions are to different degrees of diversification, another element of the GLR-model is integrated with a twist. The degree of diversification is modeled as the degree to which different areas of competence or technological fields in which the MNC is active are coupled. Therefore, landscapes depend on P high-level policy decisions (technological domains) and D detailed decisions that have to be made within each policy decision, such that $P \times D$ is the total number of decisions each firm makes. Each decision can take the values 0 or 1 and a firm has thus 2^{PxD} possible overall decision combinations to choose from. Each high-level policy is simply equal to the state of the majority of the corresponding detailed decisions, i.e. if {1 0 0} than this policy would equal zero and for the configuration {1 0 1} it would equal 1. The parameters K_w and K_b regulate how much the decisions within a high-level policy depend on each other and how much they depend on other high-level policies, respectively. Hence, while K_w determines the number of other operative decisions on which a focal operative decision's performance contribution is based and thus can be compared to the parameter K in the original nk-model as determining basic complexity, K_b determines how much this focal decision depends on the state of policy decision different from the own one. Therefore, if K_b is high, this can be interpreted as low, or closely related diversification, while if K_b is low, this is comparable to a situation of unrelated diversification.

Table 30: Parameters of the modified GLR-model

Parameters related to the industry characteristics	P*	Number of policy decisions that the MNC faces on its industry's technological landscape. Policy decisions are equal to the value that is most represented among the operative decisions
	D*	Number of operative decisions that the MNC faces on its industry's technological landscape.
	K_w	Number of dependencies between operative decisions within each policy area
	K_b*	Probability that the performance contribution of a focal detailed decision is affected by the resolution of each
	E_{dyn}	Probability that the performance contribution for each operative decision for each possible combination of influence factors changes.
Parameters related to the MNC characteristics	X*	Number of market characteristics co-determining operative decisions' performance contribution
	X_{REL}	Probability that a focal market characteristic influences each operative decision.
Parameters related to MNC's subsidiaries' search behavior	IOI	Probability that a subsidiary absorbs the knowledge of an intra-MNC peer once identified as similar.
	Strictness	The percentage of market characteristics that have to be equal in a potential source subsidiary to consider it sufficiently similar.

** Parameter is equal to that in the original GLR-model. Others are additional or adapted.*
(cf. Gavetti, Levinthal, & Rivkin, 2005:698)

Moreover, supplementing the traditional NK-model, the GLR-model generates "families of landscapes". The performance contribution of each decision of the distinct country landscapes potentially depends on one or more of X observable industry characteristics, which has been introduced in the GLR model. Altogether this constitutes for each country a distinct influence matrix. For each of the X industry characteristics the parameter X_{REL} determines the probability that it influences each decision's performance contributions of each possible configuration of its influencing factors and its own state. Thus, while the factors K_w and K_b determine the degree of complexity as in the GLR-model, X_{REL} determines the degree of local dependence, that is whether the industry is rather international (high local dependence) or rather global (everywhere almost same conditions).

For a given set of the parameters P, D, X, K_w, K_b, and X_{REL} the computer then initializes each simulation run a new influence matrix (all model parameters in Table 30). Since the industry characteristics can take two states, 0 or 1, there are 2^X different industry landscapes possible. In the GLR-model the computer then generates one target landscape and 2^{X-1} source landscapes to draw analogy from. In our model, however, out of these 2^X, one country landscape is chosen randomly for each subsidiary. These country landscapes can be thus more or less similar to each other as concerns the state of the X industry characteristics. This forces subsidiaries to get information on the local contexts of the peer subsidiaries from which they want to gather innovative knowledge before their engagement in knowledge transfer to accelerate innovation, because otherwise they would implement insights valid for a totally different context, but not in the own one.

A further difference is the introduction of dynamism as the rate of change in the industry characteristics, E_{DYN}, which determines the dynamism of the environment. More precisely, the parameter E_{DYN} indicates the probability for every single detailed choice's performance contribution to change for each possible configuration of its own state and all relevant other factors.

IV.3.3. The MNC as a network of subsidiaries and the integration process

Each subsidiary[10] is initialized as an array of detailed decisions in its local context, the resulting individual payoff, which is determined by its individual landscape being a combination of the MNCs technological environment and the subsidiaries local market characteristics. Given the above elaborated model, each subsidiary's payoff can be written as a function of the configuration of the operative decisions and environmental characteristics:

$$\pi_s(\{d_1, d_2, \dots, d_{PxD}\}, [x_1, x_2, \dots, x_X], X_{REL}, K_w, K_b)$$
$$= \frac{1}{PxD}\sum_{i=1}^{PxD}\left(\pi_i\left(d_i, d_{j(i)}^1 \dots d_{j(i)}^{K_w}, p_{q(i)}^1 \dots p_{q(i)}^{T_i(K_b)}, x_{r(i)}^1 \dots x_{r(i)}^{M_i(X_{REL})}\right)\right)$$
$$, i \notin j(i), i \notin q(i), i \cup\ j(i) \subseteq a(i)$$

where:

$\pi_i(.)$ is the performance contribution of a particular operative decision i;

$d_{j(i)}^k$ is the k-th element of the vector q of technological areas' policy decisions that influence $\pi_i(.)$;

$j(i)$ is the set of indexes of other decisions that influence the decision with index i;

$a(i)$ is the set of indexes of other decisions that relate to p_i;

$p_{q(i)}^t$ is the t-th element of the vector q of technological areas' policy decisions that influence $\pi_i(.)$;

$q(i)$ is the set of indexes of other policies that influence the decision with index i;

p_i is the policy decision of the technological area to which decision i relates to;

$x_{r(i)}^m$ is the m-th element of the vector r of market characteristics that influence $\pi_i(.)$;

$T(.)$ is the number of market characteristics that influence $\pi_i(.)$, which depends on the degree of relatedness of diversification, the probability K_b;

[10] Herein, we do not model the role of HQs for the impact of Internal Open Innovation strategies of its subsidiaries. However, to include the role of HQs as a knowledge broker as well as studying the impact of hierarchy in general and vertical knowledge flows would be interesting extensions of the proposed model.

$M(.)$ is the number of market characteristics that influence $\pi_i(.)$, which depends on the relevance of the local market environments, probability X_{REL};

The overall MNC performance is the average of the performance levels of its subsidiaries. Like this, performance will always on all levels result between 0 and 1 and be comparable. The performance of an MNC is thus given by the following formula:

$$\pi_{MNC} = \frac{\sum \pi_s}{S};$$

where S is the number of subsidiaries and s is a given subsidiary.

Our model constitutes a fundamental elaboration of the GLR-model in that in its original version, firms can choose only one time, that is at the beginning of the exploration of a new landscape, a certain starting point as an educated guess based on analogy drawn from more or less broad and deep experience of its managers, rather than simply start anywhere at random. In contrast to that, subsidiaries in our model constantly have the chance to jump out of valleys of attraction based on exchange of knowledge with peer subsidiaries of their MNC group the knowledge of whom likewise is not perfect but subject to optimization efforts.

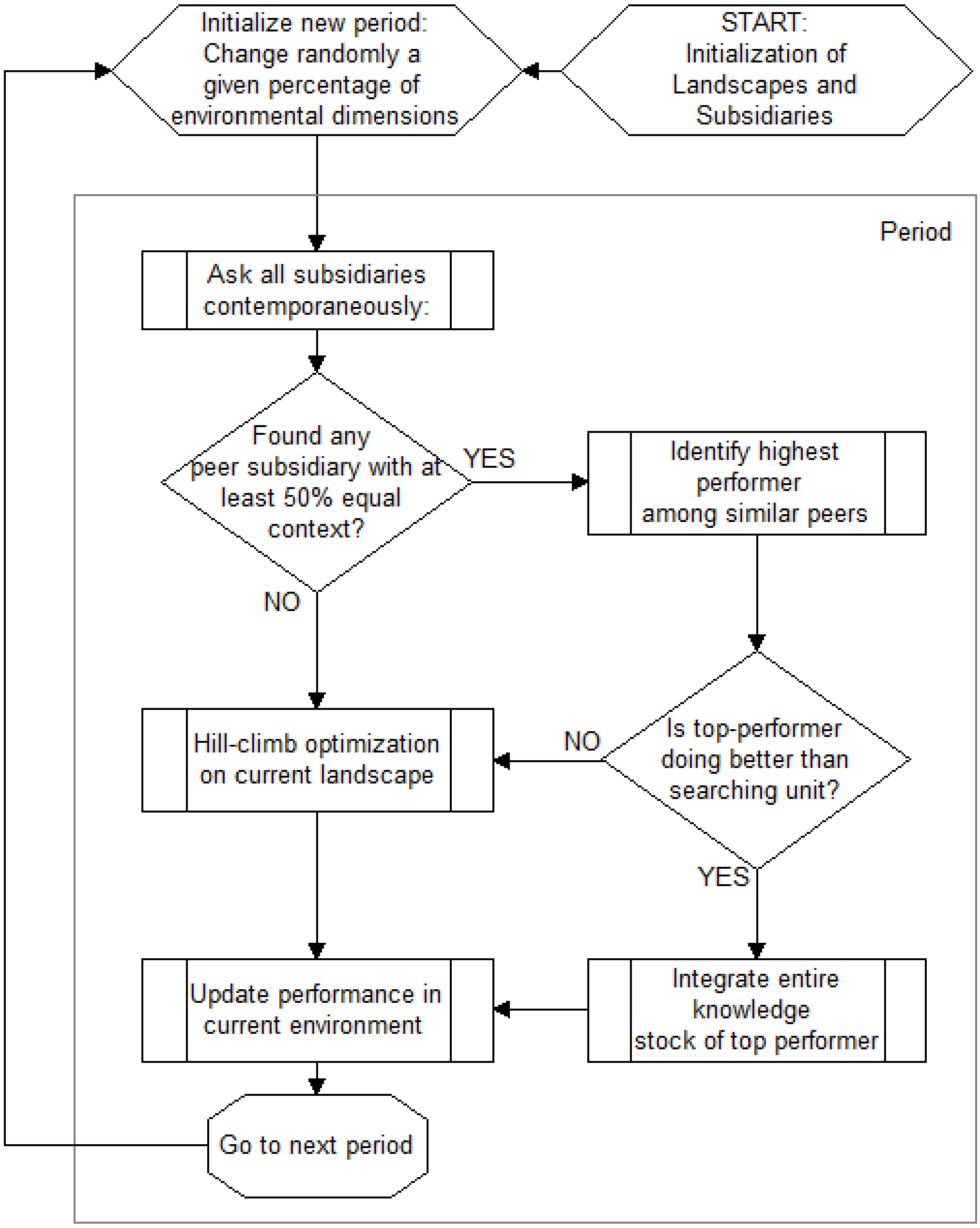
Hence, there are two fundamental differences between our model and the original model. Firstly, the experience of the subsidiaries co-evolves throughout the model and the performance that any single one holds is not necessarily already a local let alone the global optimum of the particular local landscape from which knowledge is drawn. Secondly, this exchange of knowledge on what is a valuable, innovative combination of decisions is not exchanged once, but might be exchanged constantly. More precisely, internal open innovation (IOI) is modeled as the probability that a given subsidiary in a given period would engage in the effort of knowledge transfer, while it allows every other subsidiary to access its knowledge stock. However, even if a subsidiary eventually engages in such an effort, this does not mean that knowledge transfer takes place. This is due to the division of the process into a pre-transfer phase and the actual transfer phase. In the former, the searching subsidiary compares its own local environment to that of its peers and consequently—amongst those that exhibit the same set of environmental conditions as the searching one itself—chooses the top-performer, in case there is any that performs at least as good as the searching subsidiary itself plus a risk margin of 20%. In the transfer phase then, the states of all operative decisions of the thus found top-performer amongst the peers are copied. The reason why we do not want to leave out of the model a risk margin is that the in cases where two subsidiaries perform equally well, no knowledge transfer should take place because it would represent an unnecessary cost plus the risk of integrating knowledge overestimated in its value, thus suffering a reduction of performance.[11]

We do specify the following additional assumptions that are fundamental for our research question. Firstly, subsidiaries can gather perfect information about the source's environmental state. Secondly, the searching subsidiary does not limit its transfer to one policy area, but gathers the knowledge on all decisions. Thirdly, the communication between the source and receiver subsidiaries is flawless. All three assumptions help to focus on the key argument and allow for a parsimonious model, but we might want to relax them in future elaborations of the model.

The parameters of the overall model are thus describes by those that describe the industry, i.e. whether it is global or international, high-tech or low-tech, dynamic or static, and those that describe the MNC, i.e. how many subsidiaries in different country markets it counts and how open this are towards knowledge of their corporate group peers' knowledge. The overall process of knowledge integration within the MNC is illustrated in Figure 19. The model was coded and run in NetLogo. A screenshot with an example run with only three subsidiaries and the general landscape configuration in the middle is provided in Figure 23.

[11] The exact choice of the risk margin is obviously arbitrary and whether it has a major influence in its own right should be analyzed in future studies.

Figure 19: Flowchart of simulation of intra-MNC knowledge integration



IV.4. Results & Propositions

IV.4.1. Main results and derived propositions

In the following the results of our simulation model are presented, highlighting the direct effects and interactions of environmental complexity and dynamism on the impact of Internal Open Innovation (IOI) of MNC subsidiaries. We present these results in form of two distinct tables for international (Table 31) and global (Table 32) industries. The parameter values regarding the industry where set to 3 policy decisions with 4 decisions and the country landscapes where modeled with 4 local market dimensions, which are values chosen also in the original GLR-model. It was tested for sensitivity of results to the tight or lose coupling of the policy decisions by setting K_b to 0.2 and 0.8 finding that the absolute performance values changed, while however the conclusions remained largely the same.

The parameters for low, medium, and high IOI where set to 0, 0.2, and 0.5, those for zero, low, medium, and high dynamism (E_{DYN}) to 0, 1, 5, and 10, while those for low and high complexity (K_w) where set to 1 and 3, respectively. The number of subsidiaries was set to 10. In order to distinguish international industries, the parameter X_{REL} was set to 0.5. That means that the probability that any given decision's contribution is affected by the state of any given environmental factor X is 50%. For global industries this was set to 0.2[12]. In the two comparison scenarios "Medium IOI" and "High IOI" the percent change vis-à-vis the baseline scenario is reported, together with an indication of the one-tailed significance level. The static models tend to stabilize completely between the 40th and 70th period. Therefore, all models have been run for slightly the double amount of periods, i.e. 150.

The fact that in international industries local context may differ widely can be deemed one of the principal reasons behind the significant impact of distance on the success of knowledge transfer (Davenport, 2005). This in turn might be the case because of the interdependence between local context factors with the nature of the effects of particular combinations of operative and strategic decisions but also because of the impact that the local context has on the very implementation of these decisions. In other words, it is both the demand-side environment and the working environment, or culture, which can be quite different from country to country.

[12] It could be argued that 0 was a more appropriate value for environmental relevance (X_{REL}) in order to simulate global industries, but in reality even the most global industries exhibit some minimum differences in how to do business in different country markets. However, results for any other combination of variables can be requested from the authors.

We find that in the presence of such profound differences, the effect that the environmental dynamism has on the convenience of IOI is fundamentally different (Table 31). While in high complexity environments, medium and high dynamism offers opportunities to improve performance through the implementation of IOI in the MNC subsidiary network, in low complexity environments, it is the opposite. However, at zero dynamism, excessive IOI can actually be detrimental to innovation performance. This could be explained by a too early homogenization of the subsidiary network. That means, that subsidiaries decide at the first slow down of their own innovation process to gather innovative knowledge from a similar peer in order to switch to a currently higher performing innovation path that, however, offers less long-term potential.

Table 31: Innovation Performance across different scenarios in International Industries

Observations: 200 simulations per scenario		*International Industries (X_{REL} = 0.5)*							
	Complexity:	Low complexity (K_w = 1)				High complexity (K_w = 3)			
	Dynamism: (E_{DYN})	Zero (0)	Low (.01)	Medium (.05)	High (.1)	Zero (0)	Low (.01)	Medium (.05)	High (.1)
Mean Perfor-mance over 150 periods	Zero IOI (s.d.)	.5927 (.0118)	.5905 (.0126)	.5932 (.0139)	.5916 (.0122)	.6007 (.0100)	.6004 (.0100)	.5994 (.0105)	.5999 (.0095)
	Medium IOI (s.d.)	.5935 (.0149)	.5928 (.0135	.5949 (.0141	.5935 (.0138	.6008 (.0116)	.6003 (.0105)	.6022 (.0103)	.6016 (.0110)
	High IOI (s.d.)	.5889 (.0128)	.5888 (.0139	.5942 (.0144	.5933 (.0142	.5994 (.0122)	.5996 (.0121)	.6014 (.0112)	.6004 (.0106)
%-change from zero to Medium IOI (p-values)		0.14% (.2671)	**0.39%* (.0296)**	0.27% (.1253)	***0.32%$^{+}$ (.0657)***	0.01% (.4846)	-0.01% (.4661)	**0.47%* (.0049)**	**0.28%* (.0529)**
%-change from zero to High IOI (p-values)		**-.63%** (.0010)**	*-0.28% (.1016)*	0.16% (.2446)	*0.29%$^{+}$ (.0954)*	-0.22% (.1345)	-0.13% (.2220)	**0.35%* (.0247)**	0.08% (.3142)
%-change from Medium to High IOI (p-values)		**-0.77%** (.0006)**	**-0.67%** (.0019)**	-0.11% (.3213)	-0.03% (.4448)	-0.23% (.1329)	-0.12% (.2639)	-0.12% (.2356)	-0.20% (.1207)

1-tailed t-test significance levels: +0.10 * 0.05 ** 0.01. Diversification high/unrelated (K_b = .2)

In the language of NK-landscapes, this means that since the landscape is relatively smooth, valleys of attraction are larger and thus chance is higher that subsidiaries too early switch through IOI to a valley of attraction that leads to a lower local optimum. This happens in those cases where the source subsidiary went already farther on its innovation path. This finding can be explained by the consistent difference that exists among subsidiaries operating in different countries. In effect, knowledge developed locally by a given subsidiary can be less functional for a subsidiary belonging to another country. Environmental complexity and turbulence are generally understood as the two major constituencies of (perceived) environmental uncertainty (Duncan, 1972). Therefore we formulate the following propositions:

Proposition 1: In international industries that are exposed to high complexity environments with
(a) medium and high levels of dynamism, a medium level of IOI throughout the MNC subsidiary network has, ceteris paribus, the most positive impact on innovation performance, while
(b) IOI has, ceteris paribus, no significant impact at zero and low levels of dynamism.

Proposition 2: In international industries that are exposed to low complexity environments with
(a) medium and high levels of dynamism, IOI throughout the MNC subsidiary network has, ceteris paribus, no significant impact on innovation performance, while
(b) IOI is, ceteris paribus, inversely u-shaped related to innovation performance at low levels of dynamism and
(c) a high level of IOI has, ceteris paribus, a negative impact on innovation performance at entirely static environments.

Table 32: Innovation Performance across different scenarios in Global Industries

Observations: 200 simulations per scenario		*Global Industries (X_{REL} = 0.2)*							
	Complexity:	Low complexity (K_w = 1)				High Complexity (K_w = 3)			
	Dynamism: (E_{DYN})	Zero (0)	Low (.01)	Medium (.05)	High (.1)	Zero (0)	Low (.01)	Medium (.05)	High (.1)
Mean Performance over 150 periods	Zero IOI (s.d.)	.6437 (.0285)	.6459 (.0280)	.6428 (.0261)	.6470 (.0296)	.6463 (.0213)	.6463 (.0222)	.6470 (.0233)	.6459 (.0206)
	Medium IOI (s.d.)	.6489 (.0298)	.6505 (.0301)	.6508 (.0284)	.6465 (.0315)	.6508 (.0219)	.6500 (.0224)	.6525 (.0230)	.6557 (.0237)
	High IOI (s.d.)	.6481 (.0289)	.6454 (.0297)	.6514 (.0323)	.6509 (.0353)	.6474 (.0241)	.6517 (.0238)	.6521 (.0239)	.6512 (.0239)
%-change from zero to Medium IOI (p-values)		**0.80%* (.0364)**	**0.71%* (.0531)**	**1.25%** (.0019)**	-0.08% (.4349)	**0.70%* (.0234)**	**0.58%* (.0493)**	**0.84%** (.0095)**	**1.52%** (.0000)**
%-change from zero to High IOI (p-values)		***0.68%+ (.0603)***	-0.07% (.4410)	**1.34%** (.0011)**	0.60% (.1255)	0.18% (.3041)	**0.85%** (.0094)**	**0.78%* (.0162)**	**0.82%** (.0071)**
%-change from Medium to High IOI (p-values)		-0.13% (.3942)	**-0.77%* (.0426)**	0.08% (.4317)	***0.68%+ (.0953)***	***-0.52%+ (.0689)***	0.27% (.2065)	-0.06% (.4348)	**-0.68%* (.0246)**

Significance levels: +0.10 * 0.05 ** 0.01. Diversification high/unrelated (K_b = .2).

We find fundamentally different effects in the case of global industries (Table 32). Results are illustrated for more intuitive comparison in Figure 21 and Figure 22. For high complexity environments, we find that the impact of medium levels of IOI on innovation performance increases with environmental dynamism. This can be interpreted as suggesting that in global industries, where chances are higher to find peers with very similar states of environment, the subsidiaries have better chances to jump actually to a valley of attraction with a higher local optimum, that is discover that a peer in a different country with almost the same key environmental factors posses knowledge about a better performing set of innovative knowledge. This is all the more important in cases where the value of once locally generated knowledge erodes faster and only little time is given to find a well performing new combination of knowledge before the next changes in the environment erode also these insights. Therefore we propose the following relationships:

Proposition 3: In global industries, which are exposed to high complexity environments,
(a) the positive effect of medium levels of IOI increases linearly with environmental dynamism, while
(b) high levels of IOI increase innovation performance almost equally from low to high levels of dynamism, exhibiting a significantly lower positive impact than medium IOI only in cases of high dynamism.

For low complexity environments, we find a quite different effect of environmental dynamism on the relationship between IOI and innovation performance. First of all, in low complexity environments, high levels of IOI are convenient only in case of medium dynamism; but then its effect is amongst the highest. Furthermore, in low complexity environments, medium levels of IOI appear to impact innovation performance in an inverse u-shaped manner across increasing levels of environmental dynamism. The highest effect can be observed in both cases at medium levels of environmental dynamism, where however the difference between medium and high level IOI is not significant.The fact that at very high degrees of environmental dynamism there is no significant effect of IOI at no level, is interesting, since intuition could lead to the conclusion that external knowledge comes in always helpful when the own knowledge erodes very fast. But it appears that in this case a similar reasoning applies as for international industries. That is, that the fact that in low complexity environments, as e.g. low-tech industries, development paths in the own environment are quite foreseeable, i.e. there are little peaks and large valleys of attraction, makes it less attractive to engage time and resources into knowledge acquisition from outside with the peril to engage on a new development path that might actually lead to a lower local optimum. Table 33 summarizes the findings of the simulations.

Proposition 4: In global industries that are exposed to low complexity environments,
- *(a) IOI has no significant effect at no level in cases of high environmental dynamism, while*
- *(b) a medium level of IOI is moderated by environmental dynamism in its positive impact on innovation performance in an inversely u-shaped manner and*
- *(c) a high level of IOI impacts positively on innovation performance only in cases of medium environmental dynamism.*

IV.4.2. Sensitivity analysis

In order to confirm that analysis actually models the standard diversified MNC, we did run all scenarios also with the parameter K_b at .8, indicating high dependence of operative decisions on other technological areas (policies). The overview of the results for undiversified MNCs is presented in Table 34 and Table 35. The results show clearly that the issue of IOI and hence intra-firm knowledge integration is drastically different for not or related diversified MNCs. This confirms our intuition that it is necessary to separate the analysis from each other. Although herein we focus on the interpretation of intra-firm knowledge integration in diversified MNCs, an in-depth analysis of what these results mean and what can be concluded for not diversified MNCs deserves further attention in its own right. As to the analysis herein, it shall be noted, however, that the general tendency is that

The fact that no further sensitivity analyses could have been carried out is due to resource constraints. Although we are confident about the model and that we chose valid and intuitive parameters, also based on previous simulation studies in extant literature this issue should be addressed in future elaborations and replications of this model.

Table 33: Overview of results

Complexity / Dynamism	Low ($K_w = 1$)	High ($K_w = 3$)
None ($E_{DYN} = 0$)	• IOI is **positively** related to innovation performance in global industries, while • in international industries, IOI has a **negative** impact at least in case of high levels	• The effect of IOI is **n-shaped** related to innovation performance, but • In international industries, IOI has **no effect** at all
Low ($E_{DYN} = 0.01$)	• IOI is **n-shaped** related to innovation performance in global industries • Also in international industries, IOI has an **n-shaped** effect on innovation performance, but the potential improvement is lower	• In global industries, IOI **positively** impacts innovation performance and more so at high levels • In international industries IOI has **no significant effect** at all
Medium ($E_{DYN} = 0.05$)	• In global industries, environments with medium levels of dynamism provide the **highest potential** to improve innovation performance by means of IOI • In international industries there is **no effect** at all	• In global industries, IOI has an equally **positive** impact on innovation performance • In international industries, IOI has an equally **positive** impact on innovation performance, but the relative increase **lower than in global industries**
High ($E_{DYN} = 0.1$)	• In global industries, IOI has no effect at medium levels, and a **positive but hardly significant** one at high levels • In international industries, IOI has likewise **only slightly significant positive effect**, but equally for medium and high levels	• In global industries, in this scenario, the **positive effect of medium IOI is highest across all scenarios** and the overall relationship **n-shaped**, although high level IOI still improves innovation performance compared to zero IOI • In international industries, **medium IOI has only modest** although significant effect on innovation performance, while **at high levels it has none**

IV.5. Conclusions

In this study we focused on the concept of openness in the innovation process within multinational companies' (MNCs) subsidiary networks. We believe that the opening of subsidiaries' innovation process towards their peers within the MNC network might not be positive per se, but highly contingent on the environment. Looking at the MNC as a network in which different levels of openness can be implemented we highlight how MNC subsidiaries in more or less common problem contexts depend in their joint innovation effort crucially on the interplay between two major environmental characteristics.

We contribute to research in two fundamental ways. Firstly, we develop the notion of Internal Open Innovation of MNCs'. Secondly, we develop a model that integrates central contingencies of the innovation impact of Internal Open Innovation of MNCs. This helps to develop an intuition that and how these factors could interact on the outcomes of MNCs' more or less open innovation strategies. Based on very common and intuitive assumptions and a simple agent-based model, we establish several propositions, while the simulation approach permits us to disentangle the effects in focus independently from other issues. This is crucial because if in an empirical study the effect of intra-MNC knowledge integration is not per se positive this might have several other reasons like e.g. erroneous beliefs ("false knowledge") on the part of the knowledge providers or inadequate absorptive capacity on the part of the knowledge receivers. Herein, we can show that even if everything else is perfect, intra-firm knowledge integration might not have per se a linearly positive effect on innovation performance.

We find that in case of MNC subsidiary networks sensitive to the differences across subsidiaries' problem contexts, that is international industries as opposed to global industries with a single worldwide equal context, ceteris paribus, medium to high degrees of dynamism in the MNC's environment should encourage the implementation of internal open innovation strategies in high complexity industries, while IOI can proof beneficial in low but not too low dynamic environments in case of low complexity industries.

Moreover, we find that this relation is ambiguous when dynamism is at a medium level. Although environmental complexity already alters significantly the degree of the positive and negative relation in low and high dynamic environments, in cases of medium dynamic environments, complexity a strong mediator changing even the nature of the relationship from positive to negative. In particular we find support for our proposition that in these cases of medium dynamism, MNCs can profit from medium levels of internal open innovation if complexity is low, while there is no such effect in cases of high complexity. On the contrary, high levels of internal open innovation will result in worse innovation performance. However, if companies are unsure in what category their environment falls, a moderate level of IOI can hardly harm innovation performance whereas in many cases it actually might foster it.

The intuition is that in stable environments subsidiaries that exchange knowledge during the innovation process can explore different strands of research and adopt the one that yields better results early on and these results remain valid. In instable contexts a highly profitable innovation might be adopted from heterogeneous subsidiaries, but does not remain valid for long and from the point on that the environment changes both restart their search from the homogenized knowledge, which exhibits less potential solutions than searching with different knowledge backgrounds. This can have a long term negative effect.

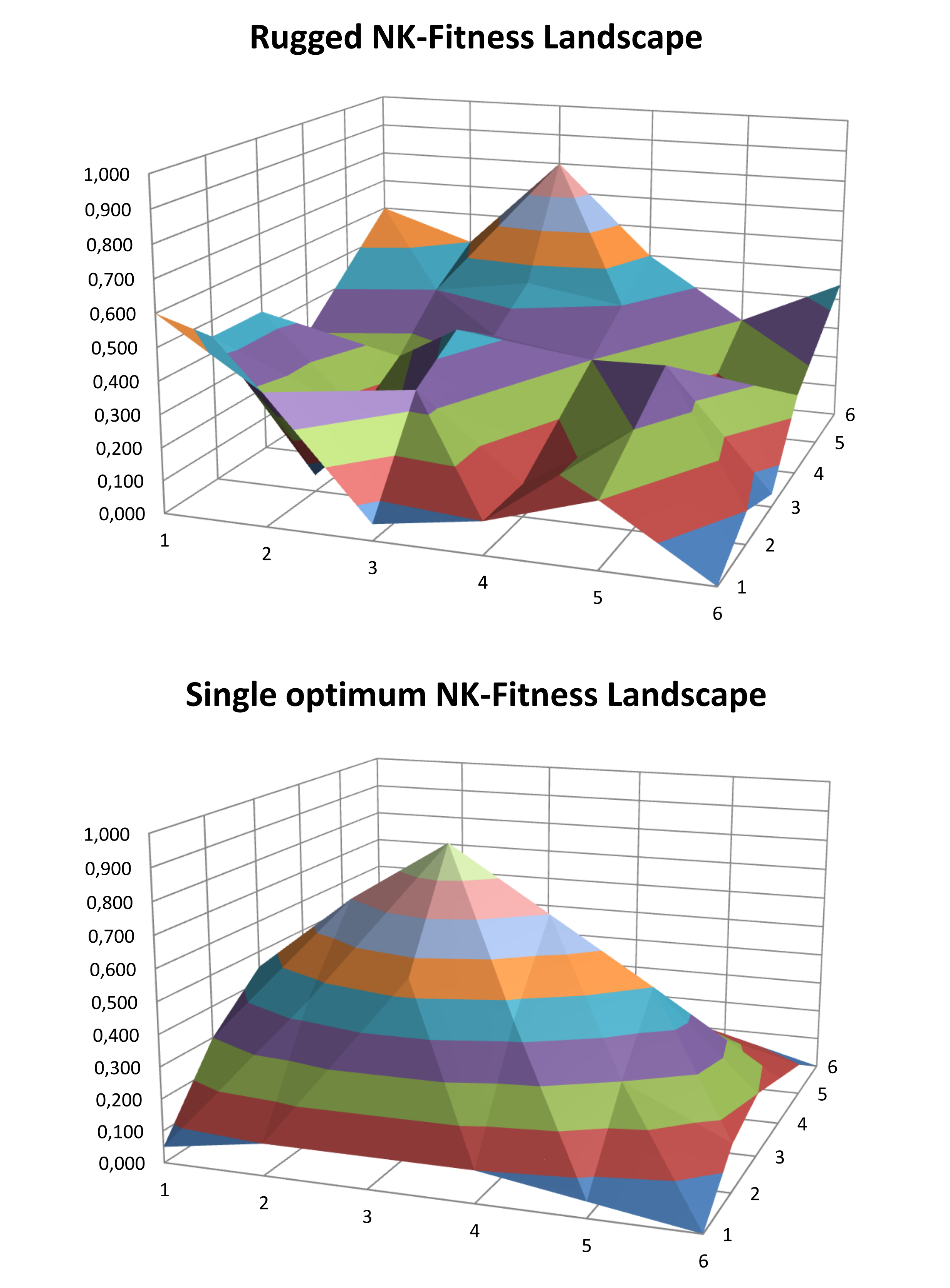
Finally, it can be claimed that this research could also have managerial implications once empirically underpinned. Generally, we argue that the analysis of subsidiaries' varying degrees of openness and the contingencies that moderate its impact on innovation performance can contribute to a better understanding of how MNCs should incentivize their subsidiaries to collaborate in the innovation process.

However, a limitation is that we assume that managers can perfectly understand and foresee whether their problem context is similar to that of peer subsidiaries or not. This limitation could be tackled in future studies. Moreover, it seems promising to investigate whether there is and if so of what nature is a potential trade-off between internal innovation collaboration, i.e. with peer subsidiaries, and external innovation collaboration, i.e. with local sources from which arrive knowledge spillovers. For both cases our simulation model provides a sound fundament to theorize these potentially complex relationships.

Moreover, a further limitation can be seen in the fact that some studies have shown that cultural differences can lead to problems when systems built to share knowledge are deployed outside the original cultural context, as e.g. the group of Western countries (Ardichvili, Maurer, & W. Li, 2006; Voelpel & Han, 2005; Young, Kuo, & Myers, 2012). Since a knowledge management system can reflect the Western values of the designers (Nonaka & Takeuchi, 1995), such cultural issues can be important in the consideration of planning and managing knowledge sharing. In fact, since such cultural differences could influence the success of knowledge transfer between subsidiaries and therewith also that of IOI beyond the issue of disseminative and absorptive capacities of the involved units, it would be an interesting supplement to our model that could be addressed in future studies to investigate how the thus assumed differences in communication approaches might alter our findings.

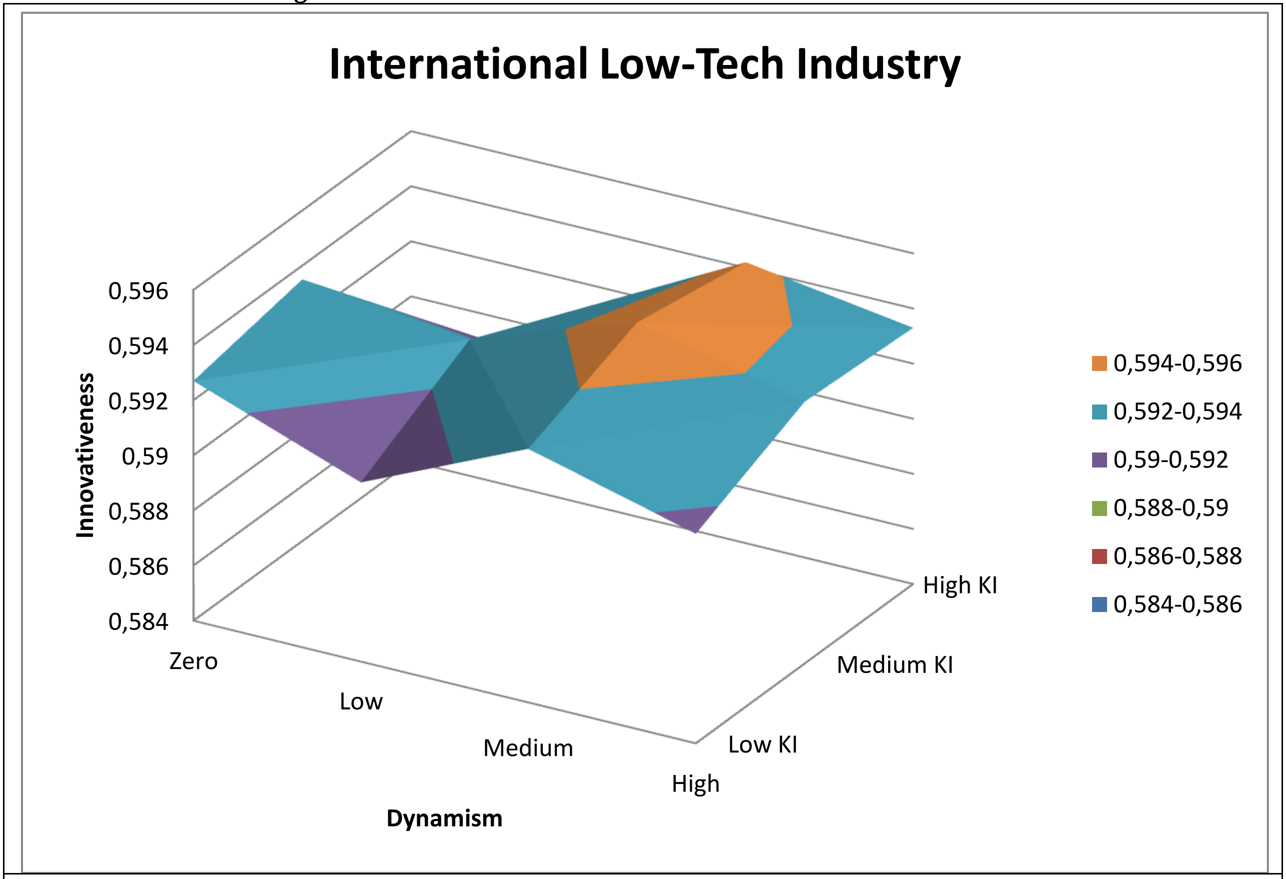
IV.6. Appendix

Figure 20: Examples of NK-fitness landscapes



Source: Based on Gavetti & D. A. Levinthal (2000:119-120)

Figure 21: Interaction of Intra-MNC Knowledge Integration (KI) and Dynamism in International Low- and High-Tech Industries



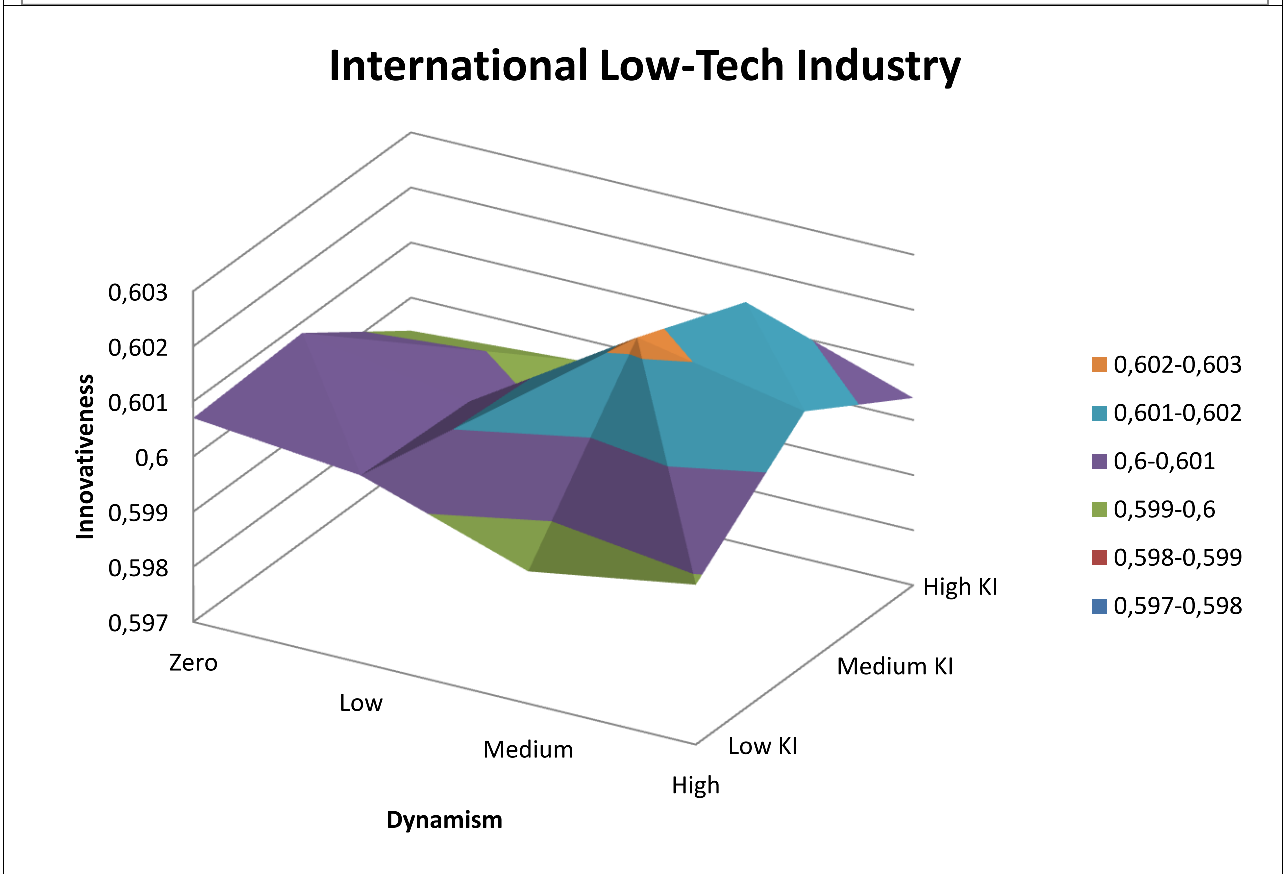


Figure 22: Interaction of Intra-MNC Knowledge Integration (KI) and Dynamism in Global Low- and High-Tech Industries

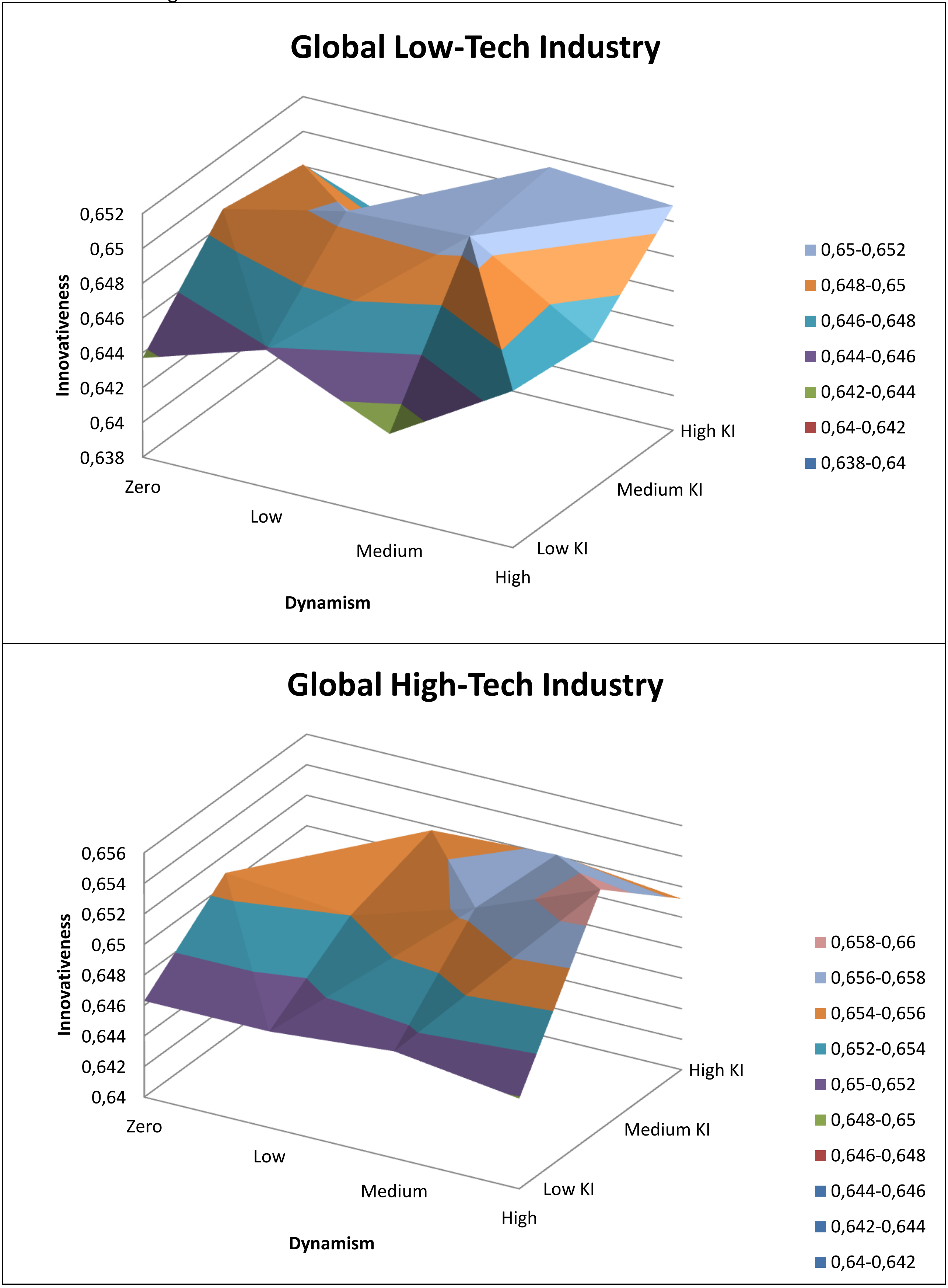


Table 34: Innovation Performance across different scenarios in International Industries (low/related diversification)

Observations: 200 simulations per scenario		*Global Industries (X_{REL} = 0.2)*							
	Complexity:	Low complexity (K_w = 1)				High Complexity (K_w = 3)			
	Dynamism: (E_{DYN})	Zero (0)	Low (.01)	Medium (.05)	High (.1)	Zero (0)	Low (.01)	Medium (.05)	High (.1)
Mean Performance over 150 periods	Zero IOI	.5683	.5687	.5689	.5686	.5779	.5787	.5773	.5771
	(s.d.)	(.0108)	(.0091)	(.0090)	(.0091)	(.0094)	(.0085)	(.0071)	(.0074)
	Medium IOI	.5687	.5703	.5696	.5691	.5773	.5776	.5778	.5786
	(s.d.)	(.0126)	(.0107)	(.0099)	(.0099)	(.0104)	(.0080)	(.0085)	(.0072)
	High IOI	.5685	.5674	.5706	.5694	.5751	.5763	.5779	.5781
	(s.d.)	(.0114)	(.0109)	(.0108)	(.0107)	(.0109)	(.0092)	(.0089)	(.0081)
Change from Zero IOI to…	Medium IOI	0.06%	**0.29%**	0.11%	0.09%	-0.11%	-0.19%	0.07%	**0.26%**
	(p-values)	(.3699)	**(.0374)**	(.2361)	(.2961)	(.2099)	(.0627)	(.2873)	**(.0255)**
	High IOI	0.03%	*-0.23%*	**0.30%**	0.14%	**-0.49%**	**-0.41%**	0.09%	0.17%
	(p-values)	(.4344)	*(.0783)*	**(.0381)**	(.2193)	**(.0002)**	**(.0027)**	(.2601)	(.1194)
Medium	to High IOI	-0.03%	**-0.52%**	0.18%	0.05%	**-0.38%**	**-0.23%**	0.02%	-0.09%
	(p-values)	(.4372)	**(.0014)**	(.1559)	(.3932)	**(.0027)**	**(.0445)**	(.4562)	(.2460)
Change in %-change relative to high diversification in %-points	Medium IOI	-0.08%	-0.10%	-0.16%	-0.23%	-0.11%	-0.17%	-0.40%	-0.02%
	High IOI	0.66%	0.05%	0.14%	-0.15%	-0.27%	-0.28%	-0.26%	0.09%
	Medium to High IOI	0.74%	0.15%	0.30%	0.08%	-0.15%	-0.11%	0.14%	0.11%

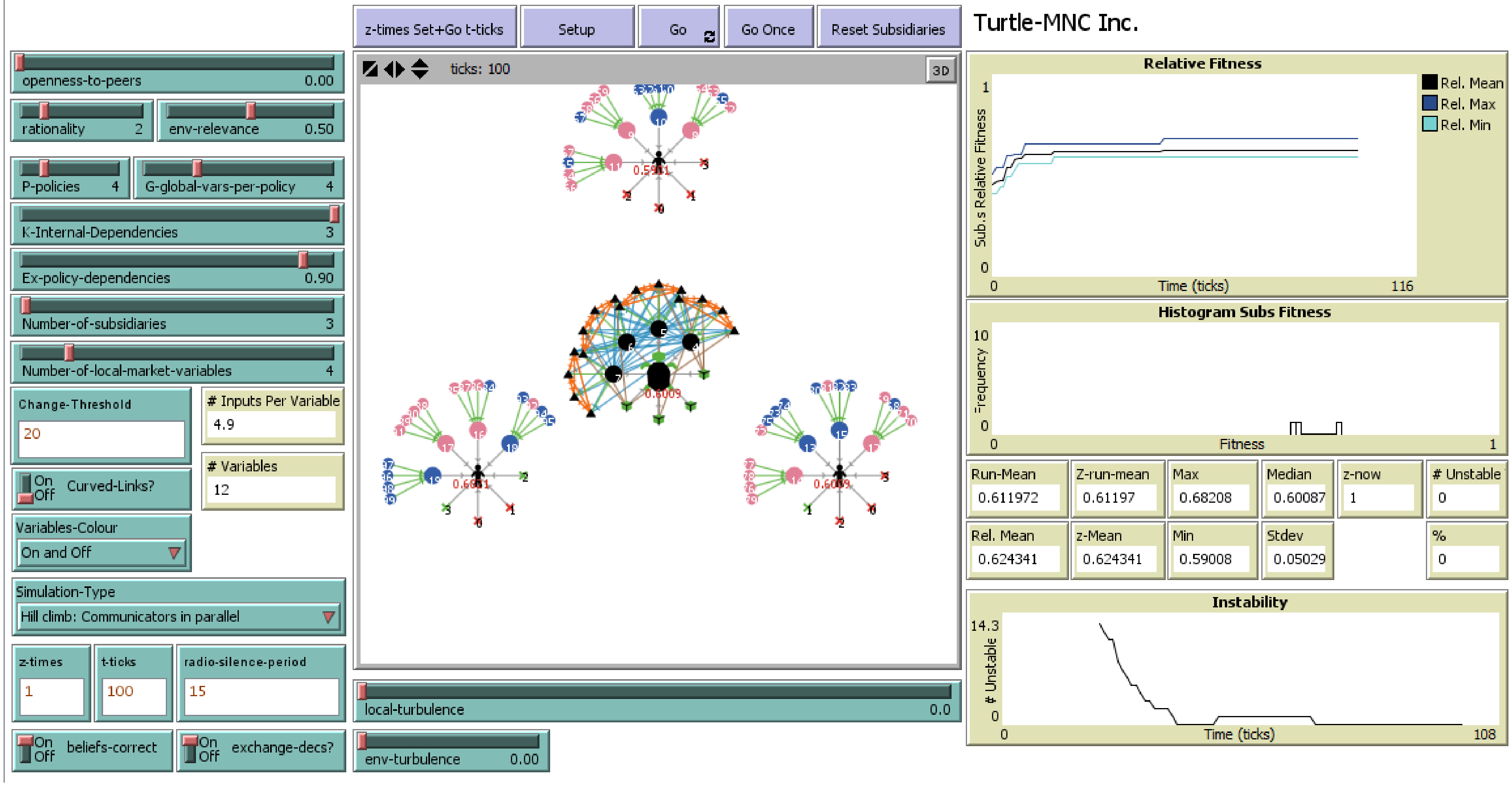
Significance levels: +0.10 * 0.05 ** 0.01. Diversification K_b = .8.

Table 35: Innovation Performance across different scenarios in Global Industries (low/related diversification)

Observations: 200 simulations per scenario		*Global Industries (X_{REL} = 0.2)*							
	Complexity:	Low complexity (K_w = 1)				High Complexity (K_w = 3)			
	Dynamism: (E_{DYN})	Zero (0)	Low (.01)	Medium (.05)	High (.1)	Zero (0)	Low (.01)	Medium (.05)	High (.1)
Mean Performance over 150 periods	Zero IOI	.6316	.6306	.6323	.6304	.6353	.6361	.6353	.6359
	(s.d.)	(.0222)	(.0226)	(.0222)	(.0227)	(.0165)	(.0163)	(.0160)	(.0160)
	Medium IOI	.6308	.6355	.6359	.6332	.6387	.6370	.6381	.6381
	(s.d.)	(.0238)	(.0244)	(.0220)	(.0227)	(.0181)	(.0177)	(.0168)	(.0175)
	High IOI	.6325	.6337	.6335	.6345	.6364	.6366	.6367	.6369
	(s.d.)	(.0227)	(.0266)	(.0251)	(.0238)	(.0178)	(.0181)	(.0177)	(.0175)
Change from Zero IOI to…	Medium IOI	-0.13%	**0.78%**	**0.56%**	*0.45%*	**0.55%**	0.14%	**0.44%**	*0.35%*
	(p-values)	(.3659)	**(.0186)**	**(.0597)**	*(.0950)*	**(.0200)**	(.2990)	**(.0407)**	*(.0891)*
	High IOI	0.14%	*0.49%*	0.20%	**0.65%**	0.18%	0.08%	0.22%	0.16%
	(p-values)	(.3520)	*(.1122)*	(.2851)	**(.0351)**	(.2586)	(.3812)	(.2012)	(.2677)
Medium	to High IOI	0.27%	-0.29%	-0.36%	0.20%	*-0.37%*	-0.06%	-0.22%	-0.18%
	(p-values)	(.2308)	(.2475)	(.1683)	(.2956)	*(.0949)*	(.4157)	(.2043)	(.2326)
Change in %-change relative to high diversification in %-points	Medium IOI	-0.93%	0.07%	-0.69%	0.53%	-0.15%	-0.44%	-0.40%	-1.17%
	High IOI	-0.54%	0.56%	-1.14%	0.05%	0.00%	-0.77%	-0.56%	-0.66%
	Medium to High IOI	0.39%	0.48%	-0.45%	-0.48%	0.15%	-0.32%	-0.16%	0.50%

Significance levels: +0.10 * 0.05 ** 0.01. Diversification K_b = .8.

Figure 23: Example of a simple run with only three subsidiaries in low dynamic high complexity environment



V. General Conclusion

V.1. Introduction

Resource advantages have been recognized as fundamental drivers of sustainable competitive advantage (Barney, 1991) and knowledge is increasingly argued to be the most valuable resource and the principal determination of firm boundaries (Kogut & Zander, 1992; Spender & Grant, 1996). However, knowledge is heterogeneous and needs to be successfully integrated to appropriate potential complementarities between distinct knowledge stocks in distinct knowledge repositories within the firm. These complementarities, which bear an enormous value potential, can exist within one corporate function and require architectural knowledge and recombination of for example different product and process technologies (Henderson & Clark, 1990) as well as across corporate functions, a particularly strong case being the complementarity between technological and market knowledge (Iansiti & Clark, 1994). It is thus essential for management to understand how knowledge can be integrated in a way to realize all this value potential in form of high-performing innovations.

While both inter- and intra-firm knowledge transfer and integration are widely discussed regarding Absorptive Capacity (Lane et al., 2006; Van Wijk et al., 2008; Volberda et al., 2010), the level of analysis of intra-firm knowledge integration is either individuals, groups, business units, or subsidiaries. Thus, in this highly relevant research stream, the level of functional departments has been largely ignored, which might have however important implications knowledge integration success, because complementary functions might exhibit fundamental differences that go beyond knowledge characteristics like tacitness. Moreover, complementary functions might exhibit different degrees of heterogeneity, as for example in the case of the technological and market knowledge domains. These differences are particularly relevant in multinational corporations that can be regarded as a network of subsidiaries in heterogeneous market contexts. While technological knowledge holds universally, i.e. physical properties and causalities do not change from country to country, market knowledge depends qua definition on the market to which it relates. However, it is not clear from literature how the nature of the relationship between knowledge integration and innovation performance is influenced by environmental characteristics like for MNCs in international or global industries.

These three aspects, the department level Absorptive Capacity in general, its role at the highly complementary R&D-M&S interface, and the environmental characteristics to that MNCs are exposed, are therefore treated in detail in three studies. Since each chapter based on a separate study concludes with a detailed discussion of findings and their implications, these shall not be repeated again. Instead, the main results of each paper shall be sketched out in the following section in order to draw a general conclusion regarding the overall research theme of this dissertation and present a related research agenda in the last section.

V.2. Summary of Findings

The three studies in presented in this dissertation in chapters II through IV are all concerned with the relationship between intra-firm knowledge transfer and innovation performance. In response to the identified relevant research gaps regarding the relationship between intra-firm knowledge integration and innovation performance, it is investigated how Absorptive Capacity of functionally specialized departments can help to understand the dynamics behind successful intra-firm knowledge integration. It is investigated whether more intra-firm knowledge integration always leads to better performance in contexts where the different units are exposed to heterogeneous environments in one of the two complementary corporate functions, as is the case for many of today's big corporations since they are selling their products in ever larger shares of the world's markets.

Table 36: Overview of Research Findings

	Chapter II	Chapter III	Chapter IV
Research Questions	• What does Absorptive Capacity (AC) refer to on the level of functionally specialized departments? • What kinds of prior related knowledge determine departmental ACs? • How are departmental ACs related to push- and pull-innovations?	• What effect do formal and informal integration mechanisms have on departmental ACs? • What effects have departmental ACs on Innovation Performance? • How do these effects differ between R&D and Marketing departments?	• What is the optimal degree of intra-MNC knowledge integration? • How does this optimal degree depend on environmental dynamism and complexity? • Is this relationship different for international and for global industries?
Theories	• Absorptive Capacity • Cross-functional integration • Knowledge-Based and Relational View • Information processing • Push- and Pull-Innovations	• Absorptive Capacity • Cross-functional Integration	• Organizational Search • International Business
Methods	• Theory development	• Structural Equation Modeling (CFA and path model) • Data from AIDA database and own survey of R&D and M&S professionals from Italian manufacturing industries	• Agent-based computer simulation • NK-model with co-evolving related landscapes
Findings / Contributions	• At least five different boundaries can be identified in the process of knowledge integration and are present at different levels depending on the functional interface • Departmental ACs have to be distinguished into those relating to knowledge of the focal department's own functional domain (FAC) and those relating to such of other domains (CFAC) • At least three types of different prior related knowledge stocks influence these two capacities differently • FAC relates mostly to either push or pull innovations, CFAC to integrated innovations	• Out of departmental ACs, only CFAC and only for R&D departments positively impacts Innovation Performance (IPO) • Out of integration mechanisms (IM) only formal CFI mechanisms by M&S impact IPO • CFAC mediates the relation between formal CFI mechanisms and IPO for R&D • Informal CFI mechanisms might hinder the development of CFAC in R&D departments	• The optimal degree of intra-MNC knowledge integration (KI) is often a moderate level, since the relationship KI-IPO is n-shaped • Highest increase in innovativeness from knowledge integration in global high-tech industries • Uselessness or even negative effect of knowledge integration in international low-tech industries
Status & Co-Authors	• Presented at the Annual DRUID Conference 2012, Copenhagen	• Accepted at the 35^{th} DRUID Celebration Conference 2013, Barcelona, 17-19 June	• Presented at ItAIS Conference 2012 • Forthcoming at IJESMA Special Issue • Co-Authors: Sabini, L. & Valentino, A.

Regarding the first of these issues, in the study presented in chapter II, the concept of Absorptive Capacity is theoretically conceptualized on the level of functional departments based on literature from various research streams. There are several important contributions to mention: (1) The understanding of the boundaries that have to be either transcended or traversed in order to integrate knowledge across organizational units is enhanced by supplementing two important further boundaries treated separately in previous literature. (2) It is analyzed that these boundaries exhibit an almost opposed configuration of difficulty at intra- vis-à-vis cross-functional boundaries. From this it is concluded that the dynamics behind knowledge absorption at these two interface types are different and hence distinct concepts have to studied. (3) These two separate concepts depend on three distinct types of prior related knowledge, that impacts these two departmental ACs differently via enabling to overcome the identified boundaries. (4) It is concluded, that a department's AC regarding knowledge of the own functional domain (FAC) allows for higher degrees of function-specific innovations. In the case of R&D departments these are technology push-innovations, while in the case of M&S departments these are market pull-innovations. Departments' AC regarding knowledge of complementary domains permits successful cross-functional integration and hence allows for "integrated" innovations, which have a higher value potential than any single function-specific type of innovation.

In chapter III, I present an empirical investigation of the role of the thus conceptualized departmental abilities, FAC and CFAC, at the interface of research and development (R&D) and marketing and sales (M&S). I find support for the direction of knowledge from M&S to R&D since the use of formal integration mechanisms directly impacts innovation performance in case of M&S departments, while in case of R&D departments this positive effect is fully mediated by CFAC. This means it is crucial for R&D departments to be able to actually absorb—i.e. recognize the value of, assimilate, and apply—the market knowledge from R&D while M&S as a knowledge provider does not need to absorb any technological knowledge in order to foster innovation performance through the use of cross-functional integration (CFI) mechanisms. Moreover, I find a direct negative effect of informal CFI mechanisms on CFAC of R&D departments neutralized by a positive indirect effect through FAC. This means that informal integration M&S provides R&D departments with the possibility to get fast, spontaneous and unbureaucratic feedback from them in order to improve for example the estimation of the potential value of another R&D department's specialist knowledge, thus increasing its FAC. FAC in turn is a fundamental requirement of CFAC since the absorption of cross-functional knowledge requires to be complemented by FAC. Since the direct and the indirect effect of informal CFI mechanisms neutralize each other in this way, this might explain previous contrasting results regarding the impact of CFI mechanisms in that previously this differentially mediating role of FAC and CFAC has not been considered. This has important implications for practitioners in that it allows to benchmark FAC and CFAC of departments and manage them and thus intra-firm knowledge integration efficiently.

In the third study in chapter IV, we show that the problem of how to successfully integrate knowledge is only part of the issue regarding separate knowledge stocks in the firm and their role for innovation performance. Based on an agent-based computer simulation, we demonstrate that more knowledge integration is not always improving innovation performance, and how this depends on the distinct environmental factors complexity and dynamism. We find that (1) the optimal degree of knowledge integration is in many scenarios at medium levels (an n-shaped relationship), (2) knowledge integration bears the most value potential in global high-tech industries and (3) there are no positive and possibly even effects of knowledge integration in international low-tech industries.

The studies are summarized in a compact way in Table 36.

V.3. Research Agenda

The issue of intra-firm knowledge integration is so vast that obviously many research gaps are relevant and pressing. However, in the light of the specific results that emerged from the studies in this dissertation, it can be noted that while several research questions could be answered, yet more new are raised by these findings and thus new opportunities open.

While the new concepts of FAC and CFAC certainly are important for intra-firm knowledge integration, they might be likewise be crucial to inter-firm knowledge integration and more generally to firm-level AC. In fact, in extant literature on inter-firm knowledge transfer and integration, AC is a fundamental issue studied from many perspectives, but the alignment between the functional specialization of the particular unit that actually recognizes and sources new knowledge from the firm's environment with the functional nature of the knowledge is not studied so far. The question necessarily arises, whether FAC and CFAC internally developed can be actually found to have effects also at the external boundaries of the firm. This is fundamental not only to the literature on knowledge integration but maybe even more so to the stream concerned with AC in general since these departmental ACs thus would constitute important intra-organizational antecedents of firm-level AC.

Finally, recognizing that the optimal level of intra-firm knowledge integration fundamentally depends on environmental complexity and dynamism even under the assumptions of perfect knowledge and internal absorptive capacities, raises the question whether the degree of investment into the maintenance of these internal ACs likewise depends on the environment and what consequences this has for innovation performance.

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