Paper to be presented at the

35th DRUID Celebration Conference 2013, Barcelona, Spain, June 17-19

The Role of Departmental Absorptive Capacities at the R&D-Marketing Interface for Innovation Performance

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Abstract

Based on unique data from Italian manufacturing industries, we provide empirical evidence for the influence of Departmental Absorptive Capacities on Innovation Performance at the R&D-Marketing 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 which can also serve in future studies to reveal meso-foundations of the internal component of firm-level AC. 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.

Jelcodes:M10,-

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

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[1] I am very thankful for most valuable comments by Peter S. H. Leeflang and Francesco Rullani. All errors are mine.

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, only now developed (Hausberg, 2012). 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, although also Zahra & George (2002) 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. A notable exception, however, 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. 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 herein is therefore whether ACs of functionally specialized departments, in particular the complementary Research & Development and Marketing & Sales departments, mediate the relationship between different types of integration and innovation performance and whether these effects differ across the two types of departments. Hence, the aims of this study are the following. Firstly, we aim at showing 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, it shall be shown 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 (Song, Xie, & Di Benedetto, 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.

2. Hypotheses and Model

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). In the literature strand that developed thereupon, this has been refined and reconceptualized several times. 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 arises the necessarily the question of how organizational antecedents determine these different abilities, and while a large body of literature developed around AC, there has been still identified a substantial research gap (Volberda, Foss, & Lyles, 2010). 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.

Hausberg (2012) developed a framework 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 are from 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.

2.2. 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. The order of relevance of the different types of prior related knowledge is inverted at the cross-functional interface (Hausberg, 2012). 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 profit 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, Hoyer, & Rübsaamen, 2010; Song, Thieme, & Xie, 1998). Since it is only the R&D unit, that receives knowledge in this context, it is only the R&D that is incentivized to learn to integrate with the marketing and sales 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. The most salient boundaries impeding integration at intra-functional interfaces, are the semantic and pragmatic boundaries (Hausberg, 2012). 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.*

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.*

2.3. 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.

However, it can be argued that 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. Thus only one side has to be able to really integrate the others knowledge. This is particularly the case at the R&D-Marketing interface.

Although a correlation has been found also between knowledge flows from R&D to Marketing and NPD performance (Moenaert et al., 1994), 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, Heinemann, Engelen, & Neubauer, 2011; 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). Therefore, effects analogous to those in hypotheses 7-11 for intra-functional interfaces do apply at the R&D-Marketing interface only to the R&D function and hence have to developed separately as follows:

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 outcome 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 sought after. 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. It can be concluded thus, that FAC positively impacts innovation performance:

Hypothesis 11: *FAC of (a) R&D and (b) 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).*

From the above discussion, several indirect effects are implied for R&D departments. One indirect effects indicates that FAC positively mediates the effect of informal CFI mechanisms. This means that it counterbalances the negative direct effect, potentially completely neutralizing it. The other two indicate that CFAC mediates both FAC and formal CFI mechanisms (FXM), thus evidencing the role of CFAC. Since CFI aims at providing the necessary knowledge laterally directly to those who need in other functions due to task interdependence, in order to valorize them this knowledge has to be absorbed successfully. The mere collaboration without understanding is not sufficient for a receiving unit. In this case, the receiving unit is hypothesized to be the R&D unit, which heavily relies on market information to direct and orient its work towards current and better future or emerging market demand. The marketing department as an information provider does not have to understand technological knowledge that much. 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.

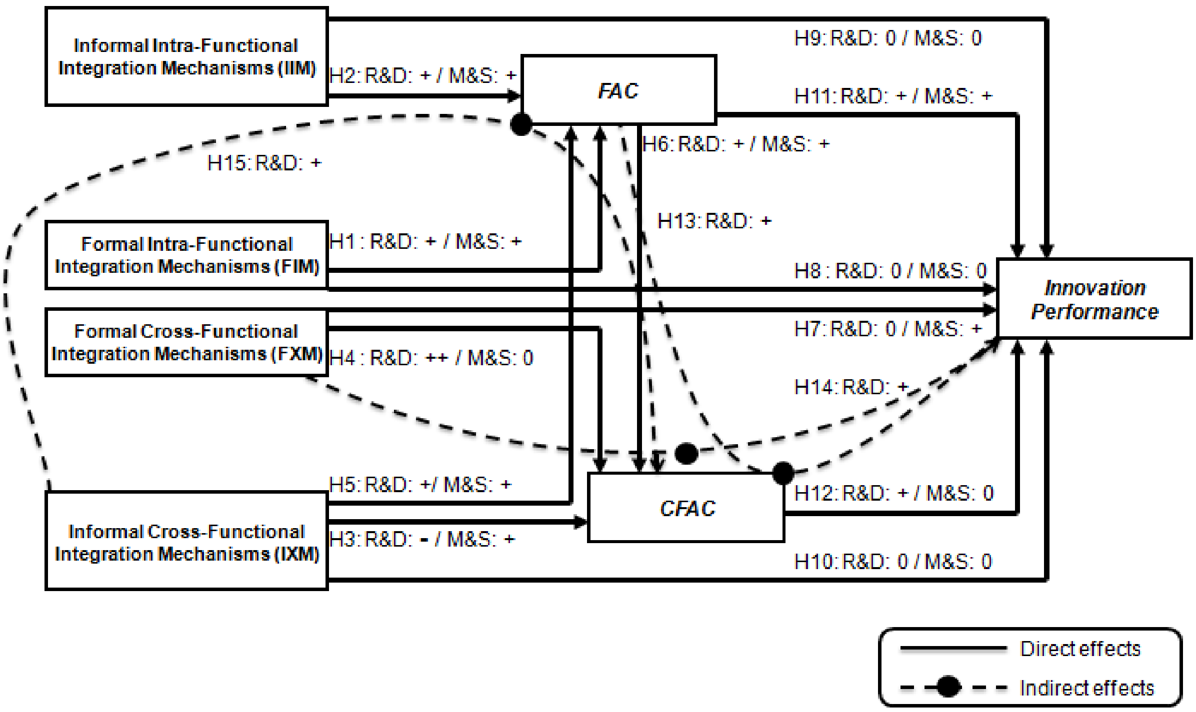
> ***Hypothesis 13:*** *FAC exhibits a positive indirect effect on innovation performance (IPO) via CFAC.*

> ***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.*

The entire set of hypotheses of the conceptual model can thus be summarized as illustrated in Figure 1.

Figure 1: Conceptual model



Control variables not illustrated in the figure.

3. Methodology

3.1. Research design and Operationalization

3.1.1. 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. This and all established scales can be found in the appendix 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.

3.1.2. Operationalization

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, 2010). 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).

In order to measure FAC and CFAC at the level of functional departments, items from literature on Absorptive Capacity and knowledge integration (Flatten, Engelen, Zahra, & Brettel, 2011; Hansen & 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 (Hausberg, 2012), which have recently been validated in several studies .

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).

3.1.3. Control variables

3.1.3.1. 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). It is controlled for this by means of a variable computed as the mean of the cost of employees per turnover ratio of all eligible firms from a particular industry sector in the AIDA database based on the 2 digit ATECO code, which is the Italian implementation of the European NACE classification. Alternatively, it is controlled by the industry average Return on Sales (ROS) as calculated based on the 2 digit ATECO code (e.g. Coombs & Bierly, 2006). Finally, common industry dummies have been used in simple regression analysis as a final check (e.g. Cassiman & Veugelers, 2006).

3.1.3.2. 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. Herein, the most common measure of firm size is applied, i.e. the logarithm of the number of full-time equivalent employees.

3.1.3.3. 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). The same measure is applied herein.

3.1.3.4. 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. The same measure is applied as in previous literature.

3.1.3.5. Environmental turbulence

Several studies find that *environmental turbulence* impacts the innovation behavior and outcomes of integration activities (Lawrence & Lorsch, 1967; Olson et al., 2001). A positive impact on innovation performance is expected. Environmental turbulence is measured by means of a formative item battery used in previous literature (Verhoef & Leeflang, 2009).

3.1.3.6. 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, Montoya-Weiss, & Schmidt, 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).

3.2. Sample size and missing data

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 to isolate the goodness of fit of each of the two models (Anderson & Gerbing, 1988). However, since the adequacy of a sample's size might be connected to the number of 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. 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 to overall model or single parameters.

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). It seems 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 paragraph on data).

The two most common imputation techniques have been chosen and imputation has been performed twice, once by dint of variable means and once via ML estimation as available in AMOS. All analyses of the measurement and structural models have been executed based on both kinds of imputation techniques. Results do not differ in conclusions, 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. This is why principally the results based on this technique are reported, while it is referred to the alternative analyses only for robustness checks that are not possible with this technique (like checking SRMR values or examining standardized residual covariance matrixes).

4. Results and Discussion

4.1. 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 then included 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 which 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 reliable enough estimations of department abilities since the process of socialization might take some time. The thus matched professionals where then contacted with the request to complete our online questionnaire. As shown in Figure 5, the distribution of experience of survey participants is inclined towards less than what can be expected as the mean experience, which is however due to an overrepresentation of younger professionals in the database itself. The effect seems to be very limited however and industry sector experience should not bias 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 its items (descriptive statistics are reported Table 4). 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 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 4, 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 non-response bias has not been a major issue (cf. Table 3).

Common method bias (CMB) was checked for by means of Harman's single factor test 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. 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.

4.2. Measurement model

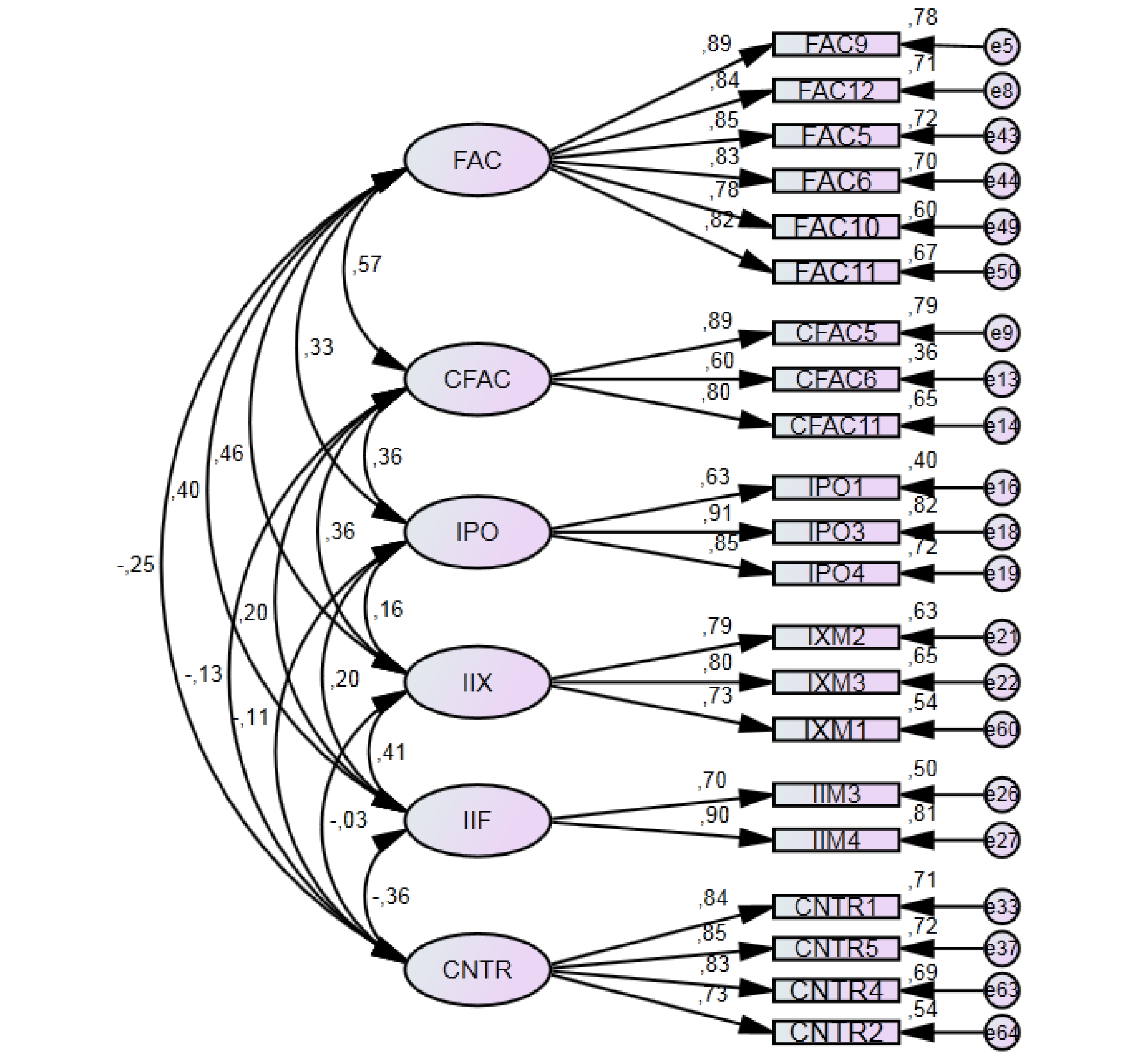
4.2.1. Reflective scales

A first check applied to every scale was that for sufficiently high inter-item correlations (cf. Table 5 through Table 8). 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, 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 2 together with 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 1.

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.

Figure 2: Measurement model for reflective scales



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)[2]. Moreover, no indication of problems with model fit could be found based on a check of the matrix of the standardized residual covariances available for the analysis with mean imputed variable means[3], since no value is larger than 2.58 (cf. Byrne, 1999:86).

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

[3] 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 1: Measurement model results (ML estimation of missing data)

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

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).

Finally, it was tested for configural and metric invariance between the two sub-groups R&D and M&S departments (cf. Byrne, 2009:197-230), both confirming full invariance across the groups R&D and M&S (Table 11). 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[4].

4.2.2. Formative Scales

For all formative scales, it is arguable whether to treat these indicators as reflective or as formative. In fact, some of those scales argued to formative herein have been previously treated as reflective (see discussion above in the corresponding paragraphs 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 (Table 9 and Table 10).

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

[4] It should be reminded that AMOS does likewise not report the estimate for multivariate normality for data with missing values, but it has to be assumed that the multivariate normality assumption was violated, because it appears to be violated as reported for the data with missing values imputed by dint of 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.

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.

4.3. Structural model

The structural model is based on the above developed hypotheses and includes the described 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), whereas there was no such indication for the M&S sub-sample (kurtosis: 1.970, c.r.: .356). However, chi-square statistic appear to be downward biased by this as it is exceptionally good (.910) as is the chi-square/d.f. value (.731).

Examining the estimates (Table 2 and Figure 3) 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).

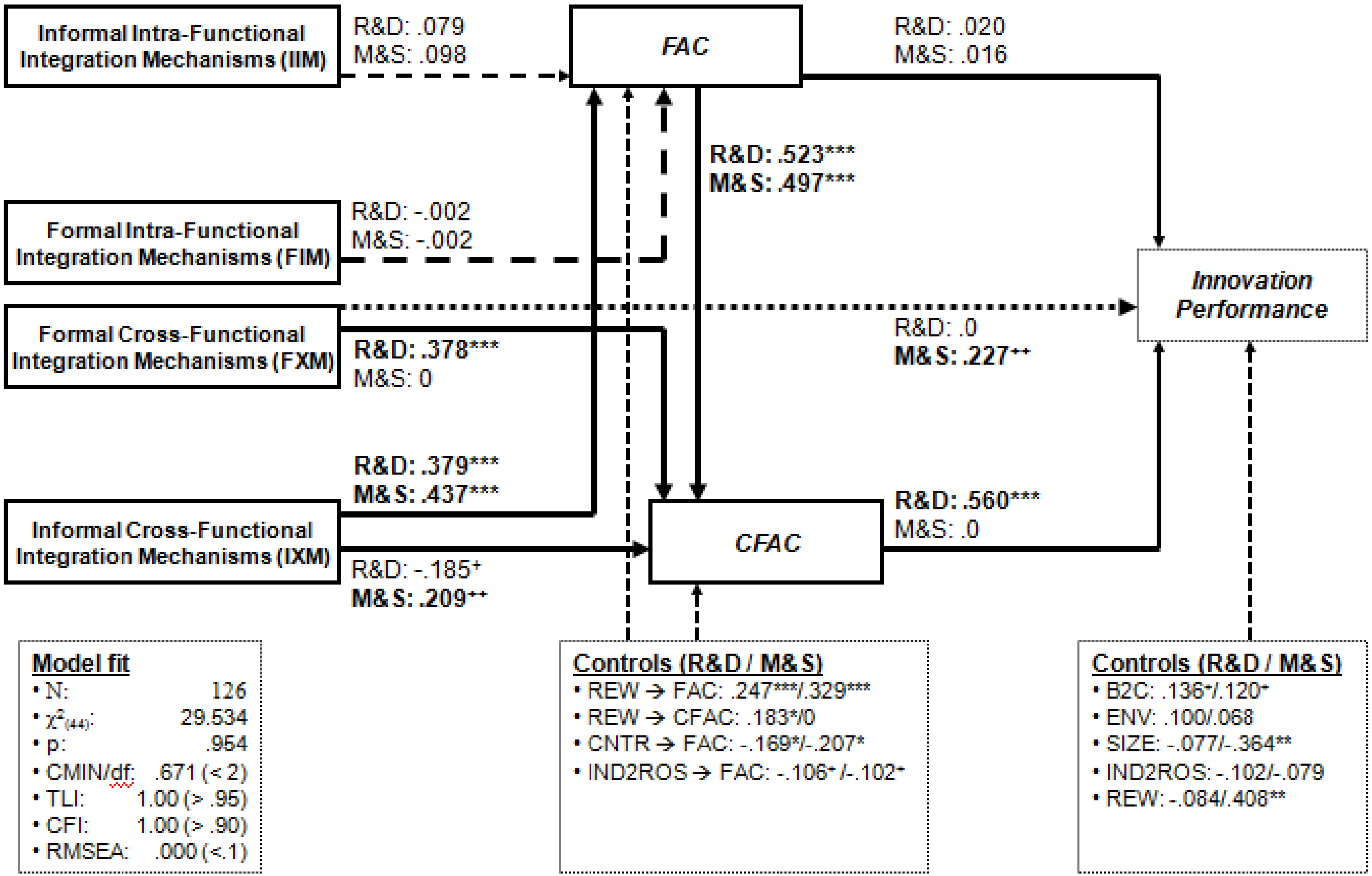
As regards the main hypotheses, it can be highlight that CFAC significantly positively impacts innovation performance as expected. This effect is robust across diverse model specifications and all models that specify a direct effect of integration mechanisms onto innovation performance had to be rejected 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.

Table 2: Structural model results (ML estimation of missing data)

DV	Hypo-thesis	Path			R^2	Standardized Estimates R&D	M&S	Expected	Result
FAC (R&D)					.357				
FAC (M&S)					.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 (R&D)					.529				
CFAC (M&S)					.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 (R&D)					.372				
IPO (M&S)					.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:									
		CFAC	<---	FAC <--- IXM		.198***	-	+	confirmed
		IPO	<---	FAC <--- FXM		.204**	-	+	confirmed
		IPO	<---	FAC <--- FAC		.283***	-	+	confirmed

Notes: n = 126; $^{+}$ < .11, $^{++}$ < .07, * < .05, ** < .01 *** < .001; $\chi^2(44) = 29.534$; p = .954; χ^2/d.f. = .671; TLI = 1.146; CFI = 1.00; RMSEA = .000; 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).

Figure 3: Pure structural model results overview (ML estimation of missing data)



For R&D departments it can be confirmed that formal CFI mechanisms (FXM) highly significantly, positively impact CFAC, while informal CFI mechanisms (IXM) have an slightly significant, negative effect on CFAC, and 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, evidence I find that these effects of formal and informal CFI mechanisms are as predicted partly inversed when considering M&S departments. Constraining the of formal CFI mechanisms (FXM) on CFAC of 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, we find support also for the interrelation of FAC and CFAC in that FAC impacts significantly and highly positive on CFAC. However, neither formal nor informal intra-functional integration mechanisms, FIM and IIM respectively, could be confirmed as positive antecedents of FAC. However, 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.

4.4. Further robustness checks

Several competing models have been tested confirm the hypothesized model. Due to limited space only three major competing models are reported here (Table 13). Most importantly, it could be argued for reversed causality. That is, a higher degree of innovation performance could increase the perception of managers of how able their department is in absorbing new external knowledge. While this model performance better than the other competing model, it still performance significantly worse than the other based on comparison of the AIC (363.604) and the other model fit indicators.

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. Finally, visual inspection for heteroskedasticity does not suggest such an issue for any of the discussed OLS models.

A major hypothesis is supported by the OLS models. 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.

5. Conclusion, Limitations and Future Research

I can conclude that in this study several contributions to seemingly mature research strands are made based on an online-survey amongst R&D and M&S professionals from the Italian manufacturing industry. Firstly, I succeeded to establish a valid and reliable empirical measurement instrument for the previously only theorized (see first paper in this thesis) 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 both for research and practice. Research can use already these simpler scales 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 the potential innovativeness from cross-functional integration is lost. In fact, it is therefore 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 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, however. 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 strand.

Appendix A: Figures & Tables

Figure 4: Manufacturing industry sectors in final sample by 2-digit ATECO code

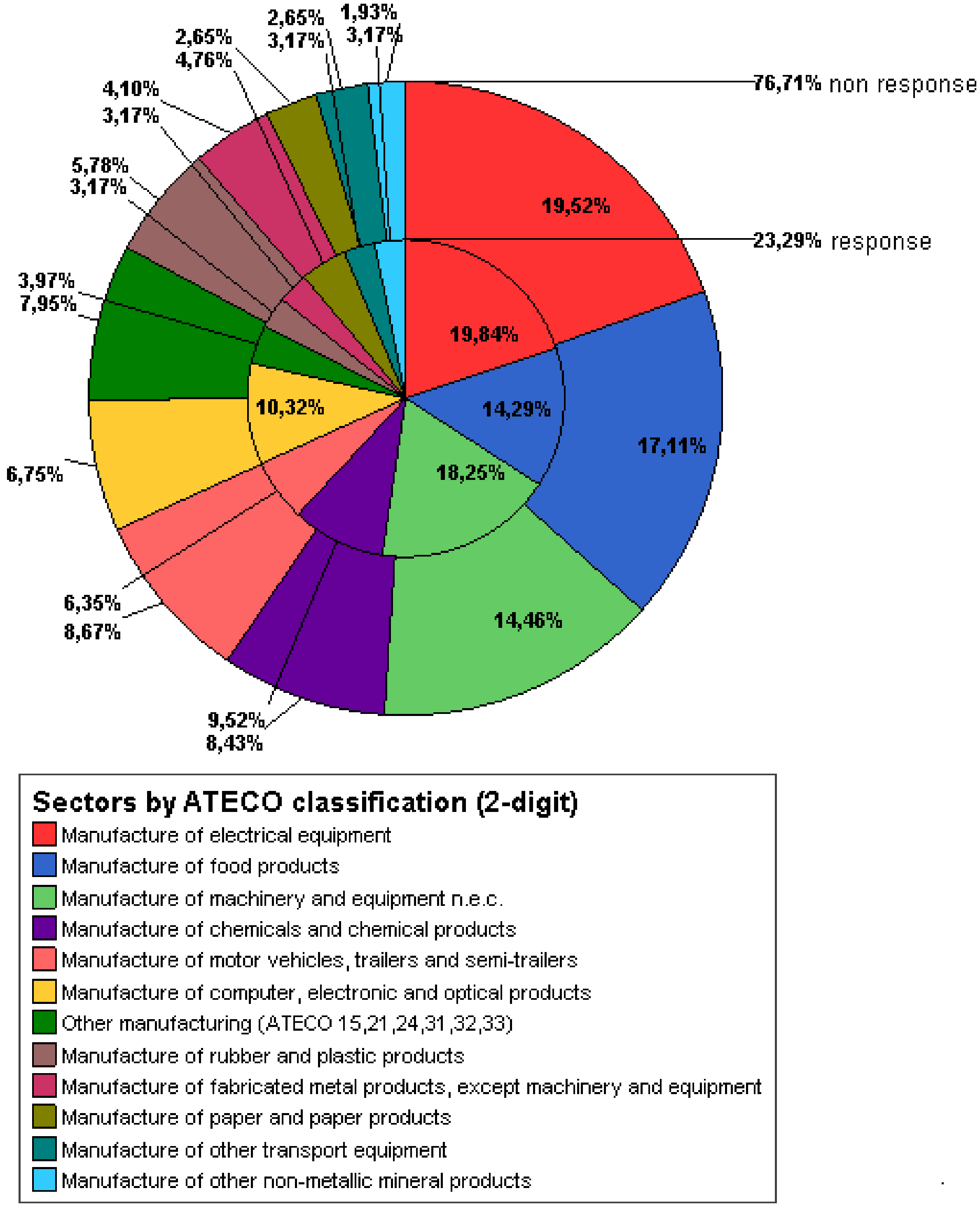


Table 3: Respondents / Non-respondents mean comparison

	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 5: Histograms: Industry Experience of respondent (EXPI), left, and ROS, right.

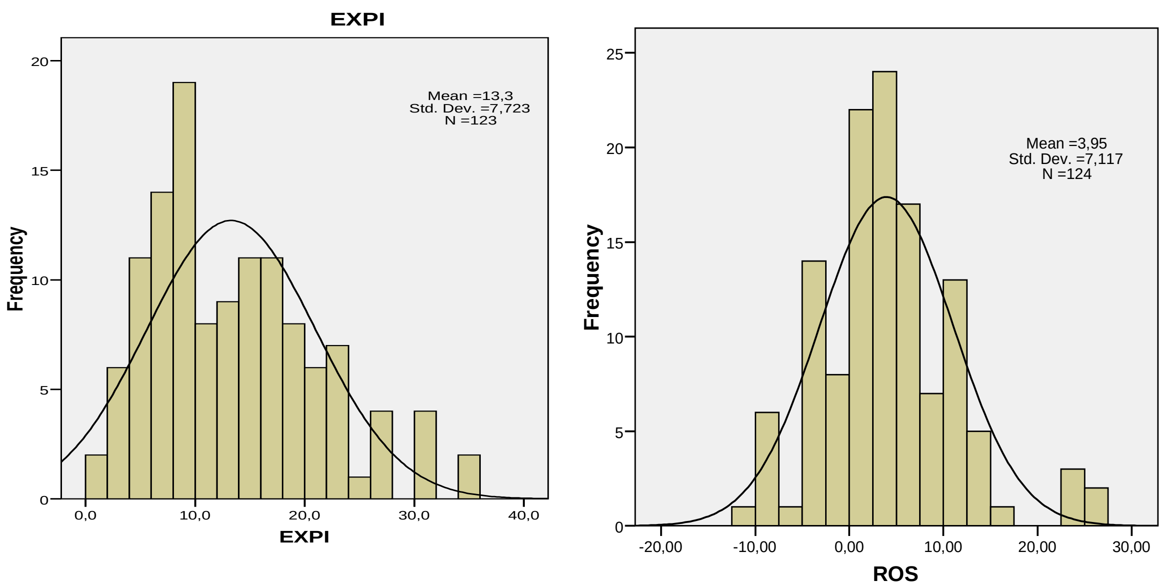


Table 4: **Descriptives**

	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 5: 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 6: 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 7: 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 8: 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 9: Inter-item correlations of formative 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 10: Inter-item correlations of formative scales 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).

Table 11: 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 12: Correlation Matrix of Constructs in Model (for results with mean imputed data)

	ENV	REW	KQO	CNTR	IIF	IIX	FIFO	FIFN	FIXN	FIXO	IPO	CFAC	FAC	ROA	ROS	ROE
REW	0,345**															
	0,000															
KQO	0,353**	0,100														
	0,000	0,266														
CNTR	-0,143	-0,302**	-0,220*													
	0,111	0,001	0,014													
IIF	0,329**	0,370**	0,210*	-0,389**												
	0,000	0,000	0,019	0,000												
IIX	0,335**	0,202*	0,333**	-0,013	0,484**											
	0,000	0,024	0,000	0,889	0,000											
FIFO	0,283**	0,235**	0,175	-0,187*	0,564**	0,305**										
	0,001	0,008	0,051	0,037	0,000	0,001										
FIFN	0,307**	0,272**	0,207*	-0,193*	0,588**	0,299**	0,982									
	0,001	0,002	0,021	0,031	0,000	0,001	0,000									
FIXN	0,228*	0,182*	0,298**	-0,046	0,245**	0,637**	0,491	0,474**								
	0,011	0,043	0,001	0,614	0,006	0,000	0,000	0,000								
FIXO	0,232**	0,167	0,287**	-0,027	0,235**	0,647**	0,484	0,455**	0,993**							
	0,009	0,063	0,001	0,766	0,008	0,000	0,000	0,000	0,000							
IPO	0,255**	0,320**	0,280**	-0,130	0,290**	0,180*	0,251	0,285**	0,224*	0,202*						
	0,004	0,000	0,002	0,149	0,001	0,044	0,005	0,001	0,012	0,024						
CFAC	0,395**	0,341**	0,531**	-0,147	0,258**	0,435**	0,166	0,210*	0,368**	0,359**	0,406**					
	0,000	0,000	0,000	0,103	0,004	0,000	0,064	0,019	0,000	0,000	0,000					
FAC	0,425**	0,466**	0,217*	-0,258**	0,462**	0,497**	0,236**	0,282**	0,330**	0,322**	0,388**	0,646**				
	0,000	0,000	0,015	0,004	0,000	0,000	0,008	0,001	0,000	0,000	0,000	0,000				
ROA	0,081	0,123	0,089	0,008	0,066	-0,035	0,100	0,114	-0,053	-0,040	0,166	0,012	0,057			
	0,367	0,171	0,323	0,927	0,467	0,696	0,267	0,205	0,560	0,660	0,064	0,895	0,528			
ROS	0,110	0,114	0,122	0,009	0,103	-0,011	0,090	0,114	-0,056	-0,036	0,182*	0,099	0,110	0,870**		
	0,222	0,205	0,177	0,923	0,252	0,907	0,320	0,207	0,535	0,688	0,042	0,272	0,223	0,000		
ROE	-0,009	-0,023	-0,106	0,155	0,137	-0,146	0,163	0,169	-0,125	-0,118	-0,083	-0,182*	-0,077	0,332**	0,292**	
	0,921	0,799	0,240	0,083	0,128	0,103	0,069	0,060	0,165	0,191	0,360	0,042	0,394	0,000	0,001	
EMPL	0,001	-0,094	-0,084	-0,012	0,067	0,070	0,026	0,011	0,001**	-0,002	-0,232**	-0,028	0,124	-0,236**	-0,165	0,097
	0,992	0,298	0,353	0,898	0,458	0,437	0,775	0,907	0,988	0,980	0,009	0,755	0,169	0,008	0,066	0,283

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

Table 13: Competing models compared

Model	χ^2	d.f.	$p(\chi^2)$	χ^2/d.f.	CFI	TLI	RMSEA	AIC
(0) Main model	30.191	44	.944	.686	1.000	1.137	.000	358.191
(1) no FAC→CFAC	69.807	45	.010	1.551	.941	.760	.067	395.807
(2) FXM→FAC	29.381	42	.929	.700	1.000	1.131	.000	361.381
(3) Reverse causality	29.642	42	.924	.706	1.000	1.128	.000	361.642

Table 14: 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.

Appendix B: Questionnaire

Table 15: 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 …	**IIF**	**IIX**
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 16: Innovation Performance

Coding	**Items** (Atuahene-Gima et al., 2005; De Luca & Atuahene-Gima, 2007; Foss et al., 2010) *(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 17: 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 18: 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) *(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			

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