# R&D collaborations: Is diversity enhancing innovation performance?

Journal Item

# R&D Collaborations: Is Diversity Enhancing Innovation Performance?

Areti Gkypali[a], Despoina Filiou[b], Kostas Tsekouras[c]*

a: Enterprise Research Centre, Warwick Business School, University of Warwick, UK (email: areti.gkypali@wbs.ac.uk)
b: Department of Management, Manchester Metropolitan University, UK (email: d.filiou@mmu.ac.uk)
c: Department of Economics, University of Patras, GR (email: tsekour@econ.upatras.gr)

**Abstract**

We develop a theoretical framework which builds on the existence of a feedback loop relationship between internal innovation efforts and the diversity of types of R&D collaborations. Such a feedback loop allows for decomposing the total effects of both internal and external knowledge sources on innovation performance in direct and indirect effects. We argue that such feedback loop lies in the heart of the interplay between the benefits and costs associated with generating knowledge internally and accessing knowledge from diverse external knowledge sources. In particular we argue that anticipated benefits from accessing knowledge from diverse external knowledge sources may be outweighed by (i) costs associated with accessing increasingly diverse knowledge through collaboration and (ii) a negative network effect on firms' internal innovation efforts. We employ Structural Equation Modelling on a bespoke dataset of Greek R&D active manufacturing firms; empirical results confirm the existence of an idiosyncratic feedback loop relationship and show that internal innovation efforts positively influence firm innovation performance. On the other hand, diversity in external collaborations has a negative impact on internal innovation efforts, elevating the importance of the optimal balance between internal R&D investments and the diversity of R&D collaborations. The same picture emerges when examining the corresponding direct and indirect effects of internal and external knowledge sources on innovation performance.

**Keywords:**
R&D collaboration diversity; innovation performance; structural equation modelling

* Corresponding Author:
University of Patras, Department of Economics
University Campus Rio, 26504 Patras, Greece
e-mail: tsekour@econ.upatras.gr

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# 1 Introduction

External collaborations and open innovation play an increasingly central role in firm innovation management and performance (e.g. Chesbrough, 2006; Lakemond et al., 2016). Extant literature has mainly explored how external collaboration, acting in tandem with internal knowledge generation efforts, may improve innovation performance (e.g. Chesbrough, 2006; Kale & Singh, 2009; Wassmer, 2010; Zidorn and Wagner, 2013; Wuyts & Dutta, 2014; Alexy et al., 2016). In this line, Lakemond et al., (2016) suggest that knowledge integration through open innovation collaboration can be essentially perceived as a knowledge governance problem. Hence, firms' decisions on the management of partners and knowledge inflows and outflows will have an impact on their innovation performance. Despite the opportunities that external collaborations offer to acquire or to access complementary and supplementary knowledge, the literature finds mixed evidence on their role in innovation performance (e.g. Laursen and Salter, 2006; Abramovsky et al., 2008; Faems et al., 2010; Chun and Mun, 2012). This is mainly due to external collaborations carrying costs of search, coordination, management and knowledge exchange which can outweigh the benefits of accessing external knowledge (Teece, 2006). Such costs can be aggravated by the need to establish management mechanisms to prevent any unintended spillovers towards the innovation partners. (Laursen and Salter, 2014).

Most of the literature assumes exogeneity of R&D activities and external knowledge sources when investigating their influence on innovation performance; however, their interrelationship has been often acknowledged by incorporating a moderating effect of internal R&D activities on the breadth and depth of external knowledge sources (Cassiman and Veugelers, 2006; Laursen and Salter, 2006; Hagerdoorn and Wang; 2012; Lin, et al., 2012). In this paper, we argue that even such moderation effects may offer only a weak approximation to the complex interplay between internal innovation efforts, knowledge sourced from R&D collaborations and firm innovation performance. Indeed, these elements of firm innovation strategy and performance are co-determined and co-evolve and this introduces interrelationships among them (Teece, 2006; Dosi and Nelson, 2014). Such interrelationships imply that internal innovation efforts and knowledge sourced from external R&D collaborations not only have direct effects on firm innovation performance but also exert indirect effects through influencing and mediating one another.

This paper proposes that such complex interrelationships can be captured in an integrative way where allowing for endogeneity, i.e. a feedback loop, between internal innovation efforts and the diversity of external R&D collaboration offering the opportunity to capture direct and indirect effects on innovation performance, otherwise ignored in relevant literature. We frame such complexity by examining the conditions that enable firms to leverage benefits from accessing knowledge from diverse external knowledge sources and how such benefits may be outweighed by: (i) costs associated with accessing increasingly diverse knowledge through collaboration and (ii) a negative network effect on firms' internal innovation efforts. In particular, internal investments in knowledge generating activities are allowed to directly influence both the diversity of external knowledge sources and firm innovation performance; at the same time, we explore the indirect effect of internal innovation efforts via the diversity of external knowledge on innovation performance. Furthermore, knowledge sourced from external R&D collaborations can have both a direct and an indirect effect on firm innovation performance, through its impact on internal knowledge generation efforts.

Our empirical exploration relies on a sample of Greek Manufacturing R&D active firms for the period 2010, highlighting the fact that the Greek economy and particularly the Greek Innovation System shares many commonalities with other Eastern and Southern small

European peripheral countries (OECD, 2012; 2014; Souitaris, 2002). We formulate and empirically test our hypotheses employing Structural Equation Modelling. Empirical findings corroborate the complexity ruling the internal – external innovation nexus which is depicted on their influence on innovation performance; perhaps more importantly, empirical findings dispute the notion of a positive influence of external R&D collaborations and offer a narrative based on the pivotal role of firms internal innovation efforts in generating and appropriating benefits from external collaborations.

The remainder of this paper is structured as follows: section 2 presents the theoretical and empirical literature forming the background to our framework and empirical hypotheses. Section 3 discusses the context of our study, and specifically the peculiarities of the Greek innovation system together with our methodology, data collection and main empirical variables. Section 4 presents our empirical model in depth, section 5 presents and discusses the empirical estimates, and finally section 6 concludes the paper.

## 2 Background and Hypotheses

### 2.1 Background and Research Framework

In the main, the literature that offers insights on framing and understanding the relationship between internal, external knowledge and innovation performance (Teece, 1986; Veugelers and Cassiman, 1999; Chesborough, 2006; Laursen and Salter, 2006) stems from the Resource (Wernefelt, 1984, Barney, 1991) and Knowledge Based (Grant, 1996; Szulanski, 1996) views, as well as the transaction cost approach (Das and Teng, 2000; Belderbos et al., 2004; Rawley, 2010). In particular, two interrelated concepts have dominated the theoretical and empirical analyses of the management of external technological and other knowledge sources.

First, on the one hand are the benefits stemming from the interplay between internal and external knowledge creation processes, manifested as the ability to form capabilities of the 'learning to learn' variety (Collis, 1994). These capabilities may reflect organizational, integrative, combinative and/or dynamic capabilities which are beneficial in boosting firms' innovation performance (Belderbos et al. 2004; Weigelt, 2009). Second, on the other hand, are the costs associated with accessing diverse types of external knowledge sources. Such costs can be further decomposed in: (i) costs incurred due to increased operational and managerial costs i.e. search, coordination, monitoring, transaction and adjustment costs, and (ii) costs attributed to a network effect which results in loss in "knowledge uniqueness" (Rochet and Tirole, 2006). Hence, the greater the diversity of the external knowledge sources accessed, the higher are the costs of leveraging the newly accessed knowledge (Nasiriyar et al., 2013) and the lower is the probability that the externally acquired knowledge is unique and results in significant yields in terms of firms' innovation performance (Parker and Alstyne, 2005; Armstrong, 2006). We argue that such costs occur because an underlying highly interactive process exists from the point of accessing new knowledge, to the point of internalizing and redeploying such knowledge internally and embedding it together with existing organizational routines (Veugelers et al., 2014; Weigelt, 2009; Zahra and George, 2002). Therefore, the processes of innovation, capability creation and the costs associated with pursuing diversity in external collaborations co-exist and jointly influence firm innovation performance (Teece, 2006).

According to extant literature, the causal relationship between internal innovation efforts and firm's diversity of R&D collaborations remains ambiguous (Rycroft, 2007). In this paper, we argue that the relevant literature has sidelined the potential endogeneity between internal innovation efforts and diversity in R&D collaborations portfolio. In such an endogeneity framework internal innovation efforts and diversity in R&D collaborations are co-determined and such *feedback loops* between them can be appropriately captured by a *system of structural equations*.

Within this context, the potential feedback loop between internal innovation efforts and the diversity of the types of R&D collaborations allows the existence and investigation of, otherwise hidden, indirect effects on innovation performance which in turn highlight the underlying complexity ruling this relationship. Figure 1 below provides a representation of such an endogenously determined system. In this context, both internal innovation efforts and the diversity of external knowledge sources may have, except for a direct impact, substantial indirect effects on innovation performance. In technical terms, both knowledge sourcing variables (i.e. internal R&D and R&D collaboration diversity) simultaneously cause and mediate each other's effect on innovation performance. The existence of mediators differs to the case of moderation examined in extant literature (Lin et al., 2012; Berchicci et al., 2016) and reflects the presence of endogeneity among the variables in the system of Figure 1.

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Insert Figure 1 around here

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In the following section, we, first, develop hypotheses on the relationships between internal R&D and diversity of external R&D collaborations (paths "a" and "b" in Figure 1). Second, we develop hypotheses on the total effects of internal R&D and diversity of R&D collaborations on innovation performance after allowing each other to act as mediators (paths "c×e" and "d×f" respectively in Figure 1).

## 2.2 Hypotheses: Internal R&D, Diversity in types of R&D Collaboration & Firm Innovation Performance

Cohen and Levinthal (1989) established a relation between internal knowledge and a firm's ability to identify, absorb, and utilize external knowledge. Existing knowledge determines the remit and level of relevant external knowledge that firms are able to perceive as useful, subsequently internalize and exploit, suggesting that there is path dependence in organisational learning. This main premise of absorptive capacity has been extended to the context of alliances and collaborations, whereby some level of commonality between partners' knowledge bases is required for effective knowledge transfer in alliances (Lane and Lubatkin, 1998; Mowery et al., 1996). Based on the above we expect a positive effect between a firm's internal innovation efforts and the diversity of its R&D collaboration portfolio. Broader and deeper investments in internal innovation efforts not only make external search more astute but also enable firms to identify the potential of more varied and broader sources of external knowledge, hence increasing the diversity of R&D collaborations (Cohen and Levinthal, 1989; Mowery et al., 1996; Faems et al., 2010). Existing research suggests a positive effect of a firm's investments in R&D on the extent of its collaborative partnerships (Lokshin et al., 2008; Dahlander and Gann, 2010; Lin et al., 2012). As a result the following hypothesis is formulated:

*$H_{1a}$: Firm's internal innovation efforts positively influence the diversity of its R&D collaborations portfolio*

Increases in the diversity of R&D collaborations portfolio can exhibit either a positive or a negative effect on a firm's internal innovation efforts as captured by investments in R&D. On the one hand, firms have to establish a knowledge base of a sufficient size in order to search, acquire, filter, exploit and redeploy effectively in their products and routines the knowledge acquired by external sources (Zahra & George, 2002; Todorova & Durisin, 2007). Moreover, Weigelt (2009) argues that the more the firm relies in external sources to outsource R&D activities the larger is the required investments in internal R&D for the external knowledge to be exploited. Establishing collaborative agreements entails a range of coordination and administration costs. Firms need to spend resources, time and effort to identify appropriate and suitable partners (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998; Kale & Singh, 2009; Wassmer, 2010), while allignment between partners' interests and objectives cannot be guaranteed over the course of the collaboration, leading to a number of such collaborations ending prematurely, due to reasons such as value missapropriation, fear of free riding and exposure to opportunistic behaviour (White & Lui, 2005). Indeed recent literature finds a concave relation between breadth of collaboration and the strenght of IP strategy (Laursen and Salter, 2014). Collaborative relationships raise coordination and managerial costs as firms have bounded cognitive abilities (Nooteboom et al. 2007) to process complexity in combining different sources of knowledge. Moreover, knowledge, as well as other resources, are context specific, which raises the costs of transfering and applying such knowledge in different contexts (Szulanski, 1996).

Therefore we argue that for small firms with limited financial and human resources and managerial capabilities, which operate in environments of low innovation dynamism, the costs of searching, coordinating, and monitoring R&D collaborations and embodying the acquired external knowledge may be compensated by reducing investments in internal R&D, as some of these resources may be diverted to the management and coordination of R&D collaborations (Carayannis and Alexander, 2002). Hence, we expect that the associated costs from searching, combining, integrating, and storing external knowledge may be harmful to internal innovation efforts as the diversity of R&D collaboration portfolios increases (Weigelt, 2009; Grimpe and Kaiser, 2010):

*$H_{1b}$: Firm's diversity of R&D collaborations portfolio negatively influences internal innovation efforts*

Firm's internal R&D activities are expected to exert *a positive and direct influence* on its innovation performance since they lie at the core of firms' dynamic capabilities and absorptive capacity (Teece, 2006). Enhancing internal knowledge base can increase the potential of incremental innovations, as firms re-combine existing internal knowledge and gain a deeper understanding of the relations and links across existing knowledge (for a review see Lane et al., 2006). As the firm's internal knowledge base increases so does the need to search for additional external innovation partners to contribute in augmenting and refining firms' knowledge base and eventually boost their innovation performance. Indeed, firms can expand their knowledge base through accessing complementary and supplementary knowledge in collaborations (e.g. Mowery et al., 1996) and such complementarities can lead to creating a new range of products and to enhanced internal competence in areas of specialization, potentially enhancing efficiency and incremental improvements (Grant and Baden-Fuller, 2004). In this respect, an indirect effect of firms' knowledge base on innovation performance exists, originating from internal innovation efforts, mediated by the diversity of R&D collaborators and resulting in innovation performance. Nevertheless, this indirect effect is associated with search, coordination, monitoring, and transaction costs, which in turn may offset the potential benefits in terms of new knowledge and capabilities creation a firm would stand to gain. Furthermore, relying heavily on a diverse portfolio of external R&D may lead to a situation where the knowledge base of the firm will tend to suffer from dilution, because the kind of knowledge accessed from external partners, bears public good properties, making it thus, less unique and easier for competitors to imitate (Grimpe and Kaiser, 2010). However, it is plausible to argue that overall the effect of internal innovation efforts on innovation performance remains positive. Hence, we develop the following hypothesis:

*$H_2$: The total effect of firm's internal innovation efforts on innovation performance is positive*

External knowledge can be considered as a valuable resource (Barney, 1991) for the firm which absorbs it under two distinct patterns: in the first case, the external source provides its knowledge through R&D collaboration exclusively to the firm. In the second case, when multiple external sources provide knowledge inputs to a variety of absorbing firms, only those firms who are able to combine and redeploy effectively the proliferated external knowledge in a unique way, may eventually create value from the obtained knowledge resources. In other words, external knowledge sourced from diverse sources is effectively combined and redeployed when it becomes embodied in firm's internal innovation efforts and realized through an increase in its innovative products and processes. This ability to exploit external and internal knowledge stems from the processes that constitute absorptive capacity (e.g. Lane et al, 2006) link external with internal absorptive capacity routines (Lewin et al., 2011) which underpin the potential for knowledge re-combination and innovation (Kogut and Zander, 1992) and eventually firm potential for adaptation and change (Zahra and George, 2002).

In the context of the first pattern presented above, the firm does not face any rivalry from other competitors, since no one else has access to the same idiosyncratic technology and hence, the external knowledge is becoming, via its exclusiveness, a valuable resource. When additional R&D collaborators come into play the value of the specific external knowledge input may be put under doubt. Every time that the firm decides to source external knowledge from one additional source, that is to increase the diversity of external knowledge sources, the odds that the exclusivity condition will be maintained are reduced (Parker and Alstyne, 2005; Armstrong, 2006; Rochet and Tirole, 2006). Such being the case, a network effect associated with the number of firms linked to external knowledge sources comes into play. This network effect increases disproportionally the potential knowledge rivals of the absorbing firm and results in undermining the exclusiveness and uniqueness of the externally sourced knowledge. Based on the above, increasing diversity of types of R&D collaborations does not contribute to the distinctive value of the external knowledge, on the contrary, it diminishes its importance as a valuable resource and therefore its direct influence on the absorbing firm's innovation performance is expected to be insignificant and rather negligible.

In this context, an additional indirect effect emerges originating from the diversity of types of R&D collaborations mediated by internal innovation process and then to firm's innovation performance. Specifically, we argue that the external knowledge sourced from an increasing number of different types of partner, becomes a valuable resource, if and only if, it is internalized, embedded, stored, combined and used together with the absorbing firm's internal innovation efforts (Weigelt, 2009; Peeters and Martin, 2015). In this case, increasing diversity of the external knowledge sources may be beneficial for the firm, if the latter possesses absorptive capacity of the appropriate type and level, which allows for an effective internalization and combination of the externally sourced knowledge sourced. However, such benefits are juxtaposed by the costs associated with the increased diversity of external knowledge sources, such as the search, coordination, monitoring, transaction and adjustment costs. Only if the benefits mentioned above exceed such costs, one should expect that the indirect effect of the diversity of external knowledge sources on the firm's innovation performance would be positive. It is reasonable to assume that, in the case of firms with low levels of absorptive capacity, low innovation dynamism, which operate in sluggish innovation environments, the costs associated with an increased diversity of R&D collaborations will exceed the respective benefits. Summing up, based on the anticipated direct and indirect effects of the diversification of R&D collaborations portfolio on innovation performance, we formulate the following testable hypothesis:

*$H_3$: The total effect of a firm's diversity of R&D collaboration on innovation performance is negative*

## 3. The Greek Innovation System, Data Collection and Variables Definition

### 3.1. The idiosyncrasies of the Greek Innovation System

It is misleading to assume that examples drawn from technologically sophisticated countries with respect to innovation can shed light on the innovative behaviour of countries with less developed technological profiles (Mishra et al., 1996; Souitaris, 2002; Gkypali and Tsekouras, 2015). In this respect, the technological status of Greek manufacturing firms and their innovation profile, is largely determined by the corresponding country-specific technological, economic, social and cultural context. Suitaris (2002) showcases that Greek idiosyncrasies in terms of technological and administrative heritage, market structure, entrepreneurial mentality and cultural issues shape an environment where the development of Greek firms has been largely based on know-how and technologies imported from abroad. Transfer of technologies in the form of foreign direct investment, licensing and imports of capital goods have been the main source of technological inputs into the Greek production system. Conte and Vivarelli (2014) argue on the importance and complementarity between technology transfer, and R&D activities in the innovation process even for firms which operate in more advanced technological environment as is the case of Italy. .

OECD in a series of "Science, Technology and Innovation" reports (2012; 2014) sketches the weaknesses and idiosyncrasies of the Greek Innovation System, showcasing that the Greek economy is not close to the world technology frontier. More specifically, the Greek Innovation System is consistently found at the bottom of the distribution in nine out of ten of the examined indices reflecting "competencies and capacity to innovate" and in eleven out of thirteen indices regarding the "interactions and skills for innovation" section. Moreover, in almost half of the indices the Greek Innovation System is placed in the bottom five of the OECD countries. In this line, Acemoglu et al., (2006) argue that firms operating in economies which lag behind the world technology frontier pursue an investment-based, instead of an innovation-based, growth strategy. The distance to the technological frontier is also closely related to the low level of the Greek IPR system, which in turn, is inextricably associated to the extent of the diversity of R&D collaborations. Moreover, when the strength of an IPR system interacts with the distance to the technological frontier, its effect on innovation performance is no longer significant (Della Malva and Santarelli, 2016). Ur Rehman (2016) argues that when firms operate in innovation systems which are distant from the world technological frontier, forging R&D alliances is beneficiary for their performance since these alliances reduce the cost associated to innovation activities. It is noticeable that these arguments do not distinguish between the diversity and the intensity of collaborations, but instead they are grounded on the performance differentials of an on-off R&D collaborations criterion. At the same time, idiosyncratic entrepreneurial activity is inevitably linked and affected by ineffective technological infrastructure related to legislation, intellectual property rights and supply of designers, a rather outdated vocational and training system, and low labour mobility (OECD, 2012; 2014).

In this respect and in order to examine the research question posed above, we have employed a sample of Greek R&D active Manufacturing firms by resorting to the GORDA (Greek Observatory of R&D Active) database. GORDA is compiled by an extensive survey at the national level carried out in 2011 providing longitudinal (2001-2010) information on Greek Manufacturing firms' R&D investments and company accounts. The field research was carried out during the second half of 2011 and referred to information on the previous year, 2010. Members of the research team have come in contact with all firms included in the population. Eventually, 316 firms replied reaching a response rate of 45%. All firms identified in the sample were called to complete a specially designed questionnaire regarding their innovation and R&D

activities[1]. After data cleaning and stratification, 300 firms with usable questionnaires remained in the sample. The longitudinal information of firms' annual financial accounts was pooled over time to create stock measures of R&D investments and other financial indices (see Table 2 for a full description of variables and measurement) and was combined with the survey data to form a cross-sectional dataset for 2010.

Our theoretical framework sketched in Figure 1 shows the types of complex relationships between three main variables that will be empirically examined: (i) diversity of R&D collaborations portfolio, (ii) internal innovation efforts and (iii) innovation performance. A methodological route capable of depicting in modeling terms the complexity of such relationships is Structural Equation Modelling (SEM) with *latent* variables. SEM is mainly interested in testing the hypothesized causal relationships among structural variables that are often *latent*. In the context of this paper, the use of latent variables serves a twofold purpose: on the one hand, we aim at capturing the heterogeneous manifestation of firm's strategic choices with respect to new knowledge production; on the other hand, latent variables are employed to account for measurement error in the observed variables. The issue of approximating a complex concept absolved of the presence of underlying errors becomes even more important in the case where available indicators are the result of a field research survey.

In this respect, the measurement of the structural parameters, the so-called measurement model, plays a crucial role since a potential misspecification of the latent variables can affect the estimation of the structural model. With respect to Structural Equation Modeling, the Confirmatory Factor Analysis (CFA) is commonly employed because it is perceived as an inextricable part of building and testing a theoretical framework. This method is used to study the dimensionality of a set of variables by inferring the presence of underlying, error-free

[1] Due to space limitations, the questionnaire employed in the field research is not included here but is available upon request.

unobserved constructs which are comprised by a set of correlated observed or response variables.

The definitions and descriptive statistics of the variables employed in the measurement model for the latent constructs are depicted in Table 1.

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In order to control for potential confounding effects between the relationship of *internal innovation efforts and diversity of R&D collaborations* we included in the estimated model control variables following relevant literature. More specifically, firms' absorptive capacity has been suggested to present a nonlinear relationship both with respect to the firm's ability to successfully interact with external knowledge sources and its ability to internalize the acquired knowledge (Laursen and Salter, 2006; Hotternot and Lopez-Bento, 2016). In the same vein, *internal innovation efforts* may be characterized by Schumpeterian patterns of innovation (Breschi, et al., 2000); hence, we have also controlled for the importance of 'creative accumulation' or 'creative destruction' by including the firm's relative R&D age.

Turning to the rest of the determinants of *diversity of R&D collaborations,* the firm's degree of participation in foreign affiliates, is expected to play a role in determining an open attitude in R&D (De Faria et al., 2010). In addition, the firms' location may influence its ability to form new R&D partnerships (Lawson et al., 2009). Finally, firm *innovation performance* is expected to be determined by financial performance as it is proxied by firm profitability as well as the internal composition of assets employed in the production process (Faems et al., 2010). According to Schumpeter, market structure is expected to influence firm's innovation performance and in this line we have also included firm's profit margin as an additional explanatory variable. Table 2 below summarizes the control variables employed in each of the structural equations.

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## 4. Empirical Model

In mathematical terms, the general structural equation model can be expressed by two basic equation blocks for the i-th observation:

$$\boldsymbol{\eta}_i = \mathbf{B}\boldsymbol{\eta}_i + \boldsymbol{\Gamma}\mathbf{x}_i + \boldsymbol{\zeta}_i \qquad (1)$$

$$\mathbf{y}_i = \boldsymbol{\alpha} + \boldsymbol{\Lambda}_y\boldsymbol{\eta}_i + \boldsymbol{\varepsilon}_i \qquad (2)$$

where $\boldsymbol{\eta}$ is a m-dimensional vector of endogenous latent variables. The first equation block represents the structural model which establishes the relationships in the form of structural equations among endogenous latent variables. The endogenous latent variables are interconnected by a system of linear equations, each of which includes also a q-dimensional vector of covariates $\mathbf{x}$, which allow the identification of the equations. The respective coefficient matrices $\mathbf{B}$ and $\boldsymbol{\Gamma}$ are a m×m parameter matrix of slopes for regressions of latent variables and a m×q slope parameter matrix for regressions of the latent variables on the independent variable, while $\zeta$ is a m-dimensional vector of residuals. $\mathbf{B}$ has zero diagonal elements and it is assumed that $\mathbf{I} - \mathbf{B}$ is not singular.

The second equation block represents measurement models which define the relationship between the latent variables and the observed variables (vector $\mathbf{y}$). $\mathbf{y}$ is a p-dimensional vector and is related to the corresponding latent variables $\boldsymbol{\eta}$ by a p×m parameter matrix of measurement slopes or factor loadings $\boldsymbol{\Lambda}_y$ (which are estimated by factor analysis), while $\boldsymbol{\varepsilon}$ is the measurement error associated with the observed variables $\mathbf{y}$ and $\boldsymbol{\alpha}$ is a p-dimensional intercept matrix for the measurement model. It is assumed that $\mathrm{E}(\boldsymbol{\varepsilon}) = \mathbf{0}$, $\mathrm{Cov}(\boldsymbol{\varepsilon}, \boldsymbol{\eta}) = 0$, $\mathrm{Cov}(\boldsymbol{\varepsilon}, \boldsymbol{\zeta}) = \mathbf{0}$, but $\mathrm{Cov}(\boldsymbol{\varepsilon}_i, \boldsymbol{\varepsilon}_j)$ and $\mathrm{Cov}(\boldsymbol{\eta}_i, \boldsymbol{\eta}_j), (i \neq j)$ might not be zero (Bollen, 1989). A quite interesting feature of this approach in conjunction to certain available estimators is that is not necessary to assume normally distributed errors terms.

At this point it is worth mentioning the complexity of the proposed structural relations among the latent variables demands additional covariates (vector $\mathbf{x}$ above) to be taken under consideration in the estimation process in order to identify the model. In this line, a meaningful set of covariates have been included in each of the four equations to be estimated. Figure 2 summarizes the measurement and the structural model. The latent variable indicators are represented by solid arrowed lines while the covariates are found in the rectangles that are connected with a broad-dashed line with the latent variables. The structural model is translated in a system of three structural equations. Based on equation (1), the system is specified as follows:

$$\mathrm{DRDCP} = \beta_{\mathrm{DRDCP}} + \beta_1 \mathrm{INTRDEF} + \boldsymbol{\gamma}_{\mathrm{DRDCP}} \mathbf{x}_{\mathrm{DRDCP}} + \zeta_{\mathrm{DRDCP}} \tag{3}$$

$$\mathrm{INTRDEF} = \beta_{\mathrm{INTRDEF}} + \beta_2 \mathrm{DRDCP} + \boldsymbol{\gamma}_{\mathrm{INTRDEF}} \mathbf{x}_{\mathrm{INTRDEF}} + \zeta_{\mathrm{INTRDEF}} \tag{4}$$

$$\mathrm{INNPERF} = \beta_{\mathrm{INNPERF}} + \beta_3 \mathrm{DRDCP} + \beta_4 \mathrm{INTRDEF} + \boldsymbol{\gamma}_{\mathrm{INNPERF}} \mathbf{x}_{\mathrm{INNPERF}} + \zeta_{\mathrm{INNPERF}} \tag{5}$$

where $\beta_1,\ldots,\beta_4$ are the structural coefficients corresponding to the testable hypotheses formulated in the context of the above presented theoretical framework. The $\boldsymbol{\gamma}_{\mathrm{SV}}$, $(\mathrm{SV}=\mathrm{DRDCP, INTRDEF, INNPERF})$ vectors denote the coefficients of the covariates of each one of the structural variables. These covariates are denoted by the $\mathbf{x}_{\mathrm{SV}}$, $(\mathrm{SV}=\mathrm{DRDCP, INTRDEF, INNPERF})$ exogenous variables matrices. It is worthy to note that both $\boldsymbol{\gamma}_{\mathrm{SV}}$ and $\mathbf{x}_{\mathrm{SV}}$ are specific for each one of the structural equations.

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Insert Figure 2 around here

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Based on the equations (3)-(5) three types of estimated effects are identified. The direct effects of $\mathrm{DRDCP}$ and $\mathrm{INTRDEF}$ on $\mathrm{INNPERF}$ are simply the coefficients $\beta_3$ and $\beta_4$ respectively. The indirect effect of $\mathrm{DRDCP}$ mediated by the $\mathrm{INTRDEF}$ is $\mathrm{IndEff}_{(\mathrm{DRDCP\text{->}INTRDEF\text{->}INNPERF})} = \beta_2 \times \beta_4$ and the indirect effect of $\mathrm{INTRDEF}$ via $\mathrm{DRDCP}$ is estimated as: $\mathrm{IndEff}_{(\mathrm{INTRDEF\text{->}DRDCP\text{->}INNPERF})} = \beta_1 \times \beta_3$. Therefore, the total effect of each one of the two knowledge generation processes on innovation performance is calculated as:

$$\mathrm{TotEff}_{\mathrm{DRDCP}} = \beta_3 + \left(\beta_2 \times \beta_4\right) \tag{6a}$$

for the effects of the DRDCP latent variable on innovation performance and

$$\mathrm{TotEff}_{\mathrm{INTRDEF}} = \beta_4 + \left(\beta_1 \times \beta_3\right) \tag{6b}$$

in the case of the RDSTOCK latent variable.

The measurement model is depicted in Eq.(2). In particular, the DRDCP latent variable is approximated by two indicators and specifically the diversity of types of R&D collaborations within Greece $\left(\mathrm{DRDCPGR}\right)$ and the diversity of types of R&D collaboration at international level $\left(\mathrm{DRDCPFGN}\right)$. Thus the corresponding measurement equations are:

$$\mathrm{DRDCPGR} = \alpha_{\mathrm{DRDCPGR}} + \lambda_{\mathrm{DRDCPGR}}\mathrm{DRDCP} + \varepsilon_{\mathrm{DRDCPGR}} \tag{7a}$$

$$\mathrm{DRDCPFGN} = \alpha_{\mathrm{DRDCPFGN}} + \lambda_{\mathrm{DRDCPFGN}}\mathrm{DRDCP} + \varepsilon_{\mathrm{DRDCPFGN}} \tag{7b}$$

The latent variable of internal innovation efforts $\left(\mathrm{INTRDEF}\right)$ is approximated by a single indicator that is firms cumulative investments on R&D activities $\left(\mathrm{RDINV}\right)$. In this respect, we formulate this part of the measurement regarding the $\left(\mathrm{INTRDEF}\right)$ latent variable as:

$$RDINV=\alpha_{RDINV}+\lambda_{RDINV}INTRDEF+\varepsilon_{RDINV} \tag{8}$$

Finally, the innovation performance latent construct $(INNPERF)$ is composed by the percentage of innovative sales to total sales and the percentage of innovative products in the whole spectrum of firm's products. In formal terms:

$$INNSALES=\alpha_{INNSALES}+\lambda_{INNSALES}INNPERF+\varepsilon_{INNSALES} \tag{9a}$$

$$INNPROD=\alpha_{INNPROD}+\lambda_{INNPROD}INNPERF+\varepsilon_{INNPROD} \tag{9b}$$

In all the latent variables measurement equations, $\lambda$ coefficients depict the variance explained, $\alpha$ coefficients denote the corresponding constant terms and $\varepsilon$ stands for the error terms of the corresponding equation. The two parts of the model in equations (3) to (5) and (7a) to (9b) are estimated simultaneously exploiting all the information conveyed by the sample analyzed.

## 5 Results and Discussion

The model is estimated with full information maximum likelihood with robust standard errors[2] that is robust to non-normality and non-independence of observations (Yuan and Bentler, 2000) which is available in MPlus 7.3 software (Muthen and Muthen, 2004). Table 3 presents unstandardized and standardized loadings of the latent variables together with their means.

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Insert Table 3 around here

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As recommended by Podsakoff, et al. (2003), we performed post hoc analyses, fitting a one-factor model to the five items to check whether variance in the data can be largely attributed to a single factor i.e. the potential existence of substantial common-method variance; however, the model did not converge and therefore, model fit indices are not available for testing. Furthermore, we examined the convergent and divergent validity of these 3 factors using the "average variance extracted" (AVE) method of Fornell and Larcker (1981). The criterion for convergent validity, needs the AVE scores of each scale (the average communalities) to be all above the benchmark of 0.50 where in this case it has been satisfied (see Table 4).

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Insert Table 4 around here

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Similarly, Fornell and Larcker's (1981) criterion for divergent validity was satisfied, the variance shared between any pair of factors (the squared inter-factor correlations) was always less than the lowest AVE score for any pair of factors. The lower part of Table 5 presents goodness of fit indices with respect to the entire model. It becomes evident that the empirically

[2] Standard errors are computed using the Huber-White sandwich estimator.

estimated model presents a very good fit to the data ($X^2$ = 36.401; df = 32; CFI = 0.989; TLI=0.982; RMSEA = 0.021; SRMR = 0.027).

Empirical results of the structural model which simultaneously estimates the existence of a direct feedback loop relationship between internal innovation efforts and the diversity of external knowledge sources and their corresponding direct influence on firm innovation performance are presented in the upper part of Table 5.

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Insert Table 5 around here

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Both the unstandardized and standardized estimates of the feedback loop relationship between internal innovation efforts and the diversity of R&D collaborations are statistically significant and they present opposing signs, thus, supporting hypotheses $H_{1a}$ and $H_{1b}$. Such empirical findings highlight a crucial link between internal innovation efforts and the diversity of external knowledge sources which is rather unexplored in relevant literature. In fact, while firms are compelled to look in multiple directions in their outside environment to seek new knowledge sources, it is imperative at the same time to devote a considerable amount of resources, in monitoring and managing the incoming knowledge flows (Moilanen et al, 2014). The more diverse are the external knowledge sources, the more firms are compelled to increase accordingly the resources devoted in managing such inflows, decreasing therefore the amount of resources devoted to the internal knowledge generation process. In this respect, an opportunity cost arises implying that firms with limited available resources need to balance the acts of investing resources in the formation of internal knowledge generation, with the development of monitoring and managerial abilities to leverage the costs of maintaining diverse external knowledge sources (Dahlander and Gann, 2010). Hence, one could argue that such a balance looks like a "Gordian Knob" which the firm has to handle with in its respective decision making processes.

The direct impact of internal innovation efforts on innovation performance is positive and statistically significant. On the contrary, the direct influence of diversity of R&D collaborations on innovation performance it is not statistically significant. This finding is in accordance with the argument that gaining access to a technology or new knowledge and being able to effectively incorporate and redeploy it internally is crucial when investigating the influence of sourcing external knowledge on innovation performance (Weigelt, 2009; Grimpe and Kaiser, 2010)[3].

As it has already been demonstrated, the structure of the estimated model showcases the existence of indirect effects from both internal innovation efforts and diversity of external knowledge sources to innovation performance. Figure 1 depicts the interchangeable mediating role with respect to innovation performance of these two latent variables. Estimation results on indirect and total effects of both internal innovation efforts and diversity of external knowledge sources are presented in Table 6.

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Insert Table 6 around here

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The total effect of internal innovation efforts on innovation performance remains positive and statistically significant even after accounting for the negative, but only marginally statistically significant impact of the corresponding indirect effect. Therefore, hypothesis $H_2$ is

[3] A consistent finding in the relevant literature concerns the nonlinear effect of the open innovation strategy on innovation performance. However, due to the latent nature of our dependent variables, estimating a quadratic effect of R&D collaborations on innovation performance and mediation effects at the same time was not computationally feasible. We have used latent moderated structural equations method (LMS; Klein & Moosbrugger, 2000) to estimate such nonlinearity but empirical results remained unchanged. The corresponding empirical results are available upon request.

not rejected. It is worth noting the driving role of internal innovation efforts in boosting firms' innovation performance since they lie at the core of firms' dynamic capabilities and absorptive capacity (Cohen and Levinthal, 1989; Teece, 2006).

Turning to $H_3$, the total effect of R&D collaborations diversity on innovation performance is negative and statistically significant and therefore hypothesis $H_3$ is not rejected. In particular, both the indirect and the total effects of diversity of external knowledge sources on innovation performance are negative while the corresponding direct effect is not statistically significant. Such a finding reinforces the argument that firms' investments in diverse external knowledge sources increase search, coordination, monitoring and transaction costs acting at the expense of internal innovation efforts, which could ultimately result in the dilution of firms knowledge base and in poor innovation performance.

In the same direction, empirical results suggest that a negative network effect is in place; an increase in the diversity of external collaborators not only does not provide added value to firm's innovation process directly, but on the contrary the same network effect devalues internally generated knowledge and therefore exerts an overall negative effect on firms' innovation activities. In policy terms, this empirical finding is in the same line with the argument of Ortega-Argiles et al. (2009) for the necessity of a targeted R&D policy addressed to particular groups of SMEs instead of a general-purpose *erga omnes* policy.

Besides the structural relationships which are of prime interest of the paper at hand, the estimated structural model includes a number of exogenous covariates for two main reasons. Estimation results of the covariates included in the estimation are presented in Table 7. Given the specificities of the Greek economy and the corresponding innovation system, results for the control variables are not surprising.

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Insert Table 7 around here

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One last thing remaining to be addressed is the sensitivity analyses undertaken to check the robustness of the empirical results. We have estimated the same model by splitting our sample using various criteria and employing multi-group analysis (Bollen, 1989). In particular, we have split our sample in high versus low technology firms and with respect to their size and estimated a multi-group model. In addition, we excluded the bottom (top) two thirds of the sample in terms of absorptive capacity, relative R&D age and knowledge stock and repeated the estimation. Estimation results in such sub-group analyses suggested that there is no moderation effect of sectoral technological intensity and firm size, while estimation results based on the narrow samples remained the same as in the full model[4].

## 6 Conclusions

It is widely acknowledged that the innovation paradigm is shifting towards an imperative for search of external actors to access new ideas for innovation, technologies and resources, or to externally commercialise internal ideas and exploit intellectual property. In this respect, the relationship between the diversity of R&D collaborations and firm's internal innovation efforts, which in turn can positively influence firms' innovation performance, is gaining increasing attention. However, the underlying complexity of the relationship between internal and external knowledge sources, ruled by potential feedback loops and the decomposition of their corresponding influence on innovation performance is largely neglected.

[4] Due to space limitations, the estimation results of the robustness tests are available upon request.

In this paper, we shed some light on the underlying relationships regulating firm internal and external knowledge sources and their corresponding influence on firm innovation performance, by employing a sample of Greek Manufacturing firms which allows us to simultaneously estimate a non-recursive system of three structural equations with latent dependent variables in order to examine mediating relationships between cumulative investments in R&D, diversity of types of R&D collaborations and firm innovation performance.

Empirical results indicate that a feedback loop relationship exists between the internal knowledge generation process and the diversity of the external knowledge sources, and that there is a tradeoff between these two aspects of firm R&D strategy. In particular, increasing firm internal R&D investments leads to a higher diversity of types of R&D collaborations, while when we consider the impact of the latter on the former, a negative relationship emerges with diversity in R&D collaborations dissipating away the resources devoted to internal R&D activities.

In addition, the architecture of the model allows distinguishing between direct and indirect effects of both investments in internal R&D and the diversity of R&D collaborations on firms' innovation performance. Investments in internal R&D exert a positive impact on firms' innovation performance although the mediation of diversity of R&D collaborations results in a weakened impact. On the other hand, the diversity of R&D collaboration sources affects firm innovation performance only indirectly and negatively, through its impact on internal R&D. We argue that such negative impact of the diversity of R&D collaborations is due to the search, management and transaction costs, exacerbated by the fact that the knowledge eventually obtained from multiple sources is of questionable commercial value to the firm due to a network effect.

Taken together these findings suggest that Greek manufacturing firms' ability to manage, absorb, store and (re-)utilise knowledge from external collaborations is a particularly difficult and ineffective process. In this respect, policy efforts should be directed in assisting firms tracking and managing their R&D collaboration partnerships. In terms of managerial implications, we showcase that the diversity of R&D collaborations should be closely linked to the growth rate of firms' knowledge base and dynamic capabilities which allow the external knowledge to be internalized and redeployed. It is worth mentioning that while our findings concern the Greek context, which comprises of firms small in size, with low innovative dynamism which face severe financial constraints, corresponding hypotheses could be examined for firms operating in other more technologically advanced innovation systems.

## References


Abramovsky, L., Kremp, E., López, A., Schmidt T., Simpson, H., 2008. Understanding co-operative innovative activity: Evidence from four European countries. Econ Innov and New Technol. 18, 243-265.

Acemoglu, D., Aghion, P., Zilibtti, F. 2006, Distance to frontier, selection and economic growth, J of the Eur Econ Assoc. 4, 37-74.

Alexy, O., Bascavusoglu-Moreau E., Salter J., 2016. Toward an aspiration-level theory of open innovation. Ind Corp Change. 25 (2), 289–306.

Armstrong, M., 2006. Competition in Two-Sided Markets. Rand J of Econ. 37 (3), 668-691.

Barney, J., 1991. Firm resources and sustained competitive advantage. J Manage. 17, 99-120.

Belderbos R., Carree M., Lokshin, B., 2004. Cooperative RD and Firm Performance. Res Policy. 33, 1477–1492.

Berchicci, L., P.J., de Jong, J. Freel, M., 2016. Remote collaboration and innovative performance: the moderating role of RD intensity", Ind Corp Change. 25 (2), 429-446

Breschi, S., Malerba, F. Orsenigo, L. 2000. Schumpeterian Patterns of Innovation and Technological Regimes. The Econ J. 110, 388- 410.

Carayannis, E.G., Alexander, J. 2002. Is technological learning a firm core competence, when, how and why? A longitudinal, multi-industry study of firm technological learning and market performance. Technov. 22, 625-643.

Cassiman, B., Veugelers, R., 2006. In search of complementarity in the innovation strategy: internal RD and external knowledge acquisition. Manage Sci. 52, 68–82.

Chesbrough, H. W. 2006. Open innovation : The new imperative for creating and profiting from technology. Boston: Harvard Business School Press.

Chun, H., S.-B. Mun, 2012. Determinants of RD cooperation in small and medium-sized enterprises. Small Bus Econ. 39, 419-436

Cohen, W. Levinthal, D. 1989. Innovation and learning: the two faces of RD. The Econ J. 99, 569-596.

Collis, D., 1994. How valuable are organizational capabilities? Strategic Manage J. 15, 143-152.

Conte, A. Vivarelli, M. 2014. Succeeding in Innovation: Key Insights on the Role of RD and Technological Acquisition Drawn from Company Data, Empir Econ. 47, 1317-1340.

Dahlander, L. Gann, D. M. 2010. How open is innovation? Res Policy. 39, 699-709.

Das, S., Teng, B.S. 2000. A resource-based theory of strategic alliances. J Manage. 26, 31–61.

de Faria, P, Lima, F, Santos, R. 2010. Cooperation in innovation activities: The importance of partners. Res Policy. 39, 1082-1092.

Della Malva, A. Santarelli, E. 2016. Intellectual property rights, distance to the frontier, and RD: evidence from microdata, Eurasian Bus Rev. 6, 1-24.

Dosi, G., Nelson, R. 2014. The Evolution of Technologies: An Assessment of the State- of- the-Art. Eurasian Bus Rev. 3, 3-46

Faems, D., de Visser, M., Andries. P., Van Looy, B. 2010. Technology alliance portfolios and financial performance: value-enhancing and cost-increasing effects of open innovation. J Prod Innov Manage. 27 ,785–796.

Fornell, C. Larcker, D.. 1981. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. J Market Res. 18, 39–50.

Gkypali A., Tsekouras K. 2015. Productive performance based on RD activities of low-tech firms: an antecedent of the decision to export? Econ Innov New Technol. 24, 801-828.

Grant, R. M. 1996. Toward a knowledge-based theory of the firm. Strategic Manage J. 17, 109-122.

Grant, R. M. Baden-Fuller, C. 2004. A knowledge accessing theory of strategic alliances. J Manage Stu. 41, 61-84.

Grimpe, C. Kaiser, U. 2010. Balancing internal and external knowledge acquisition: The gains and pains from RD Outsourcing. J Manage Stu. 47, 1483-1509.

Hottenrott, H., Lopes-Bento C. 2016. RD Partnerships and Innovation Performance: Can There be too Much of a Good Thing? J Prod Innov Manage. 33 (6), 773-794.

Kale, P. Singh, H. 2009. Managing strategic alliances: What do we know now, and where do we go from here? Acad Manage Perspect. 23, 45-62.

Klein A Moosbrugger H. 2000. Maximum likelihood estimation of latent interaction effects with the LMS method. Psychometrika. 65, 457–474.

Kogut, B., Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organ Sci. 3, 383-397.

Lakemond, N., Bengtsson, L., Laursen K., Tell F. 2016. Match manage: the use of knowledge matching and project management to integrate knowledge in collaborative inbound open innovation. Ind Corp Change. 25 (2), 333-352.

Lane, P. J., Koka, B. R. Pathak, S. 2006. The reification of absorptive capacity: A critical review and rejuvenation of the construct. Acad Manage Rev. 31, 833-863.

Lane, P. J. and Lubatkin, M. 1998. Relative absorptive capacity and inter-organizational learning. Strategic Manage J. 19, 461-477.

Laursen, L., Salter, A., 2006. Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms. Strategic Manage J. 27, 131-150.

Laursen, K. Salter, A. 2014. The paradox of openness: appropriability, external search and collaborations, Res Policy. 43, 867-878.

Lawson, B., Petersen, K.J., Cousins, P.D., Handfield, R.B. 2009. Knowledge sharing in interorganizational product development teams: The effects of formal and informal socialization mechanisms. J Prod Innov Manage. 26, 156-172.

Lewin, A. Y., Massini, S. and Peeters, C. 2011. Microfoundations of internal and external absorptive capacity routines. Organ Sci. 22, 81-98.

Lin, C., Wu, Y.-J., Change, C., Wang, W., Lee, C.-Y. 2012. The alliance innovation performance of RD alliances - the absorptive capacity perspective. Technovation. 32, 282-292.

Lokshin, B., Belderbos, R., Carree, M. 2008. The Productivity Effects of Internal and External RD: Evidence from a Dynamic Panel Data Model. Oxford B Econ Stat. 70, 399-413.

Mishra, S., Kim, D., Hoon Lee, D. 1996. Factors affecting new products success: Cross-country comparisons. J Prod Innov Manage. 13, 530-550.

Moilanen, M., S. Østbye  Woll, K. 2014. Non-RD SMEs: external knowledge, absorptive capacity and product innovation. Small Bus Econ. 43, 447-462.

Mowery, D. C., Oxley, J. E. Silverman, B. S. 1996 Strategic alliances and interfirm knowledge transfer. Strategic Manage J, Winter Special Issue 17, 77-91.

Muthen, L. K.,  Muthen, B. O. 2004. Mplus user's guide. Los Angeles: Muthen Muthen.

Nasiriyar, M.  Nesta, L.  Ludovic, D. 2013. The moderating role of the complementary nature of technological resources in the diversification-performance relationship.  Ind Corp Change. 23, 1357-1380

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gisling, V., Van Den Oord, A., 2007 Optimal cognitive distance and absorptive capacity. Res Policy. 36, 1016-1032

OECD/Eurostat. 2005. Guidelines for Collecting and Interpreting Innovation Data — The Oslo Manual. 3rd edn. Paris: OECD.

OECD 2012. "Greece", in OECD Science, Technology and Industry Outlook 2012, OECD Publishing

OECD 2014. "Greece", in OECD Science, Technology and Industry Outlook 2014, OECD Publishing

Ortega-Argilés R., Vivarelli, M. Voigt, P. 2009. RD in SMEs: A Paradox?, Small Bus Econ. 33, 3-11.

Parker, G.G. Van Alstyne, M. 2005. Two-Sided Network Effects: A Theory of Information Product Design. Manage Sci. 51, 1494-1504.

Peeters, T. Martin, X. 2015. Strategies for knowledge use in RD and their implications for innovative performance. RD Manage. 47, 47-60

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., Podsakoff, N. P. 2003. Common method biases in behavioral research: A critical review of the literature and recommended remedies. J Applied Psychol. 88, 879–903.

Rawley, E., 2010. Diversification, coordination costs, and organizational rigidity: evidence from microdata. Strategic Manage J. 31, 873–891.

Rochet, J. Tirole, J. 2006. Two sided Markets: A Progress Report. Rand J Econ. 37, 645-667

Rycroft, R.W. 2007. Does cooperation absorb complexity? Innovation networks and the speed and spread of complex technological innovation. Technol Forecast Soc Change. 74, 565–578

Souitaris V. 2002. Firm-specific competencies determining technological innovation. A survey in Greece. RD Manage. 32, 61–77.

Teece, D. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. Res Policy. 15, 285-305.

Teece, D. 2006. Reflections on profiting from innovation. Res Policy. 35, 1131–46.

Todorova, G. Durisin, B. 2007. Absorptive capacity: Valuing a reconceptualization. Acad Manage Rev. 32, 774-786.

Ur Rehman, N. 2016. Network alliances and firms' performance: a panel data analysis of Pakistani SMEs, Eurasian Bus Rev. 6, 37-52.

Veugelers, M. Burya, J. Viaeneb, S. 2010. Linking technology intelligence to open innovation. Technol Forecast Soc Change. **77**, 335–343

Veugelers, R. Cassiman, B. 1999. Make and buy in innovation strategies: evidence from Belgian manufacturing firms. Res Policy. 28, 63-80.

Wassmer, U. 2010. Alliance portfolios: A review and research agenda. J Manage. 36, 141-171.

Weigelt, C. 2009. The impact of outsourcing new technologies on integrative capabilities and performance. Strategic Manage J. 30, 595–616.

Wernerfelt, B. 1984. A Resource-Based View of the Firm. Strategic Manage J. 5, 171-180.

White, S. Lui, S. Y. 2005. Distinguishing costs of cooperation and control in alliances. Strategic Manage J. 26, 913-932.

Wuyts, S. Dutta, S. 2014. Benefiting from alliance portfolio diversity: the role of past internal knowledge creation strategy. J Manage. 40, 1653–1674.

Yuan, K. Bentler P. 2000. Three likelihood based methods for mean and covariance structure analysis with non-normal missing data. Socl Methodol. 30, 165–200.

Zahra, S. A. George, G. 2002. Absorptive capacity: A review, reconceptualization, and extension. Acad Manage Rev. 27, 185-203.

Zidorn, W. Wagner, M. 2013. The effect of alliances on innovation patterns: an analysis of the biotechnology industry. Ind Corp Change. 22, 1497-1524.

## Tables and Figures

**Table 1.** Variables Definition and Descriptive Statistics of the indicators employed in the Measurement Model

| Indicator $(y_i)$ | Definition | Scale | Descriptive Statistics: Average (St. Dev.) | Min (Max) |
|---|---|---|---|---|
| **Internal Innovation Efforts** (INTRDEF) | | | | |
| R&D Investments (RDINV) | The accumulated 'knowledge' stock as it has been approximated by firms' yearly R&D expenditures | Continuous | 0.115 (0.237) | 0.000[a] (2.067) |
| **Diversity of R&D Collaborations** (DRDCP) | | | | |
| R&D Collaborations with domestic partners (RDCOOPGR) | The ratio of the number of R&D collaborations within Greece to the total number of potential R&D collaborations with domestic partners | Continuous | 0.340 (0.234) | 0.000[a] (0.857) |
| R&D Collaborations with foreign partners (RDCOOPFOR) | The ratio of the number of collaborations outside Greece to the total number of potential R&D collaborations with foreign partners | Continuous | 0.124 (0.130) | 0.000[a] (1.036) |
| **Innovation Performance** (INNPERF) | | | | |
| Innovative sales intensity (INNSALES) | The percentage of the firm's total sales that is due to significantly improved or new products or created due to firms' R&D activities | Continuous | 0.422 (0.310) | 0.000 (1.000) |
| Innovative products intenstiy (INNPROD) | The percentage of new products in firm's total product variety | Continuous | 0.414 (0.313) | 0.000 (1.000) |

[a]: Actually smaller than 0.001

**Table 2.** Variables Definition and Descriptive Statistics of the covariates employed in the Structural Model

| Covariates $(x_i)$ | Definition | Scale | Descriptive Statistics Average (St. Dev.) | Min (Max) |
|---|---|---|---|---|
| **Internal Innovation Efforts** (INTRDEF) | | | | |
| Relative Age of R&D activities (AGERD) | Firm's relative R&D age defined as the ratio of the age of the firm when it first started R&D activities to its actual age. | Continuous | 0.571 (0.310) | 0.000 (1.000) |
| Absorptive Capacity (ABSCAP) | Firm's absorptive capacity defined as the ratio of employees with tertiary education to total number of employees | Continuous | 0.265 (0.206) | 0.000[a] (1.000) |
| Absorptive Capacity Square (ABSCAP2) | The square of the (ABSCAP) variable | Continuous | 0.113 (0.190) | 0.000[a] 1.000 |
| **Diversity of R&D Collaborations** (DRDCP) | | | | |
| Absorptive Capacity (ABSCAP) | Firm's absorptive capacity defined as the ratio of employees with tertiary education to total number of employees | Continuous | 0.265 (0.206) | 0.000[a] (1.000) |
| Absorptive Capacity Square (ABSCAP2) | The square of the (ABSCAP) variable | Continuous | 0.113 (0.190) | 0.000[a] 1.000 |
| Integration (INTGR) | Firms' degree of internalization (integration) defined as the ratio of expenditures on affiliated undertakings to total assets | Continuous | 0.048 (0.124) | 0.000 (0.776) |
| Location (LOCD) | Dummy variable that takes the value of 1 if the firm is located with the broader area of Athens and 0 otherwise | Binary | 0: 0.493 1: 0.507 | |
| **Innovation Performance** (INNPERF) | | | | |
| Profitability (PROFITAB) | The ratio of firms' 3yr averaged gross profits to 3yr averaged total assets | Continuous | 0.245 (1.054) | -0.133 (18.192) |
| Profit Margin (PROFMARG) | The difference between sales and sales costs (3yr average) divided to firms' sales (3yr average) | Continuous | 0.241 (0.216) | -2.398 (1.008) |
| Fixed to Total assets (FIXTOTAS) | The ratio of fixed assets (for the yr 2010) to total assets (for the year 2010) | Continuous | 0.408 (0.203) | 0.001 0.960 |

[a]: Actually smaller than 0.001

**Table 3.** Unstandardized and Standardized estimated loadings of the measurement model

| Construct | Indicators | Unstandardized loadings (std errors) | Standardized Loadings (std errors) | LV mean |
|---|---|---|---|---|
| INTRDEF | | | | 0.049 |
| | RDINV | 1.000<br>(0.000) | 0.598*<br>(0.149) | |
| DRDCP | | | | 0.091 |
| | RDCOOPGR | 1.000<br>(0.000) | 0.528*<br>(0.052) | |
| | RDCOOPFOR | 0.955*<br>(0.172) | 0.907*<br>(0.078) | |
| INNPERF | | | | 0.025 |
| | INNSALES | 1.000<br>(0.000) | 0.795*<br>(0.057) | |
| | INNPROD | 1.115*<br>(0.147) | 0.880*<br>(0.065) | |

Asterisk denotes statistical significance at 1%, 5% and 10% level respectively

**Table 4.** Correlation Matrix of the Latent Variables and Convergent and Divergent Validity Criteria

| Latent Variable | AVE | Correlation Matrix | | |
|---|---|---|---|---|
| | | DRDCP | RDSTOCK | INNPERF |
| DRDCP | 0.742 | 1.000 | | |
| INTRDEF | 0.598 | 0.417 | 1.000 | |
| INNPERF | 0.839 | 0.085 | 0.404 | 1.000 |

**Table 5.** Estimation Results of the Direct Effects of the Structural Model

| Right hand structural variable | Unstandardized coefficients (std errors) | Standardized coefficients (std errors) |
|---|---|---|
| | DRDCP Equation | |
| INTRDEF ($\beta_1$) | 0.625** (0.280) | 0.718* (0.149) |
| | INTRDEF Equation | |
| DRDCP ($\beta_2$) | -0.419*** (0.253) | -0.365** (0.170) |
| | INNPERF Equation | |
| DRDCP ($\beta_3$) | -0.203 (0.206) | -0.101 (0.107) |
| INTRDEF ($\beta_4$) | 0.772** (0.380) | 0.444* (0.096) |

| Goodness of Fit Statistics of the Overall Model | |
|---|---|
| $\chi^2$,df | 36.401, 32 |
| CFI | 0.989 |
| TLI | 0.982 |
| RMSEA | 0.021 |
| SRMR | 0.027 |

One, two and three asterisks denote statistical significance at 1%, 5% and 10% level respectively

**Table 6.** Estimation Results of the Indirect and Total Effects

| | Unstandardized Estimates (std errors) | Standardized Estimates (std errors) |
|---|---|---|
| Effects *from* DRDCP *to* INNPERF *mediated by* INTRDEF | | |
| $\text{IndEff}_{(\text{DRDCP->INTRDEF->INNPERF})} = \beta_2 \times \beta_4$ | -0.214* (0.090) | -0.107* (0.041) |
| $\text{TotEff}_{\text{DRDCP}} = \beta_3 + (\beta_2 \times \beta_4)$ | -0.417** (0.200) | -0.209** (0.105) |
| Effects *from* INTRDEF *to* INNPERF *mediated by* DRDCP | | |
| $\text{IndEff}_{(\text{INTRDEF->DRDCP->INNPERF})} = \beta_1 \times \beta_3$ | -0.261 (0.208) | -0.150*** (0.090) |
| $\text{TotEff}_{\text{INTRDEF}} = \beta_4 + (\beta_1 \times \beta_3)$ | 0.511** (0.243) | 0.294* (0.078) |

One, two and three asterisks denote statistical significance at 1%, 5% and 10% level respectively

**Table 7.** Estimation Results for the Exogenous Covariates Employed in the Structural Model

| Covariate | Unstandardized coefficients (std errors) | Standardized coefficients (std errors) |
|---|---|---|
| | INTRDEF Equation | |
| AGERD | 0.117** (0.061) | 0.255* (0.075) |
| ABSCAP | -0.099 (0.274) | -0.144 (0.384) |
| ABSCAP2 | 0.414 (0.417) | 0.555 (0.476) |
| | DRDCP Equation | |
| ABSCAP | 0.229 (0.171) | 0.382 (0.283) |
| ABSCAP2 | -0.318 (0.227) | -0.488 (0.354) |
| INTGR | 0.501* (0.113) | 0.503* (0.096) |
| LOCD | 0.023 (0.015) | 0.093 (0.062) |
| | INNPERF Equation | |
| PROFITAB | -0.015* (0.002) | -0.064** (0.032) |
| PROFMARG | 0.050 (0.057) | 0.044 (0.050) |
| FIXTOTAS | -0.007 (0.077) | -0.005 (0.063) |

One and two asterisks denote statistical significance at 1% and 5% levell respectively

**Figure 1** Conceptual Framework and structural relationships

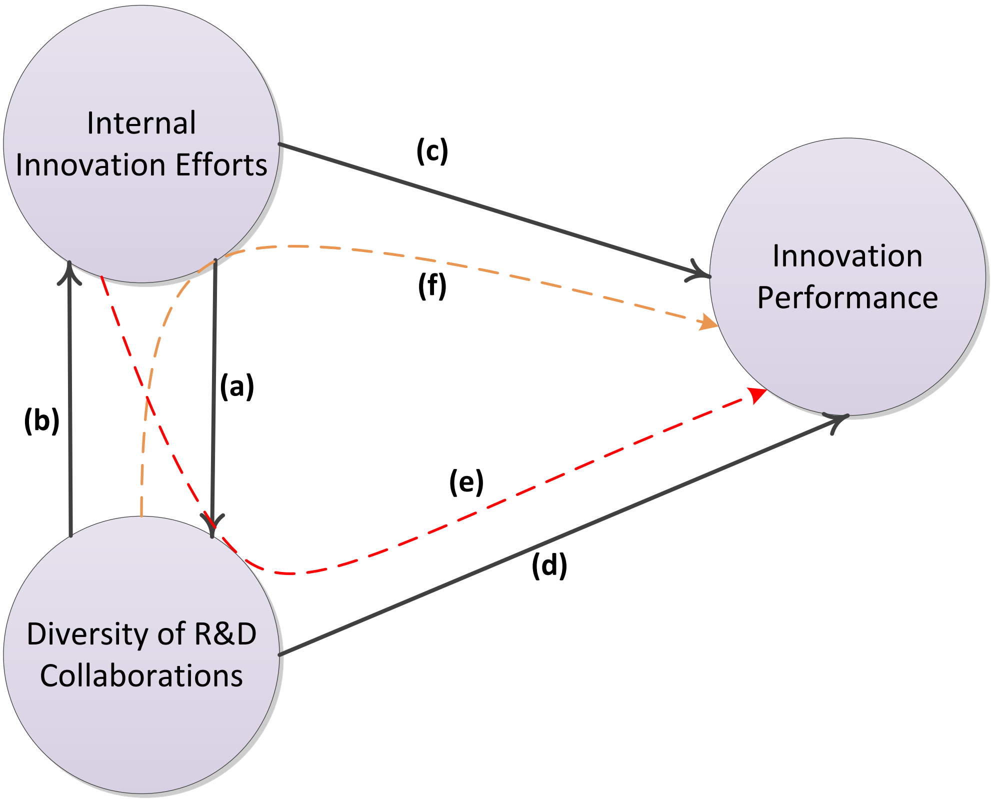

**Figure 2** The Full model