The Effects of Open Innovation on Firm Performance: A Capacity Approach[†]

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Abstract

Although open innovation (OI) has been an important research theme for over a decade, its theoretical framework has been relatively under-researched. As OI involves a wide range of innovation activities, a firm's capacities in the use of the various firm resources play a critical role in OI implementation. However, it is unclear how they affect firms' performances for little is known of OI capacities. Based on a theoretical framework derived from the literature, this study looks into the relationships between six OI capacities (inventive, absorptive, transformative, connective, innovative, and desorptive) and financial performance using the Korean Innovation Survey (KIS) 2008 data. The research model was tested using structural equation modelling (SEM) while potential differences in capacities between different firm groups were also investigated. The results indicate that 1) OI capacities are significantly associated with firms' financial performance; 2) capacities are highly correlated with one another; and 3) some capacities are differently configured between different types of firms. Findings suggest that policy makers should pay more attention to helping firms enhance OI capacities and attempt to develop relevant policies in order to complement inadequate capacities.

Keywords
Open innovation, capacity, structural equation modelling, path analysis, Korea.

1. INTRODUCTION

Studies in open innovation (OI) have witnessed considerable growth in recent years (Dahlander & Gann, 2010). However, the majority of empirical studies have investigated the effect on OI implementation of a firm's individual organisational factors, such as employee numbers, market types,

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or the amount of R&D investment. Using these factors as separate explanatory (independent) variables, we may be able to see how a single factor affects OI (e.g., whether a firm size is positively associated with OI adoption), but it is difficult to understand how these factors as a group influence OI. As OI involves the interaction of various innovation activities, identifying its holistic characteristics by grouping organisational factors which are closely related with each OI mode and examining their influences may bring us a deeper understanding of OI.

Firms will choose the most relevant OI mode depending on their resources, i.e., capacities. However, as studies have not sufficiently explored the capacities essential for success in OI, firms are not only unaware of how OI capacities affect their business performance but are also uninformed of what capacities should be complemented further in order to cope with fast-changing environments. In fact, firms in rapidly changing markets have to adapt themselves to different environments by developing "dynamic capabilities" in order to maintain their competitive advantages (Teece, Pisano, & Shuen, 1997), but insufficient knowledge of OI capacities prevents firms from assessing their current state and developing the necessary capacities with their available business resources.

To address this gap, this paper aims to investigate OI capacities focusing on the question of how OI capacities affect firms' business performance, how these capacities are interrelated, and how they are differently established from one group of firms to another. Data from 911 manufacturing firms in the 2008 Korean Innovation Survey (KIS) were selected for the analysis. Structural equation modelling (SEM) was employed for data analyses while multiple group analyses were conducted for group comparisons. The results indicated the relevance of OI capacities to financial performance, and showed significant group differences across the sample in OI capacities.

The remainder of this paper consists of five sections: Section 2 provides the theoretical background of this study and formulates the research hypotheses; Section 3 provides the research model and describes the data; Section 4 gives the results of the data analyses; Section 5 discusses the implications and limitations; and Section 6 summarizes key conclusions.

2. BACKGROUNDS AND HYPOTHESES

2.1. Open Innovation and Its Modes

The 'Open Innovation' (OI) paradigm was outlined by Chesbrough as a contrast to the traditional innovation model, which is internally focused and self-reliant (Chesbrough, 2003b). A key idea in OI is that knowledge can be transferred across a business firm's boundaries. Internal knowledge diffuses to outside the firm, while at the same time external knowledge penetrates within. Under the OI paradigm, all knowledge (internal and external) can find its way to commercialization for existing or new markets by crossing the firm's boundaries.

As OI examples accumulate, scholars have attempted to identify OI features by developing classification criteria (e.g., EIRMA, 2005; Fey & Birkinshaw, 2005; Gassmann & Enkel, 2004). Van

Der Meer (2007) classifies OI modes as "importing" and "exporting," while van de Vrande et al. (2009) similarly categorizes them as "exploitation" and "exploration" according to the direction of knowledge flow. Due to the complexity of OI however, opinions vary regarding the number of OI modes and the method of their classification (Dahlander & Gann, 2010; Huizingh, 2011). Inflow (i.e., importing or exploration) and outflow (i.e., exporting or exploitation) seems to be the dominant classification, but this classification based on knowledge direction can further include "coupled processes," which combine both external and internal knowledge flows (Enkel, Gassmann, & Chesbrough, 2009; Gassmann & Enkel, 2004). Furthermore, additional criteria can be used to construct multi-dimensional classifications. Dahlander and Gann (2010) suggest their own taxonomy by dividing inflow and outflow modes into financial and non-financial interactions. Their classification produces a two-by-two matrix, where each cell is labelled as "acquiring," "sourcing," "selling," and "revealing" (Dahlander & Gann, 2010). Huizingh (2011) groups types of OI according to whether the process or outcome is open or closed.

However, despite their different classification terms, the above studies have one crucial similarity: the direction of knowledge flow. As shown in Table 1, the varieties of OI modes are categorized into three directions: inflow, outflow, and ambidirectional flow. The inflow mode refers to OI activities related to acquiring knowledge from an outside organization, while the outflow mode refers to OI activities related to commercializing internal knowledge in an outside organization. Ambidirectional flow indicates OI modes involving both inward and outward flows.

TABLE 1. OI modes

OI mode		Definition	Summary
Inflow	In-sourcing	Exploiting external knowledge to reduce time-to-market and find new ideas	-P&G's C&D aims at proactive collaboration with external partners in at least 50% of new product development (Huston & Sakkab, 2006) -P&G's C&D is supported by state-of-art ICT such as data mining and computer simulation (Dodgson, Gann, & Salter, 2006)
	Venture investment	Invest in promising venture companies to bring new ideas	-HP's main research institute (HP Lab) collaborates closely with venture capital (Foundation Capital) to bring forth creative new ideas (Waites & Dies, 2006) -DuPont operates an incubation program, DuPont Ventures, investing in promisi ng start-ups (Kim et al., 2008)
	Customer involvement	Accessing new ideas by involving customers in the R&D or design process	-The traditional sports industry, such as Rodeo and Kayak, adopts customer ideas for improved NPD (Hienerth, 2006) -The designs of Threadless (T-shirts) are proposed and improved by a user community (Piller, 2011)
Ambidirectional flow	Co-R&D	Conducting R&D with external partners	-Intel carries out R&D collaborations with partner universities through the "Lablet" co-R&D institute (Tennenhouse, 2004)
	M&A or Alliancing	Buying potential companies or building a strategic alliance with them to absorb their knowledge	-Cisco successfully acquired 36 companies and allied with more than 100 others between the mid-1990s and the mid-2000s (Dyer, Kale, & Singh, 2004) -Google formed the "Open Handset Alliance" to enhance their complementary assets (Kim et al. 2008)
Outflow	Licensing-out	Licensing or selling unused technologies to maximize profit	-Microsoft licenses their unused technologies to venture companies (Blau, 2006) -DuPont established Technology Bank and Intellectual Assets and Licensing (IA&L) to maximize the revenue from licensing and royalties (Kim, et al., 2008)
	Venturing (spin-off)	Spin-off internal organizations to commercialize disruptive technologies	-DSM established DSM Venturing & Business Development (DV&BD) to decide whether a new idea is appropriate for spinning-off (Kirschbaum, 2005)
	Open sourcing	Open an internal project to form a new market and test customers' response	-IBM opened the source code of the XML Parser project (Chesbrough, 2004) -HP released software source code to promote RISC architecture (Lerner & Tirole, 2005) -Embedded Linux distributors use open sourcing to design custom products (West and Gallagher 2006)

Source: adapted from the related literature

2.2. Capacity Approach

Capacity is defined as "the ability to utilize an organisation's various resources" (Makadok, 2001) and can be used as a higher-order (second-order) factor consisting of multiple organisational factors. From the perspective of traditional innovation, capacity is already emphasized as a vital factor in a firm's business strategy or performance (Makadok, 2001) and this is also true for the OI paradigm. A firm may achieve competitive advantage if it effectively deploys its resources and develops relevant capacities. Since OI involves a variety of innovation activities, firms may have to develop relevant OI capacities in order to implement a specific OI mode. For example, in order to exploit external knowledge through "in-sourcing" (Table 1), firms have to enhance their "absorptive capacity" by enlarging internal R&D investment (Spithoven, Clarysse, & Knockaert, 2011) because this enables firms to effectively integrate external with internal knowledge (Cohen & Levinthal, 1990).

However, only a few studies so far have explored the theme of capacities despite its importance. Spithoven, Vanhaverbeke, and Roijakkers (2011) reviewed Cohen and Levinthal's (1990) "absorptive capacity" and suggests that capacities are vital in inflow OI modes. It is Lichtenthaler and Lichtenthaler's (2009) pioneering work that attempts to define and classify different types of OI capacities. They expanded on Gassmann and Enkel's (2004) three OI processes and their related capabilities—absorptive for inflow, multiplicative for outflow, and relational for coupled ("ambidirectional" in Table 1) process—by developing a two-dimensional knowledge framework. As shown in Table 2, the first classifying criterion (the first horizontal line in Table 2) represents the main purpose of OI activity depending on whether OI is conducted in order to identify (exploration), to keep (retention), or to commercialize (exploitation) useful knowledge, while the second (the first column in Table 2) simply refers to the location according to whether an OI activity occurs inside or outside a firm. These two criteria are combined to generate six different types of OI capacity ranging from "inventive" to "desorptive," which are thought to provide the necessary components for firms to implement their related OI activities (Lichtenthaler & Lichtenthaler, 2009).

TABLE 2. OI Capacities

	Knowledge exploration	Knowledge retention	Knowledge exploitation
Intra-firm	Inventive capacity	Transformative capacity	Innovative capacity
Inter-firm	Absorptive capacity	Connective capacity	Desorptive capacity

Source: Lichtenthaler & Lichtenthaler (2009)

"Inventive capacity" enables firms to generate creative knowledge internally (Lichtenthaler & Lichtenthaler, 2009), representing how well a firm can conduct internal R&D. This capacity constitutes a firm's basic and essential capability as it influences both OI activities (e.g., R&D collaboration or in-sourcing) and closed innovation.[1]

[1] In this case, closed innovation refers to traditional innovation that mainly focuses on internal R&D (See Chesbrough (2003a)).

“Absorptive capacity” enables firms to integrate external knowledge (Lichtenthaler & Lichtenthaler, 2009). In the OI paradigm, external as well as internal knowledge is a vital source for innovation, so a firm with strong absorptive capacity should make its boundary permeable to explore and assimilate external ideas in order to strengthen or compensate for their own low “inventive capacity” (Dyer, et al., 2004). OI modes, such as in-sourcing or venture investment, are related to this capacity.

“Innovative capacity” refers to the ability of firms to commercialize their internal or external knowledge in order to make new products or provide new services (Lichtenthaler & Lichtenthaler, 2009). This capacity represents the extent to which firms can digest internal or external ideas towards making actual profit. Innovative capacity is crucial in closed innovation, but is also closely related to certain OI modes such as customer involvement or in-sourcing. As the P&G case corroborates (Dodgson, et al., 2006; Lichtenthaler & Lichtenthaler, 2009), a wide range of information sources may contribute to increasing the success rate of innovation.

“Desorptive capacity” is the ability to make a profit outside an organisation (Lichtenthaler & Lichtenthaler, 2009) and certain OI modes such as licensing-out or spinning-off (venturing) are closely related to this capacity. Firms can make additional profit by selling or licensing their unused intellectual property (IP) (Blau, 2006) or they can spin off their internal organizations to test or commercialize new disruptive technologies that are believed to deviate from their main business areas (Kirschbaum, 2005).

Although knowledge diffusion is of primary importance in OI, firms must sometimes retain knowledge to maximize their innovation outcomes. “Transformative capacity” refers to the ability to keep knowledge inside an organization (Lichtenthaler & Lichtenthaler, 2009). This capacity enables firms to exclusively benefit from their innovation output using legal protection mechanisms such as patents.

Firms need not retain knowledge only within their own organizations. They can also retain knowledge externally by establishing close relationships with external experts or other firms (Chesbrough, 2003b), a relationship determined by “connective capacity” (Lichtenthaler & Lichtenthaler, 2009). Firms can collaborate on R&D or build strategic alliances to preserve knowledge, a better alternative considering the high cost of IP maintenance

2.3. Research Questions and Hypotheses

We use the OI capacity model and test it using data from Korean firms. More specifically, we explore within the firms three aspects related to OI capacities:

- How do OI capacities influence financial performance?
- How are OI capacities interrelated?
- How are OI capacities established differently from one group of firms to another?

2.3.1. Performance

OI capacities directly or indirectly affect the way a firm build its business strategy, and consequently influence its financial performance. Assuming that all six capacities are essential elements when a firm decides which OI modes are applicable, we presume that every OI capacity is closely associated with the firms' financial performance. However, the extent and sign of associations (i.e., positive or negative) vary. Some capacities may directly affect performance enhancement while others may indirectly or even negatively associate with performance due to potential delayed effects. We will test two hypotheses:

Hypothesis 1: All OI capacities are significantly associated with firms' financial performance.

Hypothesis 2: Some OI capacities are positively associated with performance while others are negatively associated.

2.3.2. Interrelations

Specific capacities can be an essential prerequisite for particular OI modes guiding firms' business strategy formulation. While it might be easier for us to understand OI capacities if there were a one-to-one relationship between OI modes and capacities, the complexity of OI suggests there are not only multiple effects arising from capacities but also from the complex interrelations between capacities. For example, "in-sourcing" is an OI mode exploiting external knowledge, but firms should develop multiple capacities in order to implement it. First they must develop "connective capacity" to find external experts who have valuable information. P&G's Connect and Development (C&D) initiative exploits state-of-art ICT technologies (e.g., data mining) and entrepreneur networks to enhance this particular capacity (Dodgson, et al., 2006). Secondly, "absorptive capacity" is necessary in integrating external knowledge with their internal, and in this process a high level of internal R&D (i.e., "inventive" capacity) will positively influence firms' absorptive capacity (Cohen & Levinthal, 1990). Lastly, "innovative capacity" is necessary for making a profit from in-sourcing. By strengthening this capacity, P&G enhanced its R&D productivity by nearly 60% and had several significant market successes such as with the Crest SpinBrush (Dodgson, et al., 2006; Huston & Sakkab, 2006). As this example illustrates, OI is a complex process demanding multiple capacities closely related to each other. These ideas propose the following hypothesis:

Hypothesis 3: OI capacities are closely interrelated.

2.3.3. Group Dependency

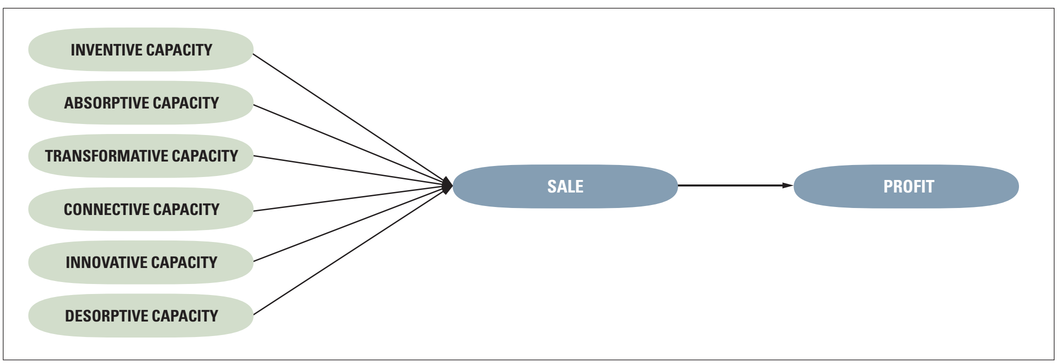
Firms typically choose OI modes that maximize their advantages and remedy their shortcomings. This suggests close relationships between firm characteristics and their OI capacities. For example, although the majority of OI case studies have focused on large multi-national firms (Dahlander & Gann, 2010), their success does not necessarily apply to other types of companies such as small and medium-sized enterprises (SMEs). SME characteristics, such as limited resources (Rothwell & Dodgson, 1994) or asymmetric relationships with large firms (Minshall, Mortara, Valli, & Probert, 2010), make their OI strategies different from those of large firms (Spithoven, Vanhaverbeke, & Roijakkers, 2012). The capacities underpinning business strategy is expected to differ between SMEs and large established firms but little is known about their capacity differences. This comparison can be extended to various groups of firms. Because firms establish their capacities according to the environment in which they find themselves and to the resources they can exploit, differences

in OI are apparent between independent and affiliated firms, R&D intensive and traditional industry firms, and firms in high and low population density areas. In this respect, by investigating various groups of firms and comparing their capacity differences, we may be able to understand why a certain group of firms favours a specific OI mode or what capacity should be developed further. This leads to the following hypotheses:
Hypothesis 4: The effects of OI capacities on financial performance will vary from one group of firms to another.
Hypothesis 4-1: OI capacities will be differently associated with firm performance according to firm size.
Hypothesis 4-2: OI capacities will be differently associated with firm performance in independent and affiliated firms.
Hypothesis 4-3: OI capacities will be differently associated with firm performance according to industry type.
Hypothesis 4-4: OI capacities will be differently associated with firm performance according to location.

2.4. The Research Model

The hypothesized causal relationships are illustrated in the research model in Figure 1

FIGURE 1. Research Model



3. METHODS

3.1. Analysis Method

Structural equation modelling (SEM) was employed for the empirical analysis. SEM is a quantitative method that achieves methodological flexibility by combining “measurement theory” from psychology with “multiple regressions” from econometrics (Blunch, 2008). As SEM consists of a variety of analysis techniques such as regression (i.e., path analysis), factor analysis, and correlation analysis, it is possible to conduct various tests simultaneously. Not only can causal relationships between OI capacity and performance be estimated but interrelationships between OI capacities can also be inferred by calculating their covariance. Differences in groups can additionally be estimated by multiple group comparisons. The SEM software package IBM SPSS AMOS 20.0 was used in this study with all coefficients estimated using the maximum likelihood (ML) method. Given that SEM is based on the analysis of covariance structure and ML assumes normal data distribution, kurtosis, multivariate kurtosis in particular, is always of serious concern (Byrne, 2009). Bootstrapping[2] was used in this study to remedy a potential non-normality problem.

3.2. Data

This study utilizes the Korea Innovation Survey (KIS) 2008 data. It is a regular large-scale innovation survey conducted by the Science and Technology Policy Institute (STEPI) and contains firm-level innovation information for the time period between 2005 and 2007. The KIS for manufacturing firms was published in 2002,[3] 2005, and 2008, but the KIS 2008 data is used because certain important information used in constructing OI capacity variables (such as technology licensing-out) was significantly missing or inadequate in the 2002 and 2005 data sets. The KIS 2008 data includes information about the innovation activities of 3,081 manufacturing firms, and a total of 911 observations were selected from the entire respondent set. This selection was based on criteria that excluded unanswered questions regarding OI capacities and unreasonable extreme values.[4] Outlier data can affect estimation negatively when researchers use ML estimation (Byrne, 2009) but no serious outlier was found when judging from the Mahalanobis distance. Among the four types of innovation activities that were dealt with in the KIS data (product, process, organisation, and marketing), only the product innovation data were analysed due to low response in the other three innovation activities. Some key descriptive statistics, such as the number of employees, are shown in Table 3.

TABLE 3. Descriptive Statistics [5]

	Sales (thousand USD)	R&D intensity (%)	Employees	R&D staff ratio (%)
Mean	235,803	9.50	389.19	9.43
Min	40	0.00	8.33	0.00
Max	33,334,648	417.96	25,000.00	87.84

Source: Korean Innovation Survey 2008 (STEPI)

[2] The original population is estimated by repeating the resampling procedure with replacement. The significances of coefficients are tested not from normal distribution but from the distribution of the estimated original population.

[3] KIS was conducted in 1997 and 2000, but these two surveys were pilot tests and not publicly disclosed.

[4] For example, "99,999,999 million KRW (Korean Won)" for production cost.

[5] All statistics in Table 3 are three-year (2005-2007) average values.

3.3. Variable Measurement

Two types of firm performances (sales and operating profit) were used for dependent variables, and sales were log transformed due to their large scales. The six OI capacities were indirectly measured using relevant items in the KIS 2008 data set.

"Inventive capacity" refers to the ability to generate knowledge within a firm and therefore the internal financial, human, and knowledge resources normally associated with this capacity were taken into account. These resources were measured according to two items on R&D personnel, i.e. the number of employees with masters or higher degrees and the number of employees doing full-time R&D; one item on the importance of internal R&D as a knowledge resource; and one item on expenditure on internal R&D. Items on financial and human resources were rescaled to six levels (from 0 to 5) to build unidimensionality with other variables.

"Absorptive capacity" refers to the ability to acquire and assimilate external knowledge, and the resources necessary for external knowledge exploitation were employed as measurement variables. Items on patents license-in and license-buy were summed to indirectly measure absorptive capacity. Ten items on the importance of various external information sources (suppliers, customers, competitors, conferences, etc.) in their innovation process were also aggregated in order to measure the total importance of external knowledge sources. Whether a firm adopted any external technology or knowledge was also taken into consideration.

"Transformative capacity" indicates the ability of a firm to protect its knowledge, and this capacity was measured using two indicators, the total number of patents and the protection activities of product innovation. The later indicator consists of seven sub-items on the importance of various protection methods (e.g. patents or trade secrets) that were summed in order to measure the total importance of protection in their innovation process.

"Connective capacity" refers to the ability of a firm to retain knowledge within itself. This capacity was measured using three indicators: an estimation of the extent to which R&D collaborations with various partners (e.g. suppliers or competitors) contribute to product innovation and its total effect; the expenditure for external R&D activities, rescaled to six levels; and finally, the number of patent cross-licensing.

"Innovative capacity" refers to the ability of a firm to commercialize from its products, measured using two indicators assessing the extent of the contribution to sales of their new products in the market and the company.

Lastly, "desorptive capacity" refers to what is necessary for external exploitation, measured using two variables on the number of license-sell and license-out.

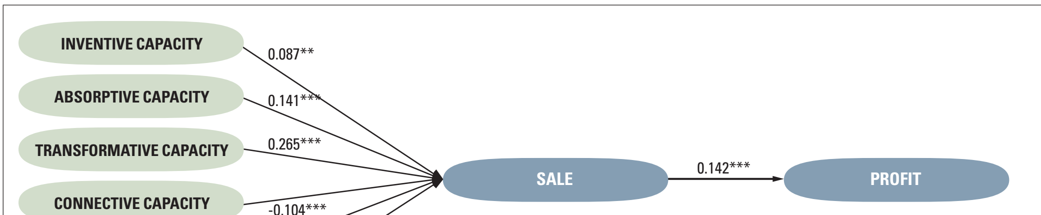
4. ANALYSIS AND RESULTS

4.1. Structural Model Results

Items on six capacities were individually summed in order to construct each latent variable. Despite some drawbacks (Oczkowski & Farrell, 1998), summed scales have been adopted by many researchers (Hult, Hurley, & Knight, 2004; Rhee, Park, & Lee, 2010, etc.) because of its simplicity and easy interpretations. Summed scales were used in this particular study for two main reasons. Firstly, measurement variables constructing one latent variable are not homogenous in terms of scales. We used secondary data rather than conduct our own survey, and therefore the variables were not initially tailored to the purposes of this study. We attempted to choose appropriate and relevant variables but inevitably there were scale mismatches. Some variables measure objective figures while others measure the subjective extent of the respondent's feelings. Secondly, summed scales make the model simpler and enables us to group comparisons easily. As the number of estimated variables decreases by adopting summed scales, simple path analyses can be conducted to see the total effects of OI capacities. Moreover, since our research interests lie in investigating differences in regression paths rather than in structural covariance and residuals, a simplified model enables us to identify group differences easily.

The coefficients of each path were also estimated. The structural model shows very satisfactory model fitness. A large χ^2 relative to its degree of freedom is crucial (Jöreskog & Sörbom, 1993), but the model shows a good χ^2/degree of freedom ratio (=2.928), reasonable when smaller than 3 (Wheaton, Muthen, Alwin, & Summers, 1977). However, since the null hypothesis in χ^2 statistics (that the data perfectly explains the model) makes researchers too easily reject the null, other goodness-of-fit statistics were used in order to assess the fitness of the model (Byrne, 2009). Most fit statistics are higher than the recommended level in the literature. GFI and AGFI are 0.995 and 0.971 respectively; TLI is 0.933; CFI is 0.986; the standardized root mean square residual (SRMR) is 0.024, which is valid if the value is smaller than 0.08 (Hu & Bentler, 1999). In addition, not only does RMSEA (=0.046), one of the most informative criteria in covariance structure modelling (Byrne, 2009) meet the recommended level, but its 90% interval at low and high confidence levels (i.e., 0.022~0.072) also satisfies cut-off values suggested by Browne and Cudeck (1993). All path regression estimates are statistically significant at the 0.05 level. Key model fit indices and path estimates are summarised in Figure 2.

FIGURE 2. Results for the Structural Model



$\chi^2(6) = 17.57 \quad \frac{\chi^2}{df} = 2.928, \quad GFI = 0.995, \quad AGFI = 0.971, TLI = 0.933, \quad CFI = 0.986,$
$RMSEA = 0.046, \quad SRMR = 0.024$

Significance level: ** $p < 0.05$, *** $p < 0.001$

As shown in Table 4, correlations were also estimated to investigate the interrelationships between each OI capacity.

TABLE 4. Correlations between OI capacities

	1	2	3	4	5	6
1. INVENTIVE	1					
2. ABSORPTIVE	0.182***	1				
3. TRANSFORMATIVE	0.414***	0.290***	1			
4. CONNECTIVE	0.211***	0.292***	0.232***	1		
5. INNOVATIVE	-0.260***	-0.161***	-0.344***	-0.233***	1	
6. DESORPTITVE	0.079**	0.162***	0.151***	0.104**	-0.078**	1

Significance level: ** $p < 0.05$, *** $p < 0.001$

All OI capacities correlates at the 0.05 level but do not correlate strongly enough to raise a multicollinearity problem, which would prevent from obtaining unique estimates of independent variables (Field, 2009). Variance inflation factors (VIFs) were computed in order to check any violation of the assumption of no serious collinearity. There is cause for concern if the largest VIF is greater than 10 or tolerance (1/VIF) is below 0.2 (Bowerman & O'Connell, 1990; Menard, 1995). For the purposes of our model, all VIF values are below 10, ranging from 1.042 to 1.248, and tolerance is above 0.2. Therefore it is possible to conclude there is no serious concern about multicollinearity in the data.

4.2. Group Comparisons

Multiple group analyses were conducted in order to investigate differences in regression estimates. For group comparisons, samples were divided according to firm size, firm type, industry, and location.

4.2.1. Firm Size

Samples were divided into two groups depending on the number of employees. The Korean Basic Act for Small and Medium-sized Enterprises defines SMEs as companies with fewer than 300 employees. 691 firms in our sample were SMEs according to this definition while 220 firms were large firms. As shown in Table 5, most model fit indices were at a satisfactory level (χ^2/df=1.991, GFI=0.994, AGFI=0.961, TLI=0.918, CFI=0.982, RMSEA=0.033) but some estimates (e.g. connective) were statistically insignificant in large firms or in SMEs.

TABLE 5. Results for Firm Size

Regression path		Large firms		SMEs	
		Estimate	p-value	Estimate	p-value
INVENTIVE →	→ SALES	0.146	**	0.100	**
ABSORPTIVE →	⇛ SALES	0.151	**	0.117	**
TRANSFORMATIVE →	⇛ SALES	0.127	0.077*	0.112	**
CONNECTIVE →	⇛ SALES	-0.006	0.927	-0.099	**
INNOVATIVE →	⇛ SALES	-0.053	0.425	-0.152	***
DESORPTIVE →	⇛ SALES	0.192	**	-0.001	0.981
SALES →	⇛ PROFIT	0.607	***	0.204	***

$\chi^2(12) = 23.89 \quad \frac{\chi^2}{df} = 1.991 \quad GFI = 0.994, \quad AGFI = 0.961, TLI = 0.918, \quad CFI = 0.982, \quad RMSEA = 0.033$

Significance level: * P<0.1, ** p < 0.05, *** p < 0.001

4.2.2. Firm Type

Firms were grouped according to whether a firm was an independent company or affiliated with a large conglomerate. In Korea, the Fair Trade Commission (FTC[6]) defines large conglomerates as firms with assets with over 4.37 billion US dollars (USD). The FTC classified 47 influential conglomerates in 2011. As shown in Table 6, conglomerates have on average 32.2 affiliates, with assets, revenue and net profit at 23.8 billion USD, 21 billion USD and 1.45 billion USD respectively (FTC, 2011). In our sample, 182 firms are affiliated companies or conglomerates while 729 firms are independent firms.

TABLE 6. General Figures on Conglomerates

(Unit: numbers, billion USD)

Category	Average	Top 3		
Number of Affiliates	32.2	SK (86)	Samsung (78)	LOTTE (78)
Assets	23.8	Samsung (202.01)	Hyundai Motors (110.85)	SK (84.86)
Sales	21	Samsung (183.20)	Hyundai Motors (108.39)	SK (97.63)
Net profit	1.45	Samsung (18.90)	Hyundai Motors (11.02)	Hyundai Heavy Industry (4.64)

Source: FTC (2011)

Path analyses were conducted in the following two groups. As shown in Table 7, model fit indices are all in the range considered satisfactory (χ^2/df=1.993, GFI=0.994, AGFI=0.961, TLI=0.930, CFI=0.985, RMSEA=0.033) but some estimates (e.g. connective capacity) are different in different groups as shown in Table 7.

[6] The Fair Trade Commission (FTC) is a ministerial-level central administrative organization in Korea. FTC is committed to four main mandates: promoting competition, strengthening consumers' rights, creating a competitive environment for SMEs, and restraining concentration of economic power (antitrust).

TABLE 7. Results According to Firm Type

Regression path	Affiliated		Independent	
	Estimate	p-value	Estimate	p-value
INVENTIVE → SALES	0.129	0.080*	0.066	0.073*
ABSORPTIVE → SALES	0.064	0.354	0.121	***
TRANSFORMATIVE → SALES	0.334	***	0.242	**
CONNECTIVE → SALES	0.041	0.571	-0.118	***
INNOVATIVE → SALES	-0.118	0.096*	-0.157	***
DESORPTIVE → SALES	-0.048	0.466	0.119	***
SALES → PROFIT	0.535	***	0.171	***

$\chi^2(12) = 23.92$ $\frac{\chi^2}{df} = 1.993$ $GFI = 0.994,$ $AGFI = 0.961, TLI = 0.930,$ $CFI = 0.985,$ $RMSEA = 0.033$
Significance level: * P<0.1, ** p < 0.05, *** p < 0.001

4.2.3. Industry

Firms were also categorized according to their industry types. In the KIS, the data industry is classified according to the Korean Standard Industry Classification (KSIC) index, ranging from KSIC 15 to 37. For comparison, sample firms were categorized into two groups: low KSIC and high KSIC. The former (15~22, 25 and 26) is relatively low R&D-intensive traditional industry, such as timber and sewing, while the firms in the latter group (23, 24, and 27~37) are relatively high R&D-intensive industries such as electronics and car manufacturing. There are 224 low KSIC and 687 high KSIC firms. χ^2/df is slightly high with 3.195 but with the exception of TLI (0.853), most fit indices meet cut-off guidelines suggested in the literature (GFI=0.990, AGFI=0.939, CFI=0.968, RMSEA=0.049). Estimates of paths and fit indices are shown in Table 8.

TABLE 8. Results According to Industry

Regression path	High KSIC		Low KSIC	
	Estimate	p-value	Estimate	p-value
INVENTIVE → SALES	0.072	**	0.172	**
ABSORPTIVE → SALES	0.122	***	0.192	**
TRANSFORMATIVE → SALES	0.283	**	0.234	0.070*
CONNECTIVE → SALES	-0.090	***	-0.111	***
INNOVATIVE → SALES	-0.201	***	-0.155	**
DESORPTIVE → SALES	0.074	**	0.106	0.073*
SALES → PROFIT	0.158	***	0.420	***

$\chi^2(12) = 38.33,$ $\frac{\chi^2}{df} = 3.195$ $GFI = 0.990,$ $AGFI = 0.939, TLI = 0.853,$ $CFI = 0.968,$ $RMSEA = 0.049$
Significance level: * P<0.1, ** p < 0.05, *** p < 0.001

4.2.4. Locations

In the KIS, data locations are divided into sixteen metropolitan areas. In this study, locations were divided into two groups according to population density. The capital area, which includes Seoul, Incheon, and Gyeonggi Province, accounts for 49.3% of the total population in 2012 (NSO, 2013). These top three densely populated places were grouped together to form a "high-density location" while the other thirteen areas were grouped together to form a "low-density location." In our sample, 502 firms were located in the high-density location and 409 firms were in the low. Path analyses were conducted for these two groups as shown in Table 9 but indicated a very poor model fit, failing to meet cut-off criteria (χ^2/df=20.34, GFI=0.950, AGFI=0.701, TLI=0.33, CFI=0.793, RMSEA=0.146).

TABLE 9. Results According to Location

Regression path		High-density location		Low-density location	
		Estimate	p-value	Estimate	p-value
INVENTIVE →	⇒ SALES	0.049	0.263	0.151	**
ABSORPTIVE →	⇒ SALES	0.150	***	0.151	**
TRANSFORMATIVE →	⇒ SALES	0.261	0.164	0.272	***
CONNECTIVE →	→ SALES	-0.057	***	-0.180	***
INNOVATIVE →	⇒ SALES	-0.210	***	-0.176	***
DESORPTIVE →	⇒ SALES	0.046	0.261	0.150	***
SALES →	⇒ PROFIT	0.175	***	0.413	***

$\chi^2(12) = 244.020$ $\frac{\chi^2}{df} = 20.34$ $GFI = 0.950,$ $AGFI = 0.701, TLI = 0.330,$ $CFI = 0.793,$ $RMSEA = 0.146$

Significance level: * P<0.1, ** p < 0.05, *** p < 0.001

4.3. Hypotheses Testing

The hypotheses were tested through the interpretation of estimates in the model. As shown in Figure 2, all path coefficients are statistically significant at the 0.05 level, supporting hypothesis 1. In addition, four OI capacities (inventive, absorptive, transformative, and desorptive) positively associate with performance (i.e., sales), while connective and innovative capacity negatively associate with sales. This supports hypothesis 2.

Interrelations between OI capacities were identified by correlation analysis. As shown in Table 4, all correlation coefficients are statistically significant at the 0.05 level (two-tailed) with innovative capacity in particular negatively correlating with other OI capacities. This supports hypothesis 3.

Multiple group analyses were conducted in order to test hypothesis 4 and its sub-hypotheses. Path analyses could have been conducted individually for different groups but this approach cannot provide us with information on whether or not the difference in estimates is statistically significant. In other words, even though a regression path is larger in one group than in another, it does not necessarily mean that a larger regression path is more influential than a smaller one. Thus, in order to see group differences, each group regression path was estimated concurrently in the single model after which the estimated differences were tested by investigating whether the χ^2 differences were statistically significant given their degree of freedom.

Firstly, for firm size as shown in Table 5, estimates were different between groups. In the large firms, transformative, connective, and innovative capacity are not different from zero at the 0.05 level but connective and innovative capacities are negatively associated with sales in the SME samples. In addition, desorptive capacity is not significant in the SMEs. Inventive and absorptive capacities are significant in both groups at the 0.05 level but their estimated differences are statistically insignificant because $\Delta\chi^2$ for these capacities are smaller than the critical value (3.84) given the Δdf (1). However, the regression path from sales to profit $\Delta\chi^2$ 2(=9.18) is greater than 3.84, suggesting significant differences in this path. This supports hypothesis 4-1.

Secondly, for the firm type, all OI capacities in the independent firms except for inventive are significantly associated with financial performance (sales). However, in the affiliated firm samples, inventive, absorptive, connective, innovative, and desorptive capacities are not different from zero at the 0.05 level. Transformative capacity and the path between sales and profit are significant in both groups at the 0.05 level but only the difference in path between sales and profit are significant, with large $\Delta\chi^2$ (=8.06). This supports hypothesis 4-2.

Thirdly, for industry type, all OI capacities are significant in the high KSIC firms while transformative and desorptive capacities do not differ from zero at the 0.05 level in the low KSIC firms. As in the cases of firm size and firm type groups, only the difference in path between sales and profit is significant. These facts corroborate hypothesis 4-3.

Lastly, for locations, all OI capacities are significantly associated with sales in the low density location samples while only absorptive, connective, and innovative capacities are significant in the high density location firms. However, statistical analysis results may not imply too much as most model fit indices such as TLI and RMSEA do not satisfy the level recommended in the literature. Therefore it is difficult to conclude that hypothesis 4-4 is supported.

5. DISCUSSION

5.1. Findings and Implications

The analysis illustrated in Figure 2 suggests that all OI capacities are significantly associated with firms' financial performance. However, in terms of their association signs (positive or negative), not all OI capacities positively associate with sales; connective and innovative capacities affected sales negatively. This may suggest that OI modes driven by these capacities can influence financial performance indirectly or directly with delay owing to potential time lag or expenses. Even though R&D collaborations with external partners can be complementary to a firm's insufficient internal R&D, the attending asymmetric protocol issues may require more of the firm's time and effort (Kitchell, 1997). When two or more different organisations work together, errors may iteratively occur until a tangible positive result is reached. This may be due to information asymmetry or differences between organisations in dealing with business. Therefore, effects on financial performance may be delayed due to accumulated miscommunication and misunderstanding between organisations, stemming from differences in interests and ways of doing research. Moreover, as the commercialization process influenced by innovative capacity involves a great deal of expenditure on marketing, financial performance may be negatively affected in the short run. Another explanation for this potential negative effect can be found in the correlations between OI capacities. As shown in Table 4, all OI capacities significantly correlated with each other. This suggests causal interrelationships between capacities. As noted by Cohen and Levinthal (1990), strong internal R&D (inventive capacity) can enhance absorptive capacity. Strong transformative capacity can also result in strong desorptive capacity as patents can be used for both protection and for an additional commercialization route (Chesborough, 2003b). Thus, a good model reflecting causal interrelations between OI capacities may help clarify the relationship between financial performance and OI capacities.

In addition to testing theoretical OI framework, this research attempted to compare firm groups in order to identify differences in OI capacities. Firstly, regarding firm size, connective and innovative capacity were not negatively associated with sales in the large firms, even though they do not differ significantly from zero (Table 5). As these capacities negatively influence sales in the SMEs with limited business resources, this result may suggest that lags and additional expenditure involved in external collaboration and commercialization do not result in poor performance in large firms. In addition, desorptive capacity was not significant for SMEs. Many studies suggest that outflow OI modes, such as patent licensing-out, are not in practice dominant in SMEs (Lee, Park, Yoon, & Park, 2010; van de Vrande, et al., 2009). This may arise from difficulties in establishing the IP or business strategies needed for opening up companies' boundaries and these difficulties could be more common for SMEs due to their lack of appropriate IP resources.

Secondly, in terms of firm type, all OI capacities (except for the inventive) in independent firms were significantly associated with sales (Table 7). However, only transformative capacity for the affiliated firms was significant at the 0.05 level. This may reflect unique characteristics of affiliated companies in the Korean industrial structure. Big companies (chaebols)' multifarious business operations ("octopus arms style diversification") cover almost every type of industry through their numerous subsidiaries. Consequently, their affiliates can easily achieve self-sustainable growth via internal transactions within their own business ecosystem. For example, a manufacturing affiliate can buy raw materials from its heavy industry affiliate, and the products of manufacturing and consumer goods affiliates can be sold using its distribution affiliate. By means of these internal transactions, affiliates may be able to achieve the benefits of OI without implementing actual OI activities. The fact that internal transaction accounted for 22.59% of total revenue of all large conglomerates and their affiliates in 2011 (FTC, 2011) and accounted for 85.3% of total contracts in the top ten large firms (Chaebul.com, 2012) indirectly support this interpretation.

Thirdly, for industry, the influences of transformative and desorptive capacities on sales were insignificant in the low KSIC firms while all OI capacities were significantly associated with sales in the high KSIC firms. These results may suggest that knowledge appropriation via intellectual property can be more commonly employed in technology-intensive industry. In traditional industry, where patents are less stressed than other factors such as cost reduction, other capacities may be more necessary and relevant for performance enhancement.

Lastly, there were no significant results in terms of location due to the poor mode fit. There can be two possible explanations. One is that as noted by Chun and Mun[7] (2012) in their analysis of the KIS 2002 data, location may not play a critical role in innovation. The other explanation is that the data information on location was not detailed enough to identify locational effects. In the KIS 2008 data, the location of the main company was too roughly segmented to indicate anything more specific than the name of the city or province where it was located. Locational effect could not be fully examined, as detailed information (whether a firm is located in an industrial complex or start-up incubator, for example) was not provided.

The results of this study provide government decision makers with certain policy implications. Of prime importance in the findings is that OI capacities significantly affect firm performance. This suggests that OI is an important factor in enhancing sales and profitability and is worth the attention of policy makers. Numerous manufacturing firms in Korea, in particular SMEs, are suffering from poor growth. With the emergence of newly developing countries such as China, Vietnam, and India, Korean SMEs are losing their competitive advantage, particularly regarding cost. Korean SMEs are often caught between technology-competitive firms in the US and EU and price-competitive firms in newly developing countries. Therefore, in order to enhance SME competitiveness, policy makers should attempt to encourage OI activity and complement insufficient OI capacities, such as through providing for transformative and desorptive capacity. Similarly, policy makers can develop appropriate policy that enhances the insufficient capacities of low technology-intensive firms or independent firms.

5.2. Limitations and Future Research Direction

There are some theoretical and methodological limitations in our study. Firstly, as secondary data were utilized, there is a possibility that measurement variables did not reflect certain unique characteristics of OI capacities correctly. More exact and interesting findings could be addressed if in future studies the questionnaires are designed for OI capacities. For example, more detailed information on location could enable the discovery of other interesting findings such as the role of location in the process of OI implementation.

Secondly, longitudinal data can be used to discover the long-term effects of OI capacities. As shown in Figure 2, empirical results suggested negative effects of connective and innovative capacities. This may imply that OI modes involved in these capacities are time- and financial-resource consuming so their effects may be negative in the short run but could be positive in the long run. However, as the data is not longitudinal,[8] we could not test whether this interpretation was apt. Once

[7] They used a binary variable whether a firm is located at seven big cities to see the influence of location.

[8] In the KIS data, certain information (such as sales) contains three-year period data, but most data on innovation activities have three-year average values.

longitudinal data is used, we may also be able to investigate how the effects of OI capacities change over time in order to see the dynamics of the capability development process.

Finally, OI theory itself should be further developed. Certain ground-breaking studies (Gassmann and Enkel, 2004; Lichtenthaler and Lichtenthaler, 2009, West and Gallagher, 2006, etc.) have attempted to investigate OI theoretically, but OI theory remains under-researched (Trott & Hartmann, 2009). Even though we empirically tested Lichtenthaler and Lichtenthaler's (2009) framework, we did not establish further details of OI capacities. As shown in Table 4, high correlation between OI capacities suggest the possibility that capacities are interrelated with causal relationships, but an alternative research model which could explain these high correlations could not be established due to lack of strong theory. Future research is needed to address this gap in the theoretical foundation of OI.

6. CONCLUSION

This study empirically tested the theoretical framework of OI as suggested by Lichtenthaler and Lichtenthaler (2009). A conceptual model between OI capacities and firms' financial performance, sales, and profits was designed and tested using the KIS 2008 data on Korean manufacturing firms. Group comparisons were also conducted in order to identify potential estimation differences according to firm size, firm type, industry, and location. The results suggest that all OI capacities were significantly associated with sales but some were negatively associated, implying the possibility of delayed effects. Group comparisons provided us with interesting findings. Desorptive capacity was not significantly related with sales in SMEs, suggesting insufficient desorptive capacity; insignificant absorptive and connective capacities in affiliated firms may suggest that their strong internal transactions may reduce their need to adopt OI; and firms in traditional industry may lack transformative and desorptive capacities. Findings suggest that policy makers should pay more attention to enhancing OI capacities and attempt to develop relevant policies that can complement insufficient capacities in each group. The contribution of this research lies in the empirical testing of the theoretical OI capacity framework. However, future research may develop the findings further by conducting a well-designed survey or using longitudinal data. The theoretical background of OI should also be further explored.

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