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To cite this article: S. Joseph Yoon, Klaus Marhold & Jina Kang (2017) Linking the firm’s knowledge network and subsequent exploratory innovation: a study based on semiconductor industry patent data, Innovation, 19:4, 463-482, DOI: 10.1080/14479338.2017.1358101

To link to this article: https://doi.org/10.1080/14479338.2017.1358101

Published online: 11 Aug 2017.

Article views: 65
Linking the firm’s knowledge network and subsequent exploratory innovation: a study based on semiconductor industry patent data

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ABSTRACT
In order to create innovation, firms in high-tech industries do not only need to possess technological knowledge in various fields, but also need to know how to connect different technologies. A firm’s knowledge resources can be expressed as a single network composed of knowledge elements (nodes) and their combinations (ties). We develop a theoretical framework to investigate the dynamics of such a knowledge network over time, accounting for the attributes and effects of knowledge accumulation. We distinguish accumulated component and architectural knowledge, and investigate their impact on subsequent exploratory innovation, i.e., the creation of new elements and new combinations. Using patent data of 111 US semiconductor companies from 2000–2010, we find an inverted U-shape relationship in creating knowledge combinations in a firm’s knowledge network as well positive relationships between knowledge elements and knowledge combinations. The results highlight the important role of the firm’s accumulated knowledge resources in creating exploratory innovation.

1. Introduction
In today’s fast-changing technological environment, firms are increasingly focusing on exploratory innovation which makes them more flexible and agile, and allows them to avoid obsolescence of their knowledge and remain competitive (Phelps, 2010; Wang, Rodan, Fruin, & Xu, 2014). For this reason, firms have been building up strong knowledge resources which can serve as sources of innovation (Grant, 1996\textsuperscript{a}, 1996\textsuperscript{b}). Innovation is intrinsically linked to two key concepts: knowledge elements and their combinations. Specifically, exploratory innovation is associated with the creation of new knowledge elements or combinations (Fleming, 2001). Following the established framework of Henderson and Clark (1990), these correspond to component knowledge (knowledge elements) and architectural knowledge (knowledge combinations). Both these dimensions are captured in the concept of the

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knowledge network, which considers individual knowledge elements as nodes and their combinations as ties. Knowledge networks have been used and recognized as a useful tool to depict and describe a firm’s existing knowledge elements and their applications (Sorenson & Fleming, 2004).

Although many researchers have studied the impacts of a firm’s knowledge resources on its innovation performance, several important research gaps remain: first, among the many studies on the antecedents of firms’ exploratory innovation, most investigated only one side of exploratory innovation by focusing on the creation of new knowledge elements (e.g., Guan & Liu, 2016; Wang et al., 2014). Only recently, Dibiaggio, Nasiriyar, and Nesta (2014) started to look at the creation of new knowledge combinations as exploratory innovation. Due to their focus on the patent level, however, their research did not include newly created knowledge elements which may affect subsequent innovation. A comprehensive view that covers both dimensions of exploratory innovation by focusing on the creation of elements and combinations at the same time, is still underexplored. Second, prior literature has not fully explained the real world performance heterogeneity exhibited by firms operating in the same industry which often possess similar knowledge elements (D’Este, 2005; Patel & Pavitt, 1997). To explain this phenomenon, Nesta and Dibiaggio (2003) stated that firms even in the same industry can show dissimilar ways of conducting their research activities and implementing their knowledge elements. This leads to the thought that not only different knowledge elements, but also the different ways of leveraging those elements result in dissimilar outputs of firms’ inventive activities. Thus, a framework that clearly distinguishes knowledge elements and combinations allows us to look at their individual roles and characteristics in facilitating subsequent innovation, as well as to analyse their effects on each other. Last, prior studies considered the knowledge network as a static factor influencing the firm’s innovative outcome and conducted a cross-sectional analysis that examined the knowledge network as a snapshot. This conflicts with the intrinsically dynamic nature of firms’ knowledge networks which are continuously changing over time through the absorption of subsequent exploratory innovation, i.e., newly created elements and combinations.

The aim of this research is to overcome these limitations by linking the firm’s knowledge network and its subsequent innovation in terms of knowledge elements and combinations, and at the same time capturing the dynamics of the knowledge network for which prior studies showed little concern. Specifically, we investigate how the accumulated knowledge elements and combinations affect the creation of new elements and combinations, which are key indicators for exploratory innovation.

Our hypotheses are tested on a panel of 111 US semiconductor companies from 2000–2010. Using patent data, we draw each firm’s knowledge network during a 5-year period and employ a sliding window approach to look at the dynamic network as new elements and combinations are created while older elements become obsolete. We find evidence for an inverted U-shape relationship between the level of accumulated combinations and the creation of new combinations. In addition, we find positive relationships between the level of accumulated elements and the creation of new combinations as well as between the level of accumulated combinations and the creation of new elements. These results suggest that both knowledge elements and combinations play an important role in facilitating subsequent exploratory innovation.

This study makes a number of important contributions: first of all, we extend the theoretical background by uncovering the relationship between a firm’s accumulated knowledge...
resources and the subsequent new exploratory innovation focusing on the dynamics of knowledge networks. Specifically, we reveal the relationships between the two types of accumulated knowledge resources of the firm and two indicators of exploratory innovation using a framework distinguishing knowledge elements and combinations. From these links, we explore the different roles and characteristics of the firm's dynamic knowledge network in facilitating subsequent innovation. Second, our research design suggests a new approach to capturing the process of knowledge accumulation. Unlike prior research which analysed binary knowledge networks, our analysis of patent data allows us to express a firm's knowledge resources as a weighted network. This approach enables us to examine the effects of the strength of ties and the size of nodes, which reflect the firm's level of accumulated knowledge and experience. Last, from a practical perspective, we advise managers to set up a suitable innovation strategy taking into account the relationship between knowledge elements and combinations. For firms with strong recombinant capabilities, it is recommended to establish an external knowledge sourcing strategy to gain access to new knowledge elements. For firms with strong technological knowledge, it is advantageous to establish a knowledge leveraging strategy to combine existing knowledge elements in new ways.

2. Theoretical background

2.1. Knowledge network as a firm's knowledge resources

The concept of the knowledge network stems from the idea that scientific or technological knowledge elements can form relationships with each other, regarding each element as a node, and each relationship between two elements as a tie (Fleming, 2001). As every invention is made up of a (re)combination of different knowledge (Makri, Hitt, & Lane, 2010; Schumpeter, 1934; Weitzman, 1998), a knowledge element is the fundamental building block of an invention (Fleming & Sorenson, 2004). Wang et al. (2014) elucidate the knowledge element as a socially defined category derived from a group of scientific or technological knowledge in a particular subject matter, and characterize it as not atomistic, but linked by joint application in previous inventions. Accordingly, prior empirical studies have considered a knowledge element to be a technological field, e.g., a detailed technology classification of the patent system, and a knowledge combination to be the relationship between those technological fields formed through an invention, e.g., a patent (Carnabuci & Operti, 2013; Fleming, Mingo, & Chen, 2007; Guan & Liu, 2016; Phelps, 2010). For example, an invention based on more than one technological field can be expressed as a collection of certain nodes and ties which represent technology classes (knowledge elements) and their relationships (knowledge combinations). If an invention is based on a single technological field, it can be expressed as a single node without ties. On the firm-level, a knowledge network can be drawn as the sum of all the inventions made by the individual researchers employed by the firm. The nodes represent knowledge elements, in this case, the technology classes of the firm's patent. The ties represent knowledge combinations of technology classes formed by co-application in a single patent. The strength of a tie and the size of a node represent the level of frequent (repeated) usage of the knowledge combination/element.

The knowledge stored in the elements and combinations of a knowledge network represents two different kinds of knowledge: component knowledge, which represents the knowledge itself as an ingredient of the invention, and architectural knowledge, which
represents the structure of the invention and how its different components are brought together (Henderson & Clark, 1990). In a similar view, Argote and Ingram (2000) distinguished individual memory which is concerned with facts, skills and can be seen as ‘know-what’, and transactive memory which is concerned with who is an expert for a certain case, what knowledge belongs to someone and can be summarized as ‘know-where’. In a knowledge network, elements (nodes) are closely associated with the concepts of component knowledge and individual memory, while combinations (ties) are associated with architectural knowledge and transactive memory.

Most prior studies on firms’ knowledge resources have focused on knowledge elements, especially their attributes and compositions (Quintana-García & Benavides-Velasco, 2008; Srivastava & Gnyawali, 2011), but showed little concern for their combinations associated with learning, experience and capabilities (Carnabuci & Bruggeman, 2009). Considering a firm’s knowledge resources as a bundle of knowledge elements without their combinations has limits in explaining the reason why firms that possess similar knowledge resources differ in their performance. A firm’s knowledge network that reflects the firm’s areas of expertise and how the firm combined them in their innovation process, however, allows representation of heterogeneity of knowledge characteristics between different firms.

2.2. Firm’s innovation based on its knowledge network

Every inventive activity is a series of search processes that determine which knowledge elements should be combined (Fleming & Sorenson, 2001; Kauffman, Lobo, & Macready, 2000). The resulting invention can either be exploratory or exploitative. Generally, exploration focuses on generating new knowledge to avoid obsolescence and to remain competitive, while exploitation pays attention to leveraging and refining existing knowledge to improve efficiency and to secure a firm’s status (March, 1991; Stettner & Lavie, 2014). Exploration and exploitation rely on distinctive organizational routines (Dosi, Nelson, & Winter, 2000). Exploration routines facilitate flexibility, risk taking and experimentation (McGrath, 2001), while exploitation routines facilitate stability, control and consistency (Benner & Tushman, 2003). In a knowledge network, exploitative invention, which is based on well-developed knowledge in a relatively familiar field, manifests itself as the repeated occurrence of existing elements or existing combinations. Exploratory invention, on the other hand, is the appearance of new elements and/or new combinations in the knowledge network. An exploratory invention results in either the appearance of new nodes and/or ties. Figure 1 shows how the knowledge network of a firm changes in accordance with the firm’s new exploitative and exploratory inventions. The formation of a new tie or a new node represents the creation of exploratory invention. For example, a tie formed between nodes e and d at time t+1 indicates a new invention created by co-application of the two technology classes e and d, which has not been conducted before. An isolated node f formed at time t+1 indicates a new invention created by using a new, but single technology class f. On the other hand, increments in the strength of a tie or the size of a node at time t+1 represent exploitative invention, i.e., repeated usage of existing knowledge combinations and/or elements.

The know-how gained from inventive activities leads to a higher success rate of subsequent inventions through organizational learning which increases the efficiency of the firm’s search process (Cohen & Levinthal, 1990). The search process in an organization can be described as a repeated trial and error experiment which is inherently uncertain (Fleming,
The easiest way to decrease inventive uncertainty is referring to prior successful experiences. When a knowledge combination succeeds, it helps to more deeply understand the knowledge elements involved in that combination (Yayavaram & Ahuja, 2008). Consequently, these elements might be given priority in combinations with new and yet unexplored elements. An element involved in various combinations can also be expected to create a synergy effect when being combined with others because of its demonstrated potential for application in different settings (Wang et al., 2014).

However, accumulated knowledge from learning increases the tendency of firms to keep doing things ‘the old way’. Organizational learning is routine-based and path-dependent (Cyert & March, 1963; Dosi, 1988; Levitt & March, 1988; Nelson & Winter, 1982; Vincenti, 1990). Repetition of the same innovation processes gradually shapes strong norms and routines within the firm. Consequently, researchers are likely to resort to known and proven combinations without considering alternative solutions or adopting new knowledge from outside the firm (Katz & Allen, 1982; Levinthal & March, 1993). Prior empirical studies in the petroleum industry (Helfat, 1994) and semiconductor industry (Stuart & Podolny, 1996) found that firms have a tendency to choose research projects from a familiar technological environment and to rely on well-known knowledge combinations which are expected to perform well due to their fit with the firms’ expertise and experience. In summary, a firm’s

![Figure 1](image1.png)

**Figure 1.** An example of the firm’s knowledge network and its changes over time due to the newly created exploitative (repeated use of existing nodes and ties) and exploratory inventions (creation of new nodes and ties).

![Figure 2](image2.png)

**Figure 2.** Conceptual diagram.

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knowledge network supports its search processes, but at the same time makes it harder to adopt new ways of thinking due to increasing organizational inertia.

3. Hypotheses

3.1. Effects of prior knowledge combinations on subsequent exploratory innovation

A firm’s knowledge network is expanded over time by acquiring and leveraging knowledge resources. Among the two key types of knowledge, architectural knowledge is represented by the knowledge combinations accumulated through past inventions. From the understanding that a firm’s innovation is based on its knowledge resources, we investigate the effects of the level of accumulated architectural knowledge on the two indicators of subsequent exploratory innovation: new knowledge combinations and new knowledge elements and arrive at the research model summarized in Figure 2.

3.1.1. Accumulated architectural knowledge and new knowledge combinations

A firm’s existing knowledge resources influence its present search process and help it decide which elements should be combined to create useful inventions. If the present level of architectural knowledge is low, the firm is lacking information on the relationship between the elements. In this situation, it is hard to create new successful innovation based on new combinations. As a firm accumulates architectural knowledge, it increases the recombinant capabilities that enhance internal knowledge exchange through connecting different technological fields and help to find new combinations (Carnabuci & Operti, 2013). In addition, architectural knowledge increases the information on the relationship between elements that are only indirectly connected with each other. Dibiaggio et al. (2014) argued that these elements have a functional substitutability and are able to stimulate new combinations because they can become alternatives when researchers conduct an experiment to combine different kinds of knowledge elements. Similarly, as architectural knowledge helps to understand knowledge elements through their relational information, the potential for new combinations is increased (Wang et al., 2014).

Conversely, if the level of architectural knowledge reaches excessively high levels, path-dependency can reduce subsequent exploratory innovation. High levels of architectural knowledge allow the firm to enhance its exploitive inventions and reuse existing combinations. The efficiency of the search processes related to exploitative innovation is increased through various mechanisms including more concise search processes, decreasing uncertainty, or increasing resource efficiency (Levinthal & March, 1993; March, 1991). This efficiency of exploitative search raises the opportunity cost of exploration and makes the creation of new combinations unattractive when compared to reusing existing combinations. In addition, the accumulated experiences of the firm turn into complex organizational routines and tend to increase organizational inertia. The organizational inertia stiffens collective learning and gives rise to phenomena such as the competency trap, myopia of learning, group think or not invented here (NIH) syndrome (Janis, 1972; Katz & Allen, 1982; Levinthal & March, 1993; Levitt & March, 1988). With the occurrence of these phenomena, the firm finds it increasingly difficult to develop exploratory innovation composed of new combinations.
In summary, increasing levels of accumulated architectural knowledge in the firm’s knowledge network help to form new combinations. At high levels, however, negative effects of inertia increasingly prevent the firm from creating exploratory innovation. Together, these positive and negative effects lead to the following hypothesis:

Hypothesis 1a: In a firm’s knowledge network, there is an inverted U-shape relationship between the level of accumulated architectural knowledge and the creation of exploratory (new) knowledge combinations.

3.1.2. Accumulated architectural knowledge and new knowledge elements
Low levels of architectural knowledge show that less focus was placed on forming combinations between existing elements. It implies that the firm does not know whether there are still lots of opportunities to combine the existing elements to create useful inventions. In this situation, the firm may perform an investigation of its existing elements to identify internal opportunities rather than focus on external knowledge sourcing, because searching for new elements externally requires more resources such as time, costs and management efforts compared to learning existing elements more deeply (Srivastava & Gnyawali, 2011). If the firm found chances to combine existing elements, researchers would not need to search for new knowledge from the outside, but would rather prefer to focus on activities using existing knowledge within the firm.

As the level of architectural knowledge is increasing, the remaining opportunities for combinations that have not yet been realized decreases. However, information on the relationship between the elements is closely related with forming recombinant capability in the organization, which enables it to identify a chance to match different elements (Fleming, 2001; Henderson & Clark, 1990; Srivastava & Laplume, 2014). Therefore, a firm with high levels of architectural knowledge is capable of seeking and distinguishing types of new elements which are appropriate for creating synergy effects with the existing elements. Consequently, the firm can aim at sourcing appropriate elements after exhausting the opportunities for combining existing elements. Additionally, high levels of architectural knowledge are also associated with exploitative invention relying on past experience and existing ways of combination, often resulting in diminishing marginal benefits of inventions (Henderson, 1995; Kim & Kogut, 1996). In terms of the firm’s motivation for new knowledge sourcing, the threat of gradually exhausting the firm’s internal potential for inventive ideas fosters a sense of crisis inside the firm (Ahuja & Lampert, 2001), and creates internal pressure to focus on exploratory innovation. As a result, the firm will turn to the outside world and introduce new elements through external knowledge sourcing.

In summary, low levels of accumulated architectural knowledge do not provide motivations for firms to acquire new elements. With increasing levels, however, firms’ recombinant capabilities grow and the opportunities to combine the existing elements diminish, adding pressure to introduce new elements. This leads to the following hypothesis:

Hypothesis 1b: In a firm’s knowledge network, there is a positive relationship between the level of accumulated architectural knowledge and the creation of exploratory (new) knowledge elements.
3.2. Effects of prior knowledge elements on subsequent exploratory innovation

Among the two types of knowledge, component knowledge is represented by the knowledge elements accumulated in the firm's knowledge network. In an extension of the argument that a firm's new innovations are affected by its accumulated knowledge, we hypothesize about the effects of the level of accumulated component knowledge on the two indicators of subsequent exploratory innovation: new knowledge combinations and new knowledge elements.

3.2.1. Accumulated component knowledge and new knowledge combinations

At a low level of component knowledge, i.e., when the firm does not possess a large expertise in the technological fields it is involved in, the chance of success in combining existing elements is low because the firm is lacking the detailed information to discover potential areas of application. The poor understanding of technological knowledge gives rise to a high failure rate in experiments. Moreover, the chance of forming new combinations is further reduced in case there are already existing combinations which have succeeded in prior experiments. This is due to the opportunity of new combination being limited by nature among the firm's existing elements (Kim & Kogut, 1996). Therefore, a firm with a low level of component knowledge finds it hard to pursue new combinations and is more likely to focus on refining and exploiting existing combinations.

Meanwhile, an increase of the firm's component knowledge, i.e., a deeper understanding of technological knowledge resources, decreases the uncertainties of matching elements and leads to a growth of recombinant potential by finding new areas of application that the firm did not pursue before. Expanding the existing applicability of each element provides new opportunities for a firm to utilize existing elements in different ways by connecting unmatched technological fields, leading to new combinations. In addition, a deeper understanding of elements helps to develop a firm's combinative capability to identify the related or well-matched attributes among the existing elements (Katila, 2002; Katila & Ahuja, 2002). It encourages a firm to find possible sets of elements and create synergy effects by combining them, resulting in the creation of subsequent new combinations.

In summary, while low levels of accumulated component knowledge provide little potential for firms to create new combinations, the formation of new combinations increases with an increase in the level of the accumulated component knowledge. This leads to the following hypothesis:

\textit{Hypothesis 2a: In a firm's knowledge network, there is a positive relationship between the level of accumulated component knowledge and the creation of exploratory (new) knowledge combinations.}

3.2.2. Accumulated component knowledge and new knowledge elements

The management of the firm's knowledge portfolio is an important task as a firm with various elements, i.e., options for future use, is able to predict new technology and market trends and to act more flexibly and be agile in response to changing environments, such as those found in many high-tech industries. If a firm sticks to a particular technology, however, it might lose its ability to compete when technological discontinuities make the firm's technologies obsolete (Agarwal & Audretsch, 2001; Danneels, 2004; Henderson, 1993; Tripsas, 1997). For these reasons, firms are trying to explore new elements. However, at very low
levels of component knowledge, because of the insufficient forecasting capabilities resulting from incomprehension of specialized technologies, the scope of the firm’s existing knowledge base will make it difficult to branch out into new fields. As the level of component knowledge increases, a deeper understanding of technological knowledge helps to increase the firm’s absorptive capacity to seek and learn about related elements associated with its existing knowledge resources (Cohen & Levinthal, 1990). It encourages a firm to expand its technological windows and broaden the areas of expertise, so the firm is able to rapidly identify the chance of finding relevant knowledge among different technological fields. Consequently, a deeper and broader technological window will facilitate the acquisition or creation of new technologies, resulting in an increasing creation of new elements.

However, as the level of component knowledge exceeds a certain level, the large amount of knowledge resources becomes excessively complicated, shaping vast knowledge management processes and routines inside the firm (Srivastava & Gnyawali, 2011). Since a firm’s resources and capabilities are limited, the interest in creating new elements decreases when managing the existing knowledge resources already requires the investment of a great amount of cost and effort. Previously secured elements also tend to primarily boost exploitative inventions as the existence of a large in-house knowledge stock diminishes the motivations and incentives for creating new elements. Moreover it is possible for previously formed elements to shape silos in organizations and bring about phenomena that hinder the exploration of new element from an unfamiliar context, e.g., group think or the NIH syndrome (Janis, 1972; Katz & Allen, 1982). For these reasons, the firm finds it increasingly difficult to create exploratory innovations composed of new elements.

In summary, while the level of accumulated component knowledge initially supports the creation of new elements, beyond a certain level, increasing internal costs and reduced benefits of managing a large knowledge stock come into play and negatively affect the formation of new elements. Together, these positive and negative effects lead to the following hypothesis:

Hypothesis 2b: In a firm’s knowledge network, there is an inverted U-shape relationship between the level of accumulated component knowledge and the creation of exploratory (new) knowledge elements.

4. Methods

4.1. Sample and data

The hypotheses of this study were tested on a dataset of 111 firms operating in the semiconductor industry (SIC 3674) from 2000–2010 using granted US patents listed in the USPTO (United States Patent and Trademark Office) database. The semiconductor industry has several characteristics that make it a suitable setting for this study. First, it is a typical high-tech industry in which building up a strong knowledge base is critical for gaining a competitive advantage. Second, the industry is known for its high propensity to patent innovations, which allows for easier tracking and measuring of the knowledge and innovation (Hall & Ziedonis, 2001, 2007). Third, the fierce competition and the rapid technological process in the industry result in the constant emergence of new knowledge fields, making it suitable for the study of knowledge elements and combinations in new inventions.
We used patent data, which includes information on the technology classification of the invention. The USPTO has maintained and updated its technology classification standard composed of 400+ main and 100,000+ subclasses, which have been considered as valid proxies for knowledge elements by prior studies (Wang et al., 2014). Because subclasses usually have a very high knowledge relatedness with each other (Hall, Jaffe, & Trajtenberg, 2001), studies accounting for technology domains as knowledge elements tend to resort to using main classes (Ahuja & Lampert, 2001; Carnabuci & Operti, 2013; Yang & Steensma, 2014; Yayavaram & Ahuja, 2008). We follow this prior literature and also use main classes as proxies for knowledge elements. To be specific, we consider primary 3-digit (main) technology classes in the firm’s granted patents as the nodes in the firm’s knowledge network. If a patent has two or more technology classes listed, it shows that the invention is derived from the useful combination of those technology classes. Thus, we operationalize that two or more technology classes within a single patent form ties between them.

In this study, we set up a 5-year window to construct each firm’s knowledge network by investigating all granted US patents that were applied for by the firm during that period. We set up the observation window in order to reflect the change of the firm’s knowledge network over time as it absorbs newly appearing innovation, and expires old ones. The 5-year period is chosen to account for the declining value of patented knowledge (Mehta, Rysman, & Simcoe, 2010; Park, Shin, & Park, 2006).

The final dataset was derived using the following procedure: at first, we extracted information on 103,787 granted patents of 157 US semiconductor companies for 2000–2014 from the USPTO database. This allowed us to verify whether the patents applied for in the period of interest (2000–2010) were ultimately granted or not. Next, we set up a 5-year window for each company to gather all of their firm’s granted patents filed in that period and, using the technology classes listed on each of the patents, identify the knowledge elements and their combinations. We constructed panel data of the firms by moving the 5-year window a total of six times, by one year each, from 2000–2004 to 2005–2009. All independent variables and control variables are calculated from the observation period or at the last year of the observation period. The dependent variables were lagged by one year to capture the causal relationship. Last, we added each firm’s financial information from the Compustat database provided by Thomson Reuters and removed entries with missing values. The final sample consists of 111 firms and 608 firm-year observations.

4.2. Variables

4.2.1. Dependent variables
This study focuses on the effects of a firm’s accumulated knowledge on its subsequent exploratory innovation. To investigate different aspects of the accumulated knowledge of a firm, we assemble the firm’s knowledge network composed of elements (technology classes as nodes) and combinations (joint occurrence of patent classes in the same patent as ties). Similarly, the firm’s exploratory innovation can be separated into two types, one in terms of new elements (new nodes) and the other one in terms of new combinations (new ties) (Fleming, 2001). Thus, the dependent variables of this study were chosen to represent these two key dimensions of exploratory innovation.

New knowledge combinations refers to the number of new ties in the knowledge network, and indicates the extent to which a firm adopts new ways of knowledge application. It is
measured as the number of new ties which appeared in focal firm i’s knowledge network in year t, the lagged year from the observation period of the independent variables from t–5 to t–1. In a similar way, New knowledge elements refers to new nodes in the knowledge network, and indicates the extent to which a firm adopts new elements. It is measured as the number of new nodes that appeared in focal firm i’s knowledge network in year t.

4.2.2. Independent variables
The independent variables of this study represent the level of accumulated knowledge within the two key dimensions of the knowledge network, i.e., the previously formed elements and combinations. We set up a 5-year observation window to construct the weighted knowledge network of each firm from year t–5 to t–1. Accumulated architectural knowledge is then defined as the mean value of the ties in focal firm i’s knowledge network and indicates the extent to which the firm possesses accumulated knowledge related to the connection between different elements. In the same way, Accumulated component knowledge is defined as the mean value of the nodes in focal firm i’s knowledge network and indicates the extent to which the firm possesses accumulated knowledge related to the elements themselves.

4.2.3. Control variables
Our study controls for the influence of other variables associated with the firm’s knowledge network. We controlled for two representative measures of network cohesion: Density indicates the overall weighted network density in firm i’s knowledge network and is measured as the total value of ties divided by the total number of possible ties in the knowledge network. Degree Centrality indicates how many relationships the nodes have and is calculated at the network level by averaging each node’s number of connections to other nodes in firm i’s knowledge network (Wang et al., 2014). We also added Number of clusters, which indicates the extent to which elements are connected together, because often a firm’s knowledge network is composed of a few disconnected clusters (Wang et al., 2014). Nodes that belong to the same cluster are far more cohesive than a pair of nodes that are on separate clusters, so it may affect the tendency to explore new inventions. We measured it as the number of network clusters in focal firm i’s knowledge network. We also controlled the effects of scale and scope on technological search which may affect the firm’s inventive activities (Henderson & Cockburn, 1994; Yayavaram & Ahuja, 2008). Firm size is defined as the number of employees of focal firm i in year t–1. R& D intensity is defined as the log-transformed value of total R&D expenses divided by total sales of focal firm i in year t–1. Last, we controlled for the Number of alliance partners, which indicates the extent of external knowledge sourcing that might affect the firm’s exploratory activities (Srivastava & Gnyawali, 2011). It is defined as the number of the focal firm’s alliance partners in the preceding 5-year period and was obtained from the SDC platinum database.

4.3. Model specification
We use a negative binomial regression model because the dependent variables, the number of new knowledge combinations and new knowledge elements, are count variables. Negative binomial regression is used when the dependent variable’s variance is bigger than its mean (Long, 1997). According to the result of the performed Hausman test, we use a fixed-effect model which assumes that each entity’s characteristics do not change over time (Hausman, 1978).
5. Results

Table 1 provides descriptive statistics and correlations for all variables. To check for the presence of possible multicollinearity problems, we conducted an additional variance inflation factor (VIF) test and the results (not reported here) showed low values (average of 2.04), which are small enough to ignore the multicollinearity problem (Kleinbaum, Kupper, Nizam, & Rosenberg, 2013; Myers, 1990). Tables 2 and 3 present the results of testing the hypotheses using the dependent variables New knowledge combinations (Table 2) and New knowledge elements (Table 3), respectively.

Model 1 in Table 2 is the baseline model, containing all the control variables. Positive effects of Firm size and R&D intensity are found in Models 1–4. It shows that the scale and scope of technological search of the firm is positively affecting the firm’s exploratory innovation. In addition, we found that the Number of clusters is positively associated with New knowledge combinations in Models 1 and 3. This result can be interpreted as the more clusters that are in the firm’s knowledge network, the more opportunities are available for the firm to connect these different clusters with each other. In Model 2, we test Hypothesis 1a which predicted an inverted U-shape relationship between the level of accumulated architectural knowledge and the subsequent creation of new knowledge combinations. The coefficient of Accumulated architectural knowledge is positive and statistically significant ($\beta = 0.466, p < .01$) while its quadratic term is negative and statistically significant ($\beta = -0.030, p < .05$). These results support Hypothesis 1a. In Model 3, we test Hypothesis 2a which predicted a positive relationship between the level of accumulated component knowledge and the subsequent creation of new knowledge combinations. The coefficient of Accumulated component knowledge is positive and statistically significant ($\beta = 0.032, p < .01$), supporting Hypothesis 2a. Model 4 is the full model containing all independent variables and its results further support our Hypotheses 1a and 2a.

Table 3 follows the same pattern in presenting the results of testing the hypotheses related to the second dependent variable, New knowledge elements. For the control variables, Models 5–8 find a negative effect of the Number of clusters. In other words, as a firm’s knowledge elements are clustered together, i.e., the number of clusters in the knowledge network is lower, it supports the firm in creating new knowledge elements. Additionally, in Models 5 and 7, a positive effect of Network density is found, which indicates that a cohesive knowledge network boosts innovation outcomes by enhancing the exchange of information. In Model 6, we test Hypothesis 1b which predicted a positive relationship between the level of accumulated architectural knowledge and the subsequent creation of new knowledge elements. The coefficient of Accumulated architectural knowledge is positive and statistically significant ($\beta = 0.097, p < .10$), supporting Hypothesis 1b. In Model 7, we test Hypothesis 2b which predicted an inverted U-shape relationship between the level of accumulated component knowledge and the subsequent creation of new knowledge elements. The coefficient of Accumulated component knowledge is negative and statistically insignificant ($\beta = -0.006, p > .10$) while its quadratic term is not found to have any effect ($\beta = 0.000, p > .10$). These findings do not support Hypothesis 2b. Model 8, the full model, further supports Hypothesis 1b but fails to provide support for Hypothesis 2b.
Table 1. Descriptive statistics and correlations.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Min.</th>
<th>Max.</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) New knowledge combinations</td>
<td>13.10</td>
<td>22.96</td>
<td>0</td>
<td>213</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) New knowledge elements</td>
<td>3.34</td>
<td>3.83</td>
<td>0</td>
<td>44</td>
<td>0.69 **</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3) Network density</td>
<td>0.33</td>
<td>0.39</td>
<td>0</td>
<td>4</td>
<td>−0.10 **</td>
<td>−0.13 **</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4) Degree centrality</td>
<td>0.32</td>
<td>0.15</td>
<td>0</td>
<td>1</td>
<td>0.01</td>
<td>−0.06</td>
<td>0.28 **</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5) Number of clusters</td>
<td>5.12</td>
<td>3.06</td>
<td>1</td>
<td>9</td>
<td>0.36 **</td>
<td>0.26 **</td>
<td>−0.38 **</td>
<td>−0.28 **</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(6) Firm size</td>
<td>5.25</td>
<td>11.52</td>
<td>0</td>
<td>99.9</td>
<td>0.75 **</td>
<td>0.40 **</td>
<td>−0.02</td>
<td>0.05</td>
<td>0.33 **</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(7) R&amp;D intensity</td>
<td>0.30</td>
<td>1.07</td>
<td>0.01</td>
<td>24.06</td>
<td>−0.04</td>
<td>−0.06</td>
<td>−0.01</td>
<td>−0.04</td>
<td>−0.06</td>
<td>−0.07</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(8) Number of alliance partners</td>
<td>1.64</td>
<td>3.28</td>
<td>0</td>
<td>30</td>
<td>0.65 **</td>
<td>0.28 **</td>
<td>−0.05</td>
<td>0.11 **</td>
<td>0.30 **</td>
<td>0.64 **</td>
<td>−0.03</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(9) Accumulated architectural knowledge</td>
<td>2.21</td>
<td>1.41</td>
<td>0</td>
<td>15</td>
<td>0.44 **</td>
<td>0.23 **</td>
<td>0.42 **</td>
<td>0.27 **</td>
<td>0.25 **</td>
<td>0.46 **</td>
<td>−0.05</td>
<td>0.41 **</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>(10) Accumulated component knowledge</td>
<td>9.39</td>
<td>11.25</td>
<td>1</td>
<td>75.10</td>
<td>0.76 **</td>
<td>0.36 **</td>
<td>0.08 *</td>
<td>0.17 **</td>
<td>0.34 **</td>
<td>0.67 **</td>
<td>−0.06</td>
<td>0.63 **</td>
<td>0.75 **</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note: **p < .01; *p < .05; two-tailed tests.
Table 2. Results of the fixed-effect negative binomial regression analysis for new knowledge combinations.

<table>
<thead>
<tr>
<th>Variable</th>
<th>New knowledge combinations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
</tr>
<tr>
<td>Constant</td>
<td>0.709***</td>
</tr>
<tr>
<td></td>
<td>(0.198)</td>
</tr>
<tr>
<td>Control Var.</td>
<td></td>
</tr>
<tr>
<td>Network density</td>
<td>1.3E-01</td>
</tr>
<tr>
<td></td>
<td>(0.233)</td>
</tr>
<tr>
<td>Degree centrality</td>
<td>−0.080</td>
</tr>
<tr>
<td></td>
<td>(0.368)</td>
</tr>
<tr>
<td>Number of clusters</td>
<td>0.033**</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td>Firm size</td>
<td>0.036***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>0.184*</td>
</tr>
<tr>
<td></td>
<td>(0.098)</td>
</tr>
<tr>
<td>Number of alliance partners</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
</tr>
<tr>
<td>Independent Var.</td>
<td></td>
</tr>
<tr>
<td>Accumulated architectural knowledge</td>
<td>0.466***</td>
</tr>
<tr>
<td></td>
<td>(0.131)</td>
</tr>
<tr>
<td>Accumulated architectural knowledge^2</td>
<td>−0.030**</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
</tr>
<tr>
<td>Accumulated component knowledge</td>
<td>0.032***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
</tr>
</tbody>
</table>

*p < .10; **p < .05; ***p < .01.
Standard errors are in parentheses.

6. Discussion

6.1. Main findings

The main idea of this study is that the accumulated knowledge within a firm’s knowledge network influences subsequent exploratory innovation. A firm’s knowledge network is a set of knowledge elements which indicate the areas of technological expertise and their combinations which indicate ways of knowledge application. We focused on the different characteristics of a firm’s accumulated knowledge within elements and combinations, i.e., the component and architectural knowledge, and distinguished their impacts on the subsequently emerging new elements and combinations. The uncovered relationships between the two types of accumulated knowledge and the two types of exploratory innovations help us comprehend the dynamics of the firm’s knowledge network.

In terms of knowledge combination, we confirmed an inverted U-shape relationship between the level of accumulated architectural knowledge and subsequent new combinations. New ways of knowledge application occur more frequently as the firm accumulates experience of combining knowledge resources, however, it slows down after reaching a certain level. It indicates that accumulated architectural knowledge helps organizational learning and broadens knowledge applicability to foster exploratory innovation, but because
of path-dependent attributes, knowledge application becomes increasingly rigid, creating inertia that makes it harder for the firm to seek new ways of doing things.

Next, the relationships between accumulated component knowledge and new combinations, and between accumulated architectural knowledge and new elements, were found to be positive. This shows that both elements and combinations in the knowledge network can be seen as positively influencing each other. The accumulation of component knowledge can be essential for creating new combinations, and the inverse relationship, i.e., the accumulation of architectural knowledge helps to form new elements, was proven as well. In other words, learning about elements as a basis for new inventions should precede the creation of new inventions by combining elements. Additionally, accumulating knowledge from the experience of combining various elements is important to extend a firm’s area of expertise by gaining new elements. These results may help a firm to understand how the two key dimensions of knowledge resources are able to enhance each other, despite the exploratory innovation may not be created automatically without managerial efforts, and to seek an exploration strategy tailored to the firm’s present situation.

In summary, a firm seeking exploratory innovation should be conscious about the path-dependent attributes of its knowledge resources, which have the nature of becoming rigid over time. In addition, by understanding the relationship between architectural and

Table 3. Results of the fixed-effect negative binomial regression analysis for new knowledge elements.

<table>
<thead>
<tr>
<th>Variable</th>
<th>New knowledge elements</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 5</td>
</tr>
<tr>
<td>Constant</td>
<td>2.089***</td>
</tr>
<tr>
<td></td>
<td>(0.294)</td>
</tr>
<tr>
<td>Control Var.</td>
<td></td>
</tr>
<tr>
<td>Network density</td>
<td>4.3E-01**</td>
</tr>
<tr>
<td></td>
<td>(0.211)</td>
</tr>
<tr>
<td>Degree centrality</td>
<td>0.159</td>
</tr>
<tr>
<td></td>
<td>(0.370)</td>
</tr>
<tr>
<td>Number of clusters</td>
<td>−0.036**</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
</tr>
<tr>
<td>Firm size</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
</tr>
<tr>
<td>Number of alliance partners</td>
<td>−0.013</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
</tr>
<tr>
<td>Independent Var.</td>
<td></td>
</tr>
<tr>
<td>Accumulated architectural knowledge</td>
<td>0.097*</td>
</tr>
<tr>
<td></td>
<td>(0.059)</td>
</tr>
<tr>
<td>Accumulated component knowledge</td>
<td>−0.006</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
</tr>
<tr>
<td>Accumulated component knowledge^2</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td>Year dummy included (all models)</td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>608</td>
</tr>
<tr>
<td>Number of firms</td>
<td>111</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>−873.237</td>
</tr>
<tr>
<td>Wald chi2</td>
<td>41.71</td>
</tr>
<tr>
<td>Prob &gt; chi2</td>
<td>0.000</td>
</tr>
</tbody>
</table>

*p < .10; **p < .05; ***p < .01.
Standard errors are in parentheses.
component knowledge, we drew two managerial implications: first, if a firm tries to create new knowledge combinations, it is helpful to adopt knowledge elements in advance and apply this component knowledge. Second, if a firm tries to gain a new element, it is useful to have an experience of combining its existing elements as this allows the firm to better identify which new elements are suitable for the firm. To extend these arguments, obtaining new knowledge elements is associated with a firm’s activities for expanding the areas of technological expertise through various knowledge sourcing modes, and combining knowledge elements is associated with a firm’s activities for developing new ways of knowledge application by utilizing its stock of knowledge. Thus, we can draw a conclusion that a firm’s knowledge sourcing activities and knowledge utilizing activities may have positive effects on boosting and enhancing each other to build a strong foundation for subsequent innovation.

6.2. Contributions

This study makes a number of important contributions: first of all, we extend the theoretical background of prior studies by revealing the relationship between knowledge elements and combinations. To this effect, we separated our viewpoint of the firm’s knowledge resources into accumulated knowledge elements and combinations, and explored their roles and characteristics respectively. We also applied these two knowledge dimensions to the firm’s exploratory innovation, i.e., the creation of new elements and combinations. This approach allowed us to uncover the inverted U-shape relationship between the level of accumulated architectural knowledge and subsequent knowledge combination. The positive effects of increasing the level of accumulated architectural knowledge diminish when the level becomes so high that path dependency and increasing inertia reduce the ability of the firm to create new knowledge combinations. We also found the mutually supporting relationship between component knowledge and architectural knowledge as they help to create each other in innovation process. These results contribute to the research on the antecedents of (exploratory) innovation. Furthermore, by linking the firm’s previously formed knowledge network and its subsequent innovation, these relationships allowed us to explore the dynamics of a knowledge network in which existing elements and combinations are influencing each other to form new elements and combinations over time.

Second, our research design suggests a new approach to analyse the process of knowledge accumulation. Although some prior studies have applied the concept of the knowledge network, they fell short of capturing the attributes of accumulation. We expressed the firm’s knowledge resources using a weighted network which enables us to capture the levels of knowledge accumulation by examining the strength of ties and the size of nodes. From this approach, we explored the differences of firms’ innovation performance depending on the level of accumulated knowledge, which can help to understand inter-firm differences within the same industry.

Finally, from a strategic perspective, we provide the managerial implication that a firm seeking exploratory innovation should consider the dynamics of its knowledge network, and set up a suitable innovation strategy to take advantage of the relationship between knowledge elements and their combinations. To be specific, if a firm has insufficient technological expertise but much experience of collaborative research, it is recommended for the firm to establish an external knowledge sourcing strategy to gain new technological elements, which enables the firm to utilize its strength of collaborative capabilities. If a firm accumulated
technological knowledge resources through its former knowledge sourcing strategies, then it will be helpful to establish a knowledge leveraging strategy to create synergy effects by connecting and collaborating with different technological fields.

6.3. Limitations and future research

While making important contributions, this study has a number of limitations that we hope can be overcome by future research in this field. First, this study uses a dataset comprised of firms from the semiconductor industry. While the semiconductor industry has served as the setting for several prior studies (Carnabuci & Operti, 2013; Dibiaggio et al., 2014; Wang et al., 2014; Yayavaram & Ahuja, 2008) on patent-based knowledge networks, and is known for its propensity to patent (Hall & Ziedonis, 2001, 2007), it is also reported that semiconductor companies exhibit very similar knowledge profiles (Patel & Pavitt, 1997). While this provides an interesting research setting to study performance heterogeneities of firms with similar knowledge bases, it might limit the generalization and application of the results to other industries. For these reasons, we expect future research to test our hypotheses using datasets covering a broad range of industries.

Second, this study focused on the nodes and ties of the knowledge network, but could not reflect other complex structural features from a social network perspective. Though we controlled for key variables including degree centrality, density, and number of clusters, additional effects from other network features such as network structure or core–periphery disparities need to be explored. We hope to see follow-up studies take full advantage of the possibilities offered by network analysis.

Third, this study focused on the conditions that facilitate subsequent exploratory innovation from a knowledge perspective, but could not consider the role of managerial intervention. Even though intra-industry firms face similar knowledge conditions, performance heterogeneity may arise due to their unique characteristics of top management team, different strategy establishment and implementation. We expect future studies to account for the impacts of different forms of managerial intervention.

Last, this study makes use of patent data. Patent data suffers from a range of known shortcomings (Kleinknecht, Van Montfort, & Brouwer, 2002; Pavitt, 1985), the effect of some of which could be reduced due to focus on a single industry. Future studies might supplement the patent data with data from other sources or try to overcome its limitations, e.g., by using patent measurements based on received citations to allow for a better distinction of inventions in terms of their usefulness and contribution.

Disclosure statement

No potential conflict of interest was reported by the authors.

References


