

Substitutability and complementarity of technological knowledge and the inventive performance of semiconductor companies

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Abstract

This paper analyses whether complementarity and substitutability of knowledge elements are key determinants of the firm's inventive performance, in addition to the more conventional measures of knowledge stock and diversity. Using patent data from 1968 to 2002 in the semiconductor industry, we find that the overall level of complementarity between knowledge components positively contributes to firms' inventive capability, whereas the overall level of substitutability between knowledge components generally has the opposite effect. Yet a relatively high level of substitutability is found to be beneficial for explorative inventions. These results suggest that a firm's inventive capacity significantly depends on its ability to align its inventive strategies and knowledge base structure.

1. Introduction

Several authors have argued that a possible source of heterogeneity in firm performance relates to differences in firms' ability to produce new knowledge (Nelson, 1991; Henderson, 1994; Henderson and Cockburn, 1994; D'Este Cukierman, 2005). In addition to a firm's R&D efforts and accumulated knowledge stock (Mansfield, 1980; Link, 1981; Griliches, 1986; Jaffe, 1986), recent findings have emphasized technological-knowledge diversity as a potent source of a firm's inventive performance (Henderson and Cockburn, 1996; Nesta and Saviotti, 2005; Garcia-Vega, 2006; Quintana-García and Benavides-Velasco, 2008). However, in contrast to what one would expect, accumulating diverse technological knowledge does not lead to technological heterogeneity among firms. Technological (Patel and Pavitt, 1997) and scientific (D'Este Cukierman, 2005) profiles are both stable over time and somewhat similar among firms competing in the same industry.

This paper examines the relational properties of knowledge elements to describe the structure of a firm's knowledge base as a determinant of the firm's inventive performance. We follow early work by Galunic and Rodan (1998), who associate the ability to combine or recombine knowledge elements with the underlying characteristics of knowledge elements. However, we depart from their framework with regard to the nature of knowledge (i.e., tacitness, dispersion, and context specificity) and based on our explanation on the relational properties of knowledge. More precisely, we (1) consider the degree of complementarity and substitutability of knowledge elements as two relational properties of knowledge that characterize the structural composition of a knowledge base and (2) examine whether and the extent to which such dimensions are conducive to economically valuable inventions.

Further, we investigate whether the capacity of a company to successfully engage in exploratory experiments is related to these two knowledge base properties. This question is related to March's (1991) distinction between exploitation (the selection and refinement of existing technologies) and exploration (the invention of new technologies). To produce more and useful knowledge, firms may allocate resources on projects by reusing and deepening existing knowledge or by broadening the scope of their capability portfolio (Katila and Ahuja, 2002). We suggest that this decision does not reflect a simple investment choice problem. The structure of the knowledge base generates specific constraints

on knowledge accumulation processes, which may condition and affect the probability distribution of the return on each type of project.

The rest of the paper is structured as follows. Building on prior work on knowledge combination, the following section discusses the relationship between a firm's knowledge base structure and its inventive performance. Section 2 presents the analytical framework, and the data set is described in Section 3. Section 4 presents the results from longitudinal studies on a sample of semiconductor companies, and Section 5 discusses the findings and suggests future areas of investigation.

2. Knowledge base structure and inventive performance

2.1. Characterizing the structure of a knowledge base

Characterizing a knowledge base as a collection of links between knowledge elements provides an interesting perspective on a firm's specific capabilities. Knowledge bases have typically been conceptualized as sets of capabilities, information, and knowledge elements on which companies draw for inventive activities and problem solving (Nelson and Winter, 1982; Winter, 1984; Dosi, 1988; Fleming, 2001). Prior studies have considered the knowledge stock accumulated in the knowledge base (Mansfield, 1980; Link, 1981; Griliches, 1986; Jaffe, 1986) and the diversity of knowledge elements (Henderson and Cockburn, 1996; Garcia-Vega, 2006) to be the main sources of differences between firms undertaking inventive activities.

However, the links between technological-knowledge elements may be more important than their diversity. Although firms are increasingly technologically diverse, firms competing in the same industry tend to exhibit similar profiles (Patel and Pavitt, 1997; Granstrand et al., 1997; Gambardella and Torrisi, 1998). Thus, in addition to the capacity to accumulate knowledge, relations between the elements of the knowledge base may reflect idiosyncratic methods of using and exploiting knowledge (Nesta and Dibiaggio, 2003; D'Este Cukierman, 2005). A series of studies have examined the relations between separate elements of a knowledge base to characterize the pattern and evolution of a firm's specific competencies. For instance, the emergence of nanotechnology from combining biotechnology and microelectronics can be traced back to the convergence of physics, engineering, molecular biology, and chemistry competencies that were increasingly integrated into the knowledge base of early entrants developing industrial applications of nanotechnology (Avenel et al., 2007). Likewise, Nesta and Dibiaggio (2003) find a similar homogenization process in the knowledge bases of biotech companies (particularly between firms that specialize in specific industries, such as the agro-food, chemistry, or pharmaceutical industries). Nonetheless, they show that the increasing differentiation in firms' knowledge base structure parallels this convergence of knowledge elements; thus, firms with similar knowledge elements tend to differentiate themselves by developing and exploiting different types of links between knowledge elements.

However, depending on the perceived nature of the links between knowledge elements, a knowledge base structure can have different meanings. According to Henderson and Clark (1990), product development requires both knowledge elements (component knowledge) and architectural knowledge ("knowledge about the ways in which the components are integrated or linked together into a coherent whole") (Henderson and Clark, 1990, p. 11). This concept has subsequently been extended to architectural competence to integrate organizational capabilities that structure problem-solving activities and that facilitate the development of new competencies (Henderson and Cockburn, 1994).

The literature on the structure of the relations between knowledge elements in problem-solving (or search) processes focuses on the interdependencies between knowledge elements, which determine how elements *should be* combined (e.g., Kauffman et al., 2000). While interdependencies are common to all firms, the elements that are integrated into a firm's knowledge base and the combinations thereof are specific to the firm and reveal idiosyncratic beliefs regarding perceived interdependencies (Yayavaram and Ahuja, 2008).

Breschi et al. (2003) consider other types of relations. Relying on the notion of relatedness, as defined in the product diversification literature (e.g., Teece et al., 1994), elements can be related if they were produced through the use of the same underlying type of knowledge. Just as product diversification is less costly if it is based on the use of common-proprietary resources (Teece, 1982), technological diversification may generate economies of scope in research activities if the same knowledge elements are relied on (Henderson and Cockburn, 1996). Furthermore, firms can enjoy learning externalities if they use a given set of problem-solving methods or tools to facilitate the development of different knowledge elements or combinations.

In this paper, we extend this view and analyze the structure of a knowledge base by delineating complementarity and substitution as two different relational properties of knowledge elements. Two complementary elements are elements whose value or usefulness increases when the elements are combined (Milgrom and Roberts, 1990). As Rosenberg (1982) shows, major inventions rely on the available complementary technologies. For example, the laser was first patented in 1960 and could not be applied to telephone signal transmission until the appropriate fiber-optic cable was developed in 1970. Complementarity is more than the simple combination of knowledge elements; it results from the intensive use of two knowledge elements through a combinatorial search process. Kodama (1995), using the example of mechatronics, explains the length of time required for the search process to establish mechanical, electronic, and material technologies as complementary technologies. The combination of ordinary and electric machinery was investigated in 1971 based on servo-motor innovations in the machine tool industry introduced by Fanuc (a spinoff of Fujitsu) and the development of Teflon coating material by Daikin Co. (Kodama, 1995). Then, new combinations were tested with communications and electronics technology later in the early 1970s, giving rise to mechatronics developed in 1975 when precision instruments were included to yield a stable and reliable solution (Kodama, 1995, p. 212). Unlike interdependent knowledge elements, complementary elements can be – and often are – used separately, and their synergy depends on the context in which they are used for specific application domains.

Substitutability characterizes the extent to which elements share similar properties in their use with other elements and, therefore, the extent to which elements tend to be combined with the same other elements. Hence, two elements are substitutable if they complement the same other elements. In a combinatorial search process, alternative options often compete.¹ Substitutable elements may reflect a transitory redundancy until

¹ For instance, in a parallel search process, as illustrated by the Manhattan project (Nelson, 1959; Lenfle, 2011), several options may be necessary under both uncertainty and time pressure. To develop the atomic bomb on time, three competing programs were launched concurrently: the traditional "gun design," wherein an explosion is used to throw two fission materials against each other and thus to create a chain reaction; "the implosion design," wherein the collapse of a plutonium core after the explosion causes the chain reaction; and the "super design," wherein nuclear fusion, not fission, is relied upon. The two first options resulted in two successful projects, "Little boy," which was dropped on Hiroshima, and "Fat Man," which was later dropped on Nagasaki (Lenfle, 2011, p. 366).

ex-post selection determines the winner. For instance, the rotary internal-combustion engine competed with the piston engine for years before it was eventually abandoned because of its insoluble pollution problems (Vincenti, 1994). However, substitutable elements may coexist for a longer period of time. For instance, the fixed landing gear system used in Northrop's plane designs persisted long after the invention and adoption of a retractable landing gear system by early aircraft designers (Vincenti, 1994).²

This framework enables us to describe a knowledge base structure as a function of the aggregate level of complementarity and substitutability of its constituent knowledge elements. The next section explains how a firm's knowledge base structure may significantly affect its ability to produce useful knowledge by altering search processes.

2.2. Knowledge combination choices and inventive performance

New knowledge is commonly considered to result from a combination or recombination of existing knowledge elements (e.g., Nelson and Winter, 1982; Dosi, 1982; Fleming, 2001; Fleming and Sorenson, 2001, 2004). This view reflects Schumpeter's (1934) conception of entrepreneurship as the distinctive talent to recognize resources that can be reconceptualized and recombined to create potentially new, valuable products and systems. History provides abundant examples of the role that great entrepreneurs have played in perceiving opportunities to recombine existing knowledge. For example, most of Edison's inventions in the telegraph industry resulted from merging electrical and mechanical technologies, two domains with which he was familiar (Usselman, 1992).

Tenants of the knowledge-based view emphasize the firm, not the individual entrepreneur, as the main driver of inventive combinations (Henderson and Clark, 1990; Kogut and Zander, 1992; Tushman and Rosenkopf, 1992; Grant, 1996a,b; Galunic and Rodan, 1998; Katila and Ahuja, 2002), as valuable invention requires the integration of a wide array of knowledge domains – that is, the combination of specialized bodies of knowledge that are generally possessed by individuals (Grant, 1996b). Thus, every invention can be viewed to result from a search process that leads to a series of combination decisions (Kauffman et al., 2000; Fleming, 2001; Fleming and Sorenson, 2001; Sorenson et al., 2006; Yayavaram and Ahuja, 2008).

However, because of the increasing number of knowledge elements, the number of combination options has grown exponentially, which has strongly limited the set of combinations that can be considered (Fleming, 2001). Selecting a combination depends on the perceived characteristics of the knowledge elements and their interrelationships (Galunic and Rodan, 1998; Marengo et al., 2000; Fleming, 2001; Yayavaram and Ahuja, 2008). At the individual inventor level, limited cognitive capacity prevents individuals from fully understanding the properties of all elements and their interactions (March and Simon, 1958; Vincenti, 1990). Firms also have a limited capacity to extend their search space because knowledge is partly tacit and context specific; thus, the transmission of knowledge distributed across specialized inventors is reduced (Galunic and Rodan, 1998). Furthermore, the search process is a cumulative and path-dependent learning process that is constrained to areas close to the markets and technologies in a firm's portfolio (Nelson and Winter, 1982; Dosi, 1988; Vincenti, 1990; Thomke et al., 1997). Empirical studies confirm that firms rely on their own experience and established knowledge bases to select research projects that are related to familiar application domains and to

² Despite the aerodynamic drag that it produced, Northrop considered the fixed system's advantageous cost, reliability, weight, and ease of maintenance.

achieve higher inventive performance when “the object of learning is related with what is already known” (Cohen and Levinthal, 1990, p. 131). For instance, Helfat (1994)'s study on R&D expenditures in the petroleum industry highlights the persistence in firms' choice of R&D projects because firms tend to focus on activities that are similar to their previous activities. Likewise, Stuart and Podolny (1996) find evidence of path dependency in inventive activities. The authors show that large Japanese semiconductor companies tend to patent in well-known technology areas and that, if firms excel in specific market domains, redeploying their expertise in other domains is difficult.

The relational structure of a firm's knowledge base may affect its search process in several ways. Henderson and Cockburn (1994) show that inventive productivity is affected by knowledge on a product's components and architectural knowledge that allows firms to better integrate and combine component knowledge. Yayavaram and Ahuja (2008) conceptualize a knowledge base structure as a set of more or less tightly coupled elements that depends on the intensity of their joint use. The authors observe that, although semiconductor companies operate in the same technological environment, they exhibit different knowledge base structures and that such differences lead to significant inventive performance heterogeneity across firms. We contend that the degree of complementarity and substitutability of knowledge elements may also influence the selection of combinations and thus inventive performance.

High complementarity reveals a nonrandom acquisition of knowledge elements and reflects a coherent knowledge base (Nesta and Saviotti, 2005). Coherence arises from specialization in R&D projects based on related technologies (Nesta and Saviotti, 2005, p. 107). Specialization leads to deep expertise on the relational properties of knowledge elements, and such expertise facilitates spillovers through the cross-fertilization of ideas and learning across projects. For instance, in a pharmaceutical company, research programs on depression likely spillover from other companies' central nervous system programs through the reuse of combinations that were used in experiments for those programs (Henderson and Cockburn, 1996). Further, elements that can be combined with several other elements have high synergistic potential; thus, the level of complementarity of a firm's knowledge elements may increase the firm's likelihood of selecting useful combinations. In turn, enhanced complementarity increases the firm's propensity of selecting new research projects in familiar technological environments that rely on well-known combinations.

A high level of substitutability also arises from specialization through broader expertise in a domain. Functional redundancy (the capacity to use different elements with similar properties) in a knowledge base informs the capacity to test different options in the same context and to provide a better understanding of the properties of elements in a broad application domain. The ability to test different combination options may be useful in immature technological environments, wherein the effects of interactions are uncertain or unknown and alternative combination options compete.

2.3. Exploration and exploitation

The above discussion regarding the structure–performance relationship suggests that, given a combination of knowledge elements with various properties, the level of substitutability and complementarity of knowledge elements could help inform the value of each combination and therefore influence the selection of the most useful combinations. Such an evaluation may differ if the properties of the knowledge elements (and thus the value of each combination) change from one project to another. Therefore, a firm's capacity to produce useful knowledge will critically depend on

its ability to create new links among knowledge elements and evolve its knowledge base. If values of the combinations remain stable, firms' inventive activities tend to focus on exploiting existing knowledge. Exploitation involves activities such as refinement, selection, efficiency, implementation, and execution in the organizational learning literature (March, 1991, p. 71) and is associated with refining previously used combinations in the recombinant search literature (Fleming, 2001).

The value of combinations may change for two (often related) reasons. First, new knowledge elements may arise that offer new combination options and that thus render previous combinations obsolete. For instance, the discovery of semiconductive materials facilitated the invention of the point contact transistor in 1947 and thus revolutionized methods for translating and controlling electric signals.³ This invention relied on the development of new elements (technologies related to signal amplification, solid-state electronics, material purification, etc.) in electronic companies' knowledge bases. These new elements rendered the vacuum tube technologies underlying previous knowledge elements obsolete and opened new combination opportunities. Electronic firms that specialized in vacuum tube technologies were among the first firms to integrate these elements and use semiconductor-related technologies in their patents. However, of eight major incumbent firms in electronics, only three (RCA, General Electric, and Westinghouse) remain significant inventors, accounting for more than 80% of incumbent patents awarded between 1952 and 1968 (Tilton, 1971).⁴

Second, research projects may be dedicated to new application domains. New problem-solving contexts may affect the relational properties of knowledge elements and thus the value of combinations. For instance, semiconductor devices that are used to amplify or switch electronic signals rely on methods that control current flow in semiconductors via capacitive coupling at an electrode (field-effect transistors).⁵ The standard technology is a metal oxide semiconductor (MOS) structure, the oxidation of which permits conductivity modulation depending on the voltage (see Sah, 1988). With similar components and materials, the order for aggregating different materials in layers will produce different electron concentrations, which slightly change a transistor's properties: nMOS have a higher electron concentration and thus a negative charge; the pMOS structure has positive charge, which enables a change in conductance depending on the voltage intensity. Where nMOS transistors are faster, they are more difficult and costly to produce. Initially, p-channel devices were introduced by General Microelectronics and Fairchild for logic and switching applications. N-channel devices were introduced by RCA to amplify signals. Research projects in logic and memory circuits for the US Air Force by RCA Research Laboratories changed the research context by placing more emphasis on power consumption. Using a patent by Frank Wanlass of the Fairchild R&D Laboratory, Gerald Herzog, who led a cutting-edge RCA project on logic circuits for the US Air Force, proposed that the nMOS and pMOS technologies be combined to reduce waste heat. Unlike other technologies, which typically have standing current even when the state is not changing, the combined solution enabled one transistor to always be off, because power is necessary to switch between the on and off states. The CMOS (complementary MOS) solution facilitated the design of the first 288-bit static RAM in 1968, which became the standard technology for high-volume applications in the 1970s.⁶

Changes in the relational properties of knowledge elements are unpredictable, and inventors may be unaware of the amplitude of change and of the properties of unknown combinations. Therefore, firms may have different abilities to adapt and explore new learning paths. Exploration refers to experimentation and risk taking (March, 1991) and is associated with knowledge from new elements or combinations (Fleming, 2001). Firms with limited exploration abilities are unable to identify new productive combinations and may not survive in a fast-changing technological environment. Among the vacuum tube companies that led the electronic industry in the 1950s, only four remained active in the semiconductor industry in 1968, three of which were among the highest patent producers (Tilton, 1971).

A firm's knowledge base structure may significantly influence its capacity to explore useful new combinations. On the one hand, the variety of unexplored combination options is relevant (Iansiti, 1998). On the other hand, unless one assumes perfect information and complete rationality, enhancing variety renders systematic experimentation ineffective (Nerkar, 2003; Fleming and Sorenson, 2001). One option is to favor a recombinant search of elements with high synergistic potential in previous projects. While this path-dependent strategy minimizes risk, it also limits the capacity to reveal new properties of knowledge elements. As Yayavaram and Ahuja (2008) suggest, to experiment with new combination structures, firms must be exposed to new beliefs and representations of the relational properties of knowledge elements. Alternatively, assuming that potential synergies exist between elements combined with the same other elements from previous projects, firms can rely on the functional similarity between elements. For instance, NEC was the first Japanese company to launch a project that used silicon for telecommunication applications because it was more resistant to high temperatures than germanium, which was the standard technology that was used for other applications (Fransman, 1995). In this example, redundancy in the firm's knowledge base (silicon and germanium have the same purpose) also provided flexibility and a direction for exploration; NEC could rapidly investigate the use of silicon with all elements that can be combined with germanium. This approach provides a clear advantage of the development of new applications (Fransman, 1995, p. 270).

3. Data and research methods

3.1. Data and sample selection

We use patent statistics to trace firms' technological competencies and to analyze their knowledge base characteristics. Patents owned by a firm represent the output of its research efforts and the codified knowledge that it has created during the inventive process (Jaffe et al., 1993; Ahuja and Katila, 2001). Patent data are commonly used to elucidate inventive capabilities,⁷ especially in the semiconductor industry (Megna and Klock, 1993; Almeida, 1996; Sørensen and Stuart, 2000; Deng, 2008). Although certain firms do not protect their inventions through patents, in the semiconductor industry, patenting is a vital part of maintaining technological competitiveness. Semiconductor firms sell products embedded with hundreds, if not thousands, of patented inventions (Hall and Ziedonis, 2007). Furthermore, despite the increasing number of patents, which is related to the strengthening of U.S. patent rights

³ See the patent application by William Shockley in 1948 (US 2569347 A).

⁴ Other companies, such as AT&T's Bell Labs, IBM, and Texas Instruments, also were major inventors but were not vacuum tube companies.

⁵ The field effect is the change in metal conductance, which is enabled by applying an external electric field.

⁶ See the Computer History Museum website (<http://www.computerhistory.org/>).

⁷ The advantages and disadvantages of using U.S. patents as an indicator of technological activity are well known and widely discussed in literatures (e.g., Pavitt, 1988, 1998; Griliches, 1990).

Table 1
Semiconductor specialists.

SEMICONDUCTOR SPECIALISTS		
ADVANCED MICRO DEVICES, INC.	INFINEON TECHNOLOGIES CORP	ORBIT SEMICONDUCTOR, INC.
ALLIANCE SEMICONDUCTOR CORP	INTEGRATED CIRCUIT SYSTEMS	RAMTRON INTERNATIONAL ORP
ALTERA CORPORATION	INTEGRATED DEVICE TECH, INC.	REALTEK SEMIC CORP
ANALOG DEVICES, INC.	INTEL CORPORATION	SEMICON, INC.
ATI TECHNOLOGIES, INC.	INTL RECTIFIER CORP	SEMTECH CORP
ATMEL CORP	LATTICE SEMICONDUCTOR CORP	SIERRA SEMIC CORP
BOWMAR INSTRUMENT CORP	LINEAR TECHNOLOGY CORP	SILICONIX, INC.
BROOKTREE CORP	LOGIC DEVICES, INC.	SIMTEK CORP
BURR-BROWN CORP	LSI LOGIC CORPORATION	SOLITRON DEVICES, INC.
CATALYST SEMICONDUCTOR, INC.	MAXIM INTEGRATED PRODUCTS	STMICROELECTRONICS, INC.
CONNEXANT SYSTEMS, INC	MEDIA TEK, INC.	SUPERTEX, INC.
CYPRESS SEMIC. CORP	MICREL, INC.	TEXAS INSTRUMENTS
CYRIX CORP	MICRO LINEAR CORP	TRIQUINT SEMIC., INC.
DALLAS SEMIC. CORP	MICROCHIP TECHNOLOGY, INC.	VITESSE SEMIC. CORP
EXAR CORP	MICRON TECHNOLOGY, INC	VLSI TECHNOLOGY, INC.
FAIRCHILD SEMICONDUCTOR	MICROSEMI CORP	XICOR, INC.
HEI, INC.	NATIONAL SEMIC.CORP	XILINX, INC.
IMP, INC.	NVIDIA CORP	ZILOG, INC.

Source: Collected by the authors.

in the 1980s,⁸ the value of patents has not depreciated (Hall and Ziedonis, 2007).

The study uses patent data from the USPTO database through the NBER U.S. Patent Citation Data File (Hall et al., 2001). To identify knowledge elements, we follow prior studies (ex. Breschi et al., 2003; Nesta, 2008) and use technological classification codes that are consistently identified for each invention by the USPTO. Because the USPTO data set only assigns a primary technology class to each patent, we rely on the International Patent Classification (IPC) system provided by the “esp@cenet” database to obtain information on the technological content of inventions and to determine the joint use of technologies in patents. The joint occurrence of technological codes in patent documents is then studied to measure the relational properties of technologies. We use IPC codes at the four-digit level to include the IPC section, class, and subclasses and to maintain a consistent level of analysis across the different technological domains. The IPC system comprises approximately 700 technological classes at the four-digit level and classifies patents according to each technology area to which they are related (Garcia-Vega, 2006; Nesta, 2008). This detailed classification system enables us to provide appropriate information on the bodies of technological knowledge that underlie firms’ inventive activities and to measure technological relatedness.

Our sample was constructed in three steps. In the first step, we identified the technological classes related to semiconductor activities.⁹ However, mapping technological classes to SIC codes is challenging. We followed prior studies and isolate technological classes that contributed to semiconductor patenting activities (Sørensen and Stuart, 2000; Yayavaram and Ahuja, 2008). Rather than implement an ad hoc selection system,¹⁰ we identified 56 specialist companies that essentially operated in the semiconductor industry from 1968 to 2002; we assumed that they dedicated their R&D activities to semiconductor-related technologies (Table 1).¹¹

⁸ The change in the patent regime in the semiconductor industry has been associated with the creation of the Court of Appeals for the Federal Circuit in 1982.

⁹ This technological space should include not only classes that describe semiconductor technologies, but also classes that are useful for developing semiconductor applications.

¹⁰ Another option would have been to gather the patents from the firms, the principal lines of business of which are in *semiconductor and related devices* (SIC 3674 or NAICS 334413). However, most of these firms are multibusiness companies whose patents may be dedicated to other businesses.

¹¹ This protocol explains why companies such as IBM that have larger product scope, although an important assignee of semiconductor patents, do not belong to this first list.

These companies were chosen on the basis of our appreciative knowledge of the field after reading professional journals and specialized websites and the source of their revenues being mainly the semiconductor market. To confirm that the companies belong essentially to this industry, we systematically visited the corporate websites and read the companies’ histories to screen for potential diversifications in other domains.¹² We then retrieved their patents for the period from 1953 to 2002 and selected classes listed in at least 100 patents for which the 56 specialist companies applied. Therefore, we retained the most-used technological classes (those listed in at least 100 patents). This procedure yielded a list with 62 relevant technology classes at the four-digit level (Table 2), defining the relevant list of technological knowledge elements.

In the next step, we identified firms that were active in the semiconductor market and that held patents in the selected technological classes during the period from 1968 to 2002. Using several sources,¹³ we obtained a list of 636 companies. Patents granted to subsidiaries, divisions, and acquired units were aggregated to the parent firms by using the “Who Owns Whom” Directory of Corporate Affiliations. In the final step, we performed a name-matching procedure to link the patent data set with COMPUSTAT. The final sample includes 144 parent companies for the time period spanning from 1968 to 2002 and yields 1673 observations. The technological classes identified as semiconductor classes account for 89.5% of the patent activities of the firms in this sample.

3.2. Variables definition

3.2.1. Dependent variables

3.2.1.1. *Overall inventive performance.* As opposed to solely examining the raw number of patents, we use patent citations to indicate patent quality (Carpenter et al., 1981; Narin et al., 1987; Pavitt, 1988; Albert et al., 1991; Karki, 1997). Patent citations refer to the

¹² The 56 firms in the sample have product portfolios that can spread over different semiconductor devices (including memory, microcomponent, general purpose logic, analog IC, discrete, optical semiconductor, sensor, data processing-related ASIC and ASSP, etc.) dedicated to different application markets (e.g., computer, telecommunication, automotive, industrial, medical, military, and aerospace applications, etc.). Some companies have marginal activities in related businesses. For instance, Texas Instruments is well known for its calculators, and developed other products such as consumer electronics and missiles in the past.

¹³ We combined information from the Semiconductor Industry Association, the Fabless Semiconductor Association, ICE reports from 1980 to 1995, and a survey by the Bureau of Economics (1977) on the semiconductor industry. The list was corroborated by several studies dedicated to the semiconductor industry.

Table 2
Semiconductor technological space.

Code	Label	Code	Label
H01L	SEMICONDUCTOR DEVICES	B23K	SOLDERING OR UNSOLDERING, WELDING, CLADDING OR PLATING
G06F	ELECTRIC DIGITAL DATA PROCESSING	G10L	SPEECH ANALYSIS OR SYNTHESIS, SPEECH RECOGNITION
G11C	STATIC STORES	H04Q	SELECTING
H03K	PULSE TECHNIQUE	H02H	EMERGENCY PROTECTIVE CIRCUIT ARRANGEMENTS
H04N	PICTORIAL COMMUNICATION	C30B	SINGLE-CRYSTAL GROWTH
H04L	TRANSMISSION OF DIGITAL INFORMATION	H03G	CONTROL OF AMPLIFICATION
G01R	MEASURING ELECTRIC MAGNETIC VARIABLES	G02F	DEVICES OR ARRANGEMENTS, THE OPTICAL OPERATION
H05K	PRINTED CIRCUITS, CASINGS	G01N	INVESTIGATING OR ANALYSING MATERIALS
G11B	INFORMATION STORAGE	G05B	CONTROL OR REGULATING SYSTEMS IN GENERAL
H03M	CODING, DECODING OR CODE CONVERSION, IN GENERAL	H02J	CIRCUIT ARRANGEMENTS OR SYSTEMS
G06K	RECOGNITION OF DATA, PRESENTATION OF DATA	H04J	MULTIPLEX COMMUNICATION
G09G	ARRANGEMENTS FOR CONTROL OF INDICATING DEVICES	G07F	COIN-FREED OR LIKE APPARATUS
H03F	AMPLIFIERS	G01V	GEOPHYSICS, GRAVITATIONAL MEASUREMENTS
G05F	SYSTEMS FOR REGULATING ELECTRIC VARIABLES	G05D	SYSTEMS FOR CONTROLLING NON-ELECTRIC VARIABLES
G03F	PHOTOMECHANICAL PRODUCTION OF TEXTURED SURFACES	B65H	HANDLING THIN OR FILAMENTARY MATERIAL,
H01H	ELECTRIC SWITCHES, RELAYS, SELECTORS	B24B	MACHINES, DEVICES, OR PROCESSES
B41J	TYPEWRITERS, SELECTIVE PRINTING MECHANISMS	H01Q	AERIALS
H01J	ELECTRIC DISCHARGE TUBES OR DISCHARGE LAMPS	G06N	COMPUTER SYSTEMS BASED ON COMPUTATIONAL MODELS
G02B	OPTICAL ELEMENTS, SYSTEMS, OR APPARATUS	G07G	REGISTERING THE RECEIPT OF CASH
G06T	IMAGE DATA PROCESSING OR GENERATION, IN GENERAL	G01P	MEASURING LINEAR OR ANGULAR SPEED, ACCELERATION
H02M	APPARATUS FOR CONVERSION	G01J	MEASUREMENT OF INTENSITY, VELOCITY
C23C	COATING METALLIC MATERIAL	H01M	PROCESSES OR MEANS
H03L	AUTOMATIC CONTROL, STARTING, SYNCHRONISATION	B01J	CHEMICAL OR PHYSICAL PROCESSES
H03H	IMPEDANCE NETWORKS	G01L	MEASURING FORCE, STRESS, TORQUE, WORK
H04M	TELEPHONIC COMMUNICATION	H01C	RESISTORS
H04B	TRANSMISSION	H03B	GENERATION OF OSCILLATIONS
H05B	ELECTRIC HEATING, ELECTRIC LIGHTING	H01F	MAGNETS, INDUCTANCES, TRANSFORMERS
H01R	ELECTRICALLY-CONDUCTIVE CONNECTIONS	G04G	ELECTRONIC TIME-PIECES
H02P	CONTROL OR REGULATION OF ELECTRIC MOTORS	G09F	DISPLAYING, ADVERTISING, SIGNS, LABELS OR NAME-PLATES
G01S	RADIO DIRECTION-FINDING, RADIO NAVIGATION	H03D	DEMODULATION OR TRANSFERENCE OF MODULATION
B41M	PRINTING, DUPLICATING, MARKING, OR COPYING PROCESSES	G03B	APPARATUS OR ARRANGEMENTS FOR TAKING PHOTOGRAPHS

Source: Collected by the authors.

number of times that each patent has been cited in subsequent patents. The more times that a patent is cited, the more significant its contribution is. In this study, a firm's inventive performance is measured by the number of prior art citations that each patent received during the first five years after it was granted.

3.2.1.2. The rate of explorative inventions. If exploration and exploitation are viewed as a continuum, the rate of explorative inventions describes the extent to which a firm introduces explorative inventions relative to its total inventive activities. This ratio indicates the exploration intensity of a firm's inventive behavior. Explorative inventions occur when the firm attempts a new combination. Accordingly, we consider a patent to be an explorative invention if it introduces a technological combination that is new to the firm. Otherwise, the patent reflects the refinement or redeployment of a previously used combination and is thus classified as an exploitative invention. The number of explorative patents in the total patent output measures the rate of a firm's explorative inventions.

3.2.2. Measuring the complementarity and substitutability of knowledge elements at the firm level

3.2.2.1. Relational properties of knowledge elements. By relational properties, we refer to either the complementarity or the substitutability of any two knowledge elements. We measure these relational properties in two steps. In the first step, we calculate the relational properties (complementary or substitutability) of any two technologies in the semiconductor technological space. Each IPC technological class represents a knowledge element. Two knowledge elements are combined when two IPC classes are jointly referenced in a patent. To avoid bias related to the sample firm's knowledge accumulation path, we count the frequency of co-occurrence of all possible pairs of semiconductor IPC classes by using the patents in the comprehensive USPTO data set. We obtain

a symmetrical 62×62 matrix C for each year between 1968 and 2002.¹⁴ The generic element (C_{jk}) of matrix C represents the number of patent documents that are classified in both technological fields j and k . This matrix provides a basis for tracing combinational behavior of knowledge elements and is used to measure the level of complementarity and substitutability of any two knowledge elements. In the second step, we compute the weighted average complementarity and the weighted average of substitutability of all a firm's semiconductor technologies. We assume that the relational properties of technologies are a given for firms and that firms first observe the relational properties of technologies and then select their technology portfolio.

3.2.2.2. Complementarity of knowledge elements. Using the survivor measure of relatedness developed by Teece et al. (1994) in a business context and later applied to technological studies (Breschi et al., 2003; Cantwell and Noonan, 2004; Nesta and Saviotti, 2005; Piscitello, 2005), we assume that if the combination of two knowledge elements provides complementary and productive services, the combination will be reproduced and expanded upon (while unproductive combinations will ultimately disappear). Thus, the number of times that the two technological classes are assigned to a patent document measures the strength of their technological complementarity. In this context, the complementarity of technologies is measured by comparing the observed frequency of each

¹⁴ Note that each year's matrix C is constructed by summing its patents over the past five years because the matrix C must discern the technological state of the art, which is clearly the weighted sum of the patents granted for the given year and previous years. In this paper, we simply sum the patents over the past five years. More complicated weighting schemes, such as the declining weight over time that is used in the permanent inventory method, could be used. However, in each case, the goal is to eliminate current technological strategies and to determine the overall state of the art stemming from previous years.

technological combination to the expected frequency upon random combination.

$$\lambda_{jk} = \frac{C_{jk} - \mu_{jk}}{\sigma_{jk}} \quad (1)$$

C_{jk} is the number of observed joint occurrences of technologies j and k in the patents in each year, μ_{jk} is the expected value of random technological co-occurrence, and σ_{jk} is its standard deviation. The expected frequency of technological co-occurrence can be calculated by using parametric or nonparametric methods. Consistent with previous studies (Teece et al., 1994; Nesta and Saviotti, 2005; Nesta, 2008; Breschi et al., 2003), we apply a parametric approach and assume that the distribution of random technological co-occurrences is hypergeometric. We normalize λ_{jk} to be bounded between 0 and unity for consistency with the substitutability measure as follows:

$$\lambda'_{jk} = \frac{\lambda_{jk} - \text{Min}\lambda_{jk}}{\text{Max}\lambda_{jk} - \text{Min}\lambda_{jk}} \quad (2)$$

3.2.2.3. Substitutability of knowledge elements. Two technological elements are considered to be substitutable when they can be combined with the same set of other technologies in the same manner. This functional similarity is commonly measured with use of the cosine index, which is applied to evaluate the proximity of the firms' technological profiles (Jaffe, 1986; Sampson, 2007) or to measure relational homogeneity between individuals or group cohesion in the social network literature (e.g., Reagans and McEvily, 2003). We apply this index to measure the level of substitutability of technological components. Using the co-occurrence matrix C , we assume that if technologies j and k are used with the same set of other IPC codes, then i and j are substitutes because they are used for similar purposes with similar applications. The cosine index is then defined as follows:

$$\zeta_{jk} = \frac{\sum_{m=1}^n C_{jm} C_{km}}{\sqrt{\sum_{m=1}^n C_{jm}^2} \sqrt{\sum_{m=1}^n C_{km}^2}} \quad (3)$$

where C_{jm} represents the joint occurrence of technology j with all other technologies m and C_{km} represents the joint occurrence of technology k with all other technologies m .

3.2.2.4. Complementarity and substitutability at the firm level¹⁵. We analyze firms' knowledge base structure in terms of the level of complementarity/substitutability between each pair of technologies. We use a firm's patent portfolio in semiconductor-related technologies as a basis to calculate the measures of complementarity and substitutability. First, we determine the degree to which each technology in a firm's patent portfolio is complementary to and can substitute for all other semiconductor technologies in the firm's patent portfolio by using the λ' and ζ measures, respectively. Because firms' knowledge stock differs for each technological class, the degree of complementarity or substitutability may be reinforced or weakened by the patent share for each technology. To consider firms' experience and knowledge in each technology, we normalize the relational properties by the firms' patent share in each technological class. A general measure to describe given

technology's relative complementarity or substitutability in a firm's patent portfolio can be calculated as follows:

$$\text{WAR}_j = \frac{\sum_{k \neq j} \tau_{kj} P_k}{\sum_{k \neq j} P_k} \quad (4)$$

where $\tau_{kj} = \{\lambda'_{kj}; \zeta_{kj}\}$ measures the complementarity or substitutability of technologies j and k and P_k is the number of patents associated with technological class k .

Likewise, the level of complementarity/substitutability at the firm level can be calculated as the weighted average complementarity/substitutability of all elements in a firm's semiconductor knowledge base. Therefore, the weighted average value of WAR_j can be calculated as follows:

$$\Lambda = \sum_{j=1}^n \frac{P_j}{\sum_{j=1}^n P_j} \text{WAR}_j \quad (5)$$

where Λ describes the overall relational properties of a firm's knowledge elements in semiconductors and can be considered the knowledge base structure at a given time. Λ reflects the overall level of complementarity when the WAR index refers to the average value of complementarity, or it reflects the overall level of substitutability when the WAR index refers to the average value of substitution. All Λ measures vary across firms and over time.

3.2.3. Control variables

We control for well-known determinants of patent production at the firm level, namely, knowledge diversity (DIV), R&D intensity (R&D INT), and size (SIZE). Knowledge diversity controls for the breadth of a firm's knowledge base and is calculated based on the number of technological classes in a firm per year. We include the logarithm for deflated corporate assets as a proxy for firm size. We add R&D intensity to consider the input variations for inventive activities.¹⁶

3.2.4. Model specification

The discrete nature of the dependent variable (citation-weighted patents) suggests that a count-data model should be used. Poisson regression is a type of regression analysis that is used to model count data and takes the following form:

$$E(y_{it} | \mathbf{X}_{it}) = e^{\mathbf{X}_{it}\beta} \quad (6)$$

where y is the citation-weighted patent counts for firm i at time t , \mathbf{X} is the vector of explanatory variables, $\mathbf{X}_{it} = \{\Lambda_{it}^{\text{subst}}; \Lambda_{it}^{\text{comp}}; \text{SIZE}_{it}; \text{R\&D INT}_{it}; \text{DIV}_{it}\}$, and β is the vector for the parameters of interest. To account for data overdispersion, we use a negative binomial regression to assess the impact of independent variables on inventive performance. To model exploration activities, we rely on the Tobit estimator to account for the lower and upper truncation of the dependent variables.

All explanatory variables are lagged one year in all the regressions. Year fixed effects are included to control for macroeconomic

¹⁵ To measure the level of complementarity and substitutability in a firm's knowledge base, the number of patents over the past five years is used to compensate for radical shifts in the firm's technological portfolio.

¹⁶ The number of observations for R&D expenditures and assets extracted from COMPUSTAT is not balanced with those from the patent data set. To address this problem and the high correlation between the knowledge stock and both firm size and R&D expenditures, we apply a rough estimate of firm size and R&D expenditures conditional on a firm's technological-knowledge stock. We then substitute the estimated values for R&D expenditures and assets for the years without observations in the database. A patent-based measure of a firm's technological-knowledge stock is computed as capitalization for present and past patents by using a perpetual inventory formula such as that for tangible capital (Griliches and Mairesse, 1984; Hall, 1990): $K_{it} = (1 - \delta)K_{it-1} + R_{it}$ (6), where K_{it} is the patent stock at time t , R_{it} is the number of patents granted to a firm at time t , and δ is the knowledge capital depreciation rate from year $t - 1$ to year t . The annual depreciation rate is assumed to be constant at 15%.

Table 3
Descriptive statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
R&D (Millions \$)	1211	385.10	947.02	0.00	5522.26
INT R&D	1211	0.14	0.32	0.00	9.25
SIZE (Millions \$)	1211	5331.84	14,896.44	0.83	102,714.80
K DIV	1130	13.75	15.28	1.00	59.00
COMP	1211	0.35	0.12	0.05	1.00
SUBST.	1211	0.42	0.11	0.12	0.88
Market DIV	1104	1.41	1.09	1.00	8.00
N of patents	1211	123.53	330.38	0.00	3565.00
Citation-weighted N of patents	1211	522.51	1652.21	0.00	20,348.00
Exploration rate	1130	0.19	0.27	0.00	1.00
Citation-weighted exploration rate	943	0.20	0.30	0.00	1.00

Table 4
Correlation matrix ($n=851$).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) R&D INT	1.00								
(2) SIZE	0.37	1.00							
(3) DIV	0.20	0.83	1.00						
(4) WAR_std	0.17	0.39	0.46	1.00					
(5) WAS_std	0.20	0.25	0.27	0.44	1.00				
(6) Market DIV (log)	0.11	0.44	0.39	0.15	0.14	1.00			
(7) Inventive performance	0.11	0.50	0.50	0.28	0.16	0.13	1.00		
(8) Exploration rate	0.09	0.44	0.36	0.22	0.23	0.18	0.22	1.00	
(9) Citation-weighted explor. rate	0.10	0.40	0.33	0.19	0.24	0.17	0.19	0.88	1.00

trends and yearly variations that ultimately affect patenting levels for all firms. We also include firm fixed effects to account for unobserved heterogeneity among firms. Finally, we augment our empirical model and include the number of businesses in which a firm is active to ensure that the inventive performance estimation is not affected by market opportunities or differences between semiconductor specialists and diversified firms.

Tables 3 and 4 list the descriptive statistics and correlations for the variables of interest. As reported in Table 4, knowledge diversity is highly correlated with size. This correlation may induce multicollinearity problems when we estimate the variables' associated

elasticity. We address this problem by estimating the expected diversity for a firm's R&D intensity and size. We compute the difference between the observed and expected diversity based on firms' R&D intensity and size. We then use the expected values in the regression models.

4. Results

Table 5 presents the results; a negative binomial regression model is used to analyze the determinants of firms' overall

Table 5
Negative binomial regression with firm fixed effects. Determinants of inventive performance.

	(1) NB FE	(2) NB FE	(3) NB FE	(4) NB FE
<i>Dependent variable: forward citation-weighted patents</i>				
R&D	0.145*** (0.049)	0.141*** (0.049)	0.180*** (0.049)	0.121** (0.055)
SIZE	0.481*** (0.020)	0.502*** (0.021)	0.514*** (0.021)	0.447*** (0.026)
DIV	0.875*** (0.041)	0.884*** (0.042)	0.896*** (0.042)	0.579*** (0.062)
COMP		0.154*** (0.046)	0.291*** (0.056)	0.194*** (0.074)
SUBST			-0.175*** (0.044)	-0.183*** (0.058)
Market DIV				-0.142** (0.056)
Constant	-22.771 (1036.308)	-21.412 (462.966)	-23.635 (1306.412)	-21.267 (532.544)
Observations	1367	1367	1367	902
Number of firms	113	113	113	97
LL	-5690.377	-5685.022	-5677.309	-3495.849
chi2	2772.391	2813.775	2918.473	2315.320

All independent variables are in logarithm.
All independent variables are lagged one year.
All equations include a full set of year dummies.
Standard errors in parentheses
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 6
Exploring the robustness of the results. Testing alternative models.

Models	(4) NB FE (citations)	(5) NB RE (patents)	(6) Poisson FE (citations)
R&D	0.121** (0.055)	0.009 (0.050)	0.105*** (0.009)
INT	0.447*** (0.026)	0.265*** (0.026)	0.380*** (0.005)
SIZE	0.579*** (0.062)	0.536*** (0.056)	0.796*** (0.009)
DIV	0.194*** (0.074)	0.103 (0.063)	0.576*** (0.016)
COMP	-0.183*** (0.058)	-0.079 (0.053)	-0.544*** (0.011)
SUBST	-0.142** (0.056)	-0.234** (0.055)	-0.114** (0.005)
Market			
DIV			
Constant	-21.267 (532.544)	-1.221*** (0.246)	
Observations	902	913	902
Number of firms	97	102	97
LL	-3495.849	-3239.466	-19,808
chi2	2315.320	1050.507	.

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

inventive performance. Model 1 includes only the control variables to provide a baseline estimate. As expected, the control variables positively and significantly affect inventive performance; this result implies that firm size, R&D efforts, and knowledge diversity are key determinants of the production of valuable patents in the semiconductor industry. Models 2 and 3 sequentially introduce the variables of interest to explore the impact of the level of complementarity and substitutability, respectively.

Consistent with our expectations, the estimated coefficient is positive and significant for the level of complementarity. The estimate in model 3 is negative and significant and thus provides strong support for our expectation that the level of substitutability in the knowledge base hinders a firm's inventive performance. Using standardized variables for the overall level of complementarity and substitutability enables us to compare their effects on firms' inventive performance. The impact of complementarity on quality-adjusted inventions is more important than that of substitutability ($\beta_{SUBST} = -0.175$, $\beta_{COMP} = 0.291$). In model 4, we include the firm's number of businesses as a robustness check in order to distinguish semiconductor specialists from diversified firms. The negative parameter estimate associated with business diversification implies that specialist firms have a comparative advantage over diversified firms in inventive activities. Unsurprisingly, specialist firms concentrate their R&D efforts on a limited number of application domains and therefore enjoy greater learning effects than their diversified counterparts.

Several econometric specifications are used to explore the sensitivity of the estimated parameters. Table 6 presents the estimation results from alternative panel-data econometric models. To compare the results, the first column in Table 6 shows estimates from the basic specifications (column 4 in Table 5). Our findings remain similar when we measure the contributions of the explanatory variables by changing the model to Poisson regression (column 6) or by applying firm random effects to the model (column 5). The use of alternative models does not invalidate our previous conclusions regarding the role played by the properties of firms' knowledge structure, as the significance and signs of the coefficients remain robust to the use of alternative estimators.

Table 7 shows estimates for the impact of the level of complementarity and substitutability on the rate of explorative patents (patents that use novel combinations). As we double-censor the

Table 7
Determinants of explorative inventive activities.

Models	(7) Patent Tobit FE	(8) CITATIONS Tobit FE
R&D	-0.055*** (0.017)	-0.074*** (0.026)
INT	-0.010 (0.009)	-0.016 (0.013)
SIZE	-0.018 (0.017)	-0.069*** (0.025)
DIV	-0.035** (0.016)	-0.104*** (0.025)
COMP	0.040*** (0.012)	0.053*** (0.019)
SUBST	-0.007 (0.026)	-0.054 (0.041)
Market		
DIV		
Constant	-1.431 (1.875)	-5.817** (2.958)
Observations	887	722
Unc.Obs	664	494
LL	-198.619	-276.191
chi2	136.331	135.937

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

observations for the rate of explorative activities, we use a Tobit regression model.¹⁷ Column 7 in Table 7 presents the results. Consistent with our expectations, we find a positive parameter coefficient for the level of substitutability. This result suggests that firms with a higher level of substitutability in their knowledge base have more explorative inventive outcomes. In addition, the negative impact of complementarity is also confirmed. The sensitivity of the estimations is tested by using other regression models and an alternative proxy to measure the rate of exploration, as presented in Table 7.

Model 8 reports the robustness of the estimates in which the rate of explorative inventions is weighted based on the number

¹⁷ The magnitude of the selectivity bias is apparently small, because the use of Heckman's method did not change the findings and the inverse Mill's ratio coefficient is not significant.

of citations to measure the usefulness of explorative patents as a dependent variable; the estimates are consistent with the previous results.

5. Discussion and conclusion

The core idea that underlies this work is that, in addition to the size (accumulated knowledge) and diversity (knowledge variety) of a firm's knowledge base, the structure of the firm's knowledge base significantly influences its inventive performance and is a source of intra-industry heterogeneity. By considering complementarity and substitutability as two properties of knowledge elements that characterize the structural composition of a firm's knowledge base, we extend the literature that emphasizes synergies resulting from knowledge integration (e.g., Grant, 1996b), coupling (Yayavaram and Ahuja, 2008), or complementary services between knowledge elements (e.g., Scott and Pascoe, 1987; Nesta and Saviotti, 2005). Our primary finding is that the selection of knowledge elements can be directed by, aside from other factors (such as a knowledge element's usefulness in an application domain or the emergence of new applications or technological trajectories), the relational properties between knowledge elements. Firms that tend to accumulate complementary knowledge exhibit higher inventive performance. However, the results of this paper show that the positive contribution of knowledge complementarity to invention performance is context dependent and potentially detrimental when the firm's objective is to develop explorative inventions. With an explorative strategy, generating substitutability in the knowledge base by investing in elements that are functionally similar to other elements in the knowledge base is beneficial because high substitutability offers alternative options that support novel experimentation.

Our empirical results are consistent with those of prior works. Several studies suggest that the selection of complementary elements through a combinatorial search process leads higher inventive performance and productivity (e.g., Nesta and Saviotti, 2005; Nesta, 2008). One explanation for this relation could be related to reduced search costs: complementary elements are elements that can be considered a single element and that are frequently combined and reused in familiar search contexts because their usefulness is well known (Yayavaram and Ahuja, 2008). Consequently, information on the usefulness of combinations accumulates over time, and thus, the need to seek further combination options is reduced (March, 1991). Further, the exploitation of complementary knowledge in familiar projects is similar to a local search in evolutionary economics (Nelson and Winter, 1982; Rosenkopf and Nerkar, 2001); firms focus on similar knowledge combinations and accumulate expertise in a domain that can be leveraged in other projects to generate economies of scope in research activities. Then, in familiar environments, integrating complementarity between knowledge elements lowers coordination and communication costs because task allocation decisions rely on well-established problem-solving routines (Nelson and Winter, 1982; Argyres, 1996).

By contrast, the level of substitutability in the knowledge base tends to negatively affect a firm's capacity to produce useful knowledge. Investing in knowledge elements that provide similar services or solutions increases functional redundancy in the knowledge base and thus decreases the scope of possibilities for problem solving. As a corollary, redundancy increases opportunity costs because the resources allocated to redundancies decrease the capacity to allocate resources to other activities. Thus, firms with high substitutability suffer the costs of knowledge diversification but do not gain many of its benefits.

This paper also aimed to elucidate the role of a knowledge base structure in a firm's ability to engage in explorative inventions. Our results suggest that the knowledge base structure affects the value of research projects, depending on the firm's need to generate new combinations. Thus, encountering the same opportunities, firms may invest in different projects and thus have different inventive performances. In a dynamic setting, knowledge base structures therefore generate different adaptive capacities. Several authors have suggested that knowledge base structures may be more or less flexible when structural reconfiguration is necessary (Kauffman et al., 2000; Yayavaram and Ahuja, 2008).

Our results support the notion that high substitutability increases flexibility and positively contributes to a firm's explorative capacity. Exploration is not a random process, and experimentation may be presumed to be guided by prior information regarding the effectiveness of existing combinations (March, 1991). Thus, testing a new combination by replacing one element with a substitute may provide more information about its underlying relational properties than conducting a random test. Thus, investing in elements that provide similar services may be critical when experimentation is important (such as during technological transition phases wherein competing technologies emerge) or when knowledge must be redeployed in different application domains that may affect the relational properties of knowledge elements (Levinthal, 1998; Adner and Levinthal, 2002). Acquiring expertise in substitute knowledge can also be argued to enlarge firms' capacity to handle and solve more complex problems in a domain. Testing different options during problem solving provides different perspectives and enables firms to encounter different representations, which ultimately provide a deeper understanding of the problem and extend firms' ability to define alternative strategies for solutions to problems.

Conversely, the level of complementarity negatively influences firms' knowledge base flexibility and hinders firms' explorative inventive capacity. Firms with a knowledge base with a high level of complementarity risk experiencing "competency traps" (Levitt and March, 1988) and "core rigidities" (Leonard-Barton, 1992). A competency trap results from specialization and lead firms to accumulate experiences and to adopt efficient routines that are inadequate in new contexts, such as those induced by technological change (Levitt and March, 1988). In other words, a search process is a path-dependent process (the combination of choices depends on the results from prior choices) that may yield suboptimal (but satisfying) solutions (Nerkar, 2003), which may become locked in when conditions change (David, 1991; March, 1991). Rigidities from a gap (characterized by an inappropriate knowledge base) between environmental requirements and a firm's capabilities (Leonard-Barton, 1992) may be particularly detrimental to the firm because such a gap often remains obscured.¹⁸

From a strategic perspective, these observations highlight the necessity for innovative firms to consider the alignment between their knowledge base and inventive strategies. A firm's inability to renew its capabilities is related to a lack of opportunities to test alternatives, which limits its capacity for experimentation. Although not necessarily determined by environmental requirements, the contribution of the level of substitutability to exploratory inventions could be dependent on a firm's level of technological maturity. Consistent with Leonard-Barton's arguments, our examples show that a firm's ability to experiment with novel combinations is essential during transition periods.

To the extent that our results can be generalized to other industries, they provide important insights that complement

¹⁸ See Siggelkow (2002) for a discussion on the importance of understanding complementarity and substitutability among activities.

analysis of technological diversification strategies. The results support other studies that associate superior inventive performance with a greater knowledge domain scope (e.g., Gambardella and Torrisi, 1998; Garcia-Vega, 2006; Quintana-García and Benavides-Velasco, 2008). Introducing new knowledge elements favors the search for novel complementarities and therefore has a stronger effect on exploratory invention (Quintana-García and Benavides-Velasco, 2008). Although we could not directly measure firms' ability to select and recombine knowledge to generate technological inventions or the processes involved in constructing these capabilities, our findings regarding the relational nature of knowledge elements can provide a guideline for decisions regarding technological diversification. Because firms broaden their competencies across different technological fields, the accumulation of knowledge elements that are substitutable with or complementary to the firm's established knowledge base may be critical in shaping the direction of technological diversification. This explanation deserves deeper study to analyze the effect of substitutability and complementarity on diversification processes.

Finally, the role of knowledge synergies in business diversification has been emphasized in the literature (Grant, 1996a,b; Teece et al., 1994; Kim and Kogut, 1996; Miller, 2006). Future research could study how the properties of a firm's knowledge base affect the propensity of the firm to enter new markets. A firm's capacity to exploit its knowledge base as a set of links between knowledge elements may provide a potent source of opportunities for the firm to expand into new businesses that can serve as platforms for market expansion. Such a capacity may also help the firm to exploit the synergies between knowledge components across different activities to render diversification profitable.

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