Quantifying the Productivity of Intangible Assets Using a Production Function Framework

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Abstract  
We propose a model to capture the main properties of knowledge assets. This model quantifies a firm's knowledge base in terms of knowledge stock, knowledge diversity, knowledge complementarity and knowledge similarity to describe the dimensions along which knowledge assets are more likely to differ across firms. Unlike conventional approaches, we describe knowledge assets based on their contributions in the context of applications and particularly emphasize the roles of complementarity and similarity as the organizational dimensions of knowledge assets. Then, we test the contribution of each dimension in a sample of 111 of the world’s largest corporations to the firm performance taking a production function framework. Panel data analysis suggests that while knowledge stocks and knowledge complementarity provide productive advantages in a static setting, knowledge diversity and knowledge similarity boost productivity growth taking a dynamic setting. Organizing activities that are based on a complementary system of knowledge are more efficient and easier to be coordinated, enhancing the level of productivity. However, knowledge similarity render redundant services and therefore can be applied interchangeably in a system of complementary knowledge to support the improvement of underlying production approaches.

Jelcodes:M10,-
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This paper develops a formal model that captures four main properties of knowledge assets: knowledge stock, knowledge diversity, knowledge complementarity and knowledge similarity. These characteristics are incorporated in a production function framework, to then raise hypotheses on the expected contribution of complementary and similar knowledge assets to productivity levels and growth. We test the contribution of these dimensions using a sample of 104 firms. Panel data analysis reveals that productive activities relying on complementary knowledge are more efficient, enhancing both the level and the growth rate of productivity. Unexploited yet available complementary knowledge assets provide "ready-to-use" technological opportunities that can be integrated coherently and at low costs into the production system. Similar knowledge assets provide redundant services and as such, they do not exhibit any significant contribution to productivity levels. As similar knowledge assets can be used as substitutes to existing and exploited technologies, they contribute significantly to productivity growth. Quantile regressions show, however, that similar knowledge assets support only incremental increases in productivity, whereas larger increases are due to the exploitation of latent complementarities and the development of new technological fields.

1. Introduction

Knowledge-based view regards knowledge as a prime source of firms’ heterogeneity and competitive advantage. A firm is considered as a ‘bundle’ of knowledge resources developed over time that are integrated and exploited in ongoing productive activities to provide business value (Grant 1996). The central insight of knowledge perspective implies that the source of firms’ idiosyncrasy is not found only in their intangible asset profiles, but also in the way such assets are applied in organizational contexts (Penrose 1959, Henderson and Clark 1990). Therefore, the capabilities of a firm lie on the way functional expertise are organized and coordinated (Zander and Kogut 1995).

Firms are different because they adopt unique arrangements and organizations in exploiting their knowledge assets to tap their rent earning potential (Henderson 1994, ?, Galunic and Rodan
1998). This question has motivated a stream of research to examine different firms’ behaviors and practices in developing and managing knowledge assets (Kogut and Zander 1992, Nonaka et al. 2000) and their implications on firm’s strategic orientation and performance (Teece et al. 1994, Kim and Kogut 1996, DeCarolis and Deeds 1999). The issues of how firms develop and deploy knowledge assets may stimulate one to wonder how such assets can be characterized to reveal their contributions to perform productive tasks as the essence of organizational capability and firm’s capacity for creating value. Understanding the strategic dimensions of knowledge resource profile and their relative productive performance provides managers with the knowledge to effectively select and configure heterogeneous resources in a way that enhances their value-creating potential (Alchian and Demsetz 1972, Peteraf 1993, Peteraf and Barney 2003).

To address this question certain studies rely on the firm production function framework to link firm performance and the combinations of tangible and intangible factors of production. While economics characterize knowledge assets in order to provide better explanations for productivity improvement (e.x. Griliches (1986), Griffith et al. (2006), Nesta (2008)), organization studies try to understand underlying properties of knowledge assets as leading to new managerial insights in dealing with them in productive activities. Relying on the study of Dierickx and Cool (1989), Knott et al. (2003) propose a model of production function to explain the contribution of intangible asset stock in firm productivity and its role to deter rival mobility. The authors assume that a firm’s knowledge profile can be revealed by the pooled amount of knowledge inputs and examine the process of knowledge accumulation. However, the study ignores the heterogeneous nature of knowledge assets and their interactions to simplify the dimensionality of the analysis. Postrel (2002) puts more emphasize on the content characteristics of a firm’s knowledge profile and analyzes a model of production function to discern the contributions of specialized capabilities and trans-specialized knowledge. Although this study provides important insights about an optimal and efficient level of specialization and divisions of knowledge, it provides little explanation about how the interactions of knowledge inputs in productive activities contribute to the setting they are applied. Understanding how value creating services underlying knowledge assets work together
requires an integrative framework that goes beyond a description of the size and the types of information and technical know-how a knowledge base contains.

In this paper, first, we develop a model that decomposes the central properties of a firm’s knowledge base in terms of knowledge stock, knowledge diversity, knowledge complementarity and knowledge similarity. This theoretical model depicts what are the value-adding potentials of knowledge assets in productive activities. Taking a production function framework allows us to formalize both firm’s resources as well as its capabilities to exploit knowledge assets in a systematic framework. While resources are “stocks of available factors owned by the firm ... such as property, plant and equipment, human capital ..., capabilities refer to a firms capacity to deploy resources ... and provide enhanced productivity of its resources” (Amit and Schoemaker 1993, p. 35).

Second, we provide an empirical test for our theoretical setting using a sample of 104 the world’s largest companies. We estimate the contributions of knowledge properties to the firm’s production function in a static (production level) and a dynamic (production growth) setting.

Third, the study traces the sources of heterogeneous behavior of the firms, by showing differentiated contribution of knowledge assets to various levels of productivity gains. We show that knowledge complementarity and knowledge similarity make different contributions for high-growth and low-growth firms to their productivity gains. Our study provides interesting findings to enhance our understanding on the nature of firms’ heterogeneity and mechanisms for integrating fragmented specialized knowledge.

2. Background

One challenge of scholars in the knowledge based view is to describe what firms know to understand how it is transferred in organizational context and how it enhances the chances of growth and survival. At first glance, knowledge assets could refer to the pool of knowledge that a firm accumulated over time. Knowledge is a non-trading intangible asset that is gradually stored and accumulated as learning occurs (Henderson 1994, Knott et al. 2003, Murray and O’Mahony 2007). Knowledge stock is expanded both by R&D activities and by the acquisition of new knowledge
from external sources (Ahuja and Katila 2001, Liebeskind et al. 1996), and is adjusted by the obsolescence of past R&D efforts (Darr et al. 1995). The path of knowledge accumulation proves to be a significant determinant in the firm’s strategic behavior and establishing a competitive position (Kim and Kogut 1996, DeCarolis and Deeds 1999).

However, knowledge is far from being homogeneous aggregate. The crucial decisions for managers are about where to go, what to accumulate and how to articulate new knowledge with existing knowledge base. The firm’s knowledge base has its foundation in the different fields of specialized knowledge. These domains represent firm’s component knowledge (Henderson and Clark 1990) and rely on both scientific and technical principals (Rosenberg 1983). Knowledge diversity reflects the breadth of component knowledge and the scope of knowledge fields the firm masters. However, because the exploitation of diverse specialized knowledge is not given to firms, the aggregation of firm’s knowledge fields is far from a representation of its knowledge assets.

This issue has motivated a large stream of research to analyze how firms deal with specialized knowledge in different tasks and integrate them into broader functional capabilities (Clark and Fujimoto 1991, Kogut and Zander 1992, Grant 1996). First, knowledge is deeply rooted in actions. The firm must bring fragmented specialist knowledge inputs together in production tasks and the applications of each knowledge input is a function of its interdependencies with other knowledge elements in the system in which it is applied. The micro analysis of functional interdependency of specialized knowledge shows how knowledge modularity (Brusoni et al. 2001), knowledge decomposability (Yayavaram and Ahuja 2008) and knowledge complexity (Fleming and Sorenson 2001, McNamara et al. 2002) affect the effectiveness of knowledge integration.

Second, knowledge is has a cognitive dimension based on the way it is transferred, translated and exploited in organizational context. Knowledge integration is not merely technological determinism. Managers are somehow free to decide about which knowledge components to develop and how efficiently organize them within organization (Grant 1996, Nickerson and Zenger 2004, Brown and Duguid 2001, Fleming 2001). They assign knowledge inputs to a function in productive activities and this activity essentially relies on their experience (Pisano 1994, West and Iansiti 2003, Kor

Third, it is shown that organizations as institutional contexts could provide mechanisms to facilitate the process of knowledge integration and coordination. Organizational routines, procedures, structure and rules through which knowledge is integrated may guide patterns of social interactions and support an efficient communication across individuals working on related activities (Nelson and Winter 1982, Grant 1996, Purvis et al. 2001, Turner and Makhija 2006).

These streams of research displays an away of contribution that reflects the variety of concepts, understandings and issues related to knowledge integration. Our paper aims to bridge together these various concepts in a generalized framework. This framework explains the nature of knowledge integration based on the relative contributions of knowledge inputs and their interactions to perform production tasks.

3. Qualifying Firm Knowledge assets

Traditionally knowledge assets, $K$, is defined as the firm’s stock of knowledge corrected for technical obsolescence (Griliches 1979): $K_{it} = p_{it} + (1 - \delta) \cdot K_{i,t-1}$, where $p$ is new knowledge acquired by firm $i$ at time $t$ and $\delta$ represents the rate of knowledge obsolescence. There is no unique way of measuring $p$, but R&D expenses and patents, either granted or applied for, have been by far the most widely used proxies to date. This approach has received a lot of attention, due both to its simplicity and to the significant improvement it has brought to our understanding of the contribution of knowledge assets to economic performance.

However, the above formulation fails to address the question of heterogeneous scientific and technical knowledge. To perform a specific task, a set of different knowledge domains must be bundled together. Managers expect particular services from each knowledge input when applying them in the context of production. In most cases, the value derive from a given knowledge input in production depend on the presence of other knowledge inputs. Knowledge assets that co-operate to
perform a given activity may fertilize each other. In this setting, knowledge inputs exhibit complementarity in deployment and application so that their productive value is reinforced when they are applied together (Bertrand, 1938; Amit and Schoemaker, 1993; Helfat, 1994; Sigglekow 2002; Nesta and Saviotti, 2005). For example, a combination of different fields of knowledge on conducting electric current, digital data store arrangements, measuring electric or magnetic properties of materials and their chemical characteristics is needed in the production of a given semiconductor chip. The notions of co-specialized assets or bilateral interdependency of Teece (1986) and interconnectedness proposed by Dierickx and Cool (1989) address such complementarity between resources.

Second, knowledge inputs may prove to show some similar patterns in application. Two types of knowledge are similar when they can be alternatively applied in accomplishing a specific task because they provide similar productive services in their applications. For instance, to interconnect devices on integrated circuits, engineers may use metal as a conductor of electricity or alternatively a form of silicon made of many small randomly-oriented crystals. Using metal needs specialized knowledge on electroplating techniques and applying liquids or other fluent materials, while silicon requires expertise on using ultra-high pressure, re-crystallization and solidification of materials. Yet, both methods provide equivalent outcomes. Their underlying knowledge inputs are functionally similar, despite the fact that they drawn from different scientific principles.¹ In this case, resources are considered similar because they are directed to the same end and be substitutes to achieve a given criterion (Bamey, 1992; Peteraf and Berge, 2003). Functional similarity reflects the flexibility of a firm to reallocate and reconfigure its organizational resources in an alternative fashion, without a change of end and outcome (Zhou and Wu, 2010).

To include these dimensions in the model, let us assume that firms are composed of a vector $P$ of $D$ productive activities, $P = [p_1, ..., p_d, ..., p_D]$. Each activity $p_d$ draws primarily on its associated scientific and technical expertise $e_d$, so that firm’s total expertise is vector $E = [e_1, ..., e_d, ..., e_D]$. However, activity $p_d$ may also benefit from the expertise developed in other activities $l$ ($l \neq d$),

¹ Research in strategy analyzes widely the question of resource similarity within and across firms and the strategic effects on firm’s behavior and performance, but the center of attention is on similarities of resource types rather than resource functionalities (St. John and Harrison 1999, Tanriverdi and Venkatraman 2005, Sampson 2007)
depending on the level of complementarity $\lambda$ and functional similarity $\gamma$ between technical expertise $e_d$ and $e_l$. The knowledge base $k$ used by the $d^{th}$ activity is therefore:

$$k_d \equiv e_d + \sum_{l \neq d} e_l \cdot \lambda_{ld} \cdot (1 - \gamma_{ld}) + \sum_{l \neq d} e_l \cdot \gamma_{ld}$$  \hspace{1cm} (1)$$

where we set $0 < \lambda_{ld} < 1$ and $0 < \gamma_{ld} < 1$. Eq.(1) means that the knowledge base $k$ available to activity $d$ is knowledge expertise $e_d$ and all other knowledge expertise $e_l$ ($l \neq d$), weighted by their associated complementarity $\lambda_{ld}$, provided that $e_d$ and $e_l$ are not entirely similar ($\gamma_{ld}$ is not equal to unity). Note the inclusion of $\sum_{l \neq d} e_l \cdot \gamma_{ld}$ as tantamount to augmenting $k_d$ with the similar services provided by $e_l$.

Generalising Eq.(1) to all productive activities within the firm yields the aggregate knowledge base $K$:

$$K \equiv \sum_d e_d + \sum_d \sum_{l \neq d} e_l \cdot \lambda_{ld} \cdot (1 - \gamma_{ld}) + \sum_d \sum_{l \neq d} e_l \cdot \gamma_{ld}$$ \hspace{1cm} (2)$$

For simplicity, let us hold both $\lambda_{ld}$ and $\gamma_{ld}$ constant across activities $d$'s and $l$'s, so that $\lambda_{ld} = \Lambda$ and $\gamma_{ld} = \Gamma$ across all productive activities within the firm. Since $\sum_d e_d$ is the firm’s knowledge stock $E$, Eq.(2) simplifies to:

$$K \equiv E \cdot [1 + (D - 1) \cdot \Lambda \cdot (1 - \Gamma) + \Gamma]$$  \hspace{1cm} (3)$$

Eq.(3) states that firm knowledge is a function of its total knowledge capital or expertise $E$, the number $D$ of knowledge fields implemented within the firm, mean knowledge complementarity $\Lambda$ and mean knowledge similarity $\Gamma$ across activities. This model provides a general framework that allows comparison of firm knowledge bases so as to understand the sources of firm heterogeneity. We essentially focus on complementarity and similarity given that knowledge stock and knowledge diversity have been widely studied in prior works (Knott et al. 2003, Boone et al. 2008, Dorroh et al. 1994, Lapr and Van Wassenhove 2001, Kavadias and Sommer 2009, ?). Complementarity and similarity represents the properties of knowledge in the context of applications. They reflect how
knowledge elements interact with each other to provide productive services and how the nature of one knowledge element influences the contributions of other elements. These interactions have important implications in firm’s practices and performance, because they must insure overall performance of partitioned specialized knowledge and the organizational value of knowledge elements.

4. Knowledge and Productivity

4.1. The Contribution of Knowledge Base Characteristics in Production Function Framework

To study the effects of complementarity and similarity on productivity, we use an augmented Cobb-Douglas production function. In this model, firm output is a function of firm traditional factor endowment of capital, labour and material augmented with firm knowledge assets:

\[ Q_{it} = A \cdot C_{it}^\sigma L_{it}^\alpha M_{it}^\rho K_{it}^\delta \]  \quad (4)

where subscripts \( i \) and \( t \) refer to the firm \( i \) and the current year \( t \), \( Q \) is output measured by sales, \( A \) is a constant, \( C \) is the gross value of plant and equipment, \( L \) is the number of employees and \( M \) is materials. Substituting (3) into eq. (4) yields:

\[ Q_{it} = A \cdot C_{it}^\sigma L_{it}^\alpha M_{it}^\rho \cdot (E^{\varpi_E} \cdot \left[ 1 + \left( D - 1 \right)^{\varpi_D} \cdot \left( 1 - \Gamma^{\varpi_{\Gamma}} \right) + \Gamma^{\varpi_{\Gamma}} \right])_{it}^{\delta K} \]  \quad (5)

Taking the same specification to represent knowledge characteristics, the dynamic model becomes:

\[ \frac{Q_{it+1}}{Q_{it}} = A \cdot Q_{it}^\beta \cdot \left( \frac{Q_{it}}{Q_{it-1}} \right)^\varphi \cdot C_{it}^\sigma L_{it}^\alpha M_{it}^\rho \times \left( E^{\varpi_E} \cdot \left[ 1 + \left( D - 1 \right)^{\varpi_D} \cdot \left( 1 - \Gamma^{\varpi_{\Gamma}} \right) + \Gamma^{\varpi_{\Gamma}} \right] \right)_{it}^{\delta K} \]  \quad (6)

where \( \varpi_K \) is the weight attributed to each of the four knowledge properties \( K = \{ E, D, \Lambda, \Gamma \} \) of firm knowledge base.

We augment the dynamic equation with two important controls. First, parameter \( \beta \) associated with initial \( Q_{it} \) allows us to control for \( \beta \)-convergence, and we expect this parameter to be negative. Second, parameter \( \varphi \) for the lagged dependent variable allows us to account for some adjustment...
costs \((1 - \varphi)\) associated with productivity growth. Equations 5 and 6 investigate whether and the extent to which both the level and the growth of productivity are associated with the properties of the knowledge base. In what follows, we develop hypotheses regarding the role of complementarity and similarity.

4.2. Production Function and Knowledge Complementarity

Our model observes the firm as a host of different knowledge components which exhibit various levels of complementarity to one another. At this stage it is important to distinguish exploited complementarities and potential complementarities, because of their differentiated contributions to productivity level and growth.

Exploiting complementarity provides enhances the level of productivity in different ways. First, it improves current efficiency because leveraging a bundle of complementary knowledge assets across different applications reduces the costs of performing activities (Parmigiani and Mitchell 2009). Joint utilization of complementary knowledge inputs leads to cost advantages and results in scope economies. Second, because complementary knowledge components match and work well together, they provide opportunities to save governance costs. They represent specific relational characteristics that defines patterns of interaction between them. These pre-defined relations facilitate coordination leading to operational improvements and productivity gain. (Teece 1980; Nayyer, 1992; Tanriverdi and Venkatraman, 2005; Nesta, 2008; Farjoun, 1998). Third, because productive activities engage technical choices that interact together, a system of complementary elements form specific pattern of actions. The re-use of knowledge components that have already proven to be complementary enables the firm to internalize the interactions in the form of organizational routines (Nelson and Winter 1982). Standardizing process and learning effects yield significant saving in costs and postpone the expense of testing new systems of configuration. Forth, investment in complementary knowledge projects is also more efficient (yet risky (Siggelkow 2002)) than independent projects. R&D activities are more productive, when they support two complementary knowledge projects as a bundle because the added value is higher than funding each project alone (Ba et al. 2001). Thereby, both investment and exploitation of complementarity renders cost advantages.
The general productivity benefits of complementarity is also acknowledged in human resource practices. Several studies demonstrate that innovative team productivity is promoted when a firm adopts a set of complementary human resource management practices (Nonaka et al. 2000, Ichnioski et al. 1997, Milgrom et al. 1991, Ichnioski and Shaw 1999). These studies suggest that innovative problem-solving teams that deploy a set of complementary practices enjoy higher employee participation improving their efficiency and economic performance. It follows that:

**Hypothesis 1**: Exploited knowledge complementarity positively contribute to the level of productivity.

Meanwhile, a firm grows in the context of making the choice of which new elements to integrate and of how to combine them. In this case, potential complementarity supports such technical progress to achieve productivity gain. Complementary components generate new value when used together additional to the value of their individual use and reinforce each other in practices. It delivers technological opportunities by enhancing synergetic effects of knowledge assets.

In order to improve coordination, bounded rational innovators may reduce complexity by considering only the strongly interactions between elements and isolate the weak interactions to have a general representation about the system (Ethiraj and Levinthal 2004). Therefore, they may ignore all possible complementarities and focus on the strongest complementarities as the core of interactions. When the firm seeks to re-optimize its production function, recombining currently available knowledge is a best and less costly strategy to follow. In this case, the existence of potential complementary components guides the experimentation of new configurations. The relative certainty and clarity of outcomes and the efficiency rationality reinforce using currently available, yet non-exploited complementary components. This is more likely to happen if the firm hosts more complementary knowledge. It provides more available and ready-to-use possibilities and allows search over a more fruitful combinatorial space. Specially, if the firm hosts emerging knowledge components, they provide greater opportunities for breakthrough recombinations, because their potential is not fully explored and experimented (Ahuja and Morris Lampert 2001). In follows that the possibilities of innovation provided by potential complementarity leads to technical progress
and enhance productivity growth (Helfat 1997, Nerkar and Roberts 2004, Nesta and Saviotti 2005). Formally stated:

**Hypothesis 2:** *Potential knowledge complementarity is positively related to productivity growth.*

4.3. Production Function and Knowledge Similarity

Knowledge similarity has received less attention compared to complementarity in the literature of strategic management. Most studies in strategy generally concern alternate assets as a source of threat that conditions competitive advantage. They argue that if the substitute resources have the same strategic implications and are distributed across firms, the returns to the holders of a given resource tend to be depressed (Wernerfelt, 1984; Barney, 1986, McEvily, Das and McCabe, 2000). Peteraf and Berge (2003) explain that bringing resources that are functionally substitute into production eliminates both scarcity and competitive advantage.

However, at firm level, the implications of similar knowledge does not seem to be well-recognized. On the one hand, knowledge similarity could be desirable because redundancy in expertise allows the firm to create cross-function absorptive capacities (Daniel 1990). Taking this approach, the redundancy of information and functions within cross-functional team takes the role of communication and diffusion of knowledge as a principle of knowledge creation and learning (Nonaka 1994). On the other hand, similar knowledge elements are the inputs that are exclusive alternatives in production process and increase the costs of the firm, while providing redundant services.

We argue that firm needs to develop similar knowledge to increase its depth of knowledge in specific functions and access to different alternatives. Specially, each knowledge alternative has its own drawbacks and benefits. For example different lithographic technologies are alternatives in manufacturing of chips and other computer components. Since each technological domain follows different level of maturity and concerns about particular complexity and cost, comparisons between them do not lead to eliminate definitively one of them in the production process. Postrel (2002) provides evidence for this argument by showing that firm may use substitutable specialized knowledge to reduce the costs of inputs and achieve the goals with an efficient knowledge profile.
Moreover, we suggest that firms can take advantage of similar knowledge assets to achieve technical and productive progress. Knowledge similarity supports explorative experimentation in problem-solving process because it generates plausible alternatives to technical problems of innovative activities (Pisano 1994). Tyre and Hauptman (1992) find that functional overlap i.e. the engagement of both engineering and manufacturing teams in new project insures innovation success, when systemic shift takes place in production approaches. This idea is confirmed by Siggelkow (2002) who suggests that firms tend to replace an organizational element with an alternative one in order to find better organizational configurations in their development paths. Therefore, the benefits of similarity depends on trade-off between efficiency and flexibility.

Based on these lines of reasoning, we expect that similarity does not contribute to the level of productivity, because firm seeks to sustain efficiency by exploiting established knowledge components and take advantage of learning to re-use and keep the structure of system to improve productivity. Because knowledge similarity provides relatively identical functions, investment in such knowledge assets increase the costs of the firm for new inputs that provide redundant and not distinctive services.

However, the advantages for substitute components arise when existing systems need to be improved. In the context of change in underlying production approaches, substitutability enhances the ease and the flexibility with which a component can be turned into another one. Similar knowledge components promote the choice of more relevant inputs by providing a repertory of alternatives that are able to perform similar functions. They therefore support the modification and the improvement of the elements of a system without breaking the system and a radical change. Such advantage is known as "economies of substitution" where a firm retains higher-performance elements of a system and replaces certain knowledge elements that need to be modified (Garud and Kumaraswamy 1995). Such a process postpones a complete destruction of existing system of knowledge that are integrated together. This argument can trace back to (Lachmann 1947) who argues that when a production plan involves a complex pattern of complementarity, a high degree of substitutability between operating factors may be required to keep the production going. This
is necessary to provide for many minor changes in order to prevent a major one. As suggested in our mathematical model, different types of relatedness between knowledge domains appear to exist side by side and may modify the marginal benefits of each other in production.

We therefore expect that:

**Hypothesis 3**: Knowledge similarity have negative effects on the level of productivity.

but,

**Hypothesis 4**: Knowledge similarity positively contributes to productivity growth.

5. Analytical setting

The choice of an appropriate measure to describe firm’s intangible assets is a challenging task. The measure must capture the characteristics of firm’s technological competencies and enable a longitudinal study to map the accumulated knowledge. The patent-based measure of knowledge is widely accepted as a proxy to trace a firm’s knowledge assets. Patent data are recorded systematically and provide detailed information on inventive activities that expected to have a significant commercial value. However, we agree that patents represent only codified knowledge and underestimate the entire intangible assets of the firms. Moreover, the rate of patenting and appropriability differ across sectors making difficult the comparison of results from one industry to another. But, since this study aims to analyze knowledge at firm level, patent data provide fruitful information to trace the components of knowledge base systematically.

We describe knowledge assets by its patent portfolio. In order to compensate for radical shifts in inventive behavior and strategy of the firm, we aggregate patent counts over the past five years. Knowledge capital is measured using patent stock with a rate of knowledge obsolescence of 15 percents per annum. Each patent is assign to one or several technological code(s). Technological classes reflect the technical subject(s) with which each patented invention is essentially concerned. Therefore, the number of technological classes to which all patent documents belong, represents the diversity of technical fields in which the firm developed and mastered knowledge. We use this measure as a proxy to reflect the breadth and the diversity of a knowledge base.
As one would expect, knowledge diversity is likely to be highly correlated to knowledge stock, because when the firm accumulates new knowledge, the probability of developing knowledge in new domains to complete its knowledge base increases specially in the industries with high rate of technological change. We treat this question statistically in our study taking the difference between the observed diversity $D$ and the expected diversity $D'$, conditional on patent stocks. This allows us to estimate the contribution of each characteristic of knowledge base more appropriately.

Technological fields assigned to patent documents provide interesting information to study underlying bodies of knowledge of invention. In the recombinant process, inventors may rely on several knowledge fields to develop patented invention. This could be reflected when a patent document is assigned to several technological fields. Relying on the patterns of joint utilization of technological classes in patent documents we study relational properties of knowledge components to measure knowledge complementarity and similarity.

6. On Complementary and Similar Technologies

We consider a general measure of weighted average relatedness $WAR_k$ of technology $k$ with respect to all other technologies within the firm to compute weighted average complementarity and similarity. Relying on Teece et al. (1994), the weighted average relatedness $WAR_k$ of technology $k$ is defined as the degree to which technology $k$ is related to all other technologies $l \neq k$ present within the firm, weighted by patent count $P_{lit}$:

$$WAR_{kit} = \frac{\sum_{l \neq k} \tau_{kl} \cdot P_{lit}}{\sum_{l \neq k} P_{lit}}$$  (7)

Replacing complementarity (similarity) to $\tau_{kl}$ index, yields the weighted average complementarity (similarity) of technology $k$ with respect to any given technologies randomly chosen within the firm.

The $WAR_{kit}$ measure assume that firm’s technological base form a network in which all technological fields are fully connected together. Therefore, all $D(D - 1)/2$ pairs of technologies are included in the computation. Although this assumption seems straightforward to identify similarity in the combinational patterns of technologies, it over-estimates knowledge complementarity,
because firms do not use effectively all possible combinations between technologies in their innovative activities. To reduce the noise in the data, first we exclude the technologies from the firm’s technological portfolio that had less that 5 patents over past five years. Second we use an alternative measure to compute the level of technological complementarity of of a firms. Following Breschi et al. (2003) and Teece et al. (1994) we include only the (m - 1) strongest links that are needed to create a connected graph that comprises all firm technologies. This captures the strongest associations across technical areas k and l and is equivalent to depicting the maximum spanning tree from graph. Then, we measure $WAC'_{kit}$ index as an alternative measure of average complementarity that includes only the strongest links between technologies within the firm.

Consequently, firm’s knowledge complementarity and similarity are defined as the weighted average of the $WAC_{kit}$ measures and $WAS_{kit}$ respectively:

$$\Lambda_{it} = \sum_l WAC_{kit}$$  \hspace{1cm} (8)

$$\Gamma_{it} = \sum_l WAS_{kit}$$  \hspace{1cm} (9)

The analytical framework to measure similarity and complementarity is similar to Breschi, et al. Breschi et al. (2003) and departs from the square symmetrical matrix obtained as follows. Let the technological universe consist of a total of $N$ patent applications. Let $p_{nk} = 1$ if patent $n$ is assigned to technology $k$, $k = \{1, \ldots, K\}$, 0 otherwise. The total number of patents assigned to technology $k$ is thus $f_k = \sum_n p_{nk}$. Now let $p_{nl} = 1$ if patent $n$ is assigned to technology $l$, 0 otherwise. Again, the total number of patents assigned to technology $l$ is $f_l = \sum_n p_{nl}$. Since two technologies may co-occur within the same patent document, then $f_k \cap f_l \neq \emptyset$ and thus the number $f_{kl}$ of observed joint occurrences of technologies $k$ and $l$ is $f_{kl} = \sum_n p_{nk}p_{nl}$. Applying the latter to all possible pairs, we then produce the square matrix $\Omega(K \times K)$ whose generic cell is the observed number of joint occurrences $f_{kl}$. This count of joint occurrences is used to construct our measure of knowledge complementarity $\Lambda$ and knowledge similarity $\Gamma$. 
6.1. Measuring Knowledge Complementarity

One can consider the number $f_{kl}$ of patents assigned to both technologies $k$ and $l$ as a hypergeometric random variable. The probability of drawing $f$ patents with both technologies $k$ and $l$ follows the hypergeometric density function (Population $N$, special members $f_k$, and sample size $f_l$):

$$P(f_{kl} = f) = \frac{{(f_k)}{f_{l}}{N-f_k}{N-f_l}}{N}$$

where $f$ is the hypergeometric random variable. Its expected frequency is:

$$\hat{f}_{kl} = E(f_{kl} = f) = \frac{f_k \cdot f_l}{N}$$

If the actual number $f_{kl}$ of co-occurrences observed between two technologies $k$ and $l$ greatly exceeds the expected frequency $\hat{f}_{kl}$ of random technological co-occurrence ($f_{kl} > \hat{f}_{kl}$), then the joint utilization of two technologies is not random; there must be a strong, non-casual complementarity between the two technology classes. Inversely, when $f_{kl} < \hat{f}_{kl}$, then technologies $k$ and $l$ do not seem to provide complementary services. Hence, a preliminary parametric-based measure of complementarity $\lambda_{Pkl}$ is $\lambda_{Pkl} = f_{kl} - \hat{f}_{kl}$. This expression may further be designed to control for the variance of the sample at use. Assuming a hypergeometric distribution, the variance of complementarity measure is:

$$\sigma^2_{kl} = \hat{f}_{kl} \cdot \left(\frac{N-f_k}{N}\right) \cdot \left(\frac{N-f_l}{N-1}\right)$$

Thus:

$$\lambda_{kl} = \frac{f_{kl} - \hat{f}_{kl}}{\sigma_{kl}}$$

Since complementarity, $\lambda_{kl}$, is a real number that can be either positive or negative, we bounded this measure by normalizing its absolute value to represent the intensity of complementarity between each pair of technologies and to make it coherent to similarity index (see equation 14).
6.2. Measuring Knowledge Similarity

Two technological fields are considered similar when they are indifferently used with the same set of other technologies. The similarity among two or more technologies is due to their profile likeness in their productive applications. The cosine index is a commonly used measure of similarity. Using the co-occurrence matrix, we assume that if technologies \( i \) and \( j \) are frequently found to be jointly related to other classes, and those classes are the same for both \( i \) and \( j \), then \( i \) and \( j \) are said to be similar, because they are used for the same purpose and have similar applications. The cosine index is then defined as:

\[
\gamma_{ld} = \frac{\sum_{k=1}^{n} f_{lk} f_{dk}}{\sqrt{\sum_{k=1}^{n} f_{lk}^2} \sqrt{\sum_{k=1}^{n} f_{dk}^2}}
\]

The more technologies \( l \) and \( k \) co-occur with the same technologies, the higher the level of similarity.

7. Data

We construct a data set that includes 104 worlds largest manufacturing firms using Fortune magazine, August 1998, that revealed the most patenting activities. Since these firms are at the forefront of performance, knowledge assets and productivity gain are essential elements to sustain their competitive position. We use archival sources to provide data on knowledge assets and financial variables at need. The measures of knowledge base are constructed using the US Patent and Trademark Office (USPTO) data provided by the National Bureau of Economic Research (Hall et al. 2001). This data source tracks over 3 millions patents granted since 1963, recording information on the company name and the date and technological field of patent grants. However, USPTO determines technology class of an invention based on the primary classification within the US.
Patent Classification System and therefore reports a unique code for technological information contained therein. But, the primary listed classes are not necessarily representative of all underlying technological fields of patent (Benner and Waldfogel 2008). To overcome this issue, we complete our data set by assigning all US patent documents to the International Patent Classification (IPC) codes as displayed on the Internet Web Site of the European Patent Office. The IPC represents the whole body of technical knowledge which may be regarded as proper to the field of patents for invention, divided into different hierarchical levels. This enables us to link technologies with one another based on their joint contributions to the inventive activities. We choose to use IPC at the three-digit level, leading to a technological space of 120 technologies.

Another issue is to capture patents assigned to all units and divisions in a corporate structure to provide an appropriate measure of firm technological capabilities. As assignees may be mentioned under different names or the names of subsidiaries, division or acquired units, we construct a patent portfolio for each parent company that also include patents assigned to all subsidiaries, using Directory of Corporate Affiliations, 2000 edition and controls for consolidation.

Financial data are derived from Compustat database which includes accounting and financial measures of a firms activities. We use firm sales are used as a proxy for output \( (Q) \), number of employees to proxy labour \((L)\), raw materials to measure intermediate materials \((M)\) and gross value of property plant and equipment to describe firm capital \((C)\). We also include the newness of capital \((NC/C)\) to control for embodied technical progress. All financial data were then deflated into 1996 US dollars using the Implicit Price Deflator provided by the U.S. Department of Commerce, Bureau of Economic Analysis. Summary statistics of the final sample are presented in Table 1.

8. Results
8.1. Preliminary results

To test the contributions of firm knowledge characteristics, we set up a model using production function framework that includes parameters determining the effects of each characteristic on productivity. For the sake of simplicity, let us start by using the following approximation:
Table 1  Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Y*</td>
<td>1683</td>
<td>23946.96</td>
<td>26636.1</td>
<td>267.92</td>
<td>184214</td>
</tr>
<tr>
<td>Log L†</td>
<td>1683</td>
<td>110.10</td>
<td>109.65</td>
<td>1.43</td>
<td>876.8</td>
</tr>
<tr>
<td>Log K*</td>
<td>1683</td>
<td>18782.13</td>
<td>27673.39</td>
<td>72.16</td>
<td>320373</td>
</tr>
<tr>
<td>Log M*</td>
<td>1683</td>
<td>2719.30</td>
<td>2698.00</td>
<td>46.33</td>
<td>24530</td>
</tr>
<tr>
<td>E</td>
<td>1683</td>
<td>1703.65</td>
<td>1859.82</td>
<td>31.15</td>
<td>15686.79</td>
</tr>
<tr>
<td>D</td>
<td>1683</td>
<td>31.08</td>
<td>15.97</td>
<td>10</td>
<td>83</td>
</tr>
<tr>
<td>Λ</td>
<td>1683</td>
<td>.27</td>
<td>.063</td>
<td>0</td>
<td>.61</td>
</tr>
<tr>
<td>Γ</td>
<td>1683</td>
<td>.46</td>
<td>.07</td>
<td>.31</td>
<td>.74</td>
</tr>
</tbody>
</table>

* in millions of dollars
† in millions

\[ K \cong E \cdot D \cdot \Lambda \cdot \Gamma \]  

or in the log form:

\[ q_{it} = a + \sigma \cdot c_{it} + \alpha \cdot l_{it} + \rho \cdot m_{it} + \sum_k (\theta_k \cdot k_{it}) + u_{it} \]  

where \( k = \{ e, d, \bar{\lambda}, \bar{\gamma} \} \) and \( \sigma, \alpha \) and \( \theta_k \) are the parameters of interest.

Eq.(17) can be estimated using ordinary least squares. The error term \( u_{it} \) is decomposed into \( \eta_i, \tau_t \) and \( \varepsilon_{it} \), where \( \eta_i \sim \text{IID}(0, \sigma^2_\eta) \) is a 1×1 scalar constant capturing persistent but unobserved individual heterogeneity across firms such as managerial capabilities, firm propensity to collaborate, the type of economic environment, etc., \( \tau_t \sim \text{IID}(0, \sigma^2_\tau) \) is a 1×1 scalar constant representing the time fixed effect which would capture positive or negative trends common to all corporations and \( \varepsilon_{it} \sim \text{IID}(0, \sigma^2_\varepsilon) \) is the individual disturbance.

Several econometric specifications have been used to test the hypotheses and Table 2 reports the main results. The first four columns represent the results in a static setting where the dependent variable is the level of production. We use Least Square Dummy Variable (LSDV) specification and the model produces significant estimates for most explanatory variables. Not surprisingly, the effects of all production factors are significant and positive suggesting that large companies enjoy productivity gains related to increases in their scale of operations. The effects related to firm’s knowledge characteristics are all significant. The results confirm the works of Griliches and show
that knowledge capital contributes positively to firm productivity. However, the negative sign for
the parameter of knowledge diversity suggests that diversified knowledge bases influence negatively
firm productivity. This negative impact could be the results of agency and coordination costs of
managing and organizing knowledge dispersed in diverse fields of knowledge and provide support
for efficiency advantages of specialization. The estimated parameter of knowledge complementarity
indicates a positive contribution of this variable to productivity and provides strong support for
the Hypothesis 1. However, the results do not confirm a significant relationship between similarity
and productivity. We know that similar knowledge components are redundant inputs with less
heterogenous applications. Because they provide imperfect substitutes, they can be applied as
options in the case of technical change. The empirical findings could not provide evidence for the
role of similarity in productivity and the negative effects expected by hypothesis 3. Columns 3 and 4
test the robustness of these preliminary findings exploring alternative measure for complementarity
taking into account only the strongest complementarity across technical areas using \( WAC' \). We
find consistent estimated parameters as previous models. In sum, the results in the static setting
support the first hypothesis but do not provide strong evidence to confirm Hypothesis 3.

Columns 4 to 8 of Table 2 test the impact of knowledge characteristics in a dynamic setting,
taking productivity growth as dependent variable. Column 5 shows the result including only com-
plementarity in the model. Consistent with literature, we find a negative sign for the lag of variable
Y, because as time goes by, the correlation of productivity growth rates and the initial produc-
tivity levels becomes more negative. The existence of \( \beta \) convergence would mean that firms with
lower level of productivity at time \( t \) have increased their productivity at higher rates than those
companies which started their productivity at higher levels. The positive parameter found for past
productivity growth indicates the adjustment cost term associated with investment growth.

Almost all knowledge base properties prove to be important for productivity improvement. Inter-
estingly, knowledge capital does not contribute to productivity growth, because having simply a
great level of knowledge stock is not sufficient to improve learning and production dynamics. This
result is somehow in the line with the literature such as Griliches and Mairesse (1984) and Knott
et al. (2003) who failure to find the significance of knowledge asset stocks on future outputs and mobility deterrence respectively. Moreover, the results suggest a positive effect for knowledge diversity to productivity growth. This indicates that holding knowledge in diverse domains is beneficial for learning and technical change. We also find a positive effect for complementarity which provides support for the Hypothesis 3. However, taking the $WAC'$ index to measure complementarity do not confirm this argument, because the positive coefficient of this variable is not significant. One explanation is that $WAC'$ represents only the strongest interactions and does not reveal all potential complementarity across knowledge elements. Moreover, the estimations show that similarity contributes positively to the productivity growth supporting the Hypothesis 4. Firms that hold knowledge in similar domains are more likely to have higher rates of productivity growth, because they have access to more alternative knowledge components that enable them to change their existing production plan and improve the existing standards.
Table 2  Linear regression estimations

<table>
<thead>
<tr>
<th>Variables</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>
</tr>
</thead>
<tbody>
<tr>
<td>Log L</td>
<td>0.384*** 0.024</td>
<td>0.384*** 0.024</td>
<td>0.377*** 0.023</td>
<td>0.375*** 0.024</td>
<td>0.094*** 0.024</td>
<td>0.095*** 0.024</td>
<td>0.088*** 0.024</td>
<td>0.091*** 0.024</td>
</tr>
<tr>
<td>Log K</td>
<td>0.265*** 0.020</td>
<td>0.265*** 0.020</td>
<td>0.282*** 0.020</td>
<td>0.282*** 0.020</td>
<td>-0.006 0.020</td>
<td>-0.005 0.020</td>
<td>-0.000 0.021</td>
<td>-0.001 0.020</td>
</tr>
<tr>
<td>Log M</td>
<td>0.233*** 0.016</td>
<td>0.233*** 0.016</td>
<td>0.218*** 0.016</td>
<td>0.217*** 0.016</td>
<td>-0.009 0.016</td>
<td>-0.011 0.016</td>
<td>-0.012 0.016</td>
<td>-0.014 0.016</td>
</tr>
<tr>
<td>E</td>
<td>0.290*** 0.016</td>
<td>0.295*** 0.016</td>
<td>0.168*** 0.016</td>
<td>0.169*** 0.017</td>
<td>0.006 0.016</td>
<td>0.005 0.016</td>
<td>-0.003 0.016</td>
<td>-0.001 0.016</td>
</tr>
<tr>
<td>D</td>
<td>-0.027 0.019</td>
<td>-0.028 0.020</td>
<td>-0.024 0.019</td>
<td>-0.024 0.020</td>
<td>0.036** 0.018</td>
<td>0.042** 0.018</td>
<td>0.036** 0.018</td>
<td>0.044** 0.018</td>
</tr>
<tr>
<td>Λ</td>
<td>0.531*** 0.118</td>
<td>0.507*** 0.127</td>
<td>0.133 0.262</td>
<td>0.284 0.246</td>
<td>0.407* 0.241</td>
<td>0.613*** 0.073</td>
<td>0.018 0.074</td>
<td></td>
</tr>
<tr>
<td>Γ</td>
<td>0.453*** 0.076</td>
<td>0.435*** 0.077</td>
<td>0.048 0.073</td>
<td>0.018 0.074</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Log Y_{0−1}</td>
<td>0.133*** 0.027</td>
<td>0.133*** 0.027</td>
<td>0.136*** 0.027</td>
<td>0.134*** 0.027</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Y_0</td>
<td>-0.171*** 0.025</td>
<td>-0.171*** 0.025</td>
<td>-0.165*** 0.025</td>
<td>-0.167*** 0.025</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>2.530*** 0.135</td>
<td>2.463*** 0.188</td>
<td>3.247*** 0.166</td>
<td>3.073*** 0.223</td>
<td>1.076*** 0.126</td>
<td>0.864*** 0.177</td>
<td>1.215*** 0.173</td>
<td>0.829*** 0.224</td>
</tr>
<tr>
<td>Observations</td>
<td>1,683 1,683</td>
<td>1,683 1,683</td>
<td>1,683 1,683</td>
<td>1,683 1,683</td>
<td>1,621 1,621</td>
<td>1,621 1,621</td>
<td>1,621 1,621</td>
<td>1,621 1,621</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.877 0.123</td>
<td>0.877 0.123</td>
<td>0.878 0.123</td>
<td>0.879 0.123</td>
<td>0.172 0.123</td>
<td>0.174 0.123</td>
<td>0.166 0.123</td>
<td>0.170 0.123</td>
</tr>
<tr>
<td>Number of firm</td>
<td>104 104</td>
<td>104 104</td>
<td>104 104</td>
<td>104 104</td>
<td>101 101</td>
<td>101 101</td>
<td>101 101</td>
<td>101 101</td>
</tr>
</tbody>
</table>

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1
All equations include a full set of year dummies.

8.2. The Non-Linear Specification

The preliminary results are based on the assumption of a linear specification of knowledge base characteristics and simplify the specification to \( K \equiv E \cdot D \cdot \Lambda \cdot \Gamma \). However, as represented in Eq.(3), the original model proposes a non-linear relationship and assumes \( K \equiv E \cdot \left[ 1 + (D - 1) \cdot \Lambda \cdot \left( 1 - \Gamma \right) \right] \). Including Eq.(3) in production function yields:
\[ Q_{it} = A \cdot C_{it}^\sigma \cdot L_{it}^\alpha \cdot M_{it}^\rho \]
\[ \times \left( E_{it}^{\omega_E} + \left[ 1 + (D' - 1)_{it}^{\omega_D'} \left( I_{it}^{\omega_I} + [(1 - \Gamma) \Lambda]^{\omega_L}_{it} \right) \right] \right) \delta \ e^{(u_{it})} \]

where the parameters \( \omega_E, \omega_D', \omega_L \) and \( \omega_I \) represent the weights associated with respectively knowledge capital, knowledge diversity, knowledge complementarity and knowledge similarity, whereas \( \delta \) represents the overall effect of firm knowledge base on firm productivity. In the log form, Eq.(18) becomes:

\[ q_{it} = a + \sigma \times c_{it} + \alpha \times l_{it} + \rho \times m_{it} \]
\[ + \delta \times \ln \left( E_{it}^{\omega_E} \left[ 1 + (D' - 1)_{it}^{\omega_D'} \left( I_{it}^{\omega_I} + [(1 - \Gamma) \Lambda]^{\omega_L}_{it} \right) \right] \right) \]
\[ + \eta \times A_{it} + u_{it} \]

Taking the same specification to represent knowledge characteristics, the dynamic model in the log form becomes:

\[ \Delta q_{it+1} = a + \beta \times q_{it} + \phi \times \Delta q_{it+1} + \sigma \times c_{it} + \alpha \times l_{it} + \rho \times m_{it} \]
\[ + \delta \times \ln \left( E_{it}^{\omega_E} \left[ 1 + (D' - 1)_{it}^{\omega_D'} \left( I_{it}^{\omega_I} + [(1 - \Gamma) \Lambda]^{\omega_L}_{it} \right) \right] \right) \]
\[ + \eta \times A_{it} + u_{it} \]

In both static and dynamic settings, all variables are expressed as deviations from firm means to eliminate the unobservable heterogeneity across firms. All variable of knowledge are positive so \( \log \left( K \equiv E \cdot [1 + (D - 1) \cdot \Lambda \cdot (1 - \Gamma) + \Gamma] \right) \) cannot have a negative value which enable us to estimate the model.

Table 3 displays the results for both static and dynamic approaches. The results remain globally consistent with the previous remarks. The estimations for complementarity and for similarity in static and dynamic settings remain quite stable across the specifications and confirm Hypotheses 1, 3 and 4. We still could not find significant evidence for the negative role of similarity to the level of productivity, so that hypothesis 3 is not supported by the estimations.
Table 3  Non-linear Least Square Model

<table>
<thead>
<tr>
<th>Variables</th>
<th>(9)</th>
<th>(10)</th>
<th>(11)</th>
<th>(12)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log L</td>
<td>0.400***</td>
<td>0.398***</td>
<td>0.074***</td>
<td>0.073***</td>
</tr>
<tr>
<td></td>
<td>[0.020]</td>
<td>[0.020]</td>
<td>[0.019]</td>
<td>[0.019]</td>
</tr>
<tr>
<td>Log K</td>
<td>0.372***</td>
<td>0.378***</td>
<td>0.003</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>[0.019]</td>
<td>[0.018]</td>
<td>[0.018]</td>
<td>[0.018]</td>
</tr>
<tr>
<td>Log M</td>
<td>0.185***</td>
<td>0.169***</td>
<td>-0.018</td>
<td>-0.019</td>
</tr>
<tr>
<td></td>
<td>[0.016]</td>
<td>[0.016]</td>
<td>[0.014]</td>
<td>[0.014]</td>
</tr>
<tr>
<td>E</td>
<td>0.258***</td>
<td>0.138***</td>
<td>-0.0855</td>
<td>-0.115</td>
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<tr>
<td></td>
<td>[0.0633]</td>
<td>[0.00345]</td>
<td>[0.0543]</td>
<td>[0.0692]</td>
</tr>
<tr>
<td>D</td>
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<td>-0.0142</td>
<td>0.078**</td>
<td>0.095**</td>
</tr>
<tr>
<td></td>
<td>0.0198</td>
<td>0.0137</td>
<td>[0.0134]</td>
<td>[0.0466]</td>
</tr>
<tr>
<td>Λ</td>
<td>0.575***</td>
<td></td>
<td></td>
<td>0.475**</td>
</tr>
<tr>
<td></td>
<td>[0.144]</td>
<td></td>
<td></td>
<td>[0.202]</td>
</tr>
<tr>
<td>Γ</td>
<td>0.188</td>
<td>0.171</td>
<td>0.532***</td>
<td>0.826***</td>
</tr>
<tr>
<td></td>
<td>[0.160]</td>
<td>[0.117]</td>
<td>[0.199]</td>
<td>[0.195]</td>
</tr>
<tr>
<td>Λ</td>
<td>0.705***</td>
<td></td>
<td></td>
<td>0.194</td>
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<tr>
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<td>[0.105]</td>
<td></td>
<td></td>
<td>[0.209]</td>
</tr>
<tr>
<td>δ</td>
<td>3.091***</td>
<td>4.049***</td>
<td>1.908***</td>
<td>1.573***</td>
</tr>
<tr>
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<td>[0.709]</td>
<td>[0.724]</td>
<td>[0.618]</td>
<td>[0.606]</td>
</tr>
<tr>
<td>∆ Log Y_{t-1}</td>
<td>0.145***</td>
<td></td>
<td>0.147***</td>
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<tr>
<td></td>
<td>[0.025]</td>
<td></td>
<td>[0.026]</td>
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</tr>
<tr>
<td>Log Y_{t}</td>
<td>-0.144***</td>
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<td>-0.145***</td>
<td></td>
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<tr>
<td></td>
<td>[0.022]</td>
<td></td>
<td>[0.022]</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
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<td>-3.331***</td>
<td>1.621**</td>
<td>2.251***</td>
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<tr>
<td></td>
<td>[0.884]</td>
<td>[0.794]</td>
<td>[0.753]</td>
<td>[0.682]</td>
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<td>Observations</td>
<td>1.621</td>
<td>1.621</td>
<td>1.621</td>
<td>1.621</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.829</td>
<td>0.833</td>
<td>0.109</td>
<td>0.107</td>
</tr>
</tbody>
</table>

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1
All equations include a full set of year dummies.

8.3. Quantile regression model and further investigation

Previous results indicate how on average, knowledge base properties explain productivity of a firm. In other words, conventional least squares regression models estimate conditional mean of dependent variable given explanatory variables. This method summarizes the estimations only for
a representative point of dependent variable. Therefore, the outliers in productivity distribution may be discarded in the estimations. However, the outliers are the firms that have shown a high-level of productivity growth and they are at the center of our study. The normality test confirms that the distribution of productivity growth shows a positive skewed distribution in our sample. Therefore, studying how knowledge base properties boost the firm productivity calls for a technique that acknowledges the entire observations along distribution and allows for firm heterogeneity in productivity gains.

We use a quantile regression model to study how the estimated parameters of explanatory variables change at different quantiles of the productivity growth rate. To control for firm and year fixed effects, we generate a transformed dataset of the variables to convert the data so that results are equivalent to a panel data set form. Table (4) display the results.

The quantile regression results confirm that the OLS model does not reveal a complete picture of the story. It is clear that the coefficients of knowledge similarity and complementarity vary over the productivity growth distribution. We find that the estimated parameter of complementarity is greater and more significant at the higher quantiles. At the 95% quantile, for example, the coefficient of knowledge complementarity on productivity growth is 0.403 and larger than at median. This result indicates that higher levels of productivity growth are more affected by complementarity than the lower levels.

However, the coefficient on similarity is significant only at the 5% quantile. The evidence here suggests therefore that similarity makes contribution only at short term and provides superior performance only for marginal productivity growth. Ethiraj and Levinthal (2004) acknowledge this process of substitution as intelligent recombination in design contexts to improve incremental performance of a system. Our results are also in line with the Makri et al. (2010) work that suggests knowledge similarities contribute to incremental renewal in innovation activities and complementarities facilitate discontinuous strategic transformations. \(^1\)

\(^1\) Makri et al. (2010) study knowledge relatedness across firms in M&A contexts. The authors define similar knowledge as identical specific area of knowledge and complementarity knowledge as different area.
Table 4: Quantile Regression Model

<table>
<thead>
<tr>
<th></th>
<th>$\theta_{.05}$</th>
<th>$\theta_{.1}$</th>
<th>$\theta_{.25}$</th>
<th>$\theta_{.5}$</th>
<th>$\theta_{.75}$</th>
<th>$\theta_{.90}$</th>
<th>$\theta_{.95}$</th>
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</thead>
<tbody>
<tr>
<td>Log $L$</td>
<td>0.060</td>
<td>0.082**</td>
<td>0.058*</td>
<td>0.056***</td>
<td>0.075***</td>
<td>0.071**</td>
<td>0.097**</td>
</tr>
<tr>
<td></td>
<td>[0.054]</td>
<td>[0.042]</td>
<td>[0.033]</td>
<td>[0.021]</td>
<td>[0.021]</td>
<td>[0.036]</td>
<td>[0.041]</td>
</tr>
<tr>
<td>Log $K$</td>
<td>-0.014</td>
<td>-0.011</td>
<td>0.021</td>
<td>0.019</td>
<td>-0.017</td>
<td>0.006</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>[0.051]</td>
<td>[0.036]</td>
<td>[0.023]</td>
<td>[0.020]</td>
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Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1
All equations include a full set of year dummies.

It seems that the benefits of similarity become exhausted sharply, because isolating the improvement of system only by using existing knowledge options locks the system and provides only minor change. Technological advances in production are more likely to achieve if the firm tries new poten-
tial complementarities that promotes the system to a higher order performance.

However, this interpretation is relevant if the firm’s knowledge base is not renewed by mastering new knowledge fields. To explore this question, we introduce a new variable in the models that accounts for technological entry. The variable *Time since DIV* denotes the time passes since new technology entry. We also include the interactions between this variable and complementarity and similarity to test how the contribution of these properties of knowledge changes if the firm’s knowledge base is isolate-i.e. firm does not acquire or develop knowledge in new technological components.

Table 5 shows the results. Model 6 displays the baseline results provided by linear regression specification. In column 13 and 14 we include the interactions of Λ and Γ with *Time since DIV* separately. We find that after technological entry the importance of complementarity does not change. Knowledge complementarity provides potential possibilities that generally are active drivers of productivity and efficiency improvement. However, a negative and significant effect for the interaction of similarity and the time after technological diversification. This results confirm again our previous findings that suggest the advantages of similar knowledge to support existing system does not last long. This argument is strongly confirmed when the interaction terms are included in the model in the same time (Comumn 15). Globally, our findings suggest that substituting certain knowledge elements to achieve technological progress will be exhausted eventually and the great productivity advance requires investments in potential yet available complementary technologies.
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Standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

All equations include a full set of year dummies.

9. Conclusion

This paper has provided a theoretical framework that decomposes knowledge asset characteristics to discern their rent-generating capacities. This generalized framework compiles knowledge assets
properties to show where knowledge values are born. We focused on knowledge stock, knowledge diversity, knowledge complementarity and knowledge similarity as four main elements to describe a firm’s knowledge assets. The empirical test of the model showed that knowledge stock and knowledge complementarity are the important contributors to the level of productivity. Obviously, firms seek for more certain outcomes in short term to make revenue. Therefore, they organize their productive activities relying on knowledge assets that have proved the strongest complementarities and positive returns. In long term, however, the firms may need to explore new configurations and search new alternatives to seize technological opportunities. Our findings showed that knowledge diversity, potential knowledge complementarity and knowledge similarity significantly support productivity growth. These elements provide important implications as potential sources to boost productivity. First, knowledge diversity reveals the breath of opportunity space. It implies the number of available opportunities for further development. Second, knowledge complementary describes the existence of potential synergetic benefits within this space. Complementarity therefore plays a central role in uncovering new productive system of integration within existing knowledge base. Third, knowledge similarity provides potentials for parallel search and alternative solutions that support the continuity and partial improvement of existing production system.

Moreover, we found that although incremental change results from substitution of similar knowledge boosts productivity, but it does not lead to important improvement. Such advance does not lead to major benefits because it supports the continuity of existing system of production. A firm can achieve greater productivity advantage if more thoroughly uses the opportunities provided by potential complementarities, because they break away existing (obsolete) procedures and suggest new patterns of interactions. Such future significant return can be reached by filtering high performing complementary knowledge components. Therefore, discovering and exploiting potential complementarity seem to be a firm-specific capability.

Our model provides important insights to the value assigned to each characteristic of knowledge assets. The study suggests interesting implications in R&D policy, knowledge resource allocation and social capital interactions. Complementarity between specialized knowledge requires specific
patterns of component linkages and coordination. When allocating the R&D budget, the complementarity of knowledge seems to burden higher investments, because it necessitates a coherent system of allocation that supports the complementary research projects at the same time (?). This is in line with the findings of (Siggelkow 2002) that shows the misperceptions of interactions between firm’s activities are more costly for complementary activities than for substitutive ones. However, similar knowledge projects could be developed in parallel, because they are not necessarily used at the same time. Firms master imperfect substitutes to hold a reserve stock of options in the case of change.

The distinction between static and dynamic settings provides interesting implications to understand which investments in knowledge projects should be pursued a priori and how optimal allocation of tasks should be organized. Depending on the dynamism of production plan, we may expect a predominant role for similarity or complementarity of knowledge for productivity. The results of our study draw managers’ attention to track the types of needed knowledge resource that support firm to achieve a balance to insure short-run return and future survival. Firms typically are committed to developing new knowledge components. They integrate them into existing knowledge organization, the relevance of which depends on their relative contributions to existing ones. This study enhances our understanding on optimal allocation of strategic resources and trade-offs among firm various objectives and economic incentives.

to balance search and stability.


References


Kim, Dong-Jae, Bruce Kogut. 1996. Technological platforms and diversification. *ORGANIZATION SCIENCE* 7(3) 283–301.


