THE ECONOMICS OF INNOVATION: THE ROLE OF ALLIANCE, ACQUISITION, AND OWNERSHIP

BY

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DISSERTATION

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~ To My Parents ~

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ABSTRACT

This dissertation examines the impact of outsourcing of external knowledge through strategic alliances and mergers and acquisitions (M&As) on the knowledge creation process of the firm. To contribute to the literature in corporate governance, the role of founding families who have both control and cash flow rights on the firms' innovation is also studied in separate chapter. While Chapter 1 gives a general introduction of the ideas and outcomes of the three studies, Chapter 2 focuses on the impact of strategic alliances on the knowledge creation process of the firms. The study distinguishes between depth and breadth of technological knowledge using the International Patent Classification (IPC) codes of the patents filed by US biotechnology firms. The finding suggests that the university-firms alliances increase the breadth and biotech-pharmaceutical alliances (or with other competitors biotech) increase the depth of knowledge. Exploring the M&A information of the same biotech firms, Chapter 3 investigates and extends the study of Chapter 2. The study analyzes the firms' choice of partners and the interplay between alliance or M&As that can influence the knowledge creation process, which is captured by a unique and large patent data. Both the studies fill the gap in the literature by distinguishing depth and breadth of knowledge and investigating the role of outsourcing knowledge through alliances and M&As. Chapter 4 presents the analysis of firm-level micro data from India. The firm performance and the role of founding families are documented by existing literature. This chapter fills up a gap in the finance and corporate governance literature by addressing the role of family owners, the large shareholders, on the innovation activities. The empirical results show that family ownership has positive

impact on the innovation activity, proxied by patent-to-R&D expenses. All the three studies take care of the potential endogeneity issues by suitable methodology and valid instruments. All the papers in this dissertation use rigorous econometric analysis to contribute to the understanding of the effect of inter-firm partnership and ownership rights on the innovation activities. The results presented in the relevant chapters challenge conventional thinking and highlight the importance of proper instruments and controls.

1

INTRODUCTION

Strategic alliances and mergers and acquisitions (M&A) are primarily known as the mechanism to enter into new markets, but in recent years the effectiveness in achieving successful innovation has become interesting area to economists and finance researchers to study the role of these inter-firm co-operations. The process of innovation, i.e. transferring technological ideas to commercialize products, creates new knowledge and enriches the knowledge stock of the firms. The new knowledge can evolve due to re-combination of existing knowledge of the firms or combination of firm's own knowledge stock with knowledge from external sources. In their influential study, Nonaka and Takeushi (1995) discussed the knowledge creation process of the firm. They argue that new knowledge is created by conversion and interaction between firms' tacit and explicit knowledge[1]. The seminal study of March (1991) and then Levinthal and March (1993) show that knowledge creation, in fact, involves exploration of tacit knowledge and exploitation of explicit knowledge. However, in most industries today, the technologies being used and being created involve technological expertise that covers a much broader range of discipline (Weitzman 1998). Thus, the types of technological knowledge required for a particular innovation can lie outside of a firm's main area of specialization. Knowledge spillovers from external sources, sometimes, play important role in this

[1] Tacit knowledge refers to the knowledge that is difficult to verbalize and transfer and it is only expressed through action-based skills, while explicit knowledge is the knowledge that can be easily codified and communicated.

context. But the main source of missing knowledge in the firm's knowledge stock is the inter-firm co-operation or collaboration. It facilitates the circulation of the tacit knowledge that largely remains embedded to the firm. Economists and strategy researchers employ the knowledge production function to find out how much new knowledge is generated which is again a function of the variety of the partners' contribution, given the firm has the required level of absorptive capacity. However, the question remains open whether the process of exploration and exploitation or simultaneously both (known as 'ambidexterity', Laursen & Salter 2006) can determine the knowledge creation. Moreover, the study of Laursen and Salter (2006) find that the diversity of knowledge generates new ideas, but it requires the expertise to turn those ideas into innovation. Moreover, often the incumbent firms fail to respond to the technological change due to their specialization in a particular area. Thus the exploration and exploration are largely studied in relation with innovation, not in connection with knowledge creation. So the question arises what kind of knowledge is developed when new ideas evolve unexpectedly from unexpected sources?

Although recent studies in finance and economics indicate that investigating the value creation by M&As has been a central issue of wide-ranging research (Andrade *et al.* 2001). Most of these studies argued that while acquiring firms get nothing or negative return, the target firms reap the harvest (Bruner 2002). However, M&A increases the managerial compensation (Firth 1991; Avery *et al.* 1998), if the corporate governance mechanism does not work properly. Shleifer and Vishney (1997) show that the dominant shareholders have greater incentive and resources to monitor the managers reducing some agency cost. Thus, apart from the knowledge creation perspective of the firms, it is interesting to investigate the role of the owners of firms on innovation activities. A number of studies also have looked into the impact of family ownership on the firm performance (Khanna & Palepu 2000; Faccio *et al.* 2001; Anderson & Reeb 2003; Villalonga & Amit 2009). These studies have mixed results, some studies find positive and some find negative impacts of family ownership on firm performance. However, statistics show that most of the firms around the world are family owned. So, the obvious question is why some firms remain family owned and controlled, if these firms cannot perform well? Scholars have shown that the new technological knowledge from R&D activities leads to superior firm performance through successful innovation (Kline & Rosenberg 1986). The question remains open what is the role of family ownership on innovation activities of the family owned firms?

In the three papers of this dissertation, I have tried to find out the solution of the questions that come into our mind from the literature of knowledge economics and economics of innovation. Interestingly, the findings have significant economic implications to explain the gap in the literature. Moreover, the findings contribute to fill up the gaps with rigorous methodology and unique datasets.

2

TECHNOLOGICAL DEPTH AND BREADTH OF KNOWLEDGE: THE ROLE OF STRATEGIC ALLIANCES

2.1. Introduction

The recombinant view of technology and innovation management theories (Schumpeter 1934; Henderson & Clark 1990) suggests that firms acquire and develop technological knowledge through combinations of new knowledge or unique combinations of existing knowledge. The previous knowledge stock of the firms determines the success of present technological innovation (Teece *et al.* 1997). Due to this path dependency, Hagedoorn (1993) argues that firms are often unable to produce new knowledge through their internal R&D investments only. To accumulate necessary knowledge, firms need external activities such as strategic alliance (Almeida *et al.* 2002), inventors mobility (Katz & Preez 2008), mergers and acquisitions (Hagedoorn & Duysters 2002), and joint ventures (Inkpen & Dinur 1998), which can be considered as direct sources and corporate venture capital investments (Schildt *et al.* 2005) and consulting the scientific publications (Murray & Stern 2007; Moodysson 2008) which can be considered as indirect sources of knowledge. The choice of any one or more than one of these strategies can have significant impact on the firms' technological knowledge[2] creation. Mody (1993) argues that mutual learning to increase technological knowledge can be a strong motive for

[2] There exist extensive studies on market knowledge and its role on firms' innovative performance (Rao *et al.* 2008; Zhou & Li 2012). In this paper I focus only technological knowledge.

strategic alliances. In this study, I investigate the impact of strategic alliances and scientific publications on the technological knowledge creation of the firm.

Strategic alliances help to acquire partner-specific relevant skills and provide the expertise to renew the firms' internal capabilities (Zahra & George 2002). Studies show that the diversity in alliance partners should enhance the capacity to develop new products and commercialize them (Fryxell 1990). This diversity can influence either the development of tacit knowledge (non-transferable) that increases generalized knowledge (Nonaka & Takeda 1995) or the explicit (transferable) knowledge that increases specialized knowledge (Grant 1996). But, these two perspectives may create conflicting strategic decision that requires further examination of the *"learning process"* of firms (Turner *et al.* 2002). In his influential study on the digital jet engine control system in UK, Prencipe (2000) theoretically shows that firms consider both specialized and generalized knowledge simultaneously. Recent works are also beginning to focus on the depth and breadth of knowledge and find that exploration intensity with depth and breath of firms' current knowledge stock can maximize the innovation performance (Quintana-Garcia & Benavides-Velasco 2008; Wu & Shanley 2009; Chiang & Hung 2010; Moorthy & Polley 2010; Zhang & Baden-Fuller 2010). Hence, the development of depth and breadth of firms' knowledge stock does not appear to be a prime candidate to explain the motive of strategic alliances, rather most of these studies have focused on the impact of depth and breadth of knowledge on the firm performance.

In addition, prior research on the nature of the firms' technological knowledge characteristics remains a subject of debate. For example, March (1991) argues that the potentiality to explore new technology requires variety in the technological knowledge stock of the firm, i.e. breadth. Other researchers posit that firms emphasize the specialization (depth) of technologies to gain economies of scale in knowledge activities (Arora & Gambardella 1994; Loasby 1998) and consider the benefits of diversification (breadth) for gaining economies of scope (Panzar & Willig 1981). Moreover, existing studies typically examine how firms develop the depth of technological knowledge from both inventors' social network and specialization of technology (Carnabuci & Bruggeman 2009) and how greater depth or breadth of technological knowledge leads to more innovation success (Miller 2006; Leiponen & Helfat 2010). In recent years, some studies demonstrate that disaggregating technological knowledge into depth and breadth dimensions how these two intangible assets improve firm performance and create shareholders' value (Grewal *et al.* 2008; Fang *et al.* 2011). So, the debate continues how to develop the depth and breadth or both simultaneously and whether this is at all important organization strategy. In sum, the contribution of strategic alliance partners to specific types of knowledge (i.e. depth and breadth) has not been studied extensively. Moreover, given that both types of knowledge appear important for the firm's long run health, understanding the role alliance partners play in their development is an issue deserving of scholarly attention.

In this paper, using a unique data set of 207 US biotechnology firms with their entire patent filing information, which is publicly accessible and codified knowledge, during the period of 1990-2006, I address the following research questions: To what extent the alliance choice influences the technological depth and breadth of knowledge? Are the types of partners important organizational choice? In addition to that I have also investigated, how does the scientific literature, source of fundamental research knowledge from universities and research institutions, affect the knowledge development process? Understanding these inter linkages is central for the technology-intensive firms to form alliances in present scenario. Thus, I extend the recombinant view mentioned above by characterizing the technology described in patents of the firm in terms of depth and breadth of technological knowledge of that firm. Drawing from the literature on technology management, I define depth as the degree of sophistication of knowledge in one specific domain and breadth as the variety of technologies over which a firm has demonstrated knowledge (Wang and von Tunzelmann 2000, Katila and Ahuja 2002). I have found that alliances with universities and research institutions developed breadth and alliances with firms, in similar or dissimilar industries, influence the depth of the firms. My findings also reveal that the knowledge absorption from public sources, e.g. scientific publications, impacts positively the depth of knowledge base of the firm.

The contributions of this paper are as follows. First, I place alliance choice in the context of knowledge creation at the firm level. Prior studies have not clearly distinguished between types of technological knowledge (e.g. depth and breadth) in examining inter-firm knowledge spillovers. To my knowledge this is the first attempt to look into the depth and breadth of technical knowledge that are developed through knowledge transfer in strategic alliance relationships. Specifically, I examine characteristics of strategic allies and alliance relationships that drive depth and breadth of knowledge creation, including the type of knowledge creation the partners are primarily involved in. Hence, my study supports the growing literature which argues that alliances and inventors' mobility and networking determine the degree of diversity of firms' knowledge stock (Rosenkopf & Almeida 2003; Nerkar & Paruchuri 2005; Katz & Preez 2008) and depth and breadth requires both external and internal knowledge sources (Zhou & Li 2012).

Second, I found that alliances with universities influence the breadth of technological knowledge of the firm. As such, this finding builds on recent research on university-industry partnership (e.g. George *et al.* 2002; Hall *et al.* 2003; Rothaermel & Thursby 2005).

Third, methodologically this study offers a unique measure of depth and breadth of technological knowledge using an algorithm and IPC (International Patent Classification) codes that represent the technology used for the inventions of the focal firms. To my best knowledge, this is the first measure that I have introduced in the literature of knowledge management.

2.2. Theoretical framework

In the technology-intensive industry, the first-mover advantage in inventions alone fails to succeed due to rapid technological change that provides the competitors with opportunities for new and improved design. So, one way for the success is to increase technological competences to a variety of technologies compared to those required by their core product lines (Brusoni *et al.* 2001). Scholars point out that the sophistication of a firm's knowledge base influences the degree of innovation novelty i.e. whether it is radical, such as, producing a new microchip, or incremental, such as changing the packaging (Henderson & Clark 1990; Freeman & Soete 1997; Tidd *et al.* 2000). However, whether it is radical or incremental innovation, to stimulate new inventions, firms depend on technological knowledge transfer (Coe & Helpman 1995). The voluntary exchange or involuntary flow of useful technological knowledge is referred to as the knowledge spillovers (de Bondt & Henriques 1995) that act as the "engine of endogenous economic growth" (Lucas 1988; Romer 1990; Grossman & Helpman 1995) by influencing innovative activities of the firm (Jaffe 1986; Levin & Reiss 1988). Evidently, the external knowledge source is as important as the firms' own knowledge base. Firms benefit from the knowledge spillovers if they have the ability to access and assimilate distinct knowledge (Cohen & Levinthal 1990).

Firms develop differentiated technology by general knowledge without a continual increase in the research resources (Branstetter 2001) and change the prices of factors significantly by specialized or sophisticated knowledge (Foray 2004). This continuous development and diversification of technological knowledge from internal and external sources constitute the lifeblood of high-technology firms. But, in the long run the technological race may result growing complexity of knowledge development process and the risk associated with R&D efforts. Establishing alliances at an exceptional rate provide a way to spread risks and technology development (Duysters & Hagedoorn 1996).

Strategic alliance is one of the mechanisms to acquire external knowledge (Inkpen 2000) for the production process, as knowledge is an important input for production (Nelson 1982). Although in an alliance, firm risks its own knowledge spillover, there also exists an opportunity to capitalize on spillovers of the partner's knowledge (Stuart & Podolny 1996; Gulati 1998; Baum *et al.* 2000; Inkpen 2000) and to gain access to other firms' capabilities (Mowery *et al.* 1998). Evidently, firms often choose strategic alliances that minimize the sum of production and transaction costs by acquiring the only essential knowledge and in which mutual learning exists as a result of *common benefit* (Khanna *et al.* 1998). So, the search for the external knowledge sources for unique information often leads to the decision to enter into a strategic collaboration.

There is a number of theoretical and empirical studies on the choice of alliance partners (Mowery *et al.* 1998; Osborn *et al.* 1998; Das & Teng 2000; Lin *et al.* 2007; Lin *et al.* 2009b; Mukherjee *et al.* 2012). However, the characteristics of alliance partners are considered as more important than the absolute number of alliances (Hagedoorn & Schakenraad 1994). Moreover, studies also indicate that the alliance portfolio of a firm depends on the types knowledge requirement (Teece 1988; Arora & Gambardella 1994). Based on the position of the partners in the industry value chain, there are three distinct choices of partners (Baum *et al.* 2000). *First*, the upstream alliances with universities and research institutes to acquire the basic and early stage research knowledge, *second*, the horizontal alliances generally with competitors are to combine resources and technologies and *third,* the downstream alliances with other industrial firms to access the manufacturing, regulatory and commercially feasible technologies (Rothaermel & Deeds 2006).

Given the different choices of alliances and diversity of partners, the very heart of the vast majority of innovation studies in economics and management literature is the question of how the attribute of the allied partner firms shape the flow of knowledge (Owen-Smith & Powell 2004). There are a number of factors (e.g. duration of the alliances, type of contracts, prior performance etc.) that a firm consider before enter into an alliance. However, mutual trust can strengthen and stabilize the alliance relationship (Morgan & Hunt 1994) that positively influence in new knowledge development.

2.2a. Knowledge creation through upstream alliances

Studies have recognized that academic research increases the productivity growth and stimulate greater private sector R&D through technology spillovers (Jaffe 1989; Adams 1990). Since the seminal works of Mansfield (1991, 1998) on the empirical evidence of university-industry linkage, a number of empirical studies have emerged on university patenting and technology transfer (e.g. Henderson *et al.* 1998; Siegel *et al.* 2003; Breschi *et al.* 2008; Crespi *et al.* 2011). Statistically, the number of US patents grated to university inventors have increased from 500 in 1982 to more than 3,100 in 1998 and the revenue of the universities from technology licensing has increased $186 million to about $1.3 billion in 1990s (Lach & Schankerman 2008). This study of Lach and Schankerman also show that research in the high-tech areas by universities is positively associated with the licensing performance. Evidently, firms in the high-tech industries often enter into upstream alliances with universities and research institutes to access to the fundamental research knowledge. There are several reasons for university-industry (firms) alliances, such as universities and research institutes often provide the solution to the fundamental scientific questions and practical implications for current commercial products (Stokes 1997), increase the ability of firms to explore new technology (Cohen *et al.* 2002) and provide critical external knowledge (Mowery & Shane 2002). In the same vein, Perkmann and Walsh (2007) argue that knowledge from universities has higher degree of novelty and helps developing radical innovation; firms often recognize universities as important source of new scientific knowledge. Moreover, firms obtain up-to-date information for the success of patent race and access to membership in the group of scientists from universities (Liebeskind *et al.* 1996). Hence, the university-firm *dyad* generates unique technological knowledge[3] and offers a competitive advantage to those firms having capability of absorbing fundamental discoveries (Bercovitz & Feldman 2007). However, the new technological knowledge from university is often ambiguous (Simonin 1999) and 'generic' in nature (Marsili 2002). This suggests the following hypothesis:

Hypothesis 1: *Upstream alliance with universities and research institutions is positively associated with the technological breadth of knowledge of the focal firm.*

2.2b. Knowledge creation through horizontal alliances

Product differentiation mitigates competition (Tirole 1988). Empirical studies on the health maintenance organizations by Dranove et al. (2003) and on the small motels by

[3] Although, both firm and university engage in explorative activities, they also need to find the way to exploit their technological capabilities and assets. Academic spin-offs originate when these exploitative activities leads to uncertainty (e.g. McEvily & Chakravarthy 2002; Prabhu *et al.* 2005).

Mazzeo (2002) show that the differentiation decreases the competitive effect in the local market. Interestingly, firms often enter alliances with the competitors to access to industrial technological knowledge and compensate its own technological knowledge required for the expansion of product heterogeneity. This acts as a device of minimizing competitive uncertainties. Thus, successful implementation of new technology to product and process often requires horizontal collaboration (Jorde & Teece 1990). Studying on alliance with direct rivals Dussauge et al. (2004) show that the degree of knowledge transfer depends on whether the alliance is to share similar resources or to share competencies. Thus, horizontal alliance largely based upon competitive aspect that emphasizes on faster acquisition of partner's knowledge and balancing learning from partner and protecting own knowledge from unintended leakage (Kale *et al.* 2000). Obviously, allying with competitors, firms often seek to limit knowledge flows and protect competencies (Narula & Santangelo 2009). This implies that, the horizontal alliance partners may be less interested in the longevity of alliance and more interested in what can be internalized. Teece et al. (1997) argue that the absorptive capability can help to exploit the diverse knowledge base to deal with the changing technology. So, the complimentary knowledge acquisition from competitors leads the firms to exploit its existing knowledge to invest in R&D activities. This suggests our next hypothesis:

Hypothesis 2: *Horizontal alliances with competitor firms positively related to the technological depth of the focal firms.*

2.2c. Knowledge creation through downstream alliances

Typical downstream alliances involve large incumbent firms (market oriented players) in similar or dissimilar industries, for example pharmaceutical firms for new biotechnology firms (Rothaermel & Deeds 2004; Rothaermel & Thursby 2005; Stuart *et al.* 2007) for the commercially feasible and marketable technology. The primary motive to form downstream alliances is not only to acquire knowledge capabilities from the partners, but also to access complementary capabilities required to finalize the development of new products and bring them to the market. At the downstream level, technological knowledge gets better understood in the process of commercialization. Teece (1992) showed that knowledge at the downstream is more explicit and codifiable than that of upstream. Thus, the commercialization and marketing activities leverage and combine partners' existing technological knowledge and capabilities through exchange of explicit knowledge (Rothaermel 2001). This suggests our next hypothesis

Hypothesis 3*: Downstream alliances positively impact the depth of technological knowledge of the focal firms.*

2.2d. Knowledge creation through public sources

Empirical studies confirm that the R&D laboratories with deep science-based capabilities and strong collaboration with universities help in innovations (Christensen 2002b). In addition to the choice of strategic partners for a direct source of knowledge spillovers, the basic science and fundamental technological knowledge are important determinants of innovation (Jaffe, 1989; Adams, 1990). Studies by Mansfield (1991), Salter and Martin

(2001) and Cohen et al. (2002) reveal that scientific knowledge spillovers from academic research (universities and public research institutions) significantly contribute to the industrial innovation. Arundel and Geuna (2004) also argue that public science is the most important source of technological knowledge. Moreover, science helps to enrich the existing technological knowledge base of the firm to increase productivity (Evenson & Kislev 1976) by minimizing the waste of valuable resources and the time lag between existing knowledge and new inventions for successful R&D. So, the transfer of knowledge from the area of science to the area of technologies[4] occurs quite often (Carlsson & Fridh 2002). Furthermore, patents built on fundamental knowledge are considered more original and they can impact positively on technological change. This is evident from the studies on university patenting ativities (Mowery *et al.* 2002; Owen-Smith & Powell 2003; Geuna & Nesta 2006; Breschi *et al.* 2008; Acosta *et al.* 2012).

A number of studies have looked into the frequency and nature of occurrence of science-technology interactions in new emerging technology domains (e.g. McMillan *et al.* 2000; Meyer 2000; Acosta & Coronado 2003). The involvement of universities and fundamental science in successful patents is also evident from studies on growing university spin-offs (Jensen & Thursby 2001; Litan *et al.* 2008), mobility of academic scientists (Kim *et al.* 2005) and increasing citations to scientific publication in patents (Hicks *et al.* 2001). Cohen and Levinthal (1990) argue that science improves the

[4] Science is the outcome of research conducted in non-industrial organizations and technology is the outcome of research in industrial organization (Clarysse *et al.* 2011). For this reason, most of the scientific articles are published by universities (as well as public research institutes) and most of the patents are filed by industries.

absorptive capacity for knowledge from basic research. Thus, by facilitating the absorption and understanding of fundamental knowledge, scientific knowledge increases productivity by allowing firms to exploit new discoveries and opportunities. This suggest the following hypothesis

Hypothesis 4: *The focal firm increases technological depth of knowledge when its innovation activities are associated with the fundamental scientific research from universities.*

2.3. Methodology

2.3a. Research settings and econometric specifications

In order to understand the impact of alliance choice on the firm's knowledge portfolio, I have taken biotechnology industry to construct a unique database for this study. Among several industries characterized by high alliance activity, biotech industry data shows highest alliance frequency (Hagedoorn 1993). In this sector, there exists a three-partner alliance chain, university – biotechnology firm – pharmaceutical firms (Stuart *et al.* 2007). I are defining the linkage between biotech firm and universities including research institutions as upstream alliance for fundamental research knowledge access, linkage between one biotech firm and other biotech firms as horizontal alliance for industrial research knowledge access and linkage between biotech firm and pharmaceutical firms as downstream alliance for applied research knowledge access.

The following econometric specification is used to estimate the coefficients of interest.

$$[1] \qquad K_{it} = \alpha_0 + \psi_1 X_{1it} + \sum_{i-1}^{3} \beta_i \gamma_{itk} + \psi_2 X_{2it} + \varepsilon_{it}$$

where, K_{it} refers to a 2×1 vector containing the dependent variables, technological depth or breadth of knowledge of firm *i* in year *t*, X_{1it} is the number of alliances when the focal firms are doing the R&D and get payments for the license. The knowledge sources are denoted by γ_{itk}, k is either the university, biotech firms or pharmaceutical firms[5]. X_{2it} is the vector of other exogenous control variables. ε_{it} is the idiosyncratic error term. Assuming the observations as being serially uncorrelated for a given firm, with homoscedastic errors across individual firms and year, I can estimate the equation (1) by OLS. The results are shown in Table 3.

However, in this analysis I confronted with some issues like whether there are easily observable characteristics of the biotechnology firms that are closely related to the alliance choice. The evidence of certain observable features of a firm are closely related to its decision to enter in alliances is all but easily documented. I can take care of all the factors that are coming out of the patent data and other financial characteristics. However, such factors do not include the role of unobserved features like superior management capability, internal culture of the firm or richness of the R&D in terms the background of the scientists. Moreover, the econometric model shown in equation (1) ignores the fact that the number of alliances by the focal firms may be endogenous with respect to the innovation activities. In that case, the error term in equation (1) would be correlated with the knowledge creation process of the firm. This may lead to non-zero expected value of

[5] Firms can enter multiple alliances with firms in different industries.

ε_{it} , even controlling for other factors as mentioned in *Appendix to Chapter 2*. Consequently, I may obtain biased estimation. For this endogeneity issue, 'two stage least square' 2SLS instrumental variable (IV) regression is applied using total number of number of alliances in the last 5 years (Z_{it}) as an instrument to get consistent estimates. In the first stage the fitted values (X_{it}^{*}) is obtained by regressing X_{1it} on the instrument Z_{it} as shown in equation (2) and in the second stage the instrumental variable estimator is obtained by regressing K_{it} on X_{it}^{*}.

$$[2] \qquad X_{1it} = \varphi_0 + \varphi_1 Z_{1it} + \sum_{i-1}^{3} \varphi_{ik}\gamma_{itk} + \varphi_2 X_{2it} + \vartheta_{it}$$

For the Hypothesis 4, I have included (θ) that represents citations to scientific research publication and rewrite the equation (1) as equation (3)

$$[3] \qquad K_{it} = \psi_0 + \psi_1 Z_{it} + \psi_2 \theta_{it} + \sum_{i-1}^{3} \beta_{ik}\gamma_{itk} + \psi_3 X_{2it} + \eta_{it}$$

I also estimate this equation by 2SLS. As all the independent variables are entered in a stepwise manner, I reported the robust standard errors to take care of heteroskedasticity in the data. Wherever applicable, I transformed variables into their natural log to improve the skewness and kurtosis of their distribution.

2.3b. The Dataset

To estimate the models, the first issue was to make a list of all US biotech firms that are engaged in the discovery of human therapeutics (*in-vivo* and *in-vitro*) during 1985 to

2006. This subfield continuously shifts its focus in targeting new technologies because of the complexity of *in-vivo* testing (Santoro & McGill 2005). So, there is a possibility to get better variations in the knowledge development of the firm than that of firms involved in human diagnostics. I have searched each of the firms' patent and product details from EPO (espacenet), Mergent Online, GEN Guides to Biotech Companies-1996 and found 395 biotech firms according to our criteria. The Recombinant Capital (Recap)[6] database provides with alliance subjects that help me to determine the area of the firms R&D[7]. The usefulness of the database has been validated by prior research (Shan *et al.* 1994; Lerner & Merges 1998; Lerner *et al.* 2003b). But, most of the firms' alliance[8] and financial details are not available. The next task was to get the details of the patent applications of these firms.

The use of patent data as an indicator of invention output has been criticized on many different grounds (see Griliches 1990). However, in the science and technology intensive industry, like biotechnology, patenting is often considered as a signal of invention activities and new product development. From this population, I constructed our sample to include every firm that filed for biotechnology patents in USPTO and EPO. So, for the patent data[9], I have used EPO worldwide statistical database (PATSTAT) created by

[6] A California-based biotechnology-consulting firm that incorporates detailed descriptions of alliances of the global biotech and pharmaceuticals industries since 1973. The database comprised of SEC (10-K, 10-Q, S-1 and 8-K) and FDA filings, press release, industry conferences and industry contacts as well as patent data. I am grateful to Mark Edwards, MD of Recap to give me the access to the database.
[7] Thanks to Frank T Rothaermel and Toby Stuart to clarify my concepts and doubts of the biotech firms in human therapeutics.
[8] I have excluded those firms having alliances less than 3 during the study period.
[9] There is no observation of university-owned patent in the sample.

European Patent Office (EPO)[10]. My focal year is the year when the firms filed for the patent rather than the year when it was granted, because the invention by the firm already has been realized when the firm files for a patent. For the citations to scientific references and speed of knowledge acquisition, I have used the database of Patent Board[11]. As it was hard to find any common identifier to match these datasets, I proceeded to do that manually by coding each of the firms with GVKEY (Standard & Poor's firm identifier) as I had to use Compustat for the financial data. I have eliminated those firms that have less than 3 patents and no alliance and financial records throughout the study period. I obtained the firm-level financial data from Standard & Poor's Compustat (Research Insights) for 1985-2006. This database provides information on all publicly traded North American firms that file 10-K forms with the Securities and Exchange Commission. The Primary Standard Industrial Classification (SIC) code reported on the Compustat represents the most important industry for each firm. In my sample the SIC codes are 2833-2836, 5122 and 8731.

For the respective alliance portfolio I have manually coded each of the firms' alliance details-whether the alliances are with university, biotechnology firms, pharmaceutical firms. To avoid any discrepancies, I have gone through each of the allying firms' website to check its type. According to transaction cost economics, licensing involves arm's length transactions and it is closest to the commercialization process, with bilateral agreements providing a higher degree of mutual control through mutual hostages (Williamson 1985;

[10] This raw database covers patent offices in more than 80 countries around the world and allows the analysis of longer time-series than is usually used in economic research.
[11] US based leading independent provider of best research tools and matrices for patent analysis and intellectual property investment. It also tracks and analyzes innovation and business value of patent assets across all industry on a global basis.

Oxley 1997). Moreover, in the innovation activities of biotechnology firms, licensing technology leads to development of therapeutic inventions. Thus, I restrict my analysis in the licensing agreements. A total of 207 firms survived after merging the dataset with Compustat for complete dataset in the analysis. Among them, there are 460 university alliances, 1053 pharmaceutical alliances and 1873 biotech alliances with 14,851 unique patents that the focal firms applied for during 1985-2006.

2.4. Measures[12]

2.4a. Dependent Variables

Technological depth and breadth of knowledge: I have taken two dimensions of the technological knowledge - depth and breadth of knowledge as our major dependent variables. Depth is the level of sophistication and breadth is the degree of heterogeneity. I have constructed the two dependent variables depth and breadth following Katila and Ahuja (2002). However, instead of considering the backward citations[13] of patents, I have taken the IPC codes that directly measures the combinations of technology used in the inventions.

To analyze the evolution of specialization of scientific field over time, I have chosen the first dependent variable as the depth of knowledge of the biotechnology firms. Depth of the knowledge also acts as a proxy for the firm's the ability of exploitation of knowledge. Following Katila and Ahuja (2002). I argue that the depth of knowledge on a particular technology increases as the firm uses the technology frequently.

[12] All the variables are defined and the data sources are mentioned in the *Appendix to Chapter 2*
[13] In case of breakthrough inventions do not depend on the prior arts, it may become impossible to capture the depth and breadth of knowledge by backward citations.

I construct technological *depth* of knowledge by counting the repetition of technologies (IPC codes) used in the focal patent, on average, in the patents the firm filed during the last 5 years[14], such that

$$Depth_{it} = \frac{\sum_{t=(n-5)}^{(n-1)} [R_{ipc}]_{it}}{[T_{ipc}]_{it}}$$

Where $[R_{ipc}]_{it}$ is the number of repetition of IPC codes and $[T_{ipc}]_{it}$ is the total number of IPC codes of the firm *i* in year *t*.

The technological *breadth* of knowledge is measured as the proportion of previously (in the last 5 years) unused technologies (IPC codes) in the firm's focal year of patents. We construct this as

$$Breadth_{it} = \frac{[U_{ipc}]_{it}}{[T_{ipc}]_{it}}$$

Where $[U_{ipc}]_{it}$ is the number of unused IPC codes and $[T_{ipc}]_{it}$ is the total number of IPC codes in the patents of the firm *i* in year *t*.

2.4b. Independent Variables

Upstream Alliance: Lerner (1994) argued that a strategic priority of a firm in the biotechnology industry is to innovate continuously to acquire and protect a competitive advantage. For this reason, the collaboration between university and industry is not new as both communities realized their mutual needs to achieve complex but varied goals. We

[14] Argote (1999) showed that in the high-technology industry, the firm's knowledge base depreciates sharply and within approximately five years it loses significant value. The choice of 5-year period for the relevant knowledge is also consistent with the studies of R&D depreciation (Griliches 1979; Griliches & Lichtenberg 1984).

use the proportion of the firms' alliances with universities and research institutions as a proxy for upstream alliance.

Horizontal Alliance: According to Hagedoorn (1993) and Kotabe and Swan (1995), the alliances with competitors determine the varying degrees of innovativeness. Teece (1992: 22) also concludes that: "To be successful, innovating organizations must form linkages, upstream and downstream, lateral and horizontal". Through the development of knowledge network, horizontal spillovers of knowledge broaden firm's learning capability and help to reduce competition by crystallizing market power (Burgers *et al.* 1993). So, to capture the effect of knowledge transfer from the competitors, I created the variable by computing the proportion of firms' alliances with biotechnology firms.

Downstream Alliance: The alliance with universities provides the firms with opportunities to improve the difficulties of successful commercialization (Peters *et al.* 1998). The proxy for downstream alliance indicates the proportion of the focal firms' alliances with pharmaceutical firms.

Science Link: Firms whose patents cite a large number of scientific papers (sometimes referred to as non-patent reference) can be assumed to be working closely with the latest scientific developments. Following previous literature, I used the total number of non-patent literature[15] (mostly scientific publications) normalized by sample standard deviation

[15] Studies argue that non-patent references are not perfect indicators of the direct application of science, as this is simply denoting a relationship between technology and science (Schmoch 1993; Meyer 2000).

as a proxy for the strength of the science link of the technological knowledge base of the firm (Narin *et al.* 1997; Meyer 2000).

2.4c. Control Variables

R&D intensity: According to Cohen and Levinthal (1990), R&D intensity is a function of prior knowledge of the firm and thus acts as a proxy for the absorptive capacity. I measured this as firm's reported spending on R&D per $1000 of assets. I have included this variable in the analysis by taking one-year lag. As R&D intensity can vary across different types of firms (large, small or entrepreneurial etc.). I have controlled for R&D expenses to capture the effect of investments as inputs supporting the knowledge creation process, not the invention itself.

Knowledge stock: The prior knowledge is important determinant for the knowledge creation process of the firm. Following the literature (Griliches & Lichtenberg 1984; Hall 1990; Bessen & Maskin 2009), the firm's knowledge stock (*kstock*) is calculated as

$$kstock_{it} = patstock_{it}(1-\delta) + npat_{it} \ldots\ldots\ldots (4)$$

Where, *patstock* is measured as dividing the number of patent (in each year of a firm) by 0.23 (15% depreciation + 8% growth backwards in time[16]). However, I have operationalized the variable by adding the last 4 years *knowledge stock* for each firm.

Alliance age: I used alliance age as the proxy of experience. This is calculated as the difference between the year of first successful alliance announcement and the last year of the dataset (2006). I have included this variable by taking natural logarithm of it. Older

[16] Assuming innovation grows at an annual rate of 8% (Hall 1990).

alliances tend to create inventions that are less important on subsequent technological development compared to new alliance.

Firm age: Firm age influence the rate of patent activities of the firms (Sorensen & Stuart 2000). I calculated the variable by subtracting the year of inception of the firm from year 2006, as my sample is from 1990-2006.

Propensity to patent: I define propensity to patent as the number of patents of the firms per worker. This is indicates the efficiency of the worker and their knowledge base and consequently it impacts on the depth and breadth of knowledge. As, this propensity varies across firms, we have included this variable as control.

Mergers and Acquisitions (M&As): Studies have showed that M&As influence knowledge transfer, absorb and creation (Cassiman *et al.* 2005; Saviotti *et al.* 2005; Bertrand & Zuniga 2006; Makri *et al.* 2010). So, in addition to the above control variables, I have also included the number of M&As in last two years of each firm.

2.5. Results

Table 1 shows the summary statistics of dependent and independent variables of the sample firms (definitions and data sources in Appendix). From this table I see that while the depth of knowledge varies from 0 to 39, breadth varies between 0 and 1. These two variables, however, are continuous. Figure 1 shows the trends of alliance and patenting activities. It seems that alliance is positively correlated with number of patents.

Figure 1. The alliances of biotechnology firms during 1990-2006 and the activities of patenting over time

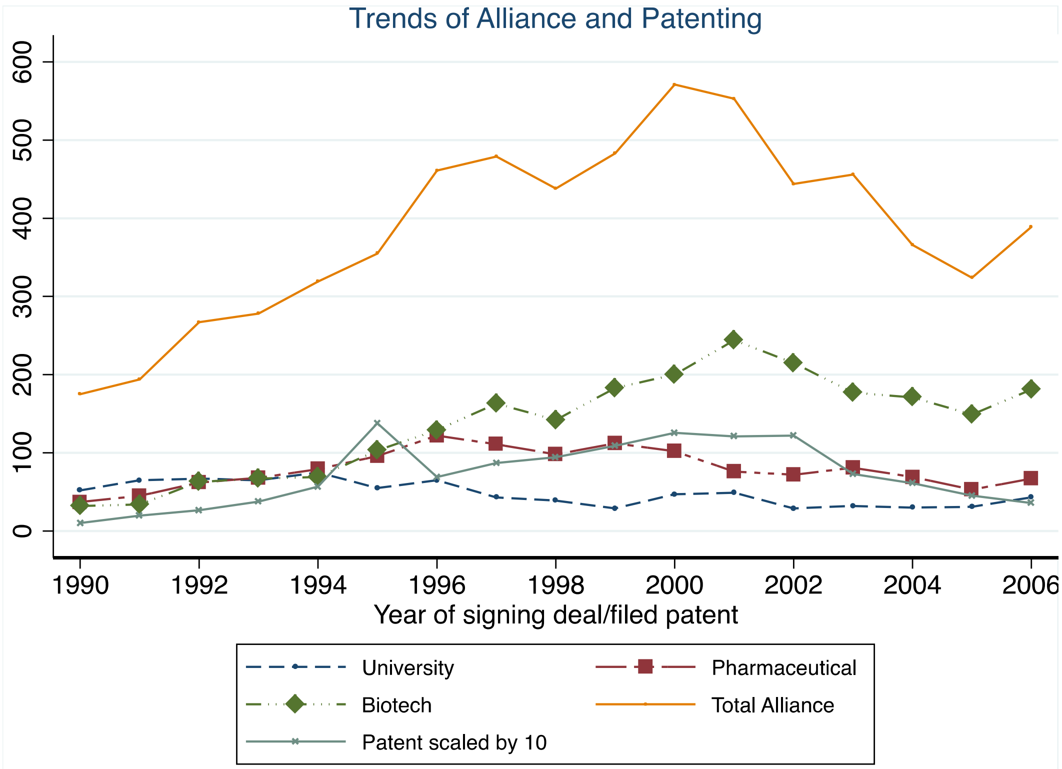

Table 1: Descriptive Statistics for the Variables

	Obs.	Mean	Std. Dev.	Min.	Max.
Depth	1822	6.44	1.58	0	39.11
Breadth	1822	0.49	0.33	0	1
Upstream alliance	1822	8.95	23.53	0	100
Downstream alliance	1822	21.73	34.93	0	100
Horizontal alliance	1822	30.90	40.18	0	100
Science links	1822	0.75	1.02	0	10.06
Alliance density	1060	0.04	0.10	0	1.50
Alliance age	1822	16.83	5.63	0	33
Firm age	1822	17.77	5.66	4	45
Patent propensity	1298	54.45	79.20	0	1000
R&D intensity	1413	0.40	0.61	0	15.79
Number of alliances	1822	1.86	2.83	0	23
Number of M&As	229	1.40	0.89	1	8
Knowledge stock	1771	134.25	306.99	1	4142.22

Notes: Science link is normalized by the sample standard deviations.

Table 2 reports the pairwise correlations of the variables in the analysis. The collinearity test suggests that none of the variables has variance inflation factor (VIF) more than 5. As there is no problematic multicollinearity, we pursued the data analysis for testing the hypotheses. From the correlation table, it is to be noted that the correlation between depth and breadth is low (r = 0.48) and negatively significant. This indicates that these variables are two distinct dimensions of technological knowledge of the firms.

Table 2. Pairwise Correlation matrix between the main variables

	1	2	3	4	5	6	7	8	9	10	11	12
Depth (1)	-											
Breadth (2)	-0.48***	-										
Upstream alliance (3)	-0.06*	0.07**	-									
Downstream alliance (4)	0.03**	-0.04	-0.10***	-								
Horizontal alliance (5)	0.17***	-0.08**	-0.13***	-0.21***	-							
Science link (6)	0.12***	-0.13***	-0.00	0.00	0.07**	-						
Alliance density (7)	0.02	0.03	0.04	-0.03	0.00	-0.04	-					
Alliance age (Log) (8)	0.16***	-0.14***	0.03	0.09***	0.18***	-0.07**	0.05	-				
Firm age (Log) (9)	0.10***	-0.10***	-0.01	0.04	0.13***	-0.15***	0.02	0.76***	-			
Patent propensity (Log) (10)	0.04	0.00	0.04	0.05	-0.13***	-0.02	-0.01	-0.19***	-0.15***	-		
R&D intensity (Log) (11)	-0.11***	0.07**	0.02	0.01	-0.15***	0.02	-0.03	-0.13***	-0.15***	0.29***	-	
Number of M&As (12)	0.03	0.01	0.01	-0.02	0.14*	-0.13	-0.04	0.27***	0.14*	-0.20**	-0.13*	-
Knowledge stock (13)	0.67***	-0.22***	-0.05	0.05*	0.24***	0.07**	0.01	0.25***	0.21***	0.01	-0.20***	0.11

Notes: * p<0.05, ** p<0.01, *** p<0.001

Hypothesis 1 states that the upstream alliance of the focal firm with universities and research institutions is positively related to the technological breadth of the focal firm. In Column 4 of Table 3 we present the coefficients of OLS estimates.

Table 3 Effect of alliances on the technological depth and breadth of knowledge

Dependent Variables	Depth			Breadth		
	(1)	(2)	(3)	(4)	(5)	(6)
Upstream alliance	-0.015***			0.001*		
	(0.004)			(0.000)		
Horizontal alliance		0.010*			-0.000	
		(0.004)			(0.000)	
Downstream alliance			-0.003			-0.000
			(0.003)			(0.000)
Science links	0.403*	0.378*	0.404*	-0.029*	-0.029*	-0.031*
	(0.185)	(0.177)	(0.185)	(0.012)	(0.012)	(0.012)
Alliance density	-0.401	-0.463	-0.522	0.151	0.163	0.160
	(0.988)	(0.921)	(0.974)	(0.098)	(0.094)	(0.098)
Alliance age	2.328*	2.353*	2.348*	-0.150*	-0.150*	-0.148*
	(0.944)	(0.940)	(0.957)	(0.064)	(0.066)	(0.065)
Firm age	-1.141	-1.162	-1.147	0.046	0.044	0.043
	(1.180)	(1.166)	(1.193)	(0.081)	(0.083)	(0.082)
Patent propensity $_{(t-1)}$	0.227	0.205	0.184	-0.014	-0.013	-0.011
	(0.126)	(0.122)	(0.122)	(0.011)	(0.011)	(0.011)
R&D intensity $_{(t-1)}$	-0.618*	-0.545*	-0.585*	0.013	0.011	0.013
	(0.275)	(0.255)	(0.265)	(0.015)	(0.015)	(0.015)
Number of M&As $_{(t-1)}$	0.668*	0.612*	0.650*	-0.035***	-0.034***	-0.036***
	(0.276)	(0.258)	(0.266)	(0.010)	(0.010)	(0.010)
Constant	-2.292	-2.839	-2.265	0.867***	0.901***	0.887***
	(2.441)	(2.427)	(2.409)	(0.138)	(0.138)	(0.137)
Observations	841	841	841	841	841	841
R-squared	0.121	0.104	0.094	0.081	0.059	0.069

Notes: Regressions are OLS, with robust standard errors in parentheses. Dependent variables are technological breadth and depth of knowledge. * p<0.05, ** p<0.01, *** p<0.001.

The effect of upstream alliance on breadth of knowledge is very small, but positive. Overall, the R^2 of the model is very low indicating that the model leaves a large fraction of variation in alliance patterns unexplained. However, as discussed earlier the estimates are biased. So, I have employed 2SLS IV regression and the results are reported in Table 4.

Table 4. Effect of alliances on the technological depth and breadth of knowledge

Dependent variables	Depth			Breadth		
	(1)	(2)	(3)	(4)	(5)	(6)
Upstream alliance	-0.500**			0.061**		
	(0.169)			(0.014)		
Horizontal alliance		0.263***			-0.006**	
		(0.067)			(0.022)	
Downstream alliance			-0.591			0.013
			(0.302)			(0.018)
Science links	0.204*	-0.436	-1.129	-0.022**	-0.008	0.008
	(0.431)	(0.380)	(1.016)	(0.015)	(0.015)	(0.027)
Alliance density	3.613	1.342	-0.083	0.025	0.075	0.107
	(4.018)	(2.509)	(8.247)	(0.120)	(0.098)	(0.200)
Alliance age	0.864**	0.734***	0.423	-0.129	-0.170*	-0.208
	(0.434)	(0.098)	(0.091)	(0.069)	(0.067)	(0.109)
Firm age	-0.654	-0.608	-0.004	0.052*	0.073**	0.104*
	(0.081)	(0.012)	(0.024)	(0.079)	(0.072)	(0.114)
Patent propensity $_{(t-1)}$	1.010*	1.346***	1.792	-0.040**	-0.047***	-0.057*
	(0.475)	(0.397)	(1.007)	(0.013)	(0.013)	(0.026)
R&D intensity $_{(t-1)}$	-0.616	0.430**	1.604**	0.021	-0.002	-0.028*
	(0.687)	(0.631)	(1.806)	(0.021)	(0.022)	(0.046)
Number of M&As $_{(t-1)}$	0.614	-0.319	-1.205	-0.029**	-0.008	0.011
	(0.667)	(0.585)	(1.384)	(0.016)	(0.017)	(0.035)
Constant	4.788	6.624**	7.780	0.711***	1.184***	0.424
	(0.219)	(0.195)	(0.389)	(0.166)	(0.168)	(0.377)
Observations	841	841	841	841	841	841
First stage regression						
R-sq of excl. instrument	0.041	0.045	0.029	0.056	0.045	0.289
Wald test of exog.	19.677	14.774	13.056	19.167	12.775	14.157
(p value)	(0.002)	(0.000)	(0.044)	(0.001)	(0.000)	(0.044)

Notes: Regressions are 2SLS, with robust standard errors in parentheses. Dependent variables are technological breadth and depth of knowledge. Number of alliances in the last 5 years (moving sum) is used as an instrument for the endogenous variable i.e. for proportion of alliances in each model. * p<0.05, ** p<0.01, *** p<0.001.

According to equation (2) and the results in Table 4, I find a clear support of the Hypothesis 1 that predicts that upstream alliance is positively associated with breadth of knowledge (in Column 4). In Column 2, I find that horizontal alliance with rival firms impact positively on the depth of knowledge of the focal firms. This supports the hypothesis 2. Moreover, Column 5 indicates that the coefficient of horizontal alliance variable has negative and statistically significant effect on depth of knowledge. This further strengthens that if the firms cannot increase its depth and breadth simultaneously, then decreasing depth may be because of increasing breadth.

To test the third hypotheses whether the downstream alliance with pharmaceutical firms can increase the technological depth, I estimated the model by focusing on the proportion of alliance with pharmaceutical firms. The result is shown in Column 2. The coefficient indicates that the alliances with pharmaceutical firms negatively related with the depth of knowledge, but the coefficient is not significant. Unlike the universities, partnership with pharmaceutical firms for marketing and commercialization knowledge may not influence the technological depth of the biotechnology firms.

In all the columns in Table 4, I have introduced a new variable science link that indicates the citations to scientific publications (non-patent references)[17]. In Column 1-3, we have tested the effect on depth and in the last 4-5 columns I tested the effect on breadth. This supports the Hypothesis 4 that predicts that the scientific publication positively associated with depth of knowledge. Interestingly, I have got only statistically significant coefficient when I consider the upstream alliance. This also suggests that as the firms increase their absorptive capacity by upstream alliance and simultaneously develop room for exploiting the existing technology. So, I confirm that consultation of scientific publications has significant impact on the knowledge development of the firm if the firm has required absorptive capability.

[17] The Durbin-Hausman-Wu test indicates that even if I include the interaction terms i.e. citations to scientific publication and proportion of upstream or downstream or horizontal alliances, I cannot reject the null hypothesis that the choice of alliances of the focal firms are exogenous. So, the choice of 2SLS estimations in this case also gives me consistent results.

In all the models, I have controlled for R&D intensity, alliance age, firms' past M&As, patent propensity and firm age. The alliance age shows positive effect on knowledge creation as new alliance has more impact on technological knowledge development. In addition to these results, I find strong positive impact of the propensity to patent on depth. These suggest that, as the innovation activities increases with respect to the workforce of the firms, the firms depth of knowledge grows. So, the firms specialize on particular technology with skilled workers. The results also show that, newer firms are more efficient in developing depth of knowledge than the older firms. Consistent with the literature that suggests new firms have more potentiality to use cutting-edge technology and bring new inventions than the older firms, our result also indicates that.

In sum, I have got support from the data for all the hypotheses derived from the existing literature, except hypothesis 3. The results are novel and important especially since other studies have not examined the relationship of two distinct dimensions of technological knowledge and alliance choice. After controlling the potential endogeneity, the results suggest that different alliance choice has different impact on the technological knowledge development process.

2.6. Robustness checks

We have performed several sensitivity tests for the robustness of the results. The results are reported in the Table 5. From the above section, it can be noted that the 2SLS estimates may not give consistent results because of the possibility of correlation between the error terms (ε_{it} and ϑ_{it}) in the equations (1) and (2). In other words, the 2SLS estimator is consistent if $Cov(Z, \varepsilon) = Cov(Z, \varepsilon | X_2) = 0$ of equation (1) and (2). However, as it was very hard to find good instruments, I tried to get consistent results with several variables as instruments. In the models in Table 4 we used the number of last 5 years alliances (moving sum). Although, the F-statistics in the first-stage (Stock *et al.* 2002) indicates that the estimator is reliable, but because of the weak instrument problem i.e. $Cov(X_1, \varepsilon)$ is very low or $\varphi \approx 0$, the 2SLS may be biased toward OLS estimate. Hahn and Hausman (2003) argue that Jackknife 2SLS estimator [18] $\overline{\beta_{Jack}} = \left(\overline{X'_{1Jack}}\ X_1\right)' (\overline{X'_{1Jack}}\ K)$ can give better results than 2SLS. Where $\overline{X_{Jack}}$ is the predicted value values of the endogenous variable, the number of alliance formation or the choice of alliance partners, obtained using jackknife to construct the identified instrument orthogonal to the error term in finite sample. In this way, the correlation between ε_{it} and ϑ_{it} becomes zero and eliminates bias.

[18] Limited information maximum likelihood (LIML) also useful provided the sample is small in size and there are many instruments. Angrist et al. (1999) point out that the Jackknife IV estimate has the desirable property of both LIML and 2SLS.

Table 5. Robustness Checks

Dependent variables	Depth			Breadth		
	(1)	(2)	(3)	(4)	(5)	(6)
Upstream alliance	-0.091***			0.012**		
	(0.027)			(0.002)		
Horizontal alliance		0.128***			-0.003*	
		(0.033)			(0.002)	
Downstream alliance			0.028**			-0.001
			(0.010)			(0.001)
Upstream alliance* Research-1 university	-0.101***			0.004**		
	(0.025)			(0.001)		
Science links	0.407*	0.841**	0.477**	-0.024*	-0.038**	-0.029**
	(0.190)	(0.286)	(0.176)	(0.011)	(0.013)	(0.011)
Alliance density	0.342*	0.592**	0.673*	-0.109	-0.394	-0.070
	(7.111)	(10.890)	(6.649)	(0.415)	(0.498)	(0.419)
Alliance age	0.933	-0.597	0.651	-0.133*	-0.097	-0.125
	(1.093)	(1.598)	(1.024)	(0.064)	(0.073)	(0.065)
Firm age	1.360	3.287	1.669	0.016	-0.033	0.004
	(1.191)	(1.762)	(1.116)	(0.070)	(0.081)	(0.070)
Patent propensity $_{(t-1)}$	0.452*	0.070	0.449*	-0.022	-0.011	-0.020
	(0.198)	(0.300)	(0.184)	(0.012)	(0.014)	(0.012)
R&D intensity $_{(t-1)}$	-0.875**	-1.229**	-0.913**	0.032	0.041	0.034
	(0.316)	(0.458)	(0.295)	(0.018)	(0.021)	(0.019)
Knowledge stock	0.031**	0.040*	0.027***	0.001*	-0.011**	-0.002*
	(0.167)	(0.286)	(0.198)	(0.067)	(0.598)	(0.652)
Number of M&As $_{(t-1)}$	0.601	1.239*	0.715*	-0.033	-0.052*	-0.040*
	(0.345)	(0.511)	(0.322)	(0.020)	(0.023)	(0.020)
Constant	-0.152	-0.502	-0.851	0.239*	0.621*	0.290*
	(0.697)	(0.671)	(0.254)	(0.103)	(0.271)	(0.213)
Observation	583	583	583	583	583	583
R-squared	0.688	0.385	0.465	0.294	0.132	0.286

Notes: In the estimation, a subsample is made by eliminating data for the years 1995, 2000-2002 from the full sample. Data shows that maximum number of patents was filed in these 4 years.
(1) Regressions are Jacknife instrumental variable, with standard errors in parentheses. Dependent variable is logarithm of technological breadth and depth of knowledge. Lagged number of alliances in the last 5 years is used as an instrument. * p<0.05, ** p<0.01, *** p<0.001.
(2) In addition, in all the models firms' previous knowledge stock and the states in which the firms are located are controlled, but not shown. Knowledge stock is calculated as $Knowledge\ stock_{it} = Patent\ stock_{it}(1-\delta) + npat_{it}$ Where, *patent stock* is measured as dividing the number of patent (firm-year) by 0.23 (15% depreciation + 8% growth backwards in time[19]). However, we have operationalized the variable by the last 4 years *knowledge stock* for each firm. We have also controlled the States (location in US) of the firms.

[19] Assuming innovation grows at an annual rate of 8% (Hall, 1990).

Thus, following the literature, I perform Jackknifed modification of 2SLS regression using the same instrument as before for all the models in Table 5. I estimate the models with different sample specifications and control variables. From the Figure 1, I see that the sample firms filed maximum number of patents during the year of 1995, 2000-2002. So, as I have aggregated the number of patents to calculate the depth and breadth, we dropped the data of these years and again. A number of studies show that industrial clusters are strongly linked with the innovation process (Antonelli 2000; Martin & Sunley 2003; Thompson 2006; Ozman 2008; Uyarra 2010), and from our data we see that the focal biotechnology firms are concentrated in few States in US like California, New Jersey, Washington etc. Thus, it makes sense to control these States. In addition to that, I also controlled the past knowledge stock of the focal firms. Here also we have found consistent results as before. In all the models I have controlled for R&D intensity, alliance age, firm age as before. Furthermore, following George et al. (2002), we have also included a dummy indicating 1 when the client university is one of the Research-1 Universities as classified by Carnegie Foundation (1994)[20]. I have included an interaction term of upstream alliance and Research-1 Universities to see if the positive impact of upstream alliance on breadth of knowledge is driven by this subset of alliances. But, I see no significant change in the previous results. In fact, unlike the 2SLS estimates, the jackknifed modification of 2SLS estimation shows a positive impact of downstream alliance on depth of knowledge (see Column 3). Overall, we conclude that my results are robust upon performing various robustness checks.

[20] These institutions offer a full range of baccalaureate programs, are committed to graduate education through the doctorate, and give high priority to research. They award 50 or more doctoral degrees1 each year. In addition, they receive annually $40 million or more in federal support: Source: *A Classification of Institutions of Higher Education,* 1994 edition (Carnegie Foundation, 1994, pp. xix-xxi).

2.7. Conclusion and economic implications

The aim of this paper is to reveal empirical evidence for the high-tech firms' knowledge creation process in course of their on-going invention activities. The paper describes the relation between (a) alliances and knowledge depth and breadth and (b) scientific reference citations and knowledge creation.

Motivated by the literature of economics in high-tech industry, I conceptualize that firms generally search for sources of dissimilar knowledge to develop the variation in the knowledge elements. As, alliances sometimes provide access to dissimilar technological knowledge (Rosenkopf & Almeida 2003) that takes some times to disseminate in the firms' knowledge base. The firms, then, learn to use this knowledge more efficiently and create excess resources. To explore these issues, I have calculated the depth and breadth of technological knowledge by the IPC codes of the patents of the firms. Further, I have categorized the types of alliances based on the allied firm's industry. The results show that university plays crucial roles in developing the breadth of knowledge while downstream alliances contribute to the exploitation of knowledge gained from fundamental research knowledge from universities. Moreover, I also find that the partnership with the rival firms enhances the depth of knowledge. This is consistent with the literature of high technology and alliance at the firm level. For instance, Mowery et al. (1996) found that alliance participants in the same SIC codes exhibited lower level of knowledge transfer (measured by changes in patent cross-citations rates) than noncompeting firms. So, this explains why the horizontal alliance does not contribute to the knowledge breadth. Although the previous literature focused on technological knowledge as a whole in this context, this paper distinguished the depth and breadth dimensions of knowledge to get evidence how knowledge is developed at the firm level. Since, it is very hard to capture the tacit part of the knowledge, I used alliance and patent data for the US biotechnology industry to analyses the hypotheses.

As, invention comes either from combining these technological components i.e. fundamental bits of knowledge (developed through broadening the knowledge base) in a novel manner (Nelson & Winter 1982a; Weitzman 1996), or through exploiting and reconfiguring existing combinations (Henderson & Clark 1990), the results clarifies the inter-relationships between strategic alliances and knowledge creation process. However my results show that the firms cannot manage all the information coming from different sources. In other words, because of the information overload, if the firm has both upstream and downstream alliances and upstream and horizontal alliances, the growth of knowledge depth and breadth of the firms becomes slower compared the case that firm has only one type of alliance at a time.

From the point of view of knowledge economics, the effect of basic research (although ambiguous) is important. As, different technologies have a potential to cross-fertilize each other (Granstrand 1998), after controlling for the Research-1 University (as per Carnegie Foundation) in the robustness checks, I also have found positive association of basic research from universities with breadth. However, establishing the causality that university research increases the firm's R&D (Jaffe 1989) and thereby knowledge depth is tricky, my results supports the hypotheses and not the *vice versa*, since I have taken care of endogeneity.

The paper has several limitations. First, I have measured technological depth and breadth from IPC codes, which gets changed over the long time. However, I have assumed that the IPC codes remain the same in the study period. I have tried to capture the effect of alliances on patenting activities and knowledge development of the 207 US biotechnology firms. Without understanding the fact that who is citing whose patents and where the scientific references are coming from (inside the firms or outside the firms), the prediction is not as strong as it should be. I have also not captured the effect of employee transfer form one firm to other. This might give us a better understanding of tacit knowledge flow that also contributes to the knowledge base of the firms. So, extending the datasets to other high-tech industries and collecting some additional information of knowledge spillovers may generalize the results. Clearly, the next step in this process is to investigate how alliances affect the knowledge creation process across the industries and across the countries. Understanding more about these issues may strengthen the findings of this paper.

3

TECHNOLOGICAL DEPTH AND BREADTH OF KNOWLEDGE THE ROLE OF MERGERS AND ACQUISITIONS

3.1. Introduction

Since the concept of Smith (1976) that workers can be differentiated in terms of their knowledge stock, the role of knowledge, as a product of past and as a driver of future technological change, has been at the center in the literature of the economics of innovation. Studies show that firms often consider strategic alliances (Baum *et al.* 2000; Rothaermel & Deeds 2006; Bercovitz & Feldman 2007; Lin *et al.* 2009b; Mukherjee *et al.* 2012) and mergers and acquisitions (M&As) (Ahuja & Katila 2001; de Man & Duysters 2005; Bertrand & Zuniga 2006; Reuer & Ragozzino 2008; Tsai & Wang 2008; Makri *et al.* 2010; Valentini 2012) to increase their technological diversity (Miller 2006) and innovation capabilities (Katz & Preez 2008; Chiang & Hung 2010). Pitts (1977) suggest that the internal growth and growth through acquisitions are equally attractive alternatives. Although, there is some evidences to the contrary (e.g. Ahuja & Katila 2001; Ranft & Lord 2002; Bertrand 2009), most of the acquiring firms achieve negative results such as decrease of firm performance, R&D capabilities, employment etc. after acquisition (e.g. Lehto & Bockerman 2008; Ornaghi 2009; Stiebale & Reize 2011).

Hence, there exist a long debate on the impact of M&A on the firms' innovation capabilities (Kogut 1989; Jensen 1993; Cassiman *et al.* 2005; Cloodt *et al.* 2006; Valentini 2011) and thereby on the knowledge integration (Leonard-Barton 1995) and production of the firms (Hagedoorn & Duysters 2002). Cassiman et al. (2005) argues that the existing studies have results with a very high variance indicating that the conclusion of these studies cannot be considered robust. In a recent study by Valentini (2012) attempt to reconcile the mixed results, but this study does not take into consideration the alliances and other integration strategies of the firms. Casal and Fontela (2007) argue that despite of the importance of critical knowledge and capabilities, the transfer of knowledge has received very little attention. Moreover, the type of the knowledge to be transferred (Bresman *et al.* 1999; Hagedoorn & Duysters 2002), and the process of knowledge integration (Haspeslagh & Jemison 1991; Larsson & Finkelstein 1999) are essential for the successful transfer of knowledge in M&As. In sum, the existing literature on knowledge diffusion and innovation and the empirical results are ambiguous in describing the knowledge creation mechanism through M&As. In this paper, I argue that the analysis of the breadth and depth of knowledge creation, two distinct horizontal and vertical dimensions of technological knowledge, can advance our understanding of the diffusion of the technological knowledge through M&As and their interdependence.

Recently, a number of studies emphasized on the technological depth and breadth of knowledge in relation with innovation activities (e.g. Prencipe 2000; Wang & Von Tunzelmann 2000; Katila & Ahuja 2002). Technological depth is referred to as the analytical sophistication or specialization of a subject which becomes complex because of the cognitive difficulty in expertise or competence, while technological breadth is the range of areas that have been investigated to develop a particular subject (Wang & Von Tunzelmann 2000). In other words, depth is the degree of sophistication embodied in knowledge components of an invention and breadth is the broader set of different components embodied in an invention. Thus, it also becomes important to have a proper "*measure*" of the depth and breadth of technological knowledge of the firms, particularly in technology-intensive industry.

Using a unique data on a sample of 214 biotechnology firms headquartered in US, I show how the acquiring firms develop the two distinct dimensions – depth and breadth of technological knowledge through M&As choosing their potential targets. Notably, I consider all the patents filed by these firms in US and other countries during 1984-2009 as products of inventions and measure the depth by the extent to which a patent draws upon a certain technology (identified by International Patent Classifications or IPC codes) more intensively than others and breadth[21] by the range of new technologies (IPC codes) included in patents. I aggregate the patent-year level data to firm-year level to obtain technological depth and breadth of the firms.

This paper contributes in several ways. First, there exist only a limited number of studies that focus on the direct consequences of M&As on firms' technological activities (e.g. Cassiman *et al.* 2005; Valentini 2012). As mentioned above, because of the

[21] I have found only a few patents without IPC codes and excluded them from the data. However their effect is negligible compared to the total patent numbers in my database. Sometimes the patent may not have main IPC codes as the invention cannot be fit into specified filed of IPC, but the patent has a set of secondary IPC codes.

conflicting results in the existing literature, it becomes difficult to understand the production of technological knowledge through M&As. Our paper provides additional insights into the role of M&A in creation of knowledge to fill up the gap in the emerging related literature (e.g. Henderson & Clark 1990; Laursen & Salter 2006; Katz & Preez 2008).

Second, most importantly, it advances our understanding of the inter-play between strategic alliances and M&As the type of partners, in creating breadth and depth of knowledge in technology-intensive firms. As such it transcends the limitation of viewing knowledge development is solely determined by strategic alliances. Because, recently M'Chirgui (2009) shows that strategic alliances influence the technological change.

Third, diversity in technological knowledge can stimulate different ideas (Laursen & Salter 2006), but if the firm lacks the expertise to resolve complex problems, these potential ideas fail (Katz & Preez 2008). Thus, separating the types of M&As based on industry, I find that related M&As (among similar industries) and unrelated M&As (among dissimilar industries) positively impact the creation of depth and breadth of knowledge respectively. This result serves as a useful perspective in M&A literature (e.g. Hagedoorn & Duysters 2002; Cloodt *et al.* 2006; Danzon *et al.* 2007; Desyllas & Hughes 2010).

Fourth, the paper contributes methodologically by developing a unique measure of the technological depth and breadth of knowledge from IPC codes. This differs from existing measures in the literature, which use backward patent citations (Katila & Ahuja 2002), in that it can better detect firms' depth and breadth of knowledge. As another methodological contribution, our econometric model addresses potential endogeneity issues in the strategic initiative decisions for knowledge development process of the focal firms.

3.2. Literature and hypotheses

The work of Theodore Levitt (1960) opened up a new avenue for many scholars by pointing out how an entire industry shakes out because of technological evolution. Among its findings, the most important and relevant concept is discontinuous technological change or breakthrough innovation that can force many firms today to think how to reconfigure their core technological knowledge, yet keeping their windows open for diverse external knowledge to sustain innovation. In other words, a balance between exploiting existing knowledge and exploring new knowledge are at the center of firms' innovation strategy (Lerner 1995; Gupta *et al.* 2006; Raisch *et al.* 2009; Hoang & Rothaermel 2010; Lavie *et al.* 2010; Al-Laham *et al.* 2011). The competitive advantage due to innovation of the firms depends on effective creation and leveraging of technological knowledge. Thus, the study of Levitt raises question in relation with technological knowledge production.

A technology can be defined as "a body of knowledge, tools, and techniques derived from both science and practical experience, that is used in development, design and application of product, processes, systems, and services" (Abetti 1989). The technological knowledge production can be explained with resource-based and knowledge-based views of the firms. The resource-based theory argues that it is the ability of firms that helps to acquire, transfer and integrate the external knowledge (from acquired firm in case of M&A) in to their own knowledge base for a competitive advantage (Barney 1996). On the other hand, the knowledge-based theory considers a firm as a source of different sets of knowledge (Lord & Ranft 2000). The unique knowledge stock of the firms and the way they integrate[22] and organized the knowledge give them a competitive advantage (Winter 1987). A large number of recent studies have argued that the knowledge-based theory is an extension of resource-based theory (Grant 1996; Malerba & Orsenigo 2000; DeCarolis 2002; Balogun & Jenkins 2003). This is because a firm can be considered as a heterogeneous entity loaded with the intangible resource i.e. knowledge (Hoskisson *et al.* 1999) which distinguish them in terms of their capabilities to focus on R&D (Rouse & Daellenbach 2002). However, the firms require dynamic capabilities to transfer, reconfigure and integrate internal, external and complementary knowledge (Teece *et al.* 1997). The dynamic capabilities, thus, allow the firm to respond to any challenges in the *Schumpeterian* competitive market. But the question remains open how the firms assimilate and integrate technological knowledge after acquiring it? The studies of Cohen and Levinthal (1989, 1990) contribute to the literature in this context. They argue that the R&D activities broaden the absorptive capacity, which is the assimilation of spillovers from external sources. This assimilation depends on three characteristics of the knowledge –complexity, proximity and maturity. The knowledge proximity depends on the firms' institutional belonging that helps the firms to absorb and assimilate the external knowledge regardless of its complexity.

[22] The synthesis of firm's specialized knowledge into situation-specific knowledge (Alavi & Tiwana 2002)

Hence, the study of Cohen and Levinthal (1989, 1990) argues that absorptive capacity is a *by-product* of R&D activities. A number of studies also show that investment in R&D increases the firms' ability to exploit external technological knowledge (Henderson & Clark 1990; Arora & Gambardella 1994; Henderson & Cockburn 1994). In fact, the firms can assimilate knowledge when the external knowledge matches with the firms' technological knowledge portfolio and transform it when the external knowledge does not fit with the existing knowledge structure, (Todorova & Durisin 2007). Recent study shows that the use of external knowledge in fact follow three steps –(a) *adoption* that is awareness that certain technological knowledge exists and acquisition of potentially valuable external knowledge by exploration, (b) *rooting* that is assimilation of valuable new knowledge through transformation (if required), and (c) *application* that is use of assimilated knowledge to create new technological knowledge and commercialize output through exploitation (Komoda 1986; Steensma 1996; Lane *et al.* 2006; Camison & Fores 2010).

A substantial body of literature has recognized the importance of external and complementary knowledge (Teece 1986; Cohen & Levinthal 1990; Antonelli 2000; Lissoni 2001; Laursen & Foss 2003; Bertrand & Zuniga 2006) acquired through strategic partnership, research joint ventures and M&As (Cohen & Levinthal 1990; Gomes-Casseres 1996; Adams & Marcu 2004). These studies show that inter-firm knowledge spillovers help in cross-fertilization of new ideas and create new technology. The need of external technological knowledge and complement to internal R&D triggered by speed of technological change often motivates firms to extend their resources through M&A

(Hagedoorn & Duysters 2002; Villalonga & McGahan 2005). In a study of 9000 deals between 1990 and 2000, Villalonga and McGahan (2005) find that the likelihood that a firm would choose acquisition over other forms of collaboration increases with the technological resources of the potential targets. Lerner *et al*. (2003b) show that firms can acquire the portfolio of patents of competitors by M&A. Moreover, studies have also found that firms often acquire alliance partners (Porrini 2004; Zollo & Reuer 2010). Hence, the strategic decision of M&A to acquire new technological knowledge and capabilities has become a well-institutionalized corporate phenomenon (Larsson *et al.* 1998; Uhlenbruck *et al.* 2006).

3.2a. Mergers and acquisitions (M&As) for knowledge production

Mergers take place when independent firms combine their resources and activities to form a new entity. In particular, in case of acquisition, one firm gets control of majority of the ownership of the acquired firm. The consequences could be two-fold in M&As. First, because of the high R&D budget in the post-M&A period, fundamental research projects get more attention and consequently the firms can increase their technological capabilities (de Man & Duysters 2005). Second, firms can do more R&D by getting scale and scope of economies than it could have done before acquisition (Cassiman *et al.* 2005). Some technological knowledge is tacit in nature and embedded in the organizational routines. In transferring this tacit knowledge, the licensing and contracting process play limited role (Mowery 1983). If the technological knowledge of the partner is very important and complimentary to the firms' existing knowledge stock for innovation, M&A becomes the best strategic choice. Additionally, if the patents of the firms have high commercial importance over a long time, the firms are more likely to acquire another firm (Higgins & Rodriguez 2006). This indicates a close link between technological knowledge development and M&A activities. Hence, acquiring the technologically rich targets provide the acquire an opportunity to expose to new and diverse knowledge (Hitt *et al.* 1996). The similarity between the technological knowledge of acquirer and targets facilitates the exchange, combine and exploit what is already known (Nonaka *et al.* 1996). On the other hand, acquiring complementary technological knowledge (which is dissimilar in nature) increases the integrating costs (Katila & Ahuja 2002) because of the complexity and challenges (Grant 1996). In sum, the knowledge development is largely affected by the similarity and complementarity of technological knowledge in M&As. Yet, the common knowledge stocks of both acquirer and acquired firms facilitate communication and integration between them, thereby expand the scope of exploitation when the technological knowledge is similar enough for learning and complementary enough to easily understand the uniqueness of the value. This suggests the following hypothesis:

Hypothesis 1. *Technology-based acquisitions positively affect the technological depth of the acquirer's knowledge.*

3.2b. Types of acquisition targets for knowledge integration

The types of target firms in M&A determine the new variation in R&D output of the acquirer. Ahuja and Katila (2001) argue that when large firm acquires small firms, the deal significantly increases the innovation activities of both firms. However, later studies find positive impact of technology-based M&As [23] on post-merger innovation, irrespective of the firm size (e.g. Cloodt *et al.* 2006). So, the question arises what factors determine the development of knowledge portfolio of the acquirer. Studies emphasize that the success in the post-M&A technological output depends on the strategic fit of the partners. For instance, technological-relatedness of the partners helps to integrate the technological knowledge of the R&D divisions of both firms (Hagedoorn & Duysters 2002; Cassiman *et al.* 2005; Cloodt *et al.* 2006). This is partly depends on the absorptive capacity of the acquirer (Cohen & Levinthal 1990), because through M&As the firm gains many knowledge components that may not be required for the firm's present or immediate future innovation projects. Controlling excess and variety of technologies is, thus, become more costly than accessing those. Loasby (1998) suggests that the firm can take advantage of only 'crucial and manageable' technologies for the innovation. Thus, the stronger the firms are in their R&D efforts, the better they can access to and exploit new complementary assets. In this way, the acquirer can only enrich its existing knowledge from target firms of R&D in related technology as the existing technological skills can leverage the absorptive capabilities with similar external knowledge. Moreover, the technology relatedness in M&As reduce the R&D efforts, shorten the time horizon of projects and more importantly, gives opportunity to emphasize on development over research (Cassiman *et al.* 2005). In addition to this, experience in similar technology domains likely to make the search process more predictable and more efficient (Lane & Lubatkin 1998). However, there exist an inverted U-shaped relationship between the technology relatedness and post-merger innovation performance in technology-intensive

[23] When the target firms provide the acquirer's with necessary recombination benefits to develop the knowledge base (Henderson & Cockburn 1996) and have granted patents (Katila & Ahuja 2002).

industry (Cloodt *et al.* 2006). Hence within limit, the technology similarity within the firms' technological knowledge domain lead to local search and exploitation of existing knowledge (Stuart & Podolny 1996). This suggests the second hypothesis:

Hypothesis 2: *Technology-based acquisitions of firms in related industries positively affect the depth of technological knowledge.*

Technological knowledge complementarities facilitate exploration through experimentation with new technologies (March 1991). The complementarity knowledge, which increases the marginal return of it when it is combined with the acquirer knowledge stock, diminishes the knowledge redundancy (unlike similarity of knowledge) and can contribute to the radically new invention (Fleming 2001). The complementary assets are not identical but they are independent and mutually supportive (Tanriverdi & Venkatraman 2005). So integrating the complementary knowledge, the acquirer can create additional, supper-additive [24] value synergies that are not captured by the technology relatedness. However, Katz and Shapiro (1985) show that firms that acquire other firms outside their core competencies find difficulty in adding value to their own R&D capabilities. Because, new knowledge from unrelated external knowledge base needs resource and longer time-span to develop the required technological know-how.

Generally, firms acquire complementary assets (e.g. regulatory knowledge, manufacturing and marketing capabilities) to increase *innovation*[25] capabilities through

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[24] See Milgrom and Roberts (1990, 1995)
[25] Defined as the commercialization of the invention.

bilateral dependence between R&D and downstream activities with market-oriented firms in vertical integration (Teece 1988, 1992). But horizontal acquisition with firms in the same industry, for instance competitors, provides complimentary technological knowledge to increase their R&D efforts (Capron 1999). The reason is the acquirer can spread its fixed costs over more R&D output to increase in scale of R&D investments (Bertrand & Zuniga 2006), although the decrease in technology competition by taking over competitors might reduce the incentive to innovate (Reinganum 1983). As in the case of taking over of competitors to gain the market power, neither a number of M&As are solely for knowledge acquisitions nor the technology-based acquisition give only the required knowledge. Thus, it is obvious that the acquirers get more knowledge from the targets than it actually requires. This suggests the next hypothesis:

Hypothesis 3: *Technology-based acquisitions of firms in unrelated industries positively affect the breadth of technological knowledge.*

3.2c. Pre-merger strategic alliances for knowledge production

A strategic alliance is a collaborative relationship among firms to integrate operational functions and share risks by working together to achieve collective advantage. It can be with universities and research institutions for scientific knowledge or with industrial partners for technological knowledge. In most of the strategic alliances[26], the established firms look for the external technological knowledge from the firms that specialize in certain inventions. The primary motivation is to mitigate the R&D costs by increasing the

[26] Strategic alliances covers both market entry and technology-related motives, for a review refer to Hagedoorn (1993). In the present context, I will consider only the latter case.

network returns to scale (Shapiro & Varian 1998) and cross licensing that gives access to multiple technologies (Grindley & Teece 1997). So, unlike M&As, strategic alliances provide the firms with only *required* and *relevant* technological knowledge from a particular technology specialized firm. In that way, firms can avoid information overload and minimize the cost for selecting wrong technologies for which it has no expertise. Clearly, in strategic alliances firms have two options – technology accession and technology acquisition. As knowledge accession (rather than acquisition) is the main advantage of strategic collaboration (Inkpen & Dinur 1998), the partnership helps to govern cooperative efforts in knowledge creation by exploiting technology (Hagedoorn 1993). This supports the recombinant view of the firm where the firm has good control of exploiting the existing knowledge. Moreover, firms in most alliances try to co-specialize in technology that brings skills and firm-specific resources. In other words, both the partners in strategic alliances focus their own technological knowledge that complements the knowledge of their partner (Zeng & Hennart 2002). Given this importance, studies have investigated the factors influencing strategic alliance choice (Hagedoorn 1993; Oxley 1999) and its effect on economic and innovative performance (Gomes-Casseres *et al.* 2006). But analysis of the effect of these collaborations on knowledge production remains a relatively under-explored area (Lin *et al.* 2009a; Yamakawa *et al.* 2011).

The invention is the process of combining knowledge components in a novel manner (Nelson & Winter 1982b; Henderson & Clark 1990). This invention depends on two types of knowledge – the *scientific knowledge* which is the core design ideas and the *technological knowledge* which is the way to integrate the knowledge components (Makri *et al.* 2010). In addition to technological knowledge search, firms also require the scientific knowledge because science helps to maintain absorptive capacity of the firm for external technological knowledge (Cockburn & Henderson 1998). Hence, the scientific knowledge provides the technique of exploring the technological knowledge.

3.2d. Collaborations with universities

Numerous studies point out that technology-intensive firms that maintain deep science-based capabilities and strong collaboration with universities, can develop radical innovation that combines significant technological novelty with fundamental research (Christensen 2002a; Bercovitz & Feldman 2007). The university scientists and their research activities are attractive for many firms in research-based industries, as new technological opportunities come with the fundamental research from the universities creating new competences (Poyago-Theotoky *et al.* 2002; Hall *et al.* 2003). Gomes-Casseres et al. (2006) point out that universities often provide the solution to the fundamental scientific questions and up-to-date information for patent races. So, as the on-going innovation requires synthesis of distinct streams of technology (Argyres 1996), the university-firm partnership has the potential to increase the diversity of new knowledge. Moreover, requirement of scientific knowledge leads to exploratory learning (Miner *et al.* 2001). This suggest the following hypothesis:

Hypothesis 4. *The acquirer enters into alliance with university and research institutions to develop breadth of technological knowledge.*

3.2e. Collaborations with industrial partners

In the strategic alliances, the trust building between the industrial partners (particularly between competitors) is essential for knowledge sharing. Moreover, to get the tacit knowledge, it is essential to have a long-term and stable[27] relationship between partners (von Hippel 1998). Prior studies suggest that firm reduces information asymmetry about the target's assets and true value by forming alliances with the target (Porrini 2004). In fact, minimization of information asymmetries in pre-merger alliance increases efficiency of M&A to outsource external knowledge, even if it is tacit in nature (Higgins & Rodriguez 2006). In many cases, it has been found that a series of strategic alliances between partners increases the probability that one partner would acquire other (Vanhaverbeke *et al.* 2002). Thus, repeating contract with the same alliance partners or expanding a prior relationship and thereby focusing on a particular technological area similar to that of firms' present project can increase the depth of both partners. So, strategic alliances may be considered as intermediate step to reach towards the M&A process (Hagedoorn & Sadowski 1999). Moreover, alliance with rival firms[28] in the same industry often compensate the firms' own technology leading to increasing depth of knowledge. This suggests the following hypothesis:

Hypothesis 5: *Strategic alliances with target competitors positively affect the depth of technological knowledge of the acquirer.*

[27] Accessing and acquiring the other firms' capabilities (ability to produce components according to the required specifications) in unfavorable conditions may sometimes lead the high-technology firms to join alliances and eventually the partnership becomes unstable (Lerner *et al.* 2003a).

[28] Firms may find little incentive to share valuable technological knowledge with rival or potential rival firms by strategic alliances. So, in horizontal alliances, knowledge leakage is one of the important concerns of the firm. Sometimes the partners co-specialize their technological knowledge.

3.3. The model

I develop a flexible model describing the production of technological knowledge, which allows us to estimate the spillovers effect from different external sources when a firm enters strategic alliances and technology-based M&As. I have assumed that the information flows from partners are utilized for the innovation activities and consequently the development of the firms' depth and breadth of knowledge.

To test the hypotheses, I use the following knowledge production model

$$[1] \qquad KNW_{it} = \beta_1 KNW_{i(t-1)} + \beta_2^{ex} X_{i\tau}^{ex} + \beta_3^{en} X_{it}^{en} + \lambda_i + \phi_t + \varepsilon_{it}$$

$$i = 1, 2, \dots N\ firms\ and\ \ t = 1, 2, \dots T\ years$$

Where, KNW_{it} is the depth or breadth for the firm i in year *t*, $X_{i\tau}^{ex}$ are potentially predetermined but not strictly exogenous firm level controls, $\tau = t\ or\ (t-1)$ and X_{it}^{en} are endogenous firm level time-variant main explanatory variables of interest. Since the production of knowledge is a continuous process, the outsourcing of the knowledge by strategic alliances and technology-based M&A depends on the previous years knowledge base, $KNW_{i\,(t-1)}$. This lagged dependent variable captures the dynamic adjustment of knowledge production. λ_i are the measure of time-invariant variables affecting depth and breadth utilized in the innovation activities. ϕ_t are the time-varying shocks. β_1, $\beta_2^{ex}$and β_3^{en} are the parameters to be estimated, where β_3^{en} determines the effect of alliances and M&A and β_2^{ex} determines the impact of firm level controls.

Equation (1) is an auto-regressive-distributed lag model of the form ADL (1,1), p=q=1. ε_{it} is the stochastic error assumed to be distributed independently across the firms and years. I assume ϕ_t equals to zero without loss of generality (Rouvinen 2002).

3.4. Data and variables[29]

3.4a. The dataset

I have found 385 publicly traded biotechnology firms headquarter in US by looking at the patents description from the Patent Board[30]. In particular, these firms are involved in human therapeutics (*in-vivo* or *in-vitro*) discoveries during 1984 to 2009. With some exception of these firms' year of foundation, almost all the firms were founded in between these years. So, I get all the patents[31] of these firms applied to USPTO or EPO[32]. In fact, these patents are first applications in either of the patent offices. I considered the date of patent filing to the patent office to capture the immediate effect of the invention. From PATSTAT[33] (April 2010), I extracted the primary as well as secondary IPC codes of each patent. I discarded those patents that do not have any IPC codes.

I obtained all the alliance data of these firms from Recombinant Capital[34]. This data is based on two crucial criteria: firstly the alliance involves cross licensing and, secondly, it involves R&D and co-development agreements. Due to these restrictions the number of firms with the alliance information shrinks to 214. I retrieve the financial data of these 214 firms from Compustat North America (Standard & Poor's Research Insight). Finally, for all these firms, I retrieve all announcements of completed acquisitions from Thomson Reuter's Security Data Corporation (SDC). The acquisitions meet the criteria that (i) they

[29] All the variables are defined along with the data sources in *Appendix to Chapter 3*
[30] US-based leading independent provider of best research tools and matrices for patent analysis and intellectual property investment
[31] I have checked fro the Patent Board that there are no patents application filed in 2010 by these firms.
[32] United States Patent and Trademark Office (USPTO); European Patent Office (EPO)
[33] EPO worldwide Patent Statistical database created by European Patent Office covers patent office of more than 80 countries.
[34] A California-based biotechnology consulting company that incorporates detailed description of alliances of the global biotech and pharmaceuticals industries since 1973. The database is based on SEC (10-K, 10-Q, S-1 and 8-K) and FDA filings, press release, industry conferences.

are announced between 1989 and 2009 and completed no later than at the end of 2009, (ii) the deal value is equal or greater than US$ 1 million, and (iii) that the acquirer purchases more than 50% of the target. The SDC database also provides us with the four digit North American Standard Industrial Classification (SIC) codes of the acquirers and the targets.

I aggregated all the data to the firm-year level and obtained an unbalanced panel of 214 firms from 1989-2009, resulting in 4494 firms-year observations for the analysis.

3.4b. Variables

Dependent variables

I use patent data[35] to identify the information of the types of technology used for a particular invention, because patents are one of the most prominent vehicles to diffuse and appropriate knowledge. I constructed the two dependent variables, depth and breadth of knowledge, following Katila and Ahuja (2002). Their study is exceptionally noteworthy in measuring the depth and breadth. They measured the technological search depth and breadth (scope) with the backward patent citations data. However, when the firm develops a breakthrough invention, by nature of the invention and the patent, it may not have any citations to prior arts (backward citations). Therefore, instead of considering backward citations[36] of patents, as done by Katila and Ahuja (2002), I have taken the IPC codes that directly measure the combinations of technology used in the inventions. Also, unlike Lerner (1994), who used 4-digit IPC codes for the study of patent scope in

[35] For the importance and applicability of patent data for inventions see Griliches (1990) survey

[36] In case of breakthrough inventions that do not depend on the prior arts, it may become impossible to capture the depth and breadth of knowledge by backward citations.

biotechnology industry, I used 8 digit IPC codes, as two IPC codes can differ at many levels.

I construct technological depth of knowledge by counting the repetition of technologies (IPC codes) used in the focal patent, on average, in the patents the firm filed during the last 5 years, such that

$$Depth_{it} = \frac{\sum_{n=(t-5)}^{(t-1)} [NRepeated_{ipc}]_{in}}{[Total_{ipc}]_{it}}$$

Where $[NRepeated_{ipc}]_{it}$ is the number of repetitions of IPC codes and $[Total_{ipc}]_{it}$ is the total number of IPC codes of the firm *i* in year *t*.

The breadth is measured as the proportion of new IPC codes, which did not appear in the previously 5 years of the firm's focal year of patents. We construct this as

$$Breadth_{it} = \frac{[New_{ipc}]_{it}}{[Total_{ipc}]_{it}}$$

Where $[New_{ipc}]_{it}$ is the number of new IPC codes that do not appear in the last 5 years patents of the firm and $[Total_{ipc}]_{it}$ is the total number of IPC codes in the patents of the firm *i* in year *t*.

Explanatory variables

The first part of the explanatory variables is related to *technology-based M&As*. This variable consists of several parts. The sample firms may act as acquirer or they may be acquired by some other firms. In the high-tech industry, such as biotechnology, the purpose of the acquirer is to get the R&D effort of the targets to fulfill its future plan of discoveries and breakthrough inventions. So, I have taken those cases when the sample firms are the acquirer. To capture the effect of the acquisition, we constructed the variable by last 5-year moving sum[37] of number of acquisitions. To distinguish the effect of M&As further, we separated acquisitions in two types. Following Higgins and Rodriguez (2006), I considered *unrelated acquisitions* for target firms engaged in over-the-counter or generic drugs, consumer products, medical devices and products and manufacturing facilities. The *related acquisitions* are those when the target firms belong to SIC 2833-2836 and engaged in only biopharmaceutical activities. I have used two interaction variables to capture the effect of prior alliances with *universities* and *competitors*.

I have used firm-specific control variables that might impact the knowledge stock of the firm. Scherer (1965) found that patenting is an increasing function of *firm size*. Larger firms often have multiple projects running simultaneously and can thus potentially exploit external knowledge better[38] (Schmidt 2010). I therefore control for the firm size by logarithm of number of employees. The skills and expertise of the workers affect the knowledge development process. Thus, we control for the number of patents per workers (*Propensity to patent*). Hall *et al*. (2005) argue that the heterogeneity across the biotech firms are due to differences in R&D spending. I have included the *logarithm of R&D expenses*. The financial condition of the firms affects the innovation activities. For this reason, I have controlled for the *leverage*, measured by the ratio of debt to equity. As the economic conditions may change over time that affects the innovation activities, we also have included fixed effects for each year.

[37] Higgins and Rodriguez (2006) find out that acquirers improve their innovation activities significantly in the first year of post-merger.
[38] Smaller firms can take more risks than larger firms. Besides they are flexible to the change of technological environment.

3.5. Descriptive statistics

Table 1(a-b) and 2 show the descriptive statistics of the data and the pairwise correlation among the variables, respectively. In Table 1a, I find that the depth varies between 0 and 39 while the breadth ranges from 0 to 1. Both variables are continuous. As breadth is a ratio of new IPC codes (not used in the last 5 years) in the focal patents of firm *i* in year *t*, the value of the index cannot exceed 1, where 1 indicates that all IPC codes of that particular year are new. Turning to Table 1b, I see that the maximum number of alliances is 23, while the maximum number of M&As is one third of it. The correlation matrix (Table 2) shows that the depth and breadth are negatively correlated (r=0.03), but it is numerically very small. This indicates depth and breadth are created simultaneously in the innovation activities.

Table 1a. Descriptive Statistics for the firms engaged in R&D related alliances and acquisitions during 1989-2009

	Obs.	Mean	Std. Dev.	Min.	Max.
Depth	4473	1.08	2.68	0	39.11
Breadth	4473	0.23	0.34	0	1
Acquisition (5 yrs.)	3408	0.69	1.81	0	20
Related acquisition	4473	6.75	24.60	0	100
Unrelated acquisition	4473	2.42	14.55	0	100
Alliances (5 yrs.)	3408	6.46	9.55	0	92
Firm size (log of employees)	2418	-2.29	1.44	6.91	3
R&D expenses	2627	55.68	31.96	0	4597
Firm age	4473	21.04	5.40	7	48
Patent propensity	2418	31.08	64.38	0	1000
Sales growth	2151	7.48	256.43	-1	11879.50
Financial leverage	2655	0.20	7.17	-141.29	186.77

Notes: The depth and breadth have been calculated from 15422 patents filed during 1984-2009 in the USPTO and EPO by 214 firms engaged in human therapeutics (*in-vitro and in-vivo*).
We considered only that M&As, where the firms are acquirers. The ‘related’ firms refer to those that belong to SIC codes 2833-2836, i.e. those are engaged only in biopharmaceutical activities. The ‘unrelated’ acquisitions include over-the-counter or generic drugs, medical and consumer devices, manufacturing facilities and organic and inorganic chemical research firms. Number of alliances and M&As are obtained by 5 years moving sum.

Table 1b. Number of strategic alliances and M&As during year 1989-2009

	Min	Max		Min	Max
Strategic alliances	1	23	*Technology-based acquisitions*	1	8
Number of alliances with universities	0	9	*Number of related acquisition*	0	8
Number of alliances with competitors	0	19	*Number of unrelated acquisition*	0	4

Notes: The minimum and maximum values are yearly basis. Alliances means when the sample firms plays either R&D firms or clients or both. Acquisitions refer to the cases when the sample firms acquire other firms. M&As data is taken from Thomson's SDC and strategic alliances data is from Recombinant Capital.

The variance inflation factors (VIFs) of all the variables are below 5, confirming that there is no problem of multi-collinearity. However, shares of alliances with universities, pharmaceuticals, biotechnology or non-medical firms are constructed in such a way that VIFs exceed 5 but remains below 10. We therefore entered universities and other industrial partners stepwise in the models.

Table 2. Correlation matrix for relevant variables used in the following analyses: System GMM in the Table 3-4.

The number listed horizontally across the top row correspond to the number and variables listed vertically on the table.

	1	2	3	4	5	6	7	8	9	10	11
1. Depth	1.00										
2. Breadth	-0.03*	1.00									
3. Acquisition (5 yrs.)	0.16***	0.04*	1.00								
4. Related acquisition	0.14***	0.06***	0.34***	1.00							
5. Unrelated acquisition	0.01	0.04**	0.15***	0.02	1.00						
6. Alliance (5 yrs.)	0.41***	0.13***	0.43***	0.31***	0.07***	1.00					
7. Firm size (Log of employees)	0.38***	0.09***	0.50***	0.28***	0.10***	0.57***	1.00				
8. Firm age	0.11***	0.07***	0.25***	0.14***	0.07***	0.18***	0.24***	1.00			
9. R&D expenses	0.28***	0.01	0.44***	0.28***	0.04*	0.50***	0.46***	0.14***	1.00		
10. Patent propensity	0.17***	0.26***	-0.10***	-0.05**	-0.01	-0.02	-0.16***	-0.08***	-0.06**	1.00	
11. Sales growth	-0.01	-0.02	-0.00	-0.01	-0.01	-0.02	-0.02	0.00	-0.01	-0.01	1.00
12. Financial leverage	0.08***	-0.00	0.03	0.02	-0.00	0.04*	0.03	-0.03	0.00	-0.01	-0.00

Notes: See *Appendix to Chapter 3* for variable definitions.

* denotes significance at the 5%, ** denotes significance at the 1% and *** denotes significance at the 0.1%.

3.6. Empirical approach

Equation (1) can bring some econometric issues. Since I have included the lagged dependent variable, there would be an autocorrelation problem. Moreover, assuming the error terms are serially uncorrelated, the vector β_3^{en} may be endogenous. This implies that β_3^{en} is correlated with ε_{it} and earlier error terms, but uncorrelated with $\varepsilon_{i(t+1)}$ and subsequent terms (Bond 2002). Moreover, some firms may have permanently higher knowledge stock due to unobserved firm-specific effects. This could be, for instance, due to a better absorptive capacity of technological knowledge for skilled scientists or past innovation experience before the present study period. There may be the case that some firms get the ownership of other firm's patents by mergers for which they had no effort in R&D (Lerner *et al.* 2003b). Besides, the firm often considers multiple strategic alliances, as Mowery *et al*. (1998) emphasize that the history of prior interactions with potential partners increases the absorptive capacity of both the partners. Prior alliances between technology-transferring firms enhance the efficiency of the knowledge transfers (von Hippel 1998). Thus, it is evident that the alliance decisions such as partner selection and alliance scope are endogenous[39]. Oxley and Sampson (2004) also pointed out this issue. In addition to that, there could be a serious endogeneity problem due to reverse causality i.e. the knowledge base can influence the choice between strategic alliances and M&As.

Consequently, a series of strong assumptions would have to be imposed on the use of panel data estimators. Because of the lagged variable on the right side of equation (2),

[39] The choice of strategic alliances and M&As depends on the net benefits of both the firms. Although, technological alliances for specific technological developments can be rather inflexible since the firm may not have full control, they are in general less costly and more flexible in the long run. Some firms forms alliances even with the competitors if quick access to market and great return are at the target.

OLS and classical error components estimators will be biased. As I do not have detailed information of the properties of error terms, maximum likelihood estimators would also be imperfect. To eliminate the effect of firm specific fixed effect λ_i, first differenced equation by two-stage least square (2SLS) can be used (Anderson & Hsiao 1981). But the 2SLS estimator is asymptotically inefficient and does not account for all available orthogonality restrictions (Bertrand & Zuniga 2006).

As a solution to this situation, Arellano and Bond (Arellano & Bond 1991) proposed a first differenced generalized method of moments (GMM) for a dynamic panel model, which is given below for Equation (1):

[2] $$\Delta KNW_{it} = \beta_1 \Delta KNW_{i(t-1)} + \beta_2^{ex} \Delta X_{it}^{ex} + \beta_3^{en} \Delta X_{it}^{en} + \Delta \phi_t + \Delta \varepsilon_{it}$$

The approach generates orthogonality restrictions by introducing all possible lags of explanatory variables as instruments. The orthogonality conditions are:

$$E\left(KNW_{i(t-n)} \Delta \varepsilon_{it}\right) = 0 \; for \; t = 3 \ldots T, n \geq 2$$

$$E\left(X_{i(t-n)} \Delta \varepsilon_{it}\right) = 0 \; for \; t = 3 \ldots T, n \geq 1$$

However, Bond (2002) shows that this first differencing may perform poorly if the series are close to being random walks. Later, Arellano and Bover (Arellano & Bover 1995) suggest that the moment conditions[40] can increase the efficiency of the estimator by

[40] The additional moment conditions are:

adding the original equations in levels to the system. The method estimates level equation together with equation (2). The procedure is called system GMM. For the differenced equations, lagged and future differences of the R&D expenses, propensity to patent, sales growth and last three years number of alliances are used as instruments. Firms generally invest more effort into current technological activities if the demand for their products, based on the current technologies, is increasing (Wu & Shanley 2009). For this reason, I have used sales growth of the firm as one of the instruments in differenced equations. We have operationalized the variable by considering the previous year's sales growth. These instruments are valid because they are correlated with the firms' R&D activities but not with the time-invariant effect or current error terms. Blundell and Bond (Blundell & Bond 1998) suggest that the estimator can solve weak instrument problems.

To analyze the effect of strategic initiatives on the knowledge production with the equation (2), I applied two-step difference-GMM to get more robust and efficient estimation than the one-step procedure. However, I have estimated the model by two-stem system GMM for sensitivity analysis.

3.6a. Results

Table 3 reports the effect of technology-based M&As and prior alliance on the production of technological depth and breadth of knowledge. In all the tables, lagged

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$E\left(\lambda_i + \varepsilon_{it}, \Delta KNW_{i(t-1)}\right) = 0 \; for \; t = 3, 4, \ldots, T$
$E\left(\lambda_i + \varepsilon_{it}, \Delta X_{i(t-1)}\right) = 0 \; for \; t = 3, 4, \ldots, T$

dependent variables are included according to Equation (2)[41]. Baltagi (2008 p. 154) argues that the estimated asymptotic standard errors would be downward biased due to small sample. So in all the models we used a '*Windmeijer correction'* (Windmeijer 2005). We reported the first and second order serial correlations. Note that we can reject the null hypothesis in the first order, but not in the second order, which is consistent with Arellano and Bond (1991). The Hansen J-statistics for overidentifying restrictions does not reject the null, indicating the validity of the instruments. The F-tests (not reported) in all the regressions indicate that independent variables are not jointly equal to zero at any conventional significance level.

[41] I have also checked the lagged depth in the model of breadth and lagged breadth in the model of depth. But I did not find any significant change in the results, which I therefore do not report, but can be requested from the authors.

Table 3. The effect of M&As and alliance on the knowledge production: Differenced-GMM-two-step robust estimates

	Depth				Breadth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Depth $_{(t-1)}$	0.062**	0.042*	0.054**	0.039***				
	(0.08)	(0.09)	(0.09)	(0.09)				
Breadth $_{(t-1)}$					0.172*	0.183**	0.141**	0.164*
					(0.07)	(0.07)	(0.08)	(0.07)
Acquisition (5 yrs.)	0.267*	0.008	0.046**	0.201**	-0.028***	-0.008**	0.033***	0.015
	(0.25)	(0.44)	(0.27)	(0.21)	(0.03)	(0.05)	(0.05)	(0.04)
Acquisition ^{2} (5 yrs.)		-0.009*				0.002		
		(0.02)				(0.00)		
Related Acquisition			0.030**				0.002*	
			(0.02)				(0.00)	
Unrelated Acquisition				-0.028				0.012**
				(0.02)				(0.10)
Acquisition (5 yrs.)*Dummy university alliance			-0.023 (0.06)	-0.036 (0.05)			0.017 (0.01)	-0.015** (0.01)
Acquisition (5 yrs.)*Dummy competitor alliance			0.068** (0.17)	0.016 (0.13)			-0.046 (0.03)	-0.043 (0.03)
Firm Size	0.968	0.916	1.086**	1.513	0.042	-0.005	-0.010	0.034
	(0.88)	(0.88)	(0.76)	(0.95)	(0.12)	(0.10)	(0.10)	(0.11)
Log of Patent propensity $_{(t-1)}$	0.258**	0.131	0.199	0.227	-0.169***	-0.176***	-0.149***	-0.148***
	(0.22)	(0.24)	(0.28)	(0.26)	(0.04)	(0.03)	(0.04)	(0.04)
Log of R&D expenses $_{(t-1)}$	-1.016	-0.859	-0.851	-1.028	-0.251*	-0.251**	-0.252**	-0.270**
	(0.62)	(0.58)	(0.64)	(0.56)	(0.10)	(0.09)	(0.08)	(0.10)
Financial leverage	0.017*	0.016*	0.026*	0.019**	-0.002	-0.012	-0.003	-0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	852	852	852	852	852	852	852	852
Arellano-Bond test for AR(1)-p	0.029	0.036	0.010	0.028	0.000	0.000	0.000	0.000
Arellano-Bond test for AR(2)-p	0.560	0.601	0.410	0.632	0.803	0.736	0.956	0.959
Hansen J-stat.-p	0.332	0.360	0.356	0.213	0.427	0.587	0.528	0.709
Diff.-in-Hansen GMM instr.-p	0.065	0.100	0.197	0.117	0.473	0.569	0.371	0.157

Notes: Instruments for the level equations are number of alliances in last 5 years and sales growth. A maximum of two lags are used.
In all the models state of firms location and industry effects are included but not reported.
Hansen test statistics of over identifying restrictions, tests for correlation among residuals and instruments, are reported (p-values only). The validity of the additional moment conditions for the level equations is shown by difference Hansen tests. The p-values for the first and second order serial correlations AR(1) and AR(2) are shown. Robust standard errors are in parentheses. * denotes significance at the 5%, ** denotes significance at the 1% and *** denotes significance at the 0.1%.

Focusing first on the effect of acquisitions, I note that the coefficient of the acquisition variable is positive and significant Column 1 supporting the Hypothesis 1 that predicts that technology-based acquisitions positively associated with the depth of knowledge of the focal firms. The coefficient for the number of acquisitions in the last 5 years (shown in Column 1) is statistically significant at the 90 percent level of confidence. The coefficient of the squared value of acquisition variable is negative and significant indicating a non-linear relationship with the depth of knowledge (Column 2). Thus the positive relation starts to decrease after a certain number of acquisitions by the focal firms. In addition to Column 1, we find the support in Column 3 and 4. Column 2 captures the effect of acquisitions whether there is a limit of acquisitions. Hypothesis 2 states that the related-acquisitions have positive effect on depth of the knowledge. Form Column 3 confirms that the related-acquisition affects the depth of knowledge positively. Similarly Column 8 shows that the unrelated acquisitions are positively related to breadth of knowledge that supports out prediction stated in Hypothesis 3. From the data I have found that all the firms have at least one strategic technology-based alliance before acquiring other firms. To find out the role of these prior alliances, I have constructed two interaction terms. First, I have included the interaction between the numbers of acquisitions as a 5-year moving sum and alliances with universities including research institutions. Second, we took the interaction term between the same acquisition variable as before and alliances with competitors. As expected and described by the Hypotheses 5, Column 3 shows that the firm has prior alliance with their competitors for increasing depth of knowledge. However, as predicted and motivated by literature, the effect of the prior alliance with universities is negative on breadth of knowledge.

Across all tables and results a couple of observations can be made from the control variables. As can be expected, the propensity to patent measured by the number of patents per employees or the employee productivity is significantly positive for depth of knowledge. This indicates that the skill of the workers play important role in assimilating and exploiting the existing knowledge. The number of employees as a proxy for the size of a firm is positively related with depth and it is statistically different from zero in most models.

3.6b. Sensitivity analysis

For robustness checks, some specification of the sample has been changed. As, the data shows large number of patents in the year 1995 and 2000-2002, the regression was run on the reduced sample eliminating data for these 4 years. Additionally, I have controlled for sub-industry as within the biotech industry there are many *sub-industry* for instance biological products, *in vitro* and *in vivo* diagnostics, medicinal chemicals etc. The biotechnology industry is highly concentrated in some of the States of US, for example California, New Jersey, Massachusetts etc. I have controlled for the States. Following the definition of exploration alliances given by literature (Koza & Lewin 1998; Lane & Lubatkin 1998; Rothaermel 2001; Rothaermel & Deeds 2004), I have also included effect of exploration alliance as an interaction term with number of acquisition variable. The firms' learning process and getting close to the tacit knowledge motivates the exploration alliance (Lane & Lubatkin 1998), which improves the absorption capacity of the firms. We have estimated the model with the sample by two-step system-GMM. Table 4 reports the results for the effect of acquisitions and the interplay between alliance and M&As. I find the results are robust and there is no significant shift of the direction of the effect.

Table 4. Sensitivity analysis: System-GMM dynamic panel-two-step robust estimates

	Depth		Breadth		Depth*Breadth	
	(1)	(2)	(3)	(4)	(5)	(6)
Depth $_{(t-1)}$	0.331**	0.322**				
	(0.12)	(0.11)				
Breadth $_{(t-1)}$			0.060**	0.070*		
			(0.20)	(0.21)		
Depth*Breadth					0.156***	0.149***
					(0.18)	(0.18)
Acquisition (5 yrs.)	0.032*	0.061**	-0.000	-0.017	0.093**	0.083*
	(0.56)	(0.64)	(0.08)	(0.09)	(0.17)	(0.16)
Related acquisition	0.017**		0.001		0.000	
	(0.03)		(0.00)		(0.01)	
Unrelated acquisition		-0.042		0.005**		-0.010
		(0.06)		(0.00)		(0.02)
Acquisition (5 yrs.)*Exploration alliance	-0.028 (0.09)	-0.046 (0.06)	-0.008 (0.01)	-0.009 (0.01)	-0.019 (0.02)	-0.021 (0.02)
Firm size	0.682	0.508	0.561**	0.606**	0.908*	0.850*
	(2.15)	(1.83)	(0.20)	(0.21)	(0.44)	(0.35)
Log of patent propensity $_{(t-1)}$	2.751***	2.567***	0.071	0.111	0.568*	0.598*
	(0.72)	(0.73)	(0.09)	(0.09)	(0.27)	(0.27)
Log of R&D expenses $_{(t-1)}$	0.368***	0.321	-0.532*	-0.482	-0.235	-0.178
	(1.87)	(1.56)	(0.26)	(0.29)	(0.52)	(0.44)
Financial leverage	0.011	0.010	0.000	0.001	0.010	0.008
	(0.02)	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)
Firm age	0.022	0.081	0.278	0.215	0.620	0.759
	(0.88)	(0.37)	(0.67)	(0.71)	(1.61)	(1.61)
Observations	653	653	653	653	653	653
Arellano-Bond test for AR(1)-p	0.029	0.015	0.001	0.001	0.012	0.009
Arellano-Bond test for AR(2)-p	0.745	0.775	0.285	0.204	0.755	0.720
Hansen J-stat.-p	0.391	0.266	0.236	0.372	0.380	0.318
Diff.-in-Hansen GMM instr.-p	0.802	0.886	0.752	0.387	0.974	0.906

Notes: Instruments for the level equations are number of alliances in last 5 years and sales growth. A maximum of two lags are used.
In all the models state of firms location and industry effects are included but not reported.
Hansen test statistics of over identifying restrictions, tests for correlation among residuals and instruments, are reported (p-values only). The validity of the additional moment conditions for the level equations is shown by difference Hansen tests. The p-values for the first and second order serial correlations AR(1) and AR(2) are shown. Robust standard errors are in parentheses. * denotes significance at the 5%, ** denotes significance at the 1% and *** denotes significance at the 0.1%.

3.7. Discussion and conclusion

In this paper I try to investigate the impact of technology-based M&As and prior alliances on the depth and breadth of knowledge by considering the dynamics of knowledge production. We use a sample of US biotechnology firms that are engaged in human therapeutics during 1989-2009. Overall, the results suggest that prior alliance with universities or research organizations and acquiring unrelated technological firms increases the breadth and diversity of their technological knowledge. Besides that, prior alliances with competitors in the same industry (other biotech firms) and related technology-based acquisitions help to increase the depth of knowledge. This has important implications as it shows that firms must be very selective in choosing their partners and targets, because their knowledge stock has significant impact on the breadth and/or depth of the R&D activities of the firm. Grossman and Hart (1986) pointed out that mutual collaboration agreements are incomplete contracts. So, an optimal level of integration is needed for both the firms to be productive. Moreover, prior literature shows that there exists an inverted U-shape relation between number of partners and knowledge creation process. For instance, Sampson (2007) points out that the speed of knowledge expansion reduces gradually as the firm reaches its maximum amount of manageable technology. Thus, in spite of a positive relation of alliances with the depth of knowledge, firms also increase their breadth of knowledge.

Most of the time, firms have shorter time-horizon of alliance partnership than the R&D timeframe in the high-technology industry (Hoang & Rothaermel 2010). So, it also becomes challenging to leverage the internal depth and breadth of knowledge by external sources through alliances. Firms try to acquire or merge with other firms for the complementary resources in such situation. My findings indicate that the biotechnology firms can increase their depth of knowledge by outsourcing knowledge from partners in a similar industry (by allying with competitors or through M&A with biotechnology or pharmaceutical firms). However, engaging in strategic alliances with rival firms may lead to leakage of critical information or technological know-how. This might jeopardize the existing competitive advantage of the biotech firms. Moreover, partners sometimes cannot decide whether to disclose important knowledge (Rosenkranz & Schmitz 2003) and to what extent. Thus, to increase depth with similar partners a long-term relationship (may be in terms of strategic equity alliances) may be more desirable than ownership by acquisition (Monteverde & Teece 1982). The longevity of the partnership increases in case of co-operative specialization of technological knowledge and decreases with the developed competitive similarities of both partners capabilities (Nakamura *et al.* 1996). Thus, managers may need to allocate more resources to internal R&D in order to build up technological breadth before they require particular complementary knowledge from rivals that increase depth of the firms. In this way they may be able to prevent unwanted spillovers of knowledge to potential competitors.

Having a clear picture of the relationship between R&D partners and knowledge production (depth and breadth), it becomes easier for firms to reduce the costs of searching appropriate partners and to reach optimal number of R&D collaborations. This explains the view of Fleming and Sorensen (2001), who argue that firms have difficulties to combine technological knowledge components when the number of interactions among components (from different sources) increases.

This paper has some limitations. First, I used the reported R&D expenses to control for the knowledge development process. Compustat reports only internally sponsored R&D. Although this data can reveal the effect of internal finance constraint of small firms, for larger firms with better access to external R&D investments the data fails to capture the effect of other research grants and external research support that biotech firms might have obtained to complement their internal R&D. Second, patent data are considered as noisy as it cannot take into account all the inventions that a firm is currently working on and that contribute to the knowledge development process. However, as a number of studies have used patent data as codified indicators of inventions, the results of the present study, which are based on all documented innovation activities, are comparable with a substantial body of prior research[42]. Third, because the inventors' and firms' names were not matched in the PATSTAT database, the data did not provide patent information of the client firms involved in the strategic alliances. It would be interesting to investigate whether both the partners are jointly working on the invention process and whether this could allow for a more direct measurement of knowledge spillovers. Fourth, as the present study is limited to one industry, future studies may investigate other industries, or analyze cross-industry samples, to see if and how much my results are specific to the biotech industry.

[42] See a number of studies (e.g. Jaffe *et al.* 1993; Cassiman *et al.* 2005; Grimpe & Hussinger 2008; Valentini 2011)

To conclude, the empirical results in this paper substantially support the theoretically developed expectations and highlight R&D collaboration strategies of high-tech firms that combine technological knowledge from different types of partners, of collaborations (alliances and M&A), and integrate knowledge for developing depth and breadth. In doing this, the study helps to clarify the complex strategic selection process of partner and target firms for the joint production of technological knowledge and sheds some light on the complicated symbiosis of alliances and M&As in innovation activities.

4

INNOVATION AND THE ROLE OF FAMILY OWNERSHIP

4.1. Introduction

Recession is a cleansing mechanism that eliminates firms, which are unable to innovate (Klette & Kortum 2004; Aghion *et al.* 2008). Recent studies in economics and finance indicate the astounding differences in innovation activities across the firms, explaining the variations in resource endowment and goals for returns on investments to the owners. One stream of literature focuses on the dynamics of ownership structure and R&D investment decision (e.g. Lee & O'Neill 2003) that influence technological innovation i.e. commercialization of technological invention. It argues that the insider owners expropriate the outside investors by diverting the corporate resources for their personal interest (La Porta *et al.* 2000; Lemmon & Lins 2003). This implies an adverse effect of ownership, as increasing ownership concentration may decrease innovation activities. However, one salient example that has attracted much attention of financial economics and corporate governance studies is the role of family ownership on firm performance. Family firms are those where a founding family exerts power over the organization and its strategic direction through ownership, top management or board positions (Villalonga & Amit 2006, 2009)[43]. Recent studies indicate that the family firms perform better than the non-

[43] Some studies typically establish the minimum control threshold such as 5, 10 or 20 percent for family owned firms (La Porta *et al.* 1999; Faccio & Lang 2002).

family firms (e.g. Villalonga & Amit 2006). This is because the founding families, who are the major shareholders, can effectively monitor the innovation activities of the firms with insider knowledge of R&D (Shleifer & Vishny 1986). Anderson and Reeb (2003) also argue that families hold their stakes for a long time, so they have an exceptional foresight for predicting firm performance. On the other hand, Morck *et al.* (2005) find that both the concentration of ownership and the control in the hands of families can have negative effect on the firm value. The negative effect is also supported by Faccio et al. (Faccio *et al.* 2001) and Eddleston and Kellermanns (Eddleston & Kellermanns 2007), for instance. These ambiguous results in literature open an avenue for further research to find out the role of family ownership on firms' innovation activities[44]. It can also raise the question why potentially innovative firms do not simply change the allocation of ownership if e.g. foreign owners are better suited to invest in new technological projects. Moreover, the existing studies indicate that the type of ownership concentration endogenously determines the innovation capability of a firm. Thus, it becomes necessary to know about the economic determinants that drive the family firms to retain their holdings and yet successfully innovate in the long run, which is also unclear from the literature. Moreover, in spite of a large number of studies that show a positive impact of institutional ownership on the R&D expenditure (Eng & Shackel 2001; Aghion *et al.* 2009) and distinguish the performance of domestic-owned and foreign-owned firms (Bloom & Van Reenen 2010), there is no empirical clear picture of the impact of family ownership on innovation.

[44] With Italian data, Mazzola et al. (Mazzola *et al.* in press) try to explain the conflicting results of family ownership on firm performance (not on innovation). However, they did not consider the potential endogeneity issue.

In this paper, I have used a unique panel data to analyze the effect of family ownership on the innovation activities of Indian firms and propose a model to explain how the family ownership and innovation decisions are jointly determined. The data used consists of percentage of all equity holdings of different owners including founding families and other accounting and financial measures of the 395 Indian firms between 2001 and 2008. These firms have all the patent records in EPO PATSTAT (2010) database. The main distinguishing features of my data is that I can observe more precisely the equity holding information from 2006 onwards due to the disclosure rules (Clause 49) in India during 2005-06 as much of the data filing to Securities and Exchange Board of India (SEBI[45]) became reliable. The panel data structure also shows us within-firm variations in innovation. In addition to control for time-varying decision of the firms to remain family owned and other sources of endogeneity, I have applied system GMM estimators (Arellano & Bover 1995; Blundell & Bond 1998).

I first analyze why the family firms are more likely to be innovative, a largely unclear question in the innovation economics and management[46]. OLS regression supports the negative effect of family ownership on innovation activities of the firms. However, consistent with the large strand of corporate finance literature (e.g. Shleifer & Vishny 1986, 1997; Anderson & Reeb 2003 etc.) that shows positive relationship of family ownership with firm performance, our results indicate that increasing the family ownership the firm increases the innovation activities. This also supports the finding of

[45] India's securities market regulators

[46] While some studies find positive effect of family ownership on firm performance as mentioned above, recent studies e.g. Chen and Hsu (2009) on Asian countries, Munari et al. (2010) on UK and European countries; and Munoz-Bullon and Sanchez-Bueno (2011) on Canada reveal a negative impact of family ownership on R&D investment.

Klette and Kortum (2004) that shows a strong positive impact of R&D (innovation) on productivity (performance). However, the crux of the paper is not only to find out a robust relation between family ownership and innovation but also to address a blurred area in the literature of corporate governance explaining why such relation exists.

Villalonga and Amit (2006) argue that the role of ownership should be investigated in three dimensions-ownership percentage, management and control. With a hand-collected[47] data of CEO on the board or top management of the firm (proxy for family control), I believe that my results have significant contribution to the literature of corporate governance.

Next, I analyze the impact of Indian family firms affiliated to business groups on the innovation activities. Business group, or business house, is a collection of affiliates, which are often publicly traded independent of each other. The system is considered to evolve in late 18th Century when British East India Company lost its monopoly over trade in India. Because of the fact that the groups create their virtual (internal) capital markets (Manos *et al.* 2007), the family firms affiliated to groups can pool and reallocate the funds according the to the investment opportunities. Although, a large number of studies have recognized that group evolved in the developing countries to mitigate the distortion of the labor and capital market (see for example, Claessens *et al.* 2000; Khanna & Palepu 2000). Moreover, the group-affiliated firms can share group-wide reputation that gives access to external creditors (Chang & Hong 2000). Although, the large business groups in India are mostly family owned firms started by family founder, there is no study to date to examine

[47] CMIE Prowess does not provide the CEO details.

the effect of these affiliated family firms on innovation[48]. Analyzing the Indian data, Khanna and Palepu (2000) and Sarkar and Sarkar (2000) document the performance of the Indian group affiliated firms. Particularly, the study of Khanna and Palepu argue that family ownership impacts the performance of group affiliates. But, the study is inconclusive to identify the innovation activities of affiliated family firms. After controlling for firm fixed-effects I find that affiliation to top business groups does not guarantee improvement of innovation. Moreover, unlike existing studies, our analysis is more detailed as I have separated the group affiliations of these family firms in three categories top 50, large and other.

The observed positive selection of increasing the percentage of family ownership and utilizing the R&D for increasing the number of patents are consistent with the prediction of our model in which the target number of patents with more R&D investments depends on the initial factors of the family firms. In my model, I demonstrate how the selection and innovation decision jointly determined.

Finally the relation between innovation and family ownership clarifies why large number of firms remains family owned and controlled across the world. More generally the fact that family firms typically have less debt, so even though these firms are badly managed (Bloom & Van Reenen 2007), they don't fall into the prey of competitive advantage trap. Bloom and Van Reenen (2010) find that these firms only have to cover the operating costs (e.g. salaries and wages), but not the capital costs like rent of the property

[48] Working on European firms Belenzon and Berkovitz (2010) and on Asian firms (Korea and Taiwan) Mahmood and Mitchell (2004) show positive impact of group firms (may or may not be family firms) on innovation.

or equipment as these were typically bought outright many years ago. This is also a fundamental question in the economics of industrial organization area as it generates economic losses by subsidizing them through cheap capital. I addressed this in the Indian context.

4.2. Theoretical framework

4.2a. Ownership structure, family ownership and business groups

The role of ownership structure on the innovation activities has got the attention of economists since Berle and Means (1932). Their study argues that more concentrated ownership leads to stronger link between owners interest and management behavior that increases the profit of the firm. The theoretical underpinning of the linkage between ownership structure and agency costs is provided by Jensen and Meckling (1976). They highlighted that owners with high stakes generally have strong incentives to maximize the firm value. The question is who are these owners? They could be an individual, such as manager, a family or family groups, financial and non-financial institutions etc. Fama and Jensen (1983) find that when managers own significantly high amount of stocks, the dominate the Board of Directors and expropriate the corporate wealth. On the other hand, families, holding majority of the shares, are interested in increasing the benefit and profits. Extant literature considers families as a special type of owners of the firm. Using a sample of German firms, Andres (2008) argue that families often invest large part of their personal wealth in their firms. So they have a strong attachment to their business. Moreover, families retain a longer horizon in their ownership which positively influence the their investment decision and their relationship with customers and suppliers.

However, in some cases, founding families sell the firms in the capital market or to the outside investors, keeping their control over the firms to increase their own welfare. Landes (2006) show that the firm performance decreases when the controlling families continue in their third and fourth generation. However, most of the works in finance and corporate governance literature have evolved against the backdrop of developed countries and very little is known (empirically) about such issues in emerging economy, particularly India.

The ownership of firms is highly concentrated in developing countries[49], particularly in India, the ownership structure differs from that of UK and US, as large shareholders who are also CEO or Board of Directors controls the management. Under new regulation of SEBI, the equity holdings are divided in promoters and non-promoters. Promoters' holdings include domestic and foreign and non-promoters holdings include institutions and non-institutions. The promoter is a person who has an overall control over the resources of the firms in the post public offering. For protection of the outside investors, SEBI requires that in post public offerings the promoters must continue to hold 20 percent shares for minimum of 3 years. By analyzing 500 largest listed firms, Chakrabarti et al. (2008) document that on average the Indian promoters own about 53 percent of the shares of the firms compared to 19 percent by Indian corporate bodies and 16 percent by foreign institutional investors. In India, the family ownership is based on pyramiding, cross-holding and family trusts, which are according to Jackling and Johl (2009) cause unique agency problems between owners and managers. This contradicts the findings of

[49] The characteristics of ownership structure are reported in details for 2980 listed firms of nine Asian countries in Claesssens et al. (2000).

Villalonga and Amit (2006). With Fortune 500 firms data, they show that family ownership is an effective way of mitigating the owner-manager conflict.

La Porta et al (1997) indicate that there exists weak legal framework in protecting investors right in the emerging countries. Moreover, in a situation of capital market imperfection, firms often look for internal accruals to start new business venture (Riyanto & Toolsema 2008). In such situation firms are often form a wider business network, known as business groups which consists of a number of groups managed by a common group of insiders (Gopalan *et al.* 2007). The Indian business groups are mostly family owned. Khanna and Palepu (2000) in the Indian context find that largest and most diversified business groups perform well as they can get the benefits of political connections. However, in a business group the influence of controlling shareholders on the firm performance depends on the degree of control (Claessens *et al.* 2000). According to Hoskisson et al. (2002), the majority shareholders of the firm can influence the allocation of scarce resources in competing investment such as innovation and monitor the utilization of the investments. This suggests that the existence of the group affiliated family firms can influence innovation activities.

4.2b. Family ownership and innovation

Large shareholders, typically founding families of firms, are the owners and controllers of most of the firms around the world (Villalonga & Amit 2009). For instance, studies documents that one-third of S&P 500 (Anderson & Reeb 2003) and Fortune 500 (Shleifer & Vishny 1986) firms are family firms. Faccio and Lang (2002) show that 44 percent of

5,232 firms of Western European countries are family owned. Even in the East Asian countries, more than two-thirds of the firms are family controlled (Claessens *et al.* 2002). However, La Porta *et al.* (1999) observe that the wealth concentration in a single entity (e.g. founding family) may lead to greater risk aversion and thereby slowing down the growth of economy[50]. So, it is desirable to diversify risks across the different shareholders and a recent study of Aghion *et al.* (2009) on US public firms shows that this is a key to the success in promoting innovation. The basic question then is, why these firms across the world remain family-controlled and successful in innovation? The studies of Anderson and Reeb (2003) and Villalonga and Amit (2006) indicate that the family firms often combine economic objectives with the traditional roles of family social unit. But Faccio *et al.* (2001) argue that if several family members become the major owners or occupy management position, the firm performance deteriorates. Thus, if innovation is the pathway through which the new technological knowledge from R&D leads to superior firm performance (Kline & Rosenberg 1986), the relationship between family ownership and innovation activities remains unclear.

However, an emerging consensus that comes out of the literature of corporate governance is the relation between family firms and firm performance, but both positive and negative. Studying the developed economy, like US market, Holderness and Sheehan (1988) argue that the performance, as measured by Tobin's Q, of non-family firms exceeds that of the family firms. Miller *et al.* (2007) empirically find that when family business that involves several family members as major owners or as managers, do not

[50] However, Sarkar and Sarkar (2000) find that Indian firm value increases if the holdings of directors exceed 25 percent.

show superior market valuations. The agency theorists, like Fama and Jensen (1983) argued that family management can solve the agency problems that could arise in other ownership structure, because family firms are better at protecting minority shareholders. This indicates that the families are likely to hold their voting rights when monitoring employees is high for competitive advantage that can benefit other shareholders (Villalonga & Amit 2010). Contrary to view, the later studies showed that family firms indeed suffer from agency problems arising from the nature of relationship of owners of the firms. For instance, Faccio *et al.* (2001) conclude that family ownership is one of the causes of East Asian crisis as it does not always benefit the minority shareholders because of the low transparency. Thus, the entrenched family control decreases the economic growth rate, as Morck *et al.* (2000) find out in the Canadian economy. Interestingly, later study by Anderson and Reeb (2003) and Bertrand et al. (2008) show the opposite results. Villalonga and Amit (2006) have also reported that the firm value increases when the founder serve as CEO or as Chairman of the board with hired CEO. Recently, Maury (2006) and Barontini and Caprio (2006) also find the similar results comparing the family-owned firms with non-family firms of European countries. Analyzing the eight East Asian economies, Claessens *et al.* (2002) show that the market-to-book value of asset has positive relation with the cash flow from the largest shareholders. Similarly, the study of Lemmon and Lins (2003) also show that East Asian firms with higher extent of controlling family ownership perform well.

To explain the mixed results, one stream of literature focused on the separation of ownership and control that can affect the firm performance. Demsetz and Villalonga

(2001) argue that without differentiating the ownership from control, the performance of the family firms cannot be correctly identified. However, Jensen and Meckling (1976) find that the separation of ownership and control decreases the firm value (e.g. Jensen & Meckling 1976), because it becomes difficult to align the actions of managers and interest of owners of the family firms. Thus, in spite of relatively large number of studies focused on the family ownership and firm performance, conflict of interest between controlling families and minority shareholders lie at the center of the corporate governance literature (Shleifer & Vishny 1986).

The basic question then is: can the theoretical arguments unequivocally predict the relationship of family-ownership and innovation success from this literature? Geroski (2005) observes that the direct effect of innovation activities on the firm performance (or vice versa) is relatively small. However, the studies on innovation argue that the persistent innovation strategy can strongly predict higher firm performance (e.g. Hall *et al.* 2005). Thus, the conflicting results in the literature[51] of family ownership and firm performance is not enough to draw a conclusion of the relationship of family ownership and innovation. However, studying the Fortune 500 firms, Shleifer and Vishny (1986) report that the founding families generally have insider knowledge of R&D activities that influence the innovation. In fact their later study reveals that more cash flow rights of the founding families in their business give them stronger incentives to monitor management (Shleifer & Vishny 1997). Thus, by holding large share ownership of the firms, the founding

[51] However, there may exist some problem with these performance indicators in the study of emerging and transition economies. For instance, positive return on equity (ROE) does not always reflect profitability of the firm, since the ratio of two negative variables can give positive value.

families invest more in R&D (Block 2012). Considering the argument of neo-classical theorists (like Romer 1990), it is obvious that the intentional investment of the founding families in R&D is conducted with the increasing returns to scale which may come through successful innovation. Moreover, developing the regional innovation systems[52] (Cooke *et al.* 1997), family firms can innovate more than non-family firms. Moreover, as the size distribution of private returns from innovation is skewed to the right and returns from innovation requires long time after the investment for innovation (Scherer 1998), the long term orientation of the founding families to the firms and transfer of family ownership from one generation to the next make the role of family ownership interesting to examine in relation with the innovation activities.

Literature on innovation shows that the firm's ownership structure positively influences the R&D spending (e.g. Lee & O'Neill 2003) and number of patents (e.g. Francis & Smith 1995; Czarnitzki & Kraft 2009) which have been used as proxy in various studies (e.g. Griliches *et al.* 1987; Hall 1993) and if investment in R&D generates new technological knowledge (Aghion & Howitt 1992) then it is expected that ownership structure and particularly family ownership has some impact on innovation activities. The underlying interesting fact is that the input (research efforts- e.g. R&D expenses) and the output (patent numbers or number of products) can be observed from available data, but the intention of the owner (inventions) is not. So to capture this effect, the present study uses patent-R&D ratio (proxy for innovation productivity), following Lanjouw and Schankerman (2004).

[52] Firms systematically interact with universities, technology transfer agencies, banks etc. (Dosi 1988) through an institutional environment of a particular region.

4.3. Specification of econometric model

As the empirical studies show mixed results, recently King and Santor (2008) argue that this could be due to incorrect model specifications and incorrect model estimation because of unobserved firm heterogeneity that biased the results.

To examine the relation between family ownership, proxied by the percentage of equity holdings and innovation, proxied by patent-to-R&D spending, I start with the knowledge production function developed by Griliches (1979). It is generally used to examine the impact of investment in firm's R&D and patent applications. The basic model has been modified in various studies according to the further factors influencing the internal characteristics of the firm and external factors of the market where the firms operate.

Suppose, Y_{it} is the innovation productivity of heterogeneous domestic firms due to the input for innovation (e.g. percentage change in shareholdings) of the firm, assuming that the firm maintains other input factors constant over the period of this study.

Following a similar model by Shyam-Sundar and Meyers (1999), I can write the innovation production equation as

$$(1) \qquad Y_{it} = \beta_0 + \beta_1 Z_{it} + \delta_t V + D_t + \epsilon_{it}$$

Where, Y_{it} is the innovation productivity of the firm i in time t. β_1 captures the effect of percentage of shares held by the owners of the firm, Z_{it} is the firm specific factors that determines the ownership structure and innovation activities, directly or indirectly and includes the treatment variables. V indicates the industry dummies, while D_t imply the dummies for each time spell (not time counter exactly but time counter of each spell e.g. 2001-2005 and 2006-2008). ϵ_{it} is assumed to be idiosyncratic error and is an unobservable term of firm *i* in time *t*.

Studying the impact of privatization on firm performance, Earle and Estrin (1997) and Demsetz and Villalonga (2001) find out the problem of endogeneity. The reverse causality that ownership structure is affected by innovation activities can be tackled with several approaches. For example, Smith et al. (1997) control for the simultaneity by analyzing the data with two-stage Tobit least-square methods, while Mueller et al. (2003) used binary logit regression. Generally, families (or promoters), compared to the average investors, have longer stakes in the firms, allowing them an exceptional foresight in predicting future performance (Anderson & Reeb 2003). So, the family ownership is potentially correlated with all error terms, time varying components and firm specific fixed effect. It may also be influenced by the serially uncorrelated measurement errors. In recent years, Benfratello and Sembenelli (2006) used IV-GMM technique to examine the foreign ownership on total factor productivity of Italian manufacturing firms. As the instruments help to find the exogenous variables uncorrelated with the dependent variable and strongly correlated with the endogenous variables, IV-GMM estimator solves the moment conditions imposing orthogonality between the error term and the set of instruments (including the exogenous regressors).

In this study, I have dealt with the endogeneity in two phases- first I adopted two-stage least square (2SLS) estimates using three instruments last 5 years total assets, employee compensation and wage intensity (see *Appendix to Chapter 4*). The regression gives us positive effect of family ownership on innovation productivity, as opposed to the OLS. But the result is not statistically significant at the 5 percent significance level. However, it gives some indication in support of the instruments. So, following Nickell et al. (1997), in the second phase I have applied GMM estimation approach as proposed by Arellano and Bond (1991)[53]. As our sample has short time dimension (8 years) with 395 firms, I have found system GMM estimators (Blundell & Bond 1998) that allows for possible endogeneity of independent variables like family ownership, domestic and foreign ownerships.

So, I further improve our model for the analysis. I consider that the firm follows the below condition for its survival in the market

$$(2) \qquad Y_{it} - Y_{it-1} = \rho\left(\overrightarrow{Y_{it}} - Y_{it-1}\right) + u_{it}$$

Where, Y_{it-1} is the productivity in (t-1) and $\overrightarrow{Y_{it}}$ is the target productivity of the firm in terms of both increased investments in R&D and number of patents, assuming that the firm employs its maximum investments of its shareholders in the innovation activities. ρ determines the speed of productivity so that the firm survives and $0 \leq \rho \leq 1$.

[53] Although Griliches and Mairesse (1995) and Blundell and Bond (1998) argue that for production function estimation regressors first-differences are possibly weakly correlated with their lagged levels, as many economic variables evolve in a random walk fashion at the micro level. So GMM estimator may not give consistent results.

The following situations may happen:

If $\rho > 1$, the firm has excess inventions for patenting at time t and it does not want to increase its productivity in near future, while $\rho = 0$ indicates that the firm thinks that its present productivity can place it in better market place in future i.e. $\overrightarrow{Y_{it}} = Y_{it}$. However, $\rho = 1$ means that the firm has a plan to increase its productivity because its present R&D activity is not enough to get the competitive advantage in future.

This leads us to get an optimal level of production of firm that can be represented by the following equation

$$(3) \qquad \overrightarrow{Y_{it}} = \sum_{j=1}^{n} \psi_j \, Z_{k,it} + \varphi_{it} + \sum_k D_k + S_t + \vartheta_{it}$$

Where, φ_{it} is the vector of firm's unobservable individual characteristics, D_k is the industry dummies for k industry. S_t indicates the year spell dummies and ϑ_{it} is the iid error term.

Plugging equation (3) into equation (2), I obtain

$$(4) \quad Y_{it} - Y_{it-1} = \left(\rho \sum_{j=1}^{n} \psi_j \, Z_{k,it} + \rho \, \varphi_{it} + \rho \sum_{k} D_k + \rho \, S_t + \rho \, \vartheta_{it} - \rho Y_{it-1} \right) + u_{it}$$

or,

$$(5) \quad Y_{it} = (1-\rho) Y_{it-1} + \left(\sum_{j=1}^{n} \rho \, \psi_j \, Z_{k,it} + \rho \, \varphi_{it} + \sum_{k} \rho \, D_k + \rho \, S_t \right) + \rho \, \vartheta_{it} + u_{it}$$

Rearranging the terms I get,

$$(6) \qquad Y_{it} = \xi Y_{it-1} + \sum_{j=1}^{n} \alpha_j \, Z_{k,it} + \mu_i + \delta_k + d_t + \epsilon_{it}$$

Where,

$$\xi = (1-\rho),\ \alpha_j = \rho\psi_j,\ \ \mu_{it} = \rho\varphi_{it}, \delta_k = \sum_k \rho\, D_k,\ \ d_t = \rho\, S_t,\ \ \epsilon_{it} = (\rho\, \vartheta_{it} + u_{it})$$

Here, I can consider the lags in the innovation system and for unobserved individual factors that are time-variant, for instances the technological knowledge of the scientists in R&D, by allowing $\mu_{it} = n\mu_{i(t-1)} + e_{it}$, to be first order autoregressive, $|n| < 1$

From equation (6), I find that

$$(7)\ \ Y_{it} = \xi Y_{it-1} + \sum_{j=1}^{n} \alpha_j\, \mathrm{Z}_{k,it} - n \sum_{j=1}^{n} \alpha_j\, \mathrm{Z}_{k,i(t-1)} + e_{it} + \delta_k(1-n) + d_t - nd_{t-1} + \epsilon_{it}$$

4.4. Data description

To estimate the equation (7), I have selected Indian firms with active R&D and those are listed in Bombay Stock Exchange (BSE). These firms are required to follow the norms set by SEBI for announcing financial accounts. Moreover, the BSE has the second largest number of domestic quoted firms on any stock exchange in the world after NYSE. This provides us around 4,000 firms from the PROWESS[54] database available through Center for Monitoring the Indian Economy (CMIE 2008). I got the accounting and financial information of these firms from this database. In addition to that I have added the information whether the founders or member of founding families are in CEO or in Board of Directors from the website of the firms and annual reports. I have extracted the entire patent filing information from PATSTAT (EPO) and found that around 10,000 active

[54] A comprehensive database contains data on firms' accounts, backgrounds & corporate governance and share prices since 1990 for large number of companies. The database includes all firms traded on India's major stock exchanges and several others including public sector enterprises. The database has been used by several papers on Indian firms e.g. Khanna and Palepu (2000); Sarkar and Sarkar (2000); Bertrand, Mehta and Mullainathan (2002) etc.

patents filed by Indian firms in various patent offices around the world. As my intention is to track the invention activities of the firms, I consider the patent filing year (first filing) as the reference year for my database. The patent application filing indicates that the firm has undergone invention activities. The next difficult thing is to match these two datasets, as there is no single common identifier. Moreover, it is obvious that all firms may not have active patents or do not file patent applications at all. Since PATSTAT has raw data of all the patents filed by more than 80 countries around the world in different patent offices, the hard task is to clean the database for use. I have cleaned the names of Indian firms[55] and taken these firm names (*strings*) to match with the firm names obtained from PROWESS. I used the Levenshtein distance algorithm (sometimes called edit distance) for coding and grouping the firm names. Using the codes, I have manually picked up the firms with similar names. This provides us with matched 428 firms that have active patents. As the ownership data is available from 2001 to 2008 in the PROWESS database version I have, after matching the two datasets, excluding state-owned firms (where Government holds more than 50% of shares of the firms) and dealing with missing data, I have 395 firms with 7065 patent and other financial data.

4.5. Variables

My main interest is to investigate the family ownership concentration on innovation activities. I have chosen the dependent variable as innovation productivity, which I measure as the number of patents per unit of R&D spending. To compare the our results consistent with the literature (Griliches *et al.* 1987; Hall 1993), I have also included the number of patents and R&D intensity as proxy for innovation. Following Khanna and

[55] I have also taken the help of Magerman et al. (2009).

Palepu (2000), I have considered the percentage of shares held by family as an individual or group as a proxy for family ownership, which is the main explanatory variable. In addition to our estimation consists of a dummy indicating 1 if the minimum threshold family ownership is 20 percent, 0 otherwise. However, in the robustness checks I have included 10 and 30 percent ownership threshold. To find out the effect of family members in management, we enter a dummy variable indicating 1 if the founder(s) or the members of founding family are in CEO position or in the Board of Directors. To understand the effect of business groups (business house) I calculated three interaction terms depending whether the firm has family ownership and fall into one of the three categories top 50 business groups, large business group and others. The business group is a dummy variable (1 whether the firm is affiliated to any business group, 0 otherwise) provided by the PROWESS database and based on business group size, group activities including qualitative judgments.

A number of control variables were included[56]. The *size* of the firm indicates the present and future prospects of innovation. Momentary increase or decrease of sales provides a signal of firm performance. I include log of sales to control for the size of the firms. The *age* of the firm is also important. Many studies on innovation have taken the number of scientists or employees or age of the firm in this respect. I have included the log of age to control for the experience of the firm, following the studies of Love et al. (1996) and Cohen and Klepper (1996) that found positive impact of age on innovation. The past *knowledge stock* significantly contribute to the present innovation activities as

[56] All the variables with their definitions and data sources are shown in the *Appendix to Chapter 4*

innovation depends largely on the combination of existing technological knowledge. So, the last 4 years' patent numbers (calculated by perpetual inventory method) have been taken to deal with the effect of past knowledge of the firms. Bloom and Van Reenan (2010) show that foreign-owned firms employ more advanced management practices than domestically owned firms. So, I have controlled the shares owned by foreign corporate bodies and institutions. I have constructed *industry dummy* equals to 1 if the firm belongs to manufacturing, information technology and chemicals[57], 0 otherwise. Securities and Exchange Board of India (SEBI) has implemented a new regulation in 2006 that makes compulsory to disclose detailed information on corporate governance and equity and share holdings. I have two year-spell dummies year 2001-2005 and year 2006-2008.

Several instruments have been tested for the analysis. For example, ROA, leverage, total average assets etc. However, I find three important variables useful. In literature of innovation, it seems widely accepted that the technological knowledge spillovers and the factor demands are substitute, given that this flow decreases the labor cost. It also indicates the structure of employment; a higher share of qualified employees results in higher per capital wages, reflecting a higher absorptive capacity of the firm. Moreover, in the family business, where lower levels of management hierarchy exist, the employee compensation costs at the operation level are consequently even higher. Werner et al. (2005) also find that the compensation strategy is a function of ownership structure. So I used the last 5 years average compensation and wage intensity (measured by wages over sales) as instrument. In addition to these, I have included last 5 years moving average assets of the firm. Along with these three instruments I have instrumented the endogenous

[57] These industries have maximum number of patents in the sample

regressor i.e. family ownership in the system GMM model by a variable *business risk*, constructed by standard deviation of sales divided by total assets, as family firms affiliated to business groups generally diversify business risks among the group members.

Table 1: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Innovation productivity (1)	1.00							
Family ownership (%) (2)	0.12*	1.00						
Foreign ownership (%) (3)	0.03*	-0.01*	1.00					
Knowledge stock (4)	0.04***	0.02*	-0.02*	1.00				
Total sales (5)	-0.03	-0.05	-0.02	-0.05	1.00			
Firm age (6)	-0.07**	-0.13***	0.01	0.08	0.10***	1.00		
Total assets (7)	-0.04	-0.05*	-0.03	-0.04	0.83***	0.11***	1.00	
Employee compensation (8)	-0.04	-0.04	-0.02	-0.07	0.42***	0.10***	0.55***	1.00

Notes: The numbers listed horizontally across the top row correspond to the number and variables listed vertically on the table. *p<0.05, *p<0.01, *p<0.001

4.6. Descriptive statistics

Tables 1 and 2 represent the correlation matrix and the summary statistics respectively of the continuous variables of interests. From the correlation matrix, I see the family ownership is positively correlated with the innovation productivity. Moreover, the family ownership is negatively associated with the size (total sales) and age of the firm. This suggests that older firms absorb more investments for their invention activities.

Table 2: Summary statistics

Panel A	Family Firms			Non-family Firms		
Number of firms	278			117		
	Mean	SD	Max	Mean	SD	Max
Innovation productivity	0.62	2.74	41.18	0.59	3.75	60.00
R&D intensity	0.10	3.12	125.60	0.01	0.02	0.19
Number of patents	3.04	9.92	113.00	2.75	20.10	282.00
Family ownership (%)	5.69	14.16	80.18	0.45	2.13	19.17
Indian corp. promoters (%)	5.90	14.23	78.58	3.53	11.71	73.70
Foreign corp. promoters (%)	0.92	5.81	90.00	2.67	11.61	76.00
Knowledge stock	287.25	314.44	1645.48	387.68	994.49	4509.43
Total sales	1181.57	6266.81	139269.46	4495.78	20315.20	270582.36
Total assets	1404.74	6982.89	150149.41	3670.76	13466.44	136872.50
Firm age (years)	32.71	20.28	108.00	43.77	20.00	90.00
Employee compensation	106.59	549.56	9553.51	231.62	711.03	8069.15

Panel B	Group Firms			Standalone Firms		
Number of firms	197			198		
	Mean	SD	Max	Mean	SD	Max
Innovation productivity	0.60	3.45	60.00	0.63	2.72	41.18
R&D intensity	0.02	0.08	1.21	0.12	3.63	125.60
Number of patents	4.34	18.89	282.00	1.56	5.79	69.00
Family ownership (%)	2.45	9.35	72.02	4.19	12.15	80.18
Indian corp. promoters (%)	7.40	16.24	78.58	1.55	6.44	66.32
Foreign corp. promoters (%)	1.16	6.42	51.59	2.47	11.48	90.00
Knowledge stock	390.42	708.99	4509.43	181.01	187.80	821.96
Total sales	1699.18	7299.98	139269.46	2795.06	16410.78	270582.36
Total assets	1898.09	8022.15	150149.41	2368.95	10976.94	136872.50
Firm age (years)	39.58	22.08	108.00	33.01	18.97	90.00
Employee compensation	140.84	578.88	9553.51	152.79	637.58	8069.15

Notes: Total number of firms 395. Family firms refer to those where the found families hold more than 20% of shares or the founding family members are in CEO position or in Board of Directors. Group firms are firms affiliated to business groups.

The summary statistics show that, out of 395 listed firms 278 firms are family owned and 197 firms are affiliated to business groups. The family firms hold maximum of 80 percent shares while the group affiliated family firms hold maximum of 72 percent of equity shares. Obviously, the firms holding more than 72 percent are standalone firms. In terms of innovation activities, the mean of innovation productivity and R&D intensity are higher for the standalone firms compared to business groups. Interestingly the family firms are younger compared to non-family firms, while the total sales and total assets are lower in the family firms than the non-family firms.

4.7. Results

Table 3 reports the OLS estimation of the level Equation (1). I have documented the results separately for the group firms and standalone firms in the Table 3. The coefficients of family ownership show negative impact on both number of patents and innovation productivity. But these are not statistically significant. This is almost the same result as Leech and Leahy (1991) found significant negative relationship between ownership concentration and profitability and growth. Although, the model can explain large variation of the data, indicated by high R-squared, the estimates are heavily biased because of unobserved heterogeneity (as Z_{it} and ϵ_{it} are correlated**.** Suppose the idiosyncratic error varies over individuals and time, such that $\epsilon_{it} = v_i + u_{it}$

Where, v_i is the founding family specific time-invariant unobserved heterogeneity e.g. unobserved technological skills that remain constant over time. But the estimates still violate the assumption of OLS that Z_{it} is uncorrelated with both v_i and u_{it}.

Table 3: Effect of family ownership on Innovation

Dependent variable	Number of Patents			Innovation Productivity		
Panel A: Group firms	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Family ownership (%)	0.202*	0.210	-0.434	-0.021	-0.021	-0.053
	(0.094)	(0.109)	(0.476)	(0.012)	(0.012)	(0.050)
Family CEO		-1.889			0.250	
		(5.155)			(0.943)	
Family ownership (%)*dummy family holding min 20%			0.620			0.031
			(0.420)			(0.047)
Firm size	1.898	1.994	1.781	-0.622	-0.643	-0.625
	(1.470)	(1.654)	(1.528)	(0.356)	(0.383)	(0.358)
Firm age	-0.695	-1.233	-0.719	0.355	0.425	0.317
	(2.102)	(2.523)	(2.210)	(0.414)	(0.401)	(0.388)
Knowledge stock	0.049***	0.049***	0.049***	0.000	0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Foreign ownership (%)	-0.164	-0.163	-0.112	0.006	0.006	0.012
	(0.188)	(0.179)	(0.128)	(0.014)	(0.016)	(0.020)
Constant	-5.515	-4.450	-2.819	4.575	4.499	4.838
	(0.905)	(0.262)	(0.918)	(0.918)	(0.780)	(0.044)
Observations	178	178	178	164	164	164
R-squared	0.743	0.753	0.744	0.143	0.144	0.148
Panel B: Standalone firms						
Family ownership (%)	-0.080**	-0.105**	0.120	-0.090*	-0.091	-0.112
	(0.031)	(0.038)	(0.164)	(0.044)	(0.048)	(0.070)
Family CEO		8.849			-2.148	
		(5.160)			(2.359)	
Family ownership (%)*dummy family holding min 20%			-0.193			0.018
			(0.160)			(0.044)
Firm size	1.330*	1.853*	1.324*	-1.011	-1.255	-1.038
	(0.662)	(0.822)	(0.655)	(0.575)	(0.699)	(0.597)
Firm age	-12.708*	-11.560*	-12.617*	1.642	1.553	1.584
	(5.841)	(4.733)	(5.877)	(1.928)	(1.795)	(2.058)
Knowledge stock	0.002	-0.005	-0.001	0.004	0.005	0.004
	(0.011)	(0.014)	(0.013)	(0.003)	(0.004)	(0.003)
Foreign ownership (%)	0.208***	0.282**	0.227***	-0.047	-0.071	-0.049
	(0.055)	(0.092)	(0.063)	(0.026)	(0.043)	(0.027)
Constant	0.641*	0.168*	0.201	0.193	0.552	0.836
	(0.024)	(0.026)	(0.042)	(0.023)	(0.081)	(0.069)
Observations	62	62	62	58	58	58
R-squared	0.446	0.498	0.422	0.312	0.327	0.309

Notes: The sample is an unbalanced panel of 395 firms that filed 7065 patents in different patent offices around the world during 2001-2008. The observation used is 2396.
All models are estimated by OLS regressions. Asymptotic standard errors robust to heteroscadasticity and autocorrelation of arbitrary form are shown in parentheses. *p<0.05, **p<0.01, ***p<0.001. Family ownership (%) variable is measured as the percentage shares held by Indian individual and Hindu undivided families (as individual or group). In all models Industry and year effect are included but not shown.

The effect of time invariant covariates did not show up in fixed effect regression models (not reported) as the effect cancels out by the within transformation. So it becomes hard to identify weather the family firms hold more shares (i.e. more cash flow rights) in reaction to superior performance of the firm or the return on their investment (including personal wealth) to the firm due to successful innovation triggers more investment to the firm. If the simultaneity exists, the family ownership variable would be upward-biased. As in the fixed effect model I permit the family ownership variables to be correlated with the random individual specific effects, it should minimize the endogeneity. So if the decision of family ownership is correlated with some unobserved variables, I assume that they are correlated with only time-invariant components of the unobserved variable, captured by the individual specific effects. In other words, the fixed effect model can give us consistent estimates of the marginal effect of regressor (FOC) provided the regressor is time varying, even if it is endogenous. But, I did not find results different from OLS. Following Wooldridge (2002), I also performed the Wald test using cluster-robust standard errors (not reported) and found that the model is not appropriate.

Table 4: Effect of family ownership on innovation

Dependent variables	Number of Patents		Innovation Productivity	
	2SLS	LIML	2SLS	LIML
	Model 1	Model 2	Model 3	Model 4
Family ownership (%)	2.716	3.803	2.581	0.327
	(2.659)	(3.848)	(7.655)	(0.216)
Family CEO	-0.487	-0.717	-0.801	-0.409
	(5.033)	(5.240)	(2.073)	(0.431)
Family ownership (%)*dummy family holding min 20%	-2.283	-3.298	-2.432	-0.318
	(2.461)	(3.575)	(7.180)	(0.204)
Firm size	3.019*	3.116*	-0.131	-0.381*
	(1.266)	(1.401)	(1.060)	(0.181)
Firm age	-0.073	-0.157	0.807	0.141
	(3.817)	(4.234)	(2.387)	(0.271)
Knowledge stock	0.048***	0.048***	-0.001	-0.000
	(0.006)	(0.006)	(0.003)	(0.000)
Foreign ownership (%)	-0.308	-0.396	-0.370	-0.062
	(0.377)	(0.481)	(1.058)	(0.041)
Constant	-45.843	-48.674	-6.994	2.727
	(27.797)	(31.819)	(33.527)	(2.234)
Observations	161	161	148	148
Durbin-Wu-Hausman				
Chi2 (1)	32.668(p=0.102)		25.499 (p=0.019)	
F	12.282 (p=0.133)		14.175 (p=0.043)	
Over identifying restriction				
Chi2 (2)	3.789 (p=0.150)		5.392 (p=0.267)	
First stage regression				
Adjusted R-squared	0.967	0.967	0.968	0.968
F	12.251	10.251	12.312	9.312
p	(0.001)	(0.042)	(0.012)	(0.005)

Notes: The sample is an unbalanced panel of 197 firms affiliated to business groups during 2001-2008. All models are estimated by 2SLS and LIML regressions. Asymptotic standard errors robust to heteroscadasticity and autocorrelation of arbitrary form are shown in parentheses. *p<0.05, **p<0.01, ***p<0.001. Family ownership (%) variable is measured as the percentage shares held by Indian individual and Hindu undivided families (as individual or group). In all models Industry and year effect are included but not shown.

The instruments applied for the equation are last 5 years average total assets, last 5 years average employee compensation and wage intensity (wage/total sales). Only firms affiliated to Business groups have been considered here.

Generally the firm's dominant shareholders give importance to the human capital to shape the managerial decision to allocate resources efficiently, especially during the economic crisis. Feliciano and Lipsey (1999) and Aitken et al. (1996) gave importance on the wage differentials between domestic and foreign owned firms. So, I used three instruments- last 5 years average of total assets of the firm, the last 5 years average of employee compensation and the wage intensity (as computed by executives and employees salaries, bonuses and other benefits over total sales of the firm) for the family ownership. Table 4 reports the two-stage least square (2SLS) instrumental variable regression. For the relevance of the instruments used, I have reported the first stage regression summary in Table 4. It shows that all instruments are (or at least one instrument) are significant at 0.1% level. The validity of the instruments is also checked with Durbin-Wu-Hausmann test. Under the null hypothesis the endogeneity should not affect the OLS estimator. That means β_{OLS} is consistent and efficient. While β_{IV} is consistent but inefficient. But, Model 3 of the Table 4 indicates the rejection of exogeneity of the family ownership. I have employed three instruments for the family ownership variable. If at least one instrument is valid, then it is necessary to test that weather other instruments are uncorrelated with the error term in the second stage. From the test reported in the table, I cannot reject the overidentifying restriction. Rather, I expect either all or no instrument be valid. I have also reported in Table 3 (Model 2 and Model 4) the limited information maximum likelihood (LIML) estimator to rule out the presence of weak instrument. Although, the 2SLS regression shows that none of the family ownership variables are significantly associated with innovation of the firm, it supports the argument that family ownership and family CEO are endogenously determined. Moreover, I have a good indication that there exists a positive impact of family ownership concentration on innovation productivity.

From equation (1), one may argue that the causality may run in both directions, e.g. higher productivity may give incentive to family owners to invest more in R&D or with the help of more investment in innovation activities, the productivity can be increased. Thus, the regressors are definitely correlated with the error terms. In this case, the fixed effect instrumental variable regression could have given a good method to handle the situation. However, the first stage statistics of the regression (results in Table 4) shows the instruments are weak and consequently a biased estimator is obtained. So, in the presence of the non-iid errors I used system GMM[58] for the equation (7), as proposed by Arellano and Bover (1995) and Blundell and Bond (1998). The GMM estimators, reported in Table 5, give the consistent and efficient estimates as the moment conditions use an optimal weighting matrix that maximizes its asymptotic variance (see Baum *et al.* 2003). Moreover, with additional instruments for the equation in levels, system-GMM is more efficient than difference-GMM. I have tried to control for the unobserved heterogeneity between large and small firms by allowing an autoregressive component in the error term.

[58] I have also tried with the difference GMM as literature in similar context recommends. The reason may be the lagged levels of the regressors act as weak instruments for the first differenced regressors. Alternatively, "system GMM", as augmented version helped to obtain efficient estimates for equation (7).

Table 5: Effect of family ownership on innovation (only Business group affiliated firms)

Dependent variable	Number of patents		R&D intensity		Innovation productivity				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Number of patents $_{(t-1)}$	0.209***	0.206***							
	(0.158)	(0.003)							
R&D intensity $_{(t-1)}$			0.556**	0.520**					
			(0.166)	(0.191)					
Innovation productivity $_{(t-1)}$					0.287**	0.323***	0.321***	0.247***	0.255***
					(0.098)	(0.026)	(0.027)	(0.030)	(0.030)
Family ownership (%)	-0.265*	-0.224***	0.010	0.013	0.007*	0.034***	0.034**	0.010*	0.010**
	(0.108)	(0.012)	(0.000)	(0.001)	(0.004)	(0.008)	(0.011)	(0.063)	(0.031)
Family CEO		0.959***		0.017		-0.351***	-0.342***	-0.246**	-0.225***
		(0.610)		(0.011)		(0.026)	(0.041)	(0.071)	(0.060)
Family ownership (%)*dummy family holding min. 20%		-2.585**		-0.013		0.165***	0.067***	0.039	0.095
		(0.913)		(0.046)		(0.053)	(0.705)	(0.126)	0.364)
Family ownership (%)*dummy top 50 BG							0.159**		
							(0.084)		
Family ownership (%)*dummy large BG								-0.056	
								(0.064)	
Family ownership (%)*dummy others BG									-0.044
									(0.092)
Firm size	-0.290	-0.841***	-0.001	-0.003	-0.090	-0.078*	-0.078*	-0.108**	-0.100**
	(1.292)	(0.064)	(0.001)	(0.002)	(0.080)	(0.032)	(0.036)	(0.030)	(0.031)
Firm age	-1.132	1.092***	-0.015	-0.011	0.117	-0.162**	-0.135**	-0.148	-0.157
	(2.484)	(0.246)	(0.008)	(0.007)	(0.161)	(0.050)	(0.049)	(0.083)	(0.080)
Knowledge stock	-0.020*	-0.019***	0.000***	0.000**	-0.000	-0.000**	-0.000***	-0.000**	-0.000*
	(0.009)	(0.000)	(0.000)	(0.010)	(0.050)	(0.100)	(0.000)	(0.000)	(0.000)
Foreign ownership (%)	0.024	0.021	0.019	0.015	0.049	0.057	0.116	0.141	0.358
	(0.059)	(0.090)	(0.018)	(0.030)	(0.275)	(0.296)	(0.349)	(1.169)	(1.171)
Sargan	147.49	149.33	152.78	153.66	213.82	222.51	254.24	230.3	229.5
df	23	29	24	29	24	28	33	33	33
p-Sargan	0.002	0.011	0.021	0.048	0.002	0.001	0.011	0.062	0.054
z_1	0.073	0.069	0.068	0.069	0.016	0.018	0.029	0.026	0.021
z_2	0.194	0.193	0.616	0.621	0.648	0.863	0.446	0.296	0.274

Notes to Table 5: The sample is an unbalanced panel of 197 firms that filed patents in different patent offices around the world during 2001-2008. All columns are estimated by system-GMM estimator. Asymptotic standard errors robust to heteroscadasticity and autocorrelation of arbitrary form are shown in italics. *p<0.05, **p<0.01, ***p<0.001. For instruments see notes to Table 4 and an additional instrument business risk. z_1 and z_2 shows the p-values of tests for first and second order serial correlation in the differenced residuals (Arellano and Bond tests for AR(1) and Ar(2) that are distributed as N(0,1) under the null of no serial correlation. The Sargan tests for overidentifying restrictions, computed as two-step estimates, is asymptotically distributed as a χ^2 under the null of instrument validity. Degrees of freedom and p-values are also reported. Family ownership (%) variable is measured as the percentage shares held by Indian individual and Hindu undivided families (as individual or group). In all models Industry and year effect are included but not shown.

In Table 5, I have included three proxies for innovation. These are number of patents, R&D intensity and innovation productivity. Model 5 indicates that family ownership affects the innovation productivity positively, which is consistent with the literature. However, I find that family ownership negatively correlated with the number of patents, shown in Model 1 and Model 2. The variable family CEO negatively impacts the innovation productivity. However when I include the subset of family ownership with a threshold value of 20 percent share holding I find the effect of family ownership on innovation productivity increases. I have reported these in Model 6-9. Apart from that the family firms affiliated to top 50-business group play positive and significant role in innovation productivity. The p-value of first and second order autocorrelation tests (z_1 and z_2) indicate no second order serial correlation and Sargan test confirms that all the instruments[59] are supporting the analysis.

4.8. Robustness checks

In Table 6, I have reported the coefficients estimated with different specifications of the variables. I have checked 10 percent and 30 percent threshold value of stake holdings by the family firms. In both the cases I found positive impact of family ownership on innovation. In our data we find that about 40 percent of total number of firms belongs to manufacturing industry. So, I have controlled this particular industry to ascertain whether our results are driven by the manufacturing industry.

[59] Instruments used are last 5 years average assets, last 5 years average employee compensation and the lagged value of all the regressors.

Table 6: Robustness checks

Dependent variables	Innovation productivity				
	Business groups				Standalone
	Model 1	Model 2	Model 3	Model 4	Model 5
Innovation productivity	0.398***	0.481***	0.388***	0.383***	0.417
	(0.036)	(0.052)	(0.021)	(0.013)	(0.348)
Family ownership (%)	0.061***	0.084***	0.031***	0.011*	0.034
	(0.015)	(0.016)	(0.002)	(0.004)	(0.082)
Family CEO	-0.126**	-0.314***	-0.229***	-0.188**	0.008
	(0.045)	(0.046)	(0.059)	(0.066)	(1.926)
Family ownership (%)*dummy family holding min. 10%	0.058***				
	(0.014)				
Family ownership (%)*dummy family holding min. 30%		0.079***			
		(0.015)			
Family ownership (%)*dummy family holding min. 20%			0.044***	0.906*	-1.139
			(0.184)	(0.345)	(2.837)
Firm size	0.002	0.005	-0.051***	-0.033	-0.365
	(0.024)	(0.021)	(0.009)	(0.022)	(0.289)
Firm age	0.184***	-0.124	-0.193	-0.240*	-0.386
	(0.051)	(0.103)	(0.098)	(0.094)	(2.862)
Knowledge stock	-0.000***	-0.000	-0.000***	-0.000**	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Manufacturing inds. Dummy	-0.293**	0.274			
	(0.103)	(0.183)			
Year 2001-05 dummy			0.303***		
			(0.033)		
Year 2006-08 dummy				-0.133***	
				(0.014)	
Sargan	119.78	218.8	126.27	219.95	213.08
df	22	22	26	26	21
p-sargan	0.000	0.002	0.005	0.000	0.019
z_1	0.098	0.012	0.015	0.052	0.027
z_2	0.739	0.865	0.667	0.947	0.443

Notes to Table 6: The sample is an unbalanced panel of 197 group firms and 198 standalone firms in 2001-2008.

All columns are estimated by system GMM estimator. Asymptotic standard errors robust to heteroscadasticity and autocorrelation of arbitrary form are shown in italics. *p<0.05, **p<0.01, ***p<0.001. The instruments applied for the equation are as Table 5. z_1 and z_2 shows the p-values of tests for first and second order serial correlation in the differenced residuals (Arellano and Bond tests for AR(1) and Ar(2)) that are distributed as N(0,1) under the null of no serial correlation. The Sargan tests for overidentifying restrictions, computed as two-step estimates, is asymptotically distributed as a χ^2 under the null of instrument validity. Degrees of freedom and p-values are also reported. In all the models, year and industry dummies are included, if not specified.

But the results (Model 1 and Model 2) are consistent with the previous findings. As discussed in the theoretical framework that financial and accounting data including ownership structure become more precise after the amendment of the disclosure rule in 2005-06. To capture this, I have included two dummy variables indicating two-year spell, i.e. 2001-2005 and 2006-2008. In Model 4, I find that the effect of the family ownership with minimum of 20 percent stake holdings has substantially increased after 2006. In summary, our results are robust.

4.9. Conclusion

Although, there is a substantial body of literature examined the firm characteristics and firm performance including innovation, there is little evidence on the relationship between ownership structure and innovation, in particular the effect of family ownership on R&D. This paper investigates the impact of family ownership concentration on innovation productivity. Using an unbalanced panel of BSE listed 395 Indian firms, I find that, after controlling for unobserved firm fixed effect and possible endogeneity, the impact of the family ownership on innovation productivity is positive. This is because family firms can establish strong research partnership with universities, research organizations and other industrial partners. Moreover, they develop regional innovation systems (Cooke *et al.* 1997). The result is also consistent with the study of Anderson and Reeb (2003) and Villalonga and Amit (2006), which looked at the firm performance under similar ownership structure.

Mueller and Philippon (2011) pointed out that family firms efficiently control the hostile labor relations than the professional managers. In India, where industry strike activities are prevalent and strong labor union exists, our results also support the fact that Indian firms with majority family ownership perform well. Another reason in support of the result is family owned firms are less sensitive to any industry shocks (Sraer & Thesmar 2007). Moreover, using the year-spell dummy for 2006-2008, I got significant results than the previous spell. This also suggests that the new regulation in 2006 make the data to be more reliable.

Although, a small proportion of Indian firms have active patents, the results confirm that the affiliation to the top 50 business groups does increase innovation activities. In our analysis, I did not consider the financial institutions as separate contributors in the R&D, because the data turned out to be time-invariant. However, the fact is financial institutions are generally professional investors with better experience about the historical returns. So, they act differently than the individual shareholders. Naturally, institutional investors choose to invest in companies with a higher productivity potential.

The implication of the results can be twofold- both optimistic and cautionary. The positive side is that the effort of the largest shareholders i.e. the family owners to promote R&D is worth mentioning. The other side of the coin is the lack of any significant positive effect of families on the number of patents can be alarming for the firms. The reason could be the family firms are generally traditional firms and they don't want to drain their money and effort in applying for the patents. However, when I analyze the paten-to-R&D ratio and include it in a dynamic model, I find interesting result that the family firms really care about the transformation of their R&D effort in to innovation output. The economic implication is that, even if the family firms attract less external R&D investments than non-family firms (Munari *et al.* 2010), a proper collaboration and network of R&D can maximize the successful innovation output with limited innovation input, giving rise to better innovation productivity for the family firms.

5

CONCLUSION

"*Just as energy is the basis of life itself and ideas the source of innovation, so is innovation the vital spark of all human change, improvement and progress*". -Theodore Levitt.

A clear understanding of how knowledge is developed in firms is as important as to understand what an innovation represents for assessing the innovativeness of organization. The knowledge-based innovation literature investigates the knowledge content of an innovation with the definition and the concept of knowledge, knowledge creation in innovation process and mechanisms by which knowledge facilitates innovation (Quintane *et al.* 2011). Studies have modeled the characteristics of knowledge and its impact on knowledge creation (Nonaka & Takeda 1995). While prior knowledge is considered to be an important source of innovation (Cohen & Levinthal 1990), the re-use of existing knowledge in association with external knowledge has also got attention to the scholars (Henderson & Clark 1990) but not with extensive clarification. For this reason recent studies have focused on the two distinct dimensions of knowledge- vertical that is depth and horizontal that is breadth of knowledge. Moreover, the inter-links between science and technology and the flow of knowledge from science to technology become crucial to investigate and explain the complexity of knowledge development process at the firm level.

With the help of this conceptual lens, I have identified the depth and breadth of technological knowledge from the patent information of the US Biotechnology firms. Although, there is a debate that not all inventions are patented so patent may not reflect true picture of innovation activities, for a secondary rich and unique datasets I used the patent data to capture the firms' technological knowledge portfolio (such as Jaffe *et al.* 1993; Makri *et al.* 2010). To find out the effect of external knowledge sources, I have taken advantage of all the alliances and M&As information of the firms during my study period. The results are excellent. These results might solve some of the unanswered questions that still remain inconclusive in related literature. For instance, the role of these strategic decisions is both positive and negative, as I have discussed in relevant chapters before. Interestingly, there also exists an inverted U-shaped impact of alliance and M&As on firm performance (Cloodt *et al.* 2006). The findings suggest me to accept both the positive and negative results but to explain the phenomena differently. Firms look for external technological knowledge and capabilities from alliances and M&As. These increase their depth and breadth simultaneously. So, without understanding the creation of these knowledge components and their effects on innovation, the role of the strategic alternatives on innovation remains unclear.

Another issue is the role of family business on innovation. The issue becomes more interesting in the context of emerging market such as India. I have taken micro data of BSE listed Indian firms for this purpose. I have tested various innovation indicators controlling for potential endogeneity to find out the true causal relationship of family ownership and innovation. The study has important economic implication. In India, where labor strikes are prevalent and strong labor union controls the innovation activities and management, family ownership (large shareholders who are founding family of the firms) helps to continue the innovation activities. Moreover, as family firms are less sensitive to industry shocks (Sraer & Thesmar 2007) and affiliation to large business groups provide internally generated funds in economic crisis (Manos *et al.* 2007), maintaining family ownership and affiliation to large business groups play positive role in the long term survival of the technology intensive firms.

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Abbreviation of the terms used in this dissertation

Terms	
BSE	Bombay Stock Exchange
CMIE	Center for Monitoring Indian Economy
EPO	European Patent office
FDA	Food and Drug Administration
IPC	International Patent Classification
In-vitro	Biological experiments conducted using components of organisms isolated from their usual biological context
In-vivo	Biological experiments conducted with living organisms in their normal, intact state
M&As	Mergers and Acquisitions
NIC	National Industrial Classification
NYSE	New York Stock Exchange
R&D	Research and Development
SEBI	Securities and Exchange Board of India
SEC	Securities and Exchange Commission
SIC	Standard Industrial Classification
USPTO	United States Patent and Trademark Office

Appendix to Chapter 2: Construct Definitions, measures and data sources

Construct Label	Conceptual Definition	Operationalization	Measure	Source
Depth	Extent to which firm specializes in technological areas	Degree to which firm leverages its current knowledge in a specific domain	During the last five years, the average number of times the firm repeatedly used the technology (IPC) in the patents it applied for	PATSTAT
Breadth	Extent to which firm has at least some minimum knowledge access to varieties of technological domains	Degree to which the firm demonstrates accessibility of new knowledge	Proportion of IPC codes in a focal year's patents that could not be found in the previous five years' list of patents by the firm	PATSTAT
Upstream alliance	Access to the sources of fundamental knowledge	Strategic alliances of Biotech firms with Universities	Proportion of alliances with university in a given year	Recap
Downstream alliance	Access to the sources of applied Knowledge	Strategic alliances of Biotech firms with Pharmaceutical firms	Proportion of alliances with pharmaceutical in a given year	Recap
Horizontal alliance	Access to the sources of Industry level knowledge	Strategic alliances of Biotech firms with Biotech firms	Proportion of alliances with pharmaceutical in a given year	Recap
Science Link	Extent to which inventions built on fundamental science as opposed to leveraging known patents	The degree to which firm's patent is citing scientific publications	Total number of scientific and academic papers cited by the patents of a firm	PATSTAT
Knowledge Stock	Knowledge capital created during the process of successful or unsuccessful inventions	Total number of patent applications (patent stock) in the last 5 years	Patent stock calculated assuming 15% annual depreciation and an 8% growth backward in times	PATSTAT
R&D Intensity	Efficiency of the firm to convert R&D investment into valuable patent	Firm's reported spending on R&D per $1000 of its total assets	R&D expenses/Total assets	Compustat
Research-1 Universities	Universities that give high priority to basic research	As classified by the *Carnegie Foundation for the Advancement of Teaching-2000*	Dummy variable=1 if the alliance with these universities, 0 otherwise	Carnegie Foundation's Website
Alliance Age	Extent to which the alliances induce knowledge creation	Year of alliance experience	Difference between 2006 and the year of first successful alliance announcement	Recap
Firm Age	Extent to which the firm is old	Difference between year of inception and last year of study period	Log of firm age	Patent Board
Propensity to Patent	The extent of skills and expertise that impacts knowledge creation	Productivity of workers	Number of patents each year per worker of the firm	PATSTAT

Appendix to Chapter 3: Variable definitions

Serial No.	Variables and Construct	Data Source
1.	Depth - During the last five years, the average number of times the firm repeatedly used the IPC codes in the patents	PATSTAT
2.	Breadth-Proportion of the new IPC codes in the focal year's patent, not used in the previous five years' list of patents	PATSTAT
3.	Number of alliances in the last 5 years (calculated by moving sum)	Recombinant Capital
4.	Number of acquisitions in the last 5 years (calculated by moving sum)	Thomson SDC
5.	Share of number of acquisitions of firms in related industries (acquisitions of related firms/total acquisition)	Thomson SDC
6.	Share of number of acquisitions of firms in unrelated industries (acquisitions of unrelated firms/total acquisition)	Thomson SDC
7.	Natural logarithm of firm age (2009-year of inception)	Company Website,GEN Guides to Biotech Companies-1996
8.	Natural logarithm of number of employees	Compustat
9.	Natural logarithm of R&D expenses	Compustat
10.	Sales growth -[$Sales_{it}$ –$Sales_{i(t-1)}$)/$Sales_{i(t-1)}$]	Compustat
11.	Propensity to patent- Number of patents/total number of workers	PATSTAT and Compustat
12.	Financial Leverage (debt/equity)	Compustat

Appendix to Chapter 4: Variable definitions

Variables	Construct
Innovation Productivity	Number of patents/R&D expenses
R&D intensity	R&D expenditure/Sales
Family Ownership (%)	Percentage of all classes of shares held by the family (shareholding of Individuals and Hindu Undivided Family) as an individual or as a group
Family CEO	Dummy indicates 1 if founding family member(s) is CEO or in BoD
Family Ownership (%)* dummy family holding min. 20%	The subset of family ownership holding minimum of 20% shares
Family Ownership (%)*dummy to 50 BG	Interaction term indicating the top 50 business groups affiliated firms with family ownership
Family Ownership (%)* dummy large BG	Interaction term indicating the large business groups affiliated firms with family ownership
Family Ownership (%)* dummy other BG	Interaction term indicating the others business groups affiliated firms with family ownership
Foreign Ownership	Percentage of common shares owned by foreign individual, corporate bodies
Firm size	Log of total Sales
Firm age	Log of firm's Age
Knowledge Stock	Number of patents in last 4 years assuming 15% annual depreciation and an 8% growth backward in times
Wage Intensity	Wage/Sales
Employee Compensation	Last 5 years average employee compensation
Total Assets (Moving average)	Last 5 years average total assets
Industry Dummy	1 if the firm belongs to Manufacturing, IT or chemical industry, 0 otherwise

Notes: The industry dummy is created by using National Industry Classification (NIC) code available in Prowess database