THE ROLE OF TECHNOLOGY SHARING AND NETWORKING IN ECOSYSTEM DEVELOPMENT IN EMERGING HIGH-TECH INDUSTRIES

EVIDENCE FROM CHIPLESS FIRMS

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DECLARATION

I Sime Tchouaso Serge hereby declare that this thesis and the work within it are my own carried out under the co-supervision of Prof John Hagedoorn and Dr Tan and where I have collaborated with others, this is clearly stated.

Signed

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1. INTRODUCTION

In the last three decades, increased global competition, shortened product lifecycles and complexity in the development of technology have forced firms to rely not only on their internal research and development capabilities but also to bring in technology from outside (externally developed technology) in order to develop new products or to serve new markets (Chesbrough, 2003; Brandenburger & Nalebuff, 1997). Strengthening of intellectual property rights worldwide and changes in organisational dynamics have further boosted technological transactions and fostered the development of a market for technology that is often mediated by the exchange of intellectual property (Teece, 1986; Chiesa et al., 2008). Firms use many mechanisms, such as alliances, mergers and acquisitions, R&D collaborations and technology licensing, which is seen as one of the most important mechanisms that firms used to exchange technology (Anand & Khanna, 2000b; Arora & Fosfuri, 2003; Fosfuri, 2006; Tidd & Trewhella, 1997).

Licensing of technology entails a transfer of intellectual property rights from a licensor (owner of the technology) to a licensee (buyer of the technology) (Hagedoorn et al., 2008). On the one hand, technological sharing through licensing enables firms to commercialise and capture value from their innovation (Anand & Khanna, 2000; Chiesa et al., 2008; Fosfuri, 2006; Megartz, 2002). On the other hand, licensing of technology enables firms to build relationship with partners and facilitates the emergence of ecosystems and networks, and it is through these networks that firms innovate and gain competitive advantage (Gulati, 1995; Lavie, 2006; Adner & Kapoor, 2010; Gulati et al., 2011; Madhavan & Prescott, 2017). Because of the importance of technology sharing and networking to firms' performance, there has been a considerable interest by scholars to understand mechanisms that firms use to exchange and capture value from their technology (Kim & Vonortas, 2006a; Madhavan & Prescott, 2017;

Miguel & Dussage, 2017). However, despite the theoretical development that has taken place recently, our understanding of the collaborative strategy of firms – in particular their licensing strategies and resultant networks and ecosystems is not yet fully developed (Gulati et al., 2011; Kim & Vonortas, 2006; Madhavan & Prescott, 2017; Miguel & Dussauge, 2017). To enhance our understanding of the cooperative strategy of firms, this thesis approaches the phenomenon through three theoretical lenses; governance modes (choice of licensing), ecosystems and networks. It develops three research questions from each lens to capture how the type of contractual agreements and networks and ecosystems that result from entering into these contractual agreements influence firms' value creation and innovation performance. This thesis thus mainly constitutes three empirical studies (papers) with each responding to a specific research question.

1.1. Research Questions and Gap

This thesis mainly addresses the roles of knowledge or technology sharing (licensing of technology) and ecosystems and network formation on value creation and value appropriation. More specifically, it responses to three empirical questions:

1. What are the conditions for high-tech firms to exchange technology through unilateral and cross licensing?
2. How do focal firms' technology and actor ecosystem complexity affect their value creation?
3. How do the quantity and quality of direct and indirect network ties affect firms' innovation performance?

The first research question on the conditions under which high-tech firms prefer to exchange technology through either cross or unilateral licensing is addressed in the first study - paper 1- of this thesis. The question is motivated by the impact that the licensing choice selected by firms to exchange technology has on the amount of value they appropriate from licensing (Chiesa et al., 2008; Megartz, 2002; Kim & Vonortas, 2006a). Licensing agreements are widely categorised into unilateral and cross licensing (Anand & Khanna, 2000; Nagoaka & Kwon, 2006). Cross and unilateral licensing are structurally different, and firms use them for different strategic reasons as each of the licensing agreement brings rewards and a corresponding degree of risks (Anand & Khanna, 2000; Chiesa et al., 2008).

In an attempt to understand firms' licensing preference, earlier studies have concentrated on either the characteristics of licensors (Arora & Fosfuri, 2001; Fosfuri, 2006; Kim &Vonortas, 2006a; Motohashi, 2006; Somaya et al., 2010) or those of licensees (Athuahene-Gima, 1993; Lowe & Taylor, 1998, Laursen et al., 2010). However, more recently researchers argue that both the firm's and partner's characteristics together determine the firm's licensing preference and call for a better understanding of these characteristics (Kim & Vonortas, 2006b; Nagaoka & Kwon, 2006; Siebert & Von Graevenitz, 2006; Siebert, 2012). To respond to this research gap, the first study - paper 1 - analyses firms' licensing preferences from both the firm and pair level characteristics and introduces new determinants for the preference of cross and unilateral licensing. Specifically, it focuses on the effect of the firm's and the licensing pair's technology and market diversification, their prior cross and unilateral licensing experience and size.

The second study - paper 2 - of the thesis moves from the licensing modes that firms use in commercialising technology to investigating the networks and ecosystems resulting from licensing on firms' performance. A substantial body of research literature has acknowledged that ecosystem orchestrators/focal firms often experience considerable differences in their performance outcomes (Adner, 2017; Gawer & Henderson, 2006). Heterogeneity in the performance of focal firms has been explained in terms of either the nature of relationships among actors (agents who undertake activities) in ecosystems (Autio & Thomas, 2014;

Jacobides et al., 2015; Rong & Shi, 2014) or the structural aspects (activities that need to materialise for the focal offer to reach end user) of ecosystems (Adner, 2017; Adner & Kapoor, 2010; Kapoor, 2018). The implicit assumptions that have driven prior research relate to the differences in the resources that partners bring to the ecosystem and the heterogeneity in focal firms' ability to coordinate activities within their ecosystems. Despite the rich insights gained from these studies, our understanding of why some focal firms' outperform others remains incomplete (Adner, 2017; Thomas & Autio, 2014). The second empirical study - paper 2 - introduces the complexity theory to the ecosystem literature and uses it to provide new insight into the heterogeneity of the performance of focal firms. The complexity theory especially the NK stream enunciates that the number and degree of interactions between components of a system affect its performance (Kauffman, 1993; Rivkin, 2000). In most high-tech settings, ecosystem generally occurs within an industry or focal firm architecture or platform (Adner & Kapoor, 2010). The architecture provides a ''blueprints'' for interactions among partners (Ozcan & Eisenhardt, 2009) and specifies way in which they can work together (Ferraro & Curses, 2009). It also provides the context in which strategies are set and how value is created and distributed within the ecosystem (Bremner et al., 2017).

The ecosystem architecture constitutes two principal components – the actor and technology (Baldwin & Clarke, 2000; Baldwin, 2014). The degree of interactions or interconnectivity of the architectural components shapes the functionality and performance of ecosystems (Cockburn & Henderson, 1996; Rivkin, 2000). Ecosystems can thus be considered as complex systems as the richness of technological interconnectivity and the degree of interactions among components (actors and technology) affect the amount of value generated by ecosystems (Glassman; 1973; Weick, 1976). By using the complexity theory in the ecosystem context, the study provides more profound insights that go beyond the actor-centric approach and technological or structuralist approach that have predominated the literature.

Finally, the last empirical study – paper 3 – explores the collaborative strategy of firms from the demand perspective. In collaborative settings, where firms are involved in the exploration and exploitation of technology, the value that is created must be distributed in some way among the collaborative parties (Miguel & Dussage, 2017). Prior collaborative literature has heavily focused on the supplier side of the equation. In addition, in the network context, the literature has mainly explored the effect of the structural features – position of firms in networks and how the quantity of resources that firms accrue from the different part of their networks influences their innovativeness (Ahuja, 2000b; Paruchuri, 2010; Podolyn & Stuart, 1995; Powel et al., 1996;; Salma & Savies- Laura, 2005; Shan et al., 1994; 2005; Singh et al., 2016; Zaheer & Bell). Very little research has been conducted to understand how the quality of resources – relational aspect of network – that firm's access from their direct and indirect ties contributes to their innovation performance (Gulati et al., 2011; Sarkar, Aulakh & Madhok, 2009). Examining the effects of the quality of ties is very important as firms occupying similar structural positions in networks may inhibit heterogeneous levels of performance as a result of differences in their partner resources (Gulati et al., 2011; Madhavan & Prescott, 2017; Wang & Rajagopalan, 2015). The third paper/study investigates licensees' performance based on the structural and relational aspects of their networks. Specially, it investigates how the quantity and quality of resources, information, knowledge and skills, which firms accrue from their direct ties (Ahuja, 2000; Podolny, 2001; Mor, 2010; Rodan & Galinic, 2004; Singh et al., 2016) and their indirect ties (Gulati, 1995; Salman & Savies- Laure, 2005; Parachuri, 2010) contribute to their innovation performance.

1.2. Thesis Purposes and Contributions of the Constituent Research Studies - Papers

The principal objective of this thesis is to enhance our understanding of how inter-firm collaboration influences firms' performance, specifically their innovativeness. The first study/paper, on the determinant of licensing, and the second study on the heterogeneity of focal firms' performance both focus on licensors – supply side, cooperation strategy of technology suppliers, while the last study – the effects of the quantity and quality ties concentrates on licensees – demand side, and focuses on cooperation strategy of buyers. Despite the apparent differences at face value between the different constituent papers, strong interdependencies and great synergies exist between these three papers. The nature of inter-firm cooperation requires that we study the collaborative strategies of firms from both a supplier and buyer perspective (Laursen & Salter, 2004). Specifically, research needs to take into account the resources and capabilities of licensors and licensees and how partners' capabilities are coordinated across ecosystems and networks as these has a tremendous impact on firms' innovation performance (Adner, 2017; Gulati, 1999; Laursen et al., 2010; Lavie, 2006; Lowe & Somaya et al., 2010; Taylor, 1998; Venkatraman, Lee & Iyer, 2008). This thesis examines the collaborative strategy of firms from both a supplier and a buyer perspective, and in so doing; it provides a more complete insights into our understanding of the collaborative strategy of firms.

The findings of the first study/paper on the determinants for cross and unilateral licensing indicate that in contrast to the firm size that has been examined in the literature, technology and market diversification may be a better predictor for licensors' licensing preference. The findings also indicate that licensors' technology market diversification and licensing experience along with differences in the licensing partners' market diversification and licensing experience, are critical determinants of licensors' licensing preference. These findings enrich the knowledge and organisation learning and the competitive perspective of the licensing literature (Arora & Gambardella, 2010; Gallasso, 2006; Nagaoka & Kwon, 2006; Nagaoka & Walsh, 2009; Siebert & Von Graevenitz, 2010; Somaya et al., 2010).

The findings of the second study/paper on the rationales for heterogeneity in focal firms' performance show that increased levels of technology and actor complexity enable focal licensors to generate superior value from their ecosystems. The joint effects of technology and actor complexity are also shown to augment focal firms' value creation. These findings contribute to both the structuralist or technology ecosystem-centric approach (Adner, 2017; Adner & Kapoor, 2010; Kapoor & Agarwal, 2016) and actor-centric approach (Autio & Thomas, 2014; Jacobides et al., 2015; Rong &Shi, 2014) of the ecosystem literature.

Finally, the findings of the last study/paper on the effects of network ties on the innovation performance of buyer firms (licensees) indicate that the quantity of partners that they license technologies from and the quality of these technologies have a significantly positive effect on their innovation. From a network perspective, this paper is closely related to the network theory on the structural and relational aspects of networks, particularly recent work by Sarkar, Aulakh and Madhok (2009), Gulati et al. (2011) and Madhavan and Prescott (2017).

Overall, this thesis contributes to the broader collaboration literature on licensing, ecosystems, alliances and networks by focusing on value creation, value capturing and innovation performance of firms. The three constituent papers or studies of this thesis each make a substantial contribution to the overall objective of the thesis, however studies 1 and 2 mainly relate to the collaborative strategies of licensors and contribute to licensing and ecosystem literature, while study 3 explores the collaborative strategies from a licensee perspective and contributes to the network and alliance literature.

1.2.1. Relationship between Overall Thesis Objectives and the Constituent Studies

Studies	Thesis purpose
Study I: Interfirm Technology Exchange Through Unilateral or Cross Licensing: Evidence from Chipless Firms in the Semiconductor Industry.	Thesis purpose I
Study II: Do Focal Firms Technology and Actor Ecosystem Complexity Affect Value Creation? Evidence from the Semiconductor Industry.	
Study III: Innovation Performance: The Effect of Quantity and Quality of Both Direct and Indirect Network Ties	Thesis purpose II

Thesis purpose I: Explore the collaborative strategies of firms from licensors (suppliers) perspective and contribute to licensing and ecosystem literature.

Thesis purpose II: Explore the collaborative strategies of firms from licensees (buyers) perspective and contribution to the ecosystem, network and alliance literature

1.3. Organisation of the Thesis

This thesis is organised around eight major chapters. Chapter 1 constitutes the introduction – offers an overview of the conceptual building block for understanding the thesis. Chapter 2 –

the literature review – provides the theoretical basis, Chapter 3 – the industry context in which the thesis is operationalised and Chapter 4 –the methodological consideration underpinnings

the thesis. At the core of the thesis are three empirical-based studies, which are presented in Chapters 5, 6 and 7. The three studies can be read independently of each other or as a block. Lastly, Chapter 8 revisits the main findings of the core studies and then discusses their theoretical and managerial implications.

A key highlight of this thesis is its contribution to our understanding of the collaborative strategy of firms. All three constituent papers of the thesis have been accepted and/or presented at prestigious management conferences – British Academy of Management (BAM), European Academy of Management (EURAM), the Academy of Management (AOM) and Strategic Management Society (SMS) with the first paper winning the best paper award at the BAM Conference 2017 at the University of Warwick.

Table 1-1: Papers' Specific Purpose and Research Question

Study I	Title	Interfirm technology exchange through unilateral or cross licensing: Evidence from chipless firms in the semiconductor industry.
	Purpose	To investigate the implications of licensors' market and technology diversification, experience and size and differential in the licensing pair technology market diversification, size, and experience on licensors' licensing preference.
	Research Question	What are the conditions for high tech firms to exchange technology through unilateral and cross licensing?
Study II	Title	How do focal firms' technology and actor ecosystem complexity affect value creation? Evidence from the semiconductor industry.
	Purpose	To explain how the level of technological interconnectedness and the degree of actors' interactions within focal firms' ecosystems influence the amount of value they generate their ecosystems.
	Research Question	How do focal firms' technology and actor ecosystem complexity affect value their creation?
Study III	Title	Innovation performance: The effect of quantity and quality of both direct and indirect network ties
	Purpose	To explain the extent to which the quantity and quality of firms' direct and indirect network ties contribute to their innovation performance.
	Research Question	How do the quantity and quality of firms direct and indirect network ties affect their innovation performance?

2. LITERATURE REVIEW

2.1. Introduction

This chapter provides the frame of reference and theoretical building blocks for understanding this thesis. Academic research is grounded within theories and the way a particular phenomenon is conceptualised may vary from one academic discipline to another. This chapter begins by defining and explaining the key terms and concepts with objectives to provide insights into how they are used within the thesis. Next, it reviews the prior literature in each of the constituent study/paper of the thesis, identifying gaps and some of the burning question in the areas of the literature. Then, it provides a rationale for why and how some of these gaps are addressed in the thesis.

2.2. Operationalisation of the Literature Review

Before defining the core concepts and how they are used in this thesis, it is imperative to explain how and where the information used in describing these concepts was retrieved. This literature review is based on a topic search in the Web of Science ISI Social Sciences Index database. This database is considered as the most comprehensive database for scholarly work on social sciences and includes thousands of journals, papers from conference proceedings, reports and dissertations. Although not all journals are included, the Web of Sciences database contains most leading management journals – Academy of Management (AMJ), Administrative Science Quarterly (ASQ), Organisational Science (OS) and Strategic Management Journal (SMJ), etc.

To carry out the review, search strings (keywords) related to the key topics examined in this thesis - each constituting paper/study are generated. These keywords are then used to search through the Web of Science ISI Social Sciences Index database. The topic search identifies words or phrases in titles, keywords, or abstracts in journals published in the business economics and management areas on the Web of Science database. Despite the fact that the search is limited to journals published on this database – which means that some scholarly works in the form of book chapters, and papers in other journals may be lacking – searching through journals in the Web of Science database identifies at least most essential works in the business and management field, and it is therefore used here to find the critical works in the areas of literature and their contributions.

2.3. Description of Key Terms and Concepts

2.4. Licensing of Technology

In most high tech industries, to develop a new technology firms can use either their own internal research and development or external methods such as acquiring another company that already possesses the technology, or enter into a technology sourcing agreement with an outside party (Steensma & Corley, 2000). Licensing is considered as one of the most important business arrangements that firms use to transfer and capture value from their technology - intellectual property (Anand & Khanna, 2000b; Arora & Forfuri, 2003; Fosfuri, 2006; Teece, 1986).

A licensing agreement constitutes a contractual arrangement whereby an organisation or individual (licensee) obtains the rights to use the intellectual property (patent or trademark, copyright, etc.) of another organisation or individual (the licensor). From a licensee perspective, through licensing a licensee can enhance its internal capabilities by bringing in technology from outside its firm boundaries. For example, when Microsoft realised it had lost precious time to Netscape and needed to get a Web browser to market fast, it licensed the software it needed to produce Internet Explorer from Spyglass Inc. Microsoft also brought in technology from several companies including Vermeer Technologies, Colusa Software and eShop Inc. to provide other Internet utilities (Shilling, 2018).

From a licensor perspective, licensing can enable the licensor to gain revenues in the form of fixed fee and/or royalty depending on the legal terms of the licensing agreement (Hagedoorn et al., 2008). Unlike selling of technology, in licensing the licensor still has control over its technology and can impose restrictions on how the licensee (s) uses its technology.

2.4.1. Motivation for Licensing

2.4.1.1. Inward Licensing – Licensees' Perspective

A firm or licensee can license in technology from outside for many reasons. Inward licensing can enable the licensee to reduce the cost of developing new technology. Developing a new technology using internal capabilities can be an expensive and risky process (Hill, 1992; Schilling & Steensma, 2002). Through inward licensing, a licensee can rapidly obtain a technology that has already been technically or commercially proven (Hill, 1997; Teece, 1986). Although inward licensing in itself may not be a source of sustainable competitive advantage – because a technology that is available for licensing is typically available to many potential licensees (Tsai & Wang, 2007), access to a needed technology, however, can substantially reduce the risks (Lowe & Taylor, 1999) and the time required to develop a new product (Leone & Reichstein, 2012), allowing the license to diversify into new markets (Killing, 1978), and exploits its own advantages more efficiently (Gold, 1987).

However, the licensee' rights to the technology can be restricted by licensing agreements inward licensing (McDonald & Leahey, 1985), which may affect certain strategic decisions on the use of the licensed technology. In addition to the lack of control, bringing in technology from outside may also affect the morale of the licensee's internal R&D staff (Atuahene-Gima

& Patterson, 1993; Sen & Rubenstein, 1989). When a licensee licenses in technology, it typically receives highly compartmentalised technology and its internal staff may not fully comprehend the knowledge used in developing the technology (McDonald & Leahey, 1985). As a result, they may grow increasingly dependent on the licensor for maintenance (Steensma & Fairbank, 1999), which may have a negative impact on their morale.

However, despite these downsides, licensees may gain valuable knowledge from working with externally acquired technology, which may enable them to develop their own proprietary technologies in the long-term. For example, Procter & Gamble's, through its ‘‘Connect and Develop’’ initiative, sources a huge amount of ideas and technologies from outside and uses them as a foundation for new products and technologies development. The firm has been able to stay innovative and competitive in multiple markets using this approach, conceptualised in some strategy literatures as the open innovation approach (Chesborough, 2003; Schilling, 2018).

2.4.1.2. Outward licensing – licensors’ perspective

A firm can generate value from its technology not only by embedding it in a new product and process but also by generating fees from outward licensing (Grindley & Teece, 1997). Outward licensing can enable the licensor’s technology to reach a large number of customers and markets than it could have done on its own (Lei & Slocum, 1991), yielding greater returns on its investment (Kollmer & Dowling, 2004; McDonald & Leahey, 1985). For example, Delphi Automotive, a supplier to the automobile industry develops a software program that can simulate various aspects of machining, including turning, milling and drilling. The company initially developed the software for its own use, but later realised it could make more money through licensing. By licensing the software to many automobile firms, its technology penetrates a broader market than it could have done if the company purses the venture alone (Schilling, 2018).

Outward licensing can also enable a firm to access complementary resources and capabilities of partners. Sometimes a firm may develop an innovation but does not possess the competencies, facilities, or scale to take the innovation to market. Through outward licensing, a firm can use partners' capabilities to perform all the value chain activities for the innovation. For example, in the biotechnology market, small and start-up firms generally license their technology to big pharmaceutical firms with marketing and distribution capabilities in order take their technology to market quickly.

Outward licensing can also serve a means to commercialise unattractive technology. By licensing out technology that is not core to the firm's business, it can restructure its business and focuses on its main projects (Bianchi et al., 2010; Kollmer & Dowling, 2004). For example, data shows that in 1994, IBM was able to restructure its business and made almost 100 million dollars from licensing fringed technology to other firms (IBM Annual Report, 1994, Grindley & Teece, 1997; Rivette, & Kline, 1999)

Outward licensing can also serve as a precursor to engage in mergers and acquisitions, alliances and joint ventures especially international joints ventures. Omnibus IP licensing agreement that combine patents, trademarks, and know-how is considered a key component of trade secret (Grindley & Teece, 1997) and plays an important role in international joints ventures (McDonald & Leahley, 1985). From outward licensing, a firm can also evaluate and learn more about the strength of partners' capabilities. O'Keeffe (2006) describes how Arm limited enters into a joint venture with Texas Instruments (USA) and Nokia (Finland) after initially licensed its CPU technology to TI and Nokia in 1993. The initial licensing deal provided TI and Nokia with an opportunity to gain a detailed understanding of Arm's technology. From the licensing arrangements, Arm, TI and Nokia found that working together would enable them to meet their priorities and customer needs more effectively and set up a joint venture in 1995. The joint venture led to the development of a new architecture known as the "Thumb" architecture. The new architecture made it possible for TI and Nokia to use Arm's processor as a programmable tool to produce System of Chip (SoC) products that were different and superior to competing products in the market (O'Keeffe, 2006).

Outward licensing may also be motivated by the desire to shape competition in the industry, that is, choosing rivals and extending the firm's dominant position in the market (Rockett, 1990). A firm can stimulate demand and prevent competitors from developing competing technologies by offering them a licence to its technology (Gallini, 1984). This strategy works well when competitors can easily imitate the primary features of the technology or when there are strong incentives to adopt a single technology as the dominant design in the industry. By licensing its technology to competitors, the licensor may prevent its technology from competing with other technology for market dominance. Although, by using this strategy, the licensor may forgo the opportunity to earn monopoly rents, doing so however may prevent potential competitors from developing their own proprietary technologies, thus enabling the licensor to gain greater revenues in the long term from a steady stream of royalties

In addition, outward technology licensing can also facilitate the diffusion of technology and enable the firm (licensor) to establish its technology as the de facto standard, especially in industries where externalities are important for commercialising technology (Shepard, 1987). For example, in the semiconductor industry, Arm Limited, a leading intellectual properties supplier was able to establish its technology as the defacto standard in the mobile and smartphone market by licensing its technology broadly to partners operating within and outside the industry. Arm's has been able to make huge profits as its chips account for more than 80% of the market share in smartphones and smart devices market (Arm's Annual Report, 2017).

However, although outward licensing may offer the licensor with a wide range of advantages, a licensor also faces risks of increased competition from licensing its technology to many partners. Increased competition results from partners gaining valuable knowledge from using licensed technology and developing their own proprietary technologies over time, which increases the number of players with similar technologies in the market. Outward licensing thus entails a trade-off, as revenues gained from licensing must be balanced against the lower price-cost margin and/or reduction in market share resulting from increased competition in the market (Arora & Fosfuri, 2003; Bianchi et al., 2011; Fosfuri, 2006). Firms use different licensing types (cross and unilateral licensing) to manage these trade-offs. Depending on the degree of competition in the market, each of the licensing types brings reward and a corresponding degree of risks to licensors (Nagaoka & Kwon, 2006). In addition to the licensing choice, firms' ability to generate value from licensing also vary across industries (Arora & Forfuri, 2003) as industries vary in function of their technology, complexity and appropriability regimes (Teece, 1998), which influence the amount of value they can appropriate from licensing. The next section builds on the growing importance of licensing in the semiconductor industry and the different types of licensing modes that semiconductor firms use to innovate and appropriate value from their innovation.

2.4.2. Importance of Licensing in the Semiconductor Industry

The importance and rate at which firms engage in technology licensing vary across industries (Anand & Khanna, 2000; Arora & Fosfuri, 2003; Hagedoorn, 1983; Nagaoka & Kwon). Based on the nature and complexity of technology and the appropriability regime, firms in certain industries engage more in licensing than others (Grindley & Teece, 1997). Because of cumulative and complex nature of the semiconductor technology, licensing is more prevalent in the semiconductor industry than in less cumulative industry settings such as the pharmaceutical, chemical and telecommunication industry (Hall & Ziedonis, 2001). In the semiconductor industry, technological development builds upon one and another and a large number of firms holds patents that constitute the "state of the art" of the industry technology (Grindley &Teece, 1997). The complex nature of the industry technology and richness of its patents entails that to innovate and capture value from innovation firms need access to other firms' technology/patents, which is not the case in industries that are not characterised by cumulative system technologies.

In addition to the patent thicket of the industry, the technology of the semiconductor industry is a key component of the electronics and computer industry. Advancement in technological development in these industries has accelerated the pace of technological development in the semiconductor. This has shortened the lifecycle of semiconductor products making it more difficult for firms to keep up with the pace of technological development, which entails that to stay competitive firms have to bring in technology from outside. These technological and IP dynamics have increased the incentive for firms to engage in licensing.

From a historical perspective, licensing is not a new phenomenon in the semiconductor industry; it goes back to almost the beginning of the industry. At the early stages, pioneering firms such as AT&T, IBM, Intel, and Texas Instrument engage in licensing either because they were forced by antitrust consent decree or by deliberate action to understand the sort of technology that other firms were developing (Grindley & Teece, 1997). These days, licensing and IP management are keys to competitiveness as fierce competition among players has put a premium on innovation. Unlike the passive nature through which licensing takes place in other industries, in the semiconductor industry licensing is at the cornerstone of firms' strategy.

Semiconductor firms use a wide range of licensing agreements and models to collaborate, learn, innovate and capture value from their innovation efforts.

2.4.3. Licensing Types and Models

Firms in the semiconductor widely used unilateral and cross licensing as mechanisms to collaborate, innovate and capture value from their technology (Anand & Khanna, 2000; Grindley & Teece, 1997; Linden & Somaya, 2003). *Unilateral licensing* constitutes a one-way transfer of technology from a licensor's (owner of technology) to the licensee (s) (acquirer of technology). It enables the firms – licensors to gain revenues in the form of a fixed fee and/or royalty depending on the codified legal term of the contract (Hagedoorn et al., 2008).

Unilateral licensing can be classified into *non-exclusive* – with no restriction or *exclusive* – restricted to a specific product or process or a particular geographical location. Exclusive licensing can lead to a situation of mutual hostages (Somaya et al., 2010). Firms can use exclusivity as a contractual hostage to safeguard licensee (s) investment in complementary assets especially when they are contracting early stage technologies (Somaya et al., 2010). Commercialising early stage technologies is full of uncertainties as firms can't determine in advance the market and demand for the technologies. When a licensor licenses its technology exclusively to partners, although licensees may face transaction hazard due to uncertainties associated with early stage technologies, they are more likely to make technology-specific complementary investments when they engage in exclusive licensing than in non-exclusive licensing. Exclusive licensing induces the licensee (s) to participate in and contributes toward the commercialisation of the technology even in the face of transaction hazards, thus creating a contractual hostage (Williamson, 1993). For example, in 2010, Toys ''R'' entered into an exclusive licensing arrangement with Amazon.com to sell toys online. The agreement prevented Amazon from selling toys of other vendors. Although, this condition benefited Toys

‘‘R’’ more than Amazon, Amazon still continues to invest in the deal for almost two years before terminating it in court.

Exclusive licensing is widely used in many high–tech industries such as the pharmaceutical, chemical, aircraft and spacecraft and machinery and equipment industry but is rarely used by firms in the semiconductor industry. This is partly because of antitrust concerns as well as historical practices of non – exclusivity that leaves very fewer innovations that could be treated as exclusive (Grindley & Teece, 1997). However, in some exceptional circumstances, firms in the semiconductor do use exclusive licensing agreements. In these cases, the licensing arrangements prohibit any sublicensing, as licensors can easily lose control of their technology if sublicensing rights are permitted.

Non-exclusive licensing, on the other hand is widely used by firms in the semiconductor industry as a key mechanism to collaborate, learn and to capture rents from their innovation. Because of important of externalities and standardisation in innovating and commercialising technology in the semiconductor industry, most collaborative relationships either begin or incorporate some degrees of non-exclusive licensing. When semiconductor firms engage in R&D collaboration or join venture, they usually use non-exclusive licensing as a mechanism to assess partners’ patents and capabilities.

Through non-exclusive licensing the firm can also institute its technology as the defacto standard in the industry. By licensing its technology non-exclusively to partners, a firm technology can reach a large number of customers quickly and becomes the defacto standard in the industry. From broad licensing, the firm can collaborate with a large number of partners and gain access to a large amount of new information, knowledge and resources, which it can use to innovate. Thus, from broad licensing the firm can gain a superior value from its technology.

Semiconductor firms use many different variances of non-exclusive licensing: single, multiple uses and perpetual licensing model. The single-use licensing model occurs when a licensor offers the licensee the rights to use its IP (single or bundle) in only one product. The single-use model offers the licensee the right to a single version of the licensor technology and if the licensee needs another version of the same technology, it may have to pay extra fees. This model of licensing is used in very limited cases.

A multi-use licensing model occurs when a licensor offers a license the rights to use its IP (single or bundle of IP) in multiple products. The multi-use licensing model provides the licensee with an unlimited number of designs for the licensor's IP. The multi-use licensing is often restricted to a specific time usually 3 years (www.fsa.org). The perpetual licensing model is when the licensing contract is not limited by a time that is the licensee has unlimited access or rights to the licensor IP. However, although the perpetual licensing model offers the licensee with unlimited access in terms of products and time, licensees may have to pay an extra fee if they want to access an updated version of the same technology. Most licensors especially chipless firms prefer to use the perpetual licensing model as it enables them to collaborate with partners for a longer period and gain maximum returns from their innovation efforts (www.fsa.org).

In addition to the fixed licensing fees, in all three licensing models above, licensees may also be required to pay royalties depending on the term of the licensing deal. The royalty payments are generally negotiated based on the percentage of products that the licensee produces using the licensor's technology (% of ASP). The % of ASP is seen as a standard for negotiating royalty rate in the semiconductor industry. The ASP range offers flexibility to both parties (licensee/licensor). In technology licensing, since the licensor cannot predict beforehand the contribution of its technology to the licensee products and the licensee cannot also predict prior to the negotiation the number of products it will produce using the licensed technology. The ASP range offers both parties the opportunity to negotiate a royalty term based on mutual risks and benefits. Licensors also sometime use a fixed and a flat rate royalty model. The flat rate royalty model is seen as the less preferred option for most chipless firms operating in the semiconductor and they only use the flat rate in exceptional circumstances.

Table 2-1: Standard Royalty Rate in Semiconductor Industry

Cumulative Volume of the Licensee Product	Royalty Rate as % of ASP of a Packaged Device
1 - 500,000	4.0%
500,001 - 10,000,000	3.5%
10,000,001 - 50,000,000	3.0%
50,000,001 - 100,000,000	2.5%
> 100,000,000	2.0%
Minimum royalty per Device	$ 0.15

Source-www.fsa.org

Another important licensing model that firms used in order to secure their long-term survival in the semiconductor industry is *cross licensing*. A cross licensing agreement occurs when two firms grant each other the right to access the other's technologies (Gallasso, 2012). Because of the cumulative nature of the semiconductor industry technology, to successfully innovate, firms need to have access to other firms' technology/patents. When a semiconductor firm needs access to a particular patent or portfolio of patents, it uses cross licensing to gain access to these patents. Cross licensing offers the firm first the freedom to operate – to generate new technology and new products/market without running the risk of infringing other firm patents. Cross licensing also enables the firm to generate revenues from its patents as it generally involves the exchange of a portfolio of patents between the licensing parties. The patent portfolios cover a designated "fields-of-use," including new patents developed within the timeframe of the agreement (Grindley & Teece, 1997). Depending on the relative strength and quality (value) of the partners' patent portfolios, cross licensing can be accompanied by a fixed fee and royalties (Anand & Khanna, 2000; Linden & Somaya, 2003; Telsio, 1979). Royalty payments in cross licensing are negotiated through a competitive rebalancing process, whereby each firm patent portfolios are evaluated by estimating its contributions to its licensing partner, with net royalty payments going to the one with the greater contributions.

Quality measures for evaluating a firm patent portfolio include the legal validity and enforceability of the patent; the technological significance of this feature to the product compared with other (non-infringing) ways of achieving the same end; and the similarity between the infringing features and the patent (Grindley & Teece, 1997). Based on these quality measures, each patent is assigned a weighting factor. For examples, a legally strong patent, which is hard to invent-around and is close to the infringing feature, is given a high relative weight. The value of each patent is arrived at by multiplying its quality weighting factor and the annual sales of the affected product base. The total value of the firm patents is the sum of the value for all the patents listed in its patent portfolios. The estimated royalty payments are the difference between the partners' patent portfolios with royalty paid by the firm with the less valuable portfolio. This royalty payment applies to the firm sales during the term of the license agreement. When the agreement expires, a similar procedure is used to re-evaluate royalty payments for the next licensing period. Occasionally, cross licensing is royalty-free when the contribution of both parties' patent portfolios are either very close or difficult to assess. The net payment in this case is very small or equal to zero.

Firms in the semiconductor use two main types of cross licensing models: Capture and fixed period model. Depending on their strategic objective, firms can use the capture or fixed period model. In the capture model, both licensing parties have the rights to use each other patents - eligible to exploit all technological fields to which the patents applied during the licensed period, usually five years, and, importantly, they also retain "survivorship" rights to use the patents until they expired, up to 20 years later. The advantage of the capture model is that is offered the licensing partners a longer period to exploit each other technology. However, depending on the strategic importance a patent (s) to a firm, it can restrict or exclude the patent (s) from the cross licensing agreement.

The fixed period cross licensing model offers both parties similar rights to use each other patents during the licensed period but partners do not possess survivorship rights after the expiration period. After the expiration period, if the licensing partners wish to engage in further cross licensing they must renegotiation the licensing contracts. The fixed model however offers the licensing partners the freedom to negotiate royalty terms that are closely related to the value of their patents as they can periodically adjust the licensing terms to take into account changes in competitive conditions and the value of the technology. For the above reasons, the fixed period model is more widely used by firms in the semiconductor industry.

As seen from the discussion above, licensing is at the heart of strategy and collaboration in the semiconductor industry. Depending on firms strategic intend, they use different licensing types and models to collaborate, learn, innovate and capture value from their innovation endeavour.

2.5. Review of the Literature Relating to the First Constituent Study – Paper 1

2.6. Licensing and Licensing Choices

Licensing of technology as an important mechanism that firms use to create and capture value from technology has been widely studied. Scholars have examined the rational why firms engage in licensing from many different perspectives. One of key perspective from which licensing has been examined is as a governance mode – why firms use licensing to organise their activities and type of licensing arrangements that they use in this process. Licensing agreements are widely categorised into unilateral and cross licensing (Anand & Khanna, 2000). Unilateral licensing constitutes a one-way transfer of technology from a licensor to a licensee (s). It enables the licensor to raise revenue from its technology but also exposes its technology to many firms. Cross licensing on the other hand is a bilateral exchange between two firms; it enables the licensing parties to access each other's technology and provide the licensor with the opportunity to curtail the number of firms with access to its technology. As specific governance mode, the licensing choice which firms select to exchange their technology influences the amount of value they appropriate from their research and development investment (Arora & Fosfuri, 2003; Hagedoorn et al., 2008; Kim & Vonotas, 2006a; Nagaoka & Kwon, 2006; Motohashi, 2008; Siebert, 2010).

Consequently, a large number of studies have examined the rationales for firms to select a particular licensing choice to exchange technology (Contractor and Lorange, 2002; Hagedoorn et al., 2008; Nagaoka & Kwon, 2006; Motohashi, 2008; Arora & Fosfuri, 2003; Kim & Vonotas, 2006a; Siebert, 2010). Earlier treatments on the determinants of licensing have relied on the firm level characteristics to explain firms' licensing preference. In this view, the internal resources and capabilities that firms possess are considered the main drivers of their licensing preference (Fosfuri, 2006; Kim & Vonotas, 2006a).

In contrast, more recently, scholars have emphasised the importance of the pair level characteristics – this perspective accentuates the importance for incorporating the firm's (licensor) characteristics as well as the partner's (licensee) characteristics in the analysis of firms' licensing propensity and preference (Kim & Vonotas, 2006a; Siebert, 2010; Nagaoka & Kwon, 2006; Motohashi, 2008). These studies thus suggest that studying the firm and pair level characteristics can advance our understanding of firms' licensing decisions and its implications on value appropriation (Kim & Vonotas, 2006; Nagaoka & Kwon, 2006; Arora & Gambardella, 2010; Siebert and Von Graevenitz, 2006; Hagedoorn et al., 2008; Motohashi, 2008).

This literature review begins by exploring the key theories that have been used to examine firms' licensing decision. Then it explicates how insights from these theories have been used in prior literature to explain the determinants of firms' licensing preference. This is followed by the rationale for the need for a better understanding of firms' licensing preference.

2.6.1. Theoretical Lenses for Understanding Firms' Licensing Preference

To understand firms' licensing decision and licensing preferences, the most important and fundamental question that needs to be responded to by economic theories is: Why do firms select licensing or use a given licensing type to exchange technology? This question is related to the notion of governance mode or, in general terms, licensing as a way of organising economic activity. In this context, several organisational theories have been used to explain firms' licensing decision such as the transaction cost economics, organisational learning, resources dependence, social relationships, contingency and game theory. However, among these theories, transaction cost and organisational learning theories have been particularly useful as it offered greater insights into our understanding of why firms prefer to license their technology using a particular licensing arrangement (Arora & Fosfuri, 2003, Fosfuri, 2006; Kim & Vonotas, 2006a; Nagaoka & Kwon, 2006; Motohashi, 2008).

2.6.1.1. Transaction Cost Theory (TCT)

Traditionally, the transaction cost economics has been the standard framework for analysing why firms engage in licensing and licensing type that they use in organising their activities (Fosfuri, 2006; Kim & Vonotas, 2006a; Nagaoka & Kwon, 2006; Somaya et al., 2010). Transaction cost theory (TCT) provides profound insights into how economics activities are organised. TCT places emphasises on the costs associated with organising an economic activity and uses the transaction cost as the unit of analysis (Coase, 1937; Williamson, 1975; 1987; 1996). According to TCT firms will select licensing or the licensing type that will enable them to appropriate the highest value from their R&D investment (Arora & Fosfuri, 2001; Kim & Vonotas, 2006a; Nagaoka & Kwon, 2006).

This approach draws on the neoclassical economics conceptualisation of the market (transactional) and the firm (hierarchical) as governance modes (Coase, 1937; Williamson, 1975). TCT sees the market and the firm as an alternative mechanism for organising economic activities and argues that for a given set of transactions to be carried out within firms or markets depends on the relative efficiency of the organisation mode. Behind the TCT are two critical assumptions underlying the behaviour of economic agents – are bounded rational and opportunistic in nature. Transaction cost theory assumes that the behaviour of agents is boundedly rational, so when they engage in economic activity or a contractual agreement, they cannot pre-plan everything but have to resolve some things as they go along, which makes all contractual agreements incomplete. Because of the incomplete nature of contracts, economic agents can act opportunistically or in their own self-interest, which increases transaction costs (Williamson, 1975).

In the licensing context, as a result of the complexity of the subject matter that is being transferred along with the risk associated to a small number of players bargaining, information symmetry, the uncertainty of innovation, technological interconnectedness, diffusion entitlement and the difficulties of contracting knowledge lead to increase in transaction costs. Specifically, transaction costs in technological licensing occur at the *ex-ante* (diffusion entitlement, costs of drafting, negotiating and safeguarding agreements) and *ex post* (monitoring, metering, dispute governance and maladaptation) (Contractor, 1981; Caves et al., 1983; Teece, 1988). As result of the different stages at which transaction costs occur, TCT scholars argues that in licensing firms are formed as a choice of governance at the *ex-ante* stage to reduce opportunistic hazards at the *ex post* stage. In other words, in licensing firms use the market to coordinate interdependent activities, which mitigates low-powered incentives of hierarchy (Kapoor, 2013; Mahoney 1992; Williamson 1985)

From a TCT perspective, licensing is seen thus to be a hybrid organisational mode between markets and hierarchies (firms). However, scholars have identified several weaknesses with transaction cost analysis of licensing decision (Arora & Forfuri, 2003; Forfuri, 2006) the first being from the analysis of the transaction cost itself. Transaction cost treatment of a licensing decision focuses solely on an isolated transaction or given licensing deal. It treats each licensing deal as an independent item with no link to previous or future transactions and does not take into account the contribution of the licensing deal to the rest of the firm's activities (Argyres & Liebeskind, 1999; Nickerson, Hamilton, & Wada, 2001). A licensing deal may affect other value-creating activities within the firm, such as production, marketing or distribution. Because of the ramifications of licensing, a licensing deal may be selected, even though the transaction cost for operationalising the licensing contract outweighs the benefits, especially if it fits well within the firm's overall strategy.

Second, as an economic activity, licensing may entail a continuous and enduring relationship between the licensing parties, which may results in the exchange of not just the licensed technology but also knowledge, information and other items that cannot be theoretically handled by transaction cost analysis (Fosfuri, 2006). These characteristics distinguish licensing from the market on the one hand and the firm on the other hand. In other words, licensing has distinct characteristics regarding the features of the items that are exchanged, which suggests the need for an additional theoretical lens for understanding the underlying mechanism of licensing and licensing choices (Klevorick et al., 1995; Kollmer & Dowling, 2004; Nelson, 1995; Nelson & Winter, 1982)

2.6.1.2. Organisational Learning

As a result of the weaknesses of TCT, organisational learning theory has been used to gain further insight into firms' licensing decision. In contrast to TCT, which analyses firms' licensing decision based on the costs and risks of licensing or licensing type, this perspective accentuates the importance of collaboration among firms. The approach highlights the benefits that firms can accrue from collaborating with each other (Klevorick et al., 1995; Nelson, 1995; Nelson & Winter, 1982), as firms engage in licensing or use a particular type of licensing for many different reasons (Kollmer & Dowling, 2004). Cooperation among licensing parties enables them to share knowledge and other resources that facilitate the development of new products and technologies or serve new markets and subsequently increases the total value resulting from the licensing deal (Argote & Epple, 1990; Nelson & Winter, 1982).

Besides, cooperation between licensing partners also enables them to build trust, routines, and norms of communication, which, in turn, facilitates the flow of information and reduces the risk of opportunistic behaviours (Argote & Epple, 1990). Increased cooperation can also facilitate the coordination of the licensed technology enabling the licensing parties to capture superior value from the technology (Nelson & Winter, 1982). Similar to the firm's choice to engage in licensing, the extent to which a firm wishes to collaborate with partners may also influence the licensing choice that it uses to create and capture value from its innovation.

However, as appealing as collaboration may sound, this literature has also identified risks associated with collaboration. The literature highlights that many alliances and collaborative agreements failed. The failures have been associated breakdown in collaboration (Kale & Singh, 2009). Breakdowns in collaboration may occur from failures in cooperation or coordination (Gulati et al., 2005; Gulati & Singh, 1998). Cooperation is the alignment of incentives or the extent to which partners are willing to work together. Cooperation challenges may occur when partners have different goals. Failure of cooperation may also occur if there is little synergy between partners' activities or if partners are each other's competitors.

Coordination, on the other hand, is the alignment of actions from which partners who want to work together develop a way to do so. Coordination challenges occur when partners do not know precisely how best to work together or are unable to anticipate what the other partner will do. Failure in coordination is more likely to occur with new partners, that is, partners who are unfamiliar with each other or operate in different locations and/or time zones.

2.6.2. Determinants of Firms' Licensing Decision

Drawing from one or all the theoretical lenses above, scholars have addressed the firm's licensing preference from both the firm - specific effects and pair's level effects (Ceccagnoli et al., 2010; Hagedoorn et al., 2008; Nagaoka & Kwon, 2006; Ruchman & McCarthy, 2016; Siebert & Von Graevenitz, 2006; Siebert, 2012; Walter et al., 2012).

2.6.2.1. Firm’s Level Characteristics

Many early studies on the determinants of licensing have concentrated mainly on the firm’s level characteristics and explored a number of factors that may influence the firm’s licensing decisions, including the appropriability regime – strength of IP protection (Hagedoorn et al., 2008; Nagaoka & Kwon, 2006; Somaya et al., 2010; Teece, 1986), the firm size (Hagedoorn et al., 2008; Kim & Vonotas, 2006; Nagaoka & Kwon, 2006; Motohashi, 2006; Ruchman & McCarthy, 2016; Siebert & Von Graevenitz, 2006; Siebert, 2012; Walter et al., 2012), potential competitors (Arora & Forfuri, 2003; Fosfuri, 2006; Motohashi, 2008; Siebert, 2012), access to complementary assets (Motohashi, 2008; Somaya et al., 2010; Teece, 1986), prior licensing experience (Kim & Vonortas, 2006; Ruchman & McCarthy, 2016), and products and technologies’ relatedness (Movery et al, 2006; Walter, 2016).

2.6.2.1.1. Appropriability Regime

In one approach to studying firms’ licensing preference, research has examined the industry dynamic within which firms operate and its implications on their licensing decision (Anand & Khanna, 2000; Arora &Merges, 2004; Hagedoorn et al., 2008). In this industry approach, scholars have explored the role of the industry appropriability regime – the strength of the industry IP protections. Anand and Khanna (2000) examine the relationship between the industry regime and firms’ licensing decision. They find that in industries where patent protections are stronger, firms engage more in licensing and tend to prefer arm’s length (unilateral) contracting rather than bilateral exchanges. In a similar vein, Arora and Merges (2004) link transaction costs associated with technology licensing to the strength of the industry appropriability regime. The authors show that in industries where licensees can easily invent around the licensed technology (weak appropriability regime) firms prefer to engage in bilateral exchange as a mechanism to reduce transaction costs. Bilateral exchange enables licensors to build a closer relationship with licensees reducing the risks of opportunistic behaviour which in common with arm length licensing. Whereas, when firms operate in stronger industry settings, they are more likely to prefer unilateral licensing as the industry appropriability regime offers them sufficient protection against imitation. The critical insight from the stream of literature is that the nature and strength of IP rights in which firms operate influence licensees' ability to imitate the licensed technology, which in turn, impacts on the transaction cost and licensors' licensing preference.

2.6.2.1.2. Firm's Size

Another important determinant that has been studied in the literature for the firm's licensing preference is the firm size. The main reason for studying the firm size stems from the role played by the resources and capabilities that are available to a firm in the way it organises its activities (Kim & Vonortas, 2006; Motohashi, 2008). The size of firms critically affects the breadth and depth of their knowledge, resources and capabilities and affects the licensing type they used to collaborate with others (Cava et al., 1983; Ceccagnoli et al., 2010; Pfeffer & Salancik, 1987; Teece, 1986).

According to this stream of literature, the firm is considered as a bundle of resources (Teece, 1988) and its licensing decision is influenced by ownership of the critical resources (Hagedoorn, 1993; Pfeffer & Salancik, 1978). In general, compared to smaller firms or start-ups, larger firms are more likely to own more resources and capabilities (Teece, 1986), which enables them to take their technology to market alone (Shane, 2001). Smaller firms, on the other hand, must either incur substantial costs from capital investments or collaborate with competitors in order to access complementary asset stocks. In a longitudinal study across different industries, Kim and Vonortas (2006) found that small firms with fewer capabilities tend to license their technology unilaterally, whereas in contrast, larger firms seem to engage relatively more in cross licensing. The central argument of Kim and Vonortas (2006) is that small firms use unilateral licensing more because it enables them to access critical resources needed to take their technology to market. Whereas, large firms engage more in cross licensing because of the additional advantages (potential learning and synergetic advantage resulting from partners' resources) that they can gain from licensing their technology to partners with large patent portfolios.

Along the line of resources dependency, some studies indicate that the size of firms is an essential source of market power (Schmalensee, 1989; Barla, 2000). Market power provides firms with legitimacy and other advantages such as economies of scope and scale. Smaller firms generally lack reputation and legitimacy in the marketplace (Barla, 2000), which can be mitigated by collaborating with more established firms (Teece, 1986). Because of resource constraints and lack of legitimacy in the marketplace, smaller licensors are more likely to have a higher preference for unilateral licensing as the licensing arrangement enables them to access complementary resources and also enhances their reputation in the market. Whereas larger licensors prefer to cross license their technology with other more significant players, as bilateral exchange enables them to broaden their technological base enhancing their ability to explore and exploit technology. The critical insight from this stream of literature is that ownership or access to critical resources is the primary driver for firms' licensing decision.

2.6.2.1.3. Access to Complementary Assets

Complementing the line of works on resources dependency, some scholars have explored how firms' licensing decision may also be influenced by their desire to access a specific set of complementary assets. Complementary assets are generally divided into tangible assets/resources (e.g. plant equipment) and intangible resources/assets (e.g. knowledge). The nature of complementary assets that firms need may influence its decision to engage in licensing and also impacts on the licensing type that they use to collaborate with partners (Teece, 1986) as tangible and intangible resources play different roles. Tangible resources facilitate the exploitation of technology, whereas intangible resources are mainly used for exploratory purposes. For example, if the firm objective is to exploit technology, then access to tangible resources such as marketing and distribution channels, manufacturing plants and financial assets would be more important to them.

In contrast, if a firm wants to explore technology then access to intangible resources is likely to be more beneficial. Cross licensing engenders greater collaboration between partners and facilitates access to more intangible knowledge. Whereas unilateral enables the firms access tangibles assets of partners. Arora and Gambardella (1994) found that in the pharmaceutical industry established firms with limited knowledge in biotechnology increasingly engaged in collaborative agreements in order to access these capabilities. This suggests that the licensing decision of firms is influenced by their desire to access requisite complementary assets.

2.6.2.1.4. Product and Technological Relatedness

Scholarly focus on resources and capabilities has also led some researchers to study the implication of licensing partners' products and technologies relatedness, conceptualised as the degree of similarities between two firms' products, markets and technologies (Koh & Venkatraman, 1991).

The findings on the effect of product market and technology relatedness on licensing decision have been mixed. On the one hand, researchers have argued that when licensing partners' product and technology are closely related they are more likely to be competitors, which influences their licensing decision or the type of licensing agreement they use to exchange their technology. For example, Hamel (1991) argues that when licensing partners possess similar technology or operate in the same market, they are more likely to select the licensing type that would enable them to curtail the level of competition in the marketplace. Siebert (2010) also found in his study of the semiconductor industry that when licensors and licensees operate in the same market or possess similar technological capabilities, they are more likely to use cross licensing as opposed to unilateral licensing. The rationale for using cross licensing is that it enables firms to reduce the degree of uncertainty and competition in the marketplace (Mcdonald & Leahey, 1985; Walter, 2016).

On the other hand, other groups of scholars argue that products and technological relatedness may increase information asymmetry, making it easier for licensing partners to share and transfer skills and capabilities, thus facilitating their ability to realise the outcome of the licensing agreement (Balakrishnan & Koza, 1993; Harrigan, 2002; Koh & Venkatraman, 1991; Merchant & Schendel, 2000). Cohen & Levinthal (1990) illustrate that when a licensor and a licensee technologies are closely related; the licensee can easily absorb and integrate the licensed technology into its production structure, enhancing the licensor's ability to capture value from the licensed technology. From this perspective, when licensing partners' technologies are closely related, the licensor may have a higher propensity to engage in unilateral licensing. Because of the ease with which partners can integrate the licensed technology, unilateral licensing to a large number of players would enable licensors to reap more value from their technology.

Because of the mixed findings on product relatedness, Walter (2016) conducted a longitudinal study in the pharmaceutical and the chemical industry to resolve the debate on products and technological relatedness on firms' licensing preference. He showed that when partners operate in a similar technological market, the risk of creating new competitors outweighs the potential benefits of absorptive potential and thus firms' licensing decisions tend to be influenced by the magnitude of competition that they will face in the marketplace by using that type of licensing.

2.6.2.1.5. Prior Licensing Experience

Another key factor that has been studied in the literature as a determinant for firms' licensing preference is their prior licensing experience (Gambardella et al., 2010; Kani & Motohashi, 2012; Kim & Vonortas, 2006; Nagaoka & Kwon, 2006; Motohashi, 2008). Cohen and Levinthal (1989) argued that firms learned or built their experience over many years through repeated engagements in similar focal activity. Through cumulative involvements in a focal activity, firms develop highly efficient organisational routines and standard operating procedures (Pisano, 1996) and consequently gain specific knowledge and skills on how to execute the focal activity. The accumulated knowledge dramatically simplifies the coordination of the focal activity and reduces costs, especially in managerial attention and resources needed to carry out the focal activity (Hoag & Rothaemel, 2010). Because of the acquired knowledge, firms are more likely to draw on the accumulated experience for future engagements (Cohen & Levinthal, 1989).

Unilateral and cross licensing are considered distinctive focal activities and firms use each type of licensing agreement for specific reasons. The characteristics of cross licensing differ from that of unilateral licensing in many respects: the mode of governance, control of partners, long-term risks and contribution to profit. This implies that as a specific focal activity, firms that engage extensively in cross licensing would have developed more in-depth knowledge of the licensing type and are therefore more likely to choose that licensing arrangement in the future. Kim and Vonortas (2006) found that firms, which frequently engage in cross licensing would have built the managerial capabilities and expertise needed to engage in the licensing type. They are more likely to have a greater cross licensing experience. When face with prospect in the future, these firms are more likely to prefer cross licensing than firms with less experiences of using the licensing type.

In a related study, Nagaoka and Kwon (2006) also showed that the probability of firms to use a particular type of licensing agreement increases with the experience they have for the specific licensing type. Licensors with huge cross licensing experience would have a higher preference for cross licensing, as they are likely to face fewer difficulties in coordinating the licensing arrangement in the future than licensors with less experience. In a similar vein, licensors that use unilateral licensing extensively would have a higher preference to license their technology unilaterally in the future.

2.6.2.2. Pair Level Characteristics for Analysing Firms Licensing Preference

Many earlier studies on the determinants of licensing have relied on firms' characteristics to explain their licensing preference. However, more recently, researchers have started to challenge this rigid firm level focus by arguing that the firm and licensing partners' characteristics together determine the firm's licensing preference (Kim & Vonotas, 2006a; Nagaoka & Kwon, 2006; Siebert & Von Graevenitz 2006; Siebert, 2010). This group of scholars contends that scholarly understanding of the determinants of licensing is incomplete and potentially flawed without an appreciation of the underlying characteristics of the firm partners. They argue that to gain a deeper understanding of the underlying factors influencing firms licensing choice, it is imperative to examine not just the firm's characteristics but also the pair-partner level characteristic.

Siebert and Von Graevenitz (2006) and Siebert (2010), for example, examined firms' licensing preference based on the effect of technological rivalry resulting from the degree of uncertainty in research and development. They show that with increasing rivalry in the technology marketplace, firms tend to prefer to cross license their technology as the mechanism enables them to alleviate the effects of competition and uncertainty in the long term. Nagaoka and Kwon (2006) studied the licensing preference of firms based on the size of the licensing pair and the nature of IP rights covered by the contract. They found that the licensing contingency between two firms is mainly influenced by the size of the potential licensor, and the larger the licensor size in terms of its technological capabilities, the higher the licensor's preference for cross licensing.

However, despite the new insights gained from these studies they failed to examine a key contingency – the market and technology diversification of the firm licensing preference. Market diversification offers firms a different sort of advantage and is considered a more informative determinant for a firm's licensing preference compared to the firm size that has previously been examined in the literature (Markides & Williamson, 1994). A large firm may operate in a single market (depth of knowledge in a single area) whereas multi-markets presence enables the firm to produce patents in a broad range of industries, enhancing the quality (breadth and depth) of its patents that can be used for cross and unilateral licensing. Further, the number of technology markets in which firms operate accelerates their learning potential, that is, the ability to absorb externally acquired knowledge and develop new products (Cohen & Levinthal, 1989), which enhances the time to market and competitive advantages vis-à-vis other players in the market (Gimeno & Woo, 1999). For more information on how this gap is addressed see Study/paper 1 in chapter 5 of the thesis.

2.7. Inter-firm Network

Inter-firm networks are prominent features in most high- tech industries and play an important role in firms' strategy (ability to compete and innovate) especially in the semiconductor industry. They are formed when two or more firms come together to achieve some common goals. These partnership agreements are typically voluntary – legal ownership agreements, informal know-how trading, etc. – involving the sharing and exchange of know-how, resources and capabilities (Ahuja, 2000; Teece, 1986; Mesquita, Ragozzino & Reuer, 2017). Licensing of technology enables firms to transfer technology and share knowledge and resources among themselves, which facilitates the formation of networks.

In the management literature, inter-firm networks have been defined in a variety of different ways. A common theme in these perspectives has been a particular aspect to which the network is associated to (Bremner et al., 2017; Oscan, 2006). For example, some scholars refer to networks as a business group – a cluster of firms that are bounded together by some formal or informal relationship (Ozman, 2006). Other scholars, like Powell, Koput and Smith-Doerr (1996) describe networks as innovation networks based on the learning that takes place between firms in these networks. These authors place more emphasis on organisation learning and see networks as a vehicle for learning and locus for innovation.

Another group of scholars, for example, Ring and Van De Ven (1994) and Oliver (1990) define networks by the nature of inter-organisational relationships and the characteristics of members within the networks. Along this line of thought, many other terms have also been used to describe networks, including networks of innovators (DeBresson & Amesse 1991), networks of organisations (Miles & Snow 1986), strategic networks (Jarillo 1988) and inter-firm networks (Grandori & Soda 1995). Despite the variations in terminology, all these definitions of network refer to what Jones, Hesterly and Borgatti (1997) call a governance mode (way of organising activities), which is also the approach adopted in this thesis.

2.7.1. Ecosystem

Ecosystems are a distinctive type of networks. According to Moore (1993), a business ecosystem is the network of organizations – including suppliers, distributors, customers, competitors, government agencies, and so on – involved in the delivery of a specific product or service through both competition and cooperation. A distinctive characteristic of the ecosystem is that partners within ecosystems generally come from different industry settings and possess different business models and technologies. Unlike other network constructs, where partners congregate around either the consumer or the supply side, ecosystems may extend beyond the vertical and horizontal ties within a single industry or organisational setting (Bremner, Eisenhardt & Hannah, 2017). Ecosystems generally contain both the production (suppliers of focal firm (s)) and user side participants such as complementary assets providers, complementors and customers (Adner, 2017; Bremner et al., 2017). Another distinctive characteristic of the ecosystem is complementarity and interdependence between partners. Within ecosystems, there is a huge amount of interdependency and complementarity among partners' activities. Interdependency results from the fact that to provide superior value for the end user, partners within an ecosystem must work together, which creates a high level of interdependency. Complementarity on the other hand results from the fact that partners' activities within ecosystem complement each other, which enable them to create more values than would be generated by a single firm. These two important attributes of the ecosystem (the production and consumption side participants and complementarity and interdependency) differentiates the ecosystem constructs from other network constructs such as clusters, innovation and business networks, industry networks and alliances (Thomas & Autio, 2014; Adner, 2017; Kapoor, 2018).

In most high-tech sectors, ecosystems generally occur within an industry or firms' architecture and are orchestrated by a lead or focal firm(s). In management literature, the orchestrator has been described based on how members (the orchestrator(s) and participants) within the ecosystem are organised. Depending on how the orchestrator(s) is positioned within the ecosystem, scholars have used different terms to describe the orchestrator. For example, when the orchestrator is localised, it has been described as a focal firm (Anderson et al., 1994; Adner & Kapoor, 2010; Teece, 2007), a central hub firm (Isansiti & Levien, 2004b; Jarillo, 1988;

Moller et al., 2005) or a platform leader (Cusumano & Gawer, 2002) or lead firms (De Meyer & Williamson, 2012).

2.8. Review of the Literature Relating to the Second Constituent Study - Paper 2

2.9. Business Ecosystem

In the management and strategy field, the team ecosystem was first introduced by Moore to invoke the notion that like biological system business organisations compose of firms from a variety of industries that work together and coevolve over time with implications on their innovation and performance (Moore, 1993). The ecosystem constructs have gained huge traction recently in both the practitioner and academic sphere (Adner, 2017). The attractiveness of the concept arises from increased concerns by managers and researchers about the interdependence between firms and their activities (Isantiti & Levien, 2004). Many industries, especially high-tech industries, are dominated by an ecosystem or network of interdependent firms working together to provide superior value to customers, and competition in these industries occurs at the level of ecosystems (Adner & Kapoor, 2010; Adner, 2017; Kapoor & Agarwal, 2016). For example, the smartphone industry is dominated by the Android and iOS ecosystems. The rival ecosystems include handset manufacturers, platform operators, software (apps) developers and network providers, with each component firm providing a unique solution that contributes to the overall value proposition of the ecosystem. Firms within the ecosystem thus co-specialised to deliver value to customers and co-evolved over time as the environmental conditions change. The ecosystem construct can hence enable us to explain in greater depth the outcomes of co-specialisation, value co-creation, co-evolution and co-capturing between interdependent firms (Moore, 1996; Adner & Kapoor, 2010; Thomas & Autio, 2014; Adner, 2017).

In the management literature, the ecosystem has been defined in a variety of ways (Thomas & Autio, 2012; Jacobides et al., 2016; Adner, 2017). For example, Moore (1993) describes the ecosystem as networks of companies working collaboratively and competitively to support new products, satisfy customer needs and eventually incorporate the next round of innovation (Bremmer et al., 2017). In a similar vein, Isantiti and Levien (2004) define an ecosystem as a set of interconnected firms organised around a focal or a keystone firm, who depend on each other for their mutual effectiveness and survival (Isantiti & Levien, 2004: 8). This way of defining the ecosystem, in which the production and the consumption side of participants are organised around a central firm is also echoed in many recent studies such as that regarding a platform (Cennamo & Gawer, 2002), a central hub firm (Jarillo, 1988; Rajala & Svahn, 2005), a lead firm (Williamson & De Meyer, 2012) and a focal firm (Hakansson & Johnson, 1994; Teece, 2007; Anderson, 2007). In addition to the participants' location emphasis in these definitions, other scholars have taken a broader perspective. For example, Adner and Kapoor (2010) and Adner (2017) see the ecosystem as the alignment structures – set of activities or technologies – of the multilateral set of partners that need to interact for the focal value proposition to reach end users (Adner, 2017). The authors explicitly include upstream suppliers and downstream complementors in their description of the ecosystem, as their activities need to come together in order for the focal value proposition to materialise.

Despite the variations in typologies used in describing the ecosystem, however, three core common and interdependent characteristics underscore the ecosystem: the value logic, partners' symbiosis and locus of coordination (Wiliiamson & De Meyer, 2012; Thomas & Autio, 2014; Bremmer et al., 2017).

2.9.1. Core Common Characteristics

2.9.1.1. Value Logic

In an ecosystem setting, firms cooperate to create value and also compete to capture value from their collective efforts. Customer value is created from interactions among partners (Adner & Kapoor, 2010; Christensen & Rosenbloom, 1995; Isantiti & Levien, 2004; Jacobides et al., 2015). Interactions facilitate the alignment of partners activities, enhancing their flexibility to respond to opportunities and challenges in the marketplace (Ianstiti & Levien, 2004). Increased flexibility enables ecosystem partners to meet customers' needs quickly and also enhance their ability to deal with changes in their internal and external environments (Iyer & Davenport, 2008; Thomas & Autio, 2012; Williamson & De Meyer, 2012).

Another source of value in the ecosystem results from complementarity between partners' activities, which lead to increase in efficiency. Complementarity between partners' resources and capabilities within ecosystems leads to higher efficiency of scale and scope (Iyer & Davenport, 2008; Jacobides et al., 2014). The efficiency of scale enables ecosystem partners to gain competitive advantages relative to competitors operating outside the ecosystem (Jarillo, 1998). Within ecosystem, partners specialised in specific activity, which increases cospecialisation. Co-specialisation among ecosystem partners leads to deeper learning enhancing the efficiency of scope.

Value can also be created within the ecosystem from innovation benefits resulting linkages of partner activities. Access to partners' resources within the ecosystem increases the potential for them to find relevant sources of knowledge from which they can use to innovate (Cohen & Levinthal, 1990). Another benefit that firms can accrue from operating within an ecosystem is network externalities resulting from lock-in (Williamson & De Meyer, 2012) and from the formation of industry standard (Katz & Shapiro, 1985, 1986). The firm technology can become an industry standard when it is used by many other players. An ecosystem offers the firm the opportunity for its technology to reach a large number of other firms and become the industry standard.

In addition to value creation, another critical element of the value logic and the ecosystem is value capturing. When partners within ecosystem participate in creating customers' value, they must also be able to capture a sufficient portion of the overall value from the co-creation process (Iansiti & Gawer & Cusumano, 2002; Levien, 2004). Value capture plays an essential role in the stability and long-term survival of the ecosystem, as partners are more likely to exit the ecosystem when they are unable to capture a fair amount of value from their contributions (Cusumano & Gawer, 2002). Focal firms as orchestrators of ecosystems are sometimes entrusted with the roles of ensuring that the value that is created within the ecosystem is distributed equitably to all ecosystem partners (Gawer & Cusumano, 2002; Isantiti & Levien, 2004). One of the ways they do that is through building a trusted relationship with partners. Trust among partners minimises the risk of opportunistic behaviour and facilitates the equitable distribution of value (Jacobides et al., 2014).

2.9.1.2. Symbiosis

Within the ecosystem, the success of a firm depends to some extent on the success of its partners, which creates mutualism or symbiosis between ecosystem partners. Symbiosis results from three elements. First, from co-specialisation, partners within ecosystems general specialise in a particular aspect of the system and provide specific input that contributes to the overall value proposition, which create interdependency between them. The second element of symbiosis results from complementarity between partners' resources. In the ecosystem settings, as a result of co-specialisation, partners' activities usually complement each other leading to additional value being created from synergetic and cumulative interactions. Lastly, partners' symbiosis also results from co-evolution whereby partners co-evolve as environmental conditions changes to maintain the stability and health of the ecosystem. Co-specialisation, complementarity and co-evolution together lead to partners' symbiosis and drive value creation and value capturing within ecosystems.

2.9.1.3. Locus of Coordination

In addition to value logic and partner symbiosis, the locus of coordination also plays an important part on the functionality of the ecosystems. The locus of coordination relates to the flow of activities within the ecosystem and the region/part where coordination challenges (bottlenecks) occur within the ecosystem. Ecosystems especially in high tech settings can generally occur within an industry or a firm's architecture (Adner & Kapoor, 2010; Kapoor & Agarwal, 2016; Jacobides et al., 2016). The architecture provides the ''blueprint'' for interactions among partners (Ozcan & Eisenhardt, 2009). Ecosystem partners usually come from different industry settings and have different technologies and business models, which complicates their alliance. The architecture links the various partners together and specifies the way in which partners can work together (Ferraro & Curses, 2009; Bremer et al., 2017). It also provides the context in which strategies are set and how value is created and distributed within the ecosystem (Jacobides et al., 2016).

According to Baldwin and Clark (2000) and Baldwin (2014), the architecture of an ecosystem constitutes a technological structure and an actor/social structure. The degree of interactions in the architectural components affects the flow of activities, the coordination, maintenance and stability of the ecosystem (Baldwin & Clark, 2000). It also affects the governance, trust and legitimacy of focal firms, which, in turn, influences the outcome of the ecosystem (Baldwin, 2014; Thomas & Autio, 2014).

These three core pillars collectively characterise the configuration of activities within the ecosystem and highlight how value is created and captured by ecosystem members. To understand how ecosystems contribute to firms' performance, scholars have studied the ecosystem based on these shared characteristics and drawn knowledge from other traditions including resource dependence (Gulati & Stych, 2007; Pfeffer & Salancik, 1978), resource-based view, core competence and relational view (Barney, 1991; Dyer & Singh, 1998; Gulati, 1995; Prahalad & Hamel, 1998), industry structure, value chain and value appropriation (Teece, 1986; Porter, 1980, 1985), source of innovation (Henderson & Clark, 1990, Von Hippel, 1998) and social embeddedness and network organisation (Burt, 1985; Coleman, 1990; Granovetter, 1995).

Using these theoretical lenses, research has examined how value is created by addressing the risks and challenges of cooperation/interdependency between partners. Value capturing strategies of firms such as controlling the key components and architecture of the ecosystem has also been examined. In addition, inspired by the interaction of the ecosystem components, scholars have examined how actors (agents that undertake activities within the ecosystem) interact and how the nature and ease with which partner technologies interconnect (alignment of activities) affect firms' performance.

2.9.2. Different Theoretical Streams

2.9.2.1. Value Creation

When considering prior works on the ecosystem, the value creation stream has focused on understanding the dynamics of cooperation among partners as a positive-sum game that allows them to create joint value and realise greater opportunities than would be created by a single firm (Hannah & Eisenhardt, 2016; Gawer & Henderson, 2007). Cooperation among partners facilitates the alignment of their activities, which enhances their flexibility and ability to respond to changes and opportunities in the marketplace (Ianstiti & Levien, 2004). The critical insight from this stream is that an increase in the number of partners within an ecosystem and increased level of cooperation among them significantly enhances their performance.

This stream of the literature, however, highlights that cooperation among partners can facilitate as well as constrain value creation. Scholars within this school of thoughts have investigated how collaboration among partners constrain value creation and provides ways through which partners can manage and deal with co-creation risks and hazards (Adner, 2012; Adner & Kapoor, 2010), what is described in the literature as bottlenecks. Bottlenecks have been conceptualised into three main types – component, adoptive and strategic. Component bottlenecks occur when a partner or component firm(s) is unable to meet its production demand, which can constrain the performance of the entire system. Hannah et al. (2016), for example, found in their study of the residential solar system industry that partners producing inefficient and low quality solar panels limited the revenue growth and collective profit of all the ecosystem partners.

In addition to component bottlenecks, joint value creation can also be inhibited by adoptive bottlenecks. Adoptive challenges occur when the technology for meeting customers' needs exists but is not adopted by partner firms, which impacts on the collective value that is created by the ecosystem. Adner (2012) describes how adoptive risks impact value creation using the Michelin Pax Run-Flat tyre case in the automotive ecosystem. The author shows that Michelin's inability to successfully commercialise Pax Run-Flat tyres was due to the slow pace of garages adopting the equipment needed to service the tyres. Although Michelin Pax Run-Flat tyres provided superior performance to those of its competitors, the unwillingness of garages to adopt the system led to the commercial failure of the Pax Run-Flat tyre.

To overcome the challenges of joint value creation, scholars have also identified several strategies that firms can use to address co-creation risks. One strategy that has been examined in the literature is investing in the system's constraining components. Ethiraj (2007) studies the PC ecosystem and describes how hardware manufacturers or focal firms generally invest around 8.5% of their R&D budget towards resolving components issues. The author indicates that investing in component constraining areas enables the focal value proposition to reach end customers quickly enhancing the overall performance of the ecosystem.

Another strategy that focal firms use to deal with component issues is encouraging other firms or partners to enter and innovate in component constraining areas (Gawer & Henderson, 2007; Ethiraj, 2007). Gawer and Henderson (2007) examined the component strategy of Intel Corporation in the PC ecosystem and describe how Intel motivates partners to enter into components that constrain its core microprocessor business by first demonstrating to them that the components are commercially viable. Then it provides partners with IP relevant in the areas for free or at lower fees to enable them to innovate in the component area. Consistent with Gawer and Henderson's work, Boudreau (2012) also found that in the PC ecosystem handheld computer manufacturers often motivate software producers to enter the ecosystem as an increase in the variety of software available in the ecosystem enhances its overall performance.

Along the line of mitigating component challenges, other scholars have also highlighted that focal firms can alleviate component challenges by operating in all components or the entire value chain of the ecosystem (Hannah & Eisenhardt, 2015). This system approach works well when products are highly sophisticated and the focal firm intends to change the ecosystem architecture rather than improve it.

Further, providing incentives to partners has also been shown to play an essential role in addressing joint value creation since incentives encourage partners to invest or adopt a system.

Many scholars have focused on this strategy (Adner, 2012; Cennamo & Gawer, 2015; Gawer & Henderson, 2007; Kapoor & Lee, 2013). For example, Adner (2012), describes how in the e-book division, Amazon encourages authors and publishers to join its ecosystem over competing ecosystems by providing them with added incentives. In a similar vein, Kapoor and Lee (2013), show that in the medical health care system in the US, in hospitals where doctors were integrated within an ecosystem they had added incentives for the hospitals to adopt new technologies or software that improved performance than in hospitals where doctors were considered as staff or mere employees.

In addition to these strategies, the timing of entry and the position of firms – components/complementors – within the ecosystem have also been examined as a mechanism for mitigating joint value creation. Adner and Kapoor (2010) investigated how the location relative to the focal firm where the co-creation challenge occurs affects innovation and value creation within the ecosystem. In a longitudinal study of the semiconductor industry, the authors show in multisided platform that greater upstream innovation challenges enhance the value that focal firms accrue from their ecosystems while greater downstream innovation challenges erode these benefits. The key insights from this study are that firms should innovate quickly when upstream innovation challenges occur and conversely, delay innovation until downstream complementors' challenges are cleared (Bremner et al., 2017). Put differently: upstream innovation challenges represent opportunities for firms to get ahead of rivals and so favour fast innovation, while downstream challenges simply stifle value creations.

2.9.2.2. Value Capturing

The value capturing stream has sought to understand how certain firms or focal firms capture value from the ecosystem by exploiting their dominant position and bargaining power. The primary focus of this stream has been on how ecosystem orchestrators, also known as ‘keystones’ (Iansiti & Levin, 2004) or ‘kingpins’ (Jacobides et al., 2015) or lead firms (Williamson & De Meyer, 2012), emerge and why they capture a disproportionate amount of value from their ecosystem. From the stream of literature, focal firms generally possess the most valuable resources and are considered the least replaceable players in the ecosystem (Jacobides & Macduffie, 2013). Because of their dominant position and strong bargaining power, they can control and dominate other players and reap a disproportionate amount of value from their ecosystems.

For example, in the smartphone ecosystems, Apple and Google occupy the most central position in the iOS and Android ecosystem respectively and capture the more significant share of the value that is created from the ecosystems (Kapoor & Agarwal, 2016). Similarly, Jacobides et al. (2016) found that in the PC ecosystem, Microsoft reaps the most significant amount of value from the ecosystem because of its dominant position within the ecosystem (Jacobides et al., 2016).

Besides bargaining power and dominant position, this literature has also identified other strategies that focal firms use to capture superior value from their ecosystems. One approach is by actively encouraging competition in other component areas while erecting barriers around their components (Jacobides et al., 2006). Barriers to entry generally result from innovation and technological upgrade. Kapoor and Agarwal (2016) illustrated in the smartphone ecosystem that one of the ways focal firms enhanced their value capturing is through technical upgrades. In a related study, Jacobides and Tae (2016) also showed that in the PC ecosystem focal firms enhanced the amount of value they appropriate from their ecosystem through innovation. Specifically, the authors show that focal firms that invest more in innovation capture more value from their ecosystem than those with a lower level of R&D investment.

Architectural control has also been studied as a strategy that enables focal firms to capture a disproportionate amount of the value from their ecosystem. For example, Ethiraj and Posen's (2013) study of the PC ecosystem revealed that firms, which maintain greater control over their architecture, create more patents and capture a higher amount of value from their ecosystem. In a similar vein to Ethiraj and Posen's study, Jacobides et al. (2015) also found that in the automotive industry, original equipment manufacturers (OEM) automakers, who had greater control over their architecture were able reap a disproportionate value from their ecosystem despite attempts at modularising the industry. Similarly, Fixon and Park (2008) also illustrate the role of architectural control in their study of Shimano and the bicycle drive train ecosystem. By introducing superior products architecture, the firm nullified the existing division of labour across the ecosystem to its advantage and captured a disproportionate amount of value (Bremner et al., 2012).

2.9.2.3. Actor-centric

Originating from the networking discipline, the actor-centric scholarly ecosystem literature focuses on the nature of interactions among actors who are agents that undertake activities with ecosystem (Autio & Thomas, 2014; Jacobides et al., 2015). Social interaction among actors creates opportunities and constraints. Interaction among actors facilitates strategic alignments and enables partners to deal with the challenges of coordination that arise when strategic incentives are not aligned (Adner & Kapoor, 2010; Autio & Thomas, 2014; Gulati et al., 2000). It also enables partners to build trust and act favourably vis-à-vis each other, which contributes positively to value creation and value capturing (Jacobides et al., 2006).

This community stream emphasises access and openness between actors and uses network measures such as centrality, structural holes and density of the ecosystem to explain performance outcomes (Adner, 2017; Autio & Thomas, 2014; Jacobides & Tae, 2015).

Strategy in the stream tends to focus on the number of actors that the focal actor is linked to as that increases its centrality and the amount of value it generates from the ecosystem.

For example, Jacobides et al. (2006) found that the number of actors to which focal firms are linked enhances their bargaining power and the value they capture from their ecosystems. An increase in the number of partners in an ecosystem increases the likelihood of serendipitous interactions between partners, which unlocks new interactions, and the combination of the interactions, in turn, increases the overall value creation of the system. The critical insight from the stream is that direct and indirect network externalities increase the amount of value that firms accrue from their ecosystems (Parker, Van Alstyne, & Choudary, 2016).

2.9.2.4. Technology Centric – the Structuralist Approach

The last stream of the ecosystem literature the structuralist approach explores the set of activities that need to occur for the focal value proposition to reach the end user (Adner, 2006; 2013; Adner & Felier, 2016; Adner & Kapoor, 2010; Kapoor & Lee, 2013). This activity focus stream places more emphasis on the flow of activities among partners and on the position of partners relative to focal firms, where coordination challenges occur within ecosystems. The alignment of partner activities is seen as the key to unlocking value creation (Adner, 2017; Adner & Kapoor, 2010).

Strategy in the ecosystem structural approach realm tends to focus on coordination of activities/technologies within the ecosystem and ease with which the focal technology can interact with those of partners. The ease of technological interaction enhances the chance for the focal value proposition to reach a large number of customers quickly. In a longitudinal study of the semiconductor industry ecosystem, Adner and Kapoor (2010) show that the ability of complementor/component firms to integrate focal technology enhances innovativeness and increases the overall value of the ecosystem.

2.9.3. Rationale for an Additional Perspective

The review above of the state of the art of the ecosystem literature indicates that the value creation and value-capturing stream offer complementary insights into the rationale for the differentials in the performance of firms. Although these streams have provided rich insights into how and why firms create and capture value from ecosystems, they do not incorporate in their analysis how the key architectural components of the ecosystem interact and the implications that this may have for value creation and value appropriation. The differentials in the amount of value that firms generate from ecosystems are influenced not just by how they motivate partners to join their ecosystem but also by the ease with which the focal technology interconnects with partner technologies and how knowledge, information and resources flows between the actors within the ecosystem. The degree of actors' interactions facilitates the coordination of technologies and enables the focal technology to reach a large number of customers. Further, the ease with which the focal technology interconnects with partner technologies provides reassurance to partners that they will extract value from participating in the ecosystem, which can play an essential role in attracting other firms to join the ecosystem. Thus, increased levels of technology and actor interactions enhance focal firms' bargaining power and position within their ecosystem (Brandenburger & Nalebuff, 1996).

Furthermore, the review also highlights that the actor-centric and structural ecosystem approaches focus on the role of relationship building and co-specialisation among partners' activities, but do not consider the role that the architecture of the ecosystem plays in shaping focal firms' performance. These streams tend to assume that the amount of value that focal firms generate from cooperating with partners is the same regardless of the magnitude of technological and actor interactions within their ecosystems. Within an ecosystem, the value is only created when the focal firm technology interconnects seamlessly with that of partners.

Interactions among actors' harness learning and enable the focal firm to develop more efficient innovative routines and this reduces the cost of coordinating the partner technologies and enhances the focal firm value creation and value capturing. In this sense, the amount of value that focal firms generate from an ecosystem is contingent on the level of technology interactions and actor interaction within their ecosystems.

In this thesis (study/paper 2) offers a slightly different explanation for the heterogeneity in the performance of focal firms, which hinges on the complexity theory. By introducing the complexity theory, we are suggesting that an ecosystem is analogous to a complex system, where interactions among the subcomponents affect the outcomes of the ecosystem (Glassman, 1973; Weick, 1976; Kauffman, 1993). In his seminal work, Kauffman (1993) defines the complexity of a system as a function of the number of subcomponents in the system, N and the level of interactions among the subcomponents, K. The complexity of the system increases when N and K increase, which creates rich interconnectivity among the subcomponents, which together produce a higher outcome than would be achieved from a slightly lower variation in the activity sets (Cockburn & Henderson, 1996). Interactions among components create a system level interaction between the components such that an improvement in one component exacerbate or mitigate the constraints imposts by the other components, thus contributing to system performance. For more details on the study, see chapter 6 of the thesis.

2.10. Review of the Literature Relating to the Third Constituent Study/Paper

2.11. Inter-firm Networks

In the last three decades, there has been a tremendous increase in the theoretical and empirical research on networks (Madhavan & Prescott, 2017). The rise is fuelled by the fact that firms' networks of relationships enable them to access partners' knowledge and resources, which when combine with their internal capabilities can significantly enhance their innovativeness

(Ahuja, 2000; Fleming, 2001; Henderson & Clark, 1990; Podolny & Stuart, 1995; Powell, 2004; Powell, 1996; Tsai, 2001). Firms network of relationships affect a variety of performance outcomes such as innovativeness, profitability and other measures such as learning and trust (Gulati, 2005: Koka & Prescott, 2002). This literature review focuses on the effect of network ties on firms' innovation performance. To synthesise this stream of the literature, this review begins by examining what has been done in earlier studies. Next, it looks at the broad lessons that have resulted from recent studies and identified gaps in the literature. Then it ends with how third study/paper of this thesis addresses some of the gaps identified in the prior literature.

2.11.1. Inter-firm Networks and Innovative Performance

In the innovative stream of the network literature, earlier studies have mainly focused on structural aspects of networks and consider the structure of firm networks as the most critical element of their environment (Ahuja, 2000; Gulati, 1995; Hite & Hesterly, 2001; Walker, Kogut, & Shan, 1997;). According to this view, firms' networks of partners embed them in a different structural position, and they benefit differently based on how they are positioned within their networks (Adler & Kwon, 2002; Burt, 1997; Coleman, 1988; Porte, 1998).

By contrast, most recent studies accentuate the importance of not just the structural features of networks but also how the attributes of firms' partners' affect and process consideration influence their innovativeness (Gulati et al., 2011; Lavie, 2007; Madhavan & Prescott, 2017; Sarkar, Aulakh & Madhok, 2009; Wang & Rajaopalan, 2015). These recent studies align closely to the relational embeddedness perspective, which holds that the structural elements and the contextual aspects of the network together play an important role in firms' innovativeness (Durkheim, 1951; Granovetter, 1985). It argues that understanding the structural and relational context of firm networks can advance our understanding of how social ties shape innovative performance (Gulati et al., 2011; Madhavan & Prescott, 2017; Sarkar, Aulakh & Madhok, 2009; Wang & Rajaopalan, 2015).

2.11.1.1. Structural Embeddedness Logic

A large number of earlier studies on inter-firm networks have focused on the structure of firm networks. This early strand of the literature underscores that the structure of firms within networks can explain performance outcomes, that is, by position of firms within networks, we can determine their performance (Portes, 1998; Coleman, 1988; Burt, 1992). Using social network analytical tools, scholars from this school though have explained the innovative performance of firms based on a variety of structural network features such as structural holes, density, size, closure, and centrality (Provan, Fish & Sydow, 2007). Below some of the critical studies and insights gained from these studies are explicated.

2.11.1.1.1. Structural Holes and Network Closure

In the structural perspective, an extensive amount of research has been devoted to the concept of structural holes (Burt, 1992) and network closure (Coleman, 1988) and how they influence a firm's environment and its innovative performance. The rationale for studying this is because networks tend to be characterised by dense clusters of strong connections, which have been conceptualised in the network literature as network closure or structural holes. A structural hole is understood as a gap between two actors or firms that influence how they access partners' resources or knowledge in a network. Burt (1992) argues that the performance of firms in networks depends on their ability to bridge structural holes between a dense groups of partners. Filling structural holes reduces the redundancy in knowledge flow, and firms that bridge structural holes have access to more novel information, which they can use to innovate. The critical insight from the structural holes' perspective is that filling structural holes facilitates access to novel information, which enhances firms' innovative performance.

On the other hand, Coleman (1988) takes quite a different view of network structure and its contribution to innovative performance. He argued that locating within a dense network confers firms with a competitive advantage. According to Coleman, a cohesive network resulting from repeated ties with stable partners engender trust and facilitates the transfer of tacit knowledge required for innovation. From the network closure perspective, the ease of knowledge transfer resulting from dense and cohesive network ties leads to an increase in firms' performance.

These two competing views on the effect of network structure have attracted huge debates and provoked increased empirical scrutiny among scholars as seen below. Walker, Kogut, and Shan (1997), for example, explore the phenomenon of structural holes and network closure in the biotechnology industry. They argue that the position of firms within networks should determine their social capital, and social capital increases with the cohesiveness or strength of firms' network of ties and diminishes with structural holes (Ozman, 2006). The authors show that network closure was a better predictor of performance than structural holes in the biotechnology industry. In line with Walker, Kogut and Shan (1997), Ahuja (2000) examines how structural holes and network closure influence firms' innovative performance in the chemical industry. The author argues that firms gain two main types of benefits from networks. First, networks enable firms to access tangible resources such as personnel, patents, distribution and marketing assets. Second, from networks, firms can also access intangible resources such as information about major technological breakthrough and failure in partners' technological development. He found that the strength of firms' network ties improves both access to tangible and intangible resources and enhances their innovative performance, whereas structural holes enhance tangible knowledge but also increase costs thus have an adverse effect of innovation.

In a related study, Hite and Hesterly (2001) also examined the effect of structural holes and network closure at different stages in the evolution of firms. Specifically, the authors looked at how structural holes and cohesiveness of start-up firms' ties influence their innovativeness as they move from an emergent to a growth stage. They found that at the initial phase, cohesive network structure was more conducive for firms' success while as firms moved towards a growth stage bridging structural holes contributed more to their success.

Other scholars have also weighed in and explored different aspects of the debate. For example, Gargiulo and Bennassi (2000) focus on the trade-off between trust resulting from cohesive ties and the flexibility resulting from bridging structural holes. Koka and Prescott (2002) postulated that social capital constitutes four different elements – information, volume, diversity and richness – and each of these dimensions' influences firms' innovative performance in a different way. Inkpen and Tsang (2005) broaden the single industry analyses that have been the focus of most studies by investigating networks in different settings such as strategic alliances, clusters and intra-firm cooperation. They showed that the efficiency of knowledge transfer is influenced by the nature of networks, and the different dimensions of social capital identified by Koka and Prescott impacts firms' innovation differently in these networks. The key insights from all these studies are that the effect of network closure – the strength of ties and structural holes on firms' innovative performance depends mainly on the external environment in which firms operate.

2.11.1.1.2. Network Density

In the structural perspective, another important structural feature that has been examined by scholars is the density of firm networks. Network density has been conceptualised using a wide range of factors, including the composition of firm networks regarding the number of partners, size and diversity. Bae and Gargiulo (2004) investigated the performance of firms in the US telecommunication industry in terms of their alliance or networks composition and partner substitutability. The authors found that when firm networks are composed of large and powerful partners (owner of critical resources), the cost of managing these partners may outweigh the benefits of the alliance. Under such circumstance, a dense network may have a more positive effect on innovation than a sparse network. Park, Mezias, and Song (2004) also found that compared to the market alliance, a technology type alliance contributes more towards firms' innovativeness as a measure of the number of patents than market-based alliances.

In this line of literature, researchers have also examined the relationship between partners' diversity and firms' innovative performance. Beckman and Haunschild (2002) found that firms that are linked to partners with diverse technological and market experience outperform those with a less diverse set of partners. In the same vein, Hoang and Rothaermel (2005) demonstrated that in the biotechnology industry firms that interact with a more diverse group of partners have higher performance than those that repeatedly engage with a single partner. Similarly, Baum, Calabrese and Silverman (2000) analyse the performance of start-ups with respect to their alliance formation and show that diversity as a measure of network efficiency enhances start-up firms' performance. However, Goerzen and Beamish (2005) reached a different conclusion in the context of multinational cooperation. According to the authors, the innovative performance of multinational firms decreases when their portfolio of partners is composed of more diverse firms than when they are less diverse. The rationale for the difference in the outcome may be that managing diverse partners in an international context with different institutional conditions may lead to an increase in costs that may outweigh the benefits gained from interacting with diverse group of partners. Similar to the structural holes and network closure above, the conflicting results from these studies reveal that the effect of network diversity on performance is varied and depends on the context and environment of the firm.

Regarding partners' size, researchers have also shown that firms' innovative performance may vary depending on the size of their partners (Dyer & Nobeoka, 2000; Hagedoorn & Duysters, 2002; Rogers, 2004; Singh & Mitchell, 2005). Among these studies, Singh and Mitchell (2005), Hagedoorn and Duysters (2002), Dyer and Nobeoka (2000) found a positive relationship between partners' size and firms' performance, whereas Rogers (2004) found the opposite result in the manufacturing industry.

2.11.1.1.3. Centrality and Innovation

Another important structural feature that scholars have linked to innovation is the firm's network centrality. Centrality relates to the position of firms in the network. Firms occupy a central position in networks when they are connected to many other firms (Bonacich, 1987; Gulati, 1995a), and centrality increases with the number of partners to which they are connected (Ecols & Tsai, 2005). Inspired by the central property of the network, scholars have investigated the impact of centrality at the direct ties level – number of ties that firms have with others, and indirect ties – firms' partners' ties to partners.

Ahuja (2000) showed that firms that occupy a central position in the network of direct and indirect ties in the chemical industry are more innovative when measured by the number of patents and new products they generate. The author attributes the positive effect to the fact that more centrally located firms are more likely to access a large pool of external resources that they can use to innovate. In line with the above studies, Baum, Calabrese and Silverman (2000) and Hagedoorn et al. (2016) also showed that the number of biotechnology firms' partners at founding is positively related to their performance measure by the multiple indicators – revenues, R&D spending, and patent generation. The central insight from these studies is that the quantity of information and knowledge that firms gained from connecting with partners significantly enhances their innovative potential.

2.11.1.2. Relational Aspect as a Complement to the Structural Logic

Although the structural features of the network contribute to firms' innovation, the relational aspects are also an important facet of networks (Gulati et al., 2011). Relational aspects of networks relates to the attributes of the firm partners (Madhavan & Prescott, 2017; Sarkar, Aulakh & Madhok, 2009). Researchers have argued most recently that the innovativeness of firms within networks is affected not just by their structural position – quantity of resources they accrue from their partners – but also by the attributes of their partners – quality of resources that partners bring to the network (Gulati; 2007; Gulati et al., 2011; Lavie, 2006). Put differently, firms' innovative potential is influenced not only by how they are connected but also with whom they are connected. The nature and source of resources they accessed from their network vary depending on whom they are connected to (Gulati et al., 2011; Madhavan & al., 2008).

According to the relational embeddedness network perspective, because of the differential in the resources that firms accrue from their network, firms occupying a similar network position may accrue differential benefits from their networks based on the source of resources and knowledge (Gulati et al., 2011; Madhavan & Prescott, 2017; Sarkar, Aulakh & Madhok, 2009; Wang & Rajaopalan, 2015). Firms that are tied to partners with sophisticated resources or knowledge base are likely to benefit more from their network of direct ties than those that are linked to partners with a relatively weak resources base (Gulati et al., 2011; Madhavan & Prescott, 2017). This suggests that research that focuses only on the structural features – quantity of resources – of networks without taking into account the implications of the richness of resources and knowledge that firms gain from the different parts of the network may not capture the full effects of network ties on innovation. Study/paper 3 of this thesis attempts to address this gap by examining how the quantity and quality of the firm direct and indirect impact its innovation performance. For more information on the study see chapter 7 of the thesis.

3. INDUSTRY AND MARKET STRUCTURE OF THE SEMICONDUCTOR INDUSTRY

3.1. Introduction

This chapter builds on the arguments expounded in the literature review section providing the context for understanding this thesis. The research gaps identified in the literature review and the three papers addressing these gaps are explored within the semiconductor industry. The market and technological dynamics in the semiconductor industry may be similar to other cumulative industries such as electronics, computer and software, but differs from those of other high-tech industries such as pharmaceutical, chemical and telecommunication industry. The industry and market dynamics within industries may influence the degree to which firms engage in collaborative relationships (Grindley & Teece, 1998).

The chapter provides a general overview of the semiconductor industry through the lens of the industry and market structure. Firms in the semiconductor industry use different business models and strategies (organisational forms) to create and capture value from their innovation. Chipless firms use licensing and ecosystem to appropriate value from their technology. As specialised firms that depend solely on licensing and ecosystem formation, the sustainability of chipless firms' strategy depends on both the threats and opportunities in their external environment and their ability to use their internal capabilities to overcome constraints in the market. The opportunities and constraints in the market result from interactions of exogenous shocks and responses by a variety of endogenous/industry players to changes in technological, market, institutional, regulatory and political factors. Thus, chipless firms' cooperative strategy must take into account their competitors' strategies, customers' and suppliers' needs and general dynamic within the semiconductor industry. This suggests that to gain a better understanding of chipless firms' strategy, it is important to examine the industry or markets in which they operate and how they position themselves within the competitive semiconductor industry.

According to Johnson et al. (2017), an industry is a group of firms producing products and services that are essentially the same. Industries are often made of several markets or market segments. A market is a group of customers that buy similar products or have needs that are similar to each other. The semiconductor industry is made of many different market segments such as networking infrastructure and servers, embedded devices and microcontrollers, microprocessors and system on chips. Within these segments, there are also sub and sub market segments. Firms in the industry occupy different market segments and position themselves differently in these market segments.

This chapter thus examines the industry and market structure of semiconductor industry from the perspective of the central actor - chipless firms and factors that shape their long-term survival including the number and power of their competitive rivals, customers and suppliers, potential new entrants and substitutes products. It begins by providing a brief history of the semiconductor industry. The history is examined through the lens of the evolution of the industry technology. In the semiconductor industry, firms use many different organisational forms to commercialise technology and the aggregate structure of the industry have emerged as an outcome of the evolution of the industry technology. A distinct feature of the industry is that although throughout its history there have been many different dominant technological designs (paradigms), the concentration of players in the industry has remained relatively high compared to other R&D and technology-intensive industries such pharmaceutical, chemical and telecommunication (Grinley & Teece, 1998). Since its creation in the 1940s, the industry has been dominated by a relatively small group of leading firms (large integrated firms) with a large number of small firms operating at the fringe of the market. However, more recently, the market shares of these leading - large integrated firms has been dwindling with small and innovative start-ups (networked firms) using the networked business model gaining more market shares.

Next, it examines the two main organisational forms - integrated and networked model that industry players use to commercialise their innovation. Competition in semiconductor industry, is seen as a competition between these two organisational forms. It also examines the market segments that key players occupy and their market shares in the different market segments. This enables us to capture how networked firms in particular chipless firms position themselves within the industry and the implication that this may have on their competitiveness. Then, ARM Holdings, a leading chipless firm is used as an example to illustrate how licensing through ecosystem formation has enabled chipless firms to gain a competitive advantage in the dynamic and fast moving semiconductor industry.

3.2. Brief History of Semiconductor Industry

3.2.1. Birth of the Industry

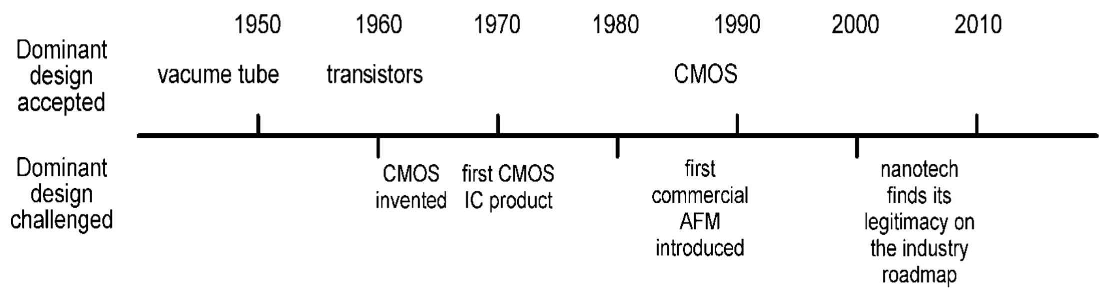
The semiconductor industry is the aggregate collection of companies engaged in the designing and manufacturing of semiconductor devices (silicon chips). The industry has its origin in the electronics and computer industry. It was launched in 1947 with the invention of the transistors at AT&T Laboratories (Bell Labs). The first transistor was produced in 1952 and was commercially used mainly in products for hearing impairment and military equipment. In 1960, the integrated circuit (IC) was subsequently invented and was primarily used for the radio, communication and space programmes (Grindley & Teece, 1987).

Over the past six decades since the invention of the transistors, the pace of technological development in the industry has been astronomical and its products are now used in almost every electronics device that has an on and off switch button.

3.3. Semiconductor Industry Technology and its Evolution

Since the creation of the semiconductor industry in the 1940s, the technology of the industry has evolved in line with Moore's law, which states that the number of transistors that can be inexpensively placed on a chip doubles every two years (Moore, 1965). Although Moore's law may have stalled now, the technology of the semiconductor industry has evolved rapidly over the years with one dominant design replacing another (see figure 3.1 below). These changes have had a huge impact on the division of labour in the industry and strategy that firms use to create and capture value from their innovation (Linden & Somaya, 2003).

Figure 3-1: Evolution of Dominant Designs in the Semiconductor Industry from 1940-2010



Source: Jiang, Tan, Thursby (2011)

From 1940 to 1980, Bipolar Technology (PCB) was the dominant design in the semiconductor industry. Under the PCB paradigm, the industry was mainly dominated by large integrated firms, who controlled their entire value chain. Using an integrated mode, they design and manufacture products using their internal capabilities and only bring in external knowledge when necessary. In PCB paradigm, other organisational modes such as the networked mode was mostly absent (Linden & Somaya, 2003). Although the networked/licensing model was absent during PCB paradigm, that does not mean there was no licensing between firms, it mainly occurred within strategic alliances. It was typically passive and did not involve the sharing of know-how among firms (Grindley & Teece, 1997).

From 1960 to 1980, a paradigmatic shift began in the industry with the invention of the complementary metal-oxide-semiconductor (CMOS) technology. In 1963, Frank Wanlass at Fairchild Semiconductor invented CMOS but the first commercial CMOS product was not introduced in the market until late 1970. Although CMOS technology was superior to bipolar technology, PCB remains the dominant technology in the industry until the early 1980s. This was because inventions that resulted from CMOS were far from clear, thus inhibiting the prospect of CMOS replacing PCB as the dominant design (Linden & Somaya, 2003). During this period, industry incumbents or leading large firms continue to elaborate on the PCB design, incrementally innovating, competing, and dominating the market with more reliable and better-performing PCB based products.

However, in the late 1980s, advancement in technological development led CMOS to replace PCB as the dominant design and ushered in a new era in the industry termed ‘‘the system on chips (SOC)’’. The system of chips facilitated the process through which a large number of transistors could be expensively placed on the same chip (Jiang, Tan & Thursby, 2011). Before the introduction of SOC, when many chips were placed on a PCB, it generated too much heat and consumed too much energy. CMOS seems to be more efficient in regulating and transmitting energy when multiple chips were placed on it, which accelerated the process for CMOS replacing PCB as the dominant design.

The development of the system on chips led to an increase in specialisation in the industry, which facilitated the entry of a large number of small and innovative firms. These new breeds of firms follow a slightly different model from incumbent large firms - IDMs traditionally design and use in-house manufacturing facilities to produce and market their chips. In contrast to IDMs, these start-up firms use a networked business model designing and licensing/outsourcing their technology to other firms especially (OEMs) who use specialised manufacturers - foundries or their own fab (factories) to manufacture their chips.

3.4. **Organisational Modes**

Nowadays, firms operating within the semiconductor industry use two main organisational modes to create and capture value from their innovation. Competition in the industry can be seen in the eye of these two modes of organising and commercialising semiconductor devices/chips: An integrated mode and a networked mode. Each of this organisational mode has advantages and downsides.

3.4.1. **Vertical Integrated Mode (IDM)**

A vertical integrated mode is when a firm designs and manufactures chips or integrated circuits (ICs) in house with little or no external licensing (Linden & Somaya, 2003). Most large firms (in terms of revenues and number of employees) in the industry such as Intel Corp, Texas Instruments, Motorola, IBM, Micron, Samsung, Toshiba, Hitachi, NEC, Infineon, Philips, Mitsubishi and STMicroelectronics adhere to this mode (see table 3.1 below for more information about these firms).

In this organisational mode, firms place more emphasises on designing and manufacturing integrated circuits internally, taking advantages of external capabilities only when necessary. Firms using this organisational mode generally host most of their technologies and capabilities in house. Rather than engaging in full blow licensing (engage in some sort of licensing here and there), they usually prefer to bring in new capabilities from outside through mergers and acquisitions (Somaya & Linden, 2003)

Table 3-1: Firm Size and Establishment Date of Top 10 Integrated Firms

Integrated Mode			
Integrated Device Manufacturers			
Firm	Est. date	Rev. Billion	No. Emp.
Samsung	1938	210.90	320,671
Intel	1968	70.80	107,100
SK Hynix	1983	35.27	22,225
Micron	1972	20.32	34,100
TI	1930	15.78	29,714
Toshiba	1890	10.7	141,256
NXP	1953	9.41	31,000
Infineon	1999	7.59	40,100
Sony	1964	6.54	117,300
Mitsubishi	1970	154	88,744

Source: IPnest (May 2018). Revenues and employees' number in 2018

The integrated organisational model has many advantages. Through an integrated mode, a firm can economise on many transaction costs that result from licensing or external sourcing of technology. The development of an integrated circuit requires extensive coordination and communication across different and interdependent stages of production (Adner & Kapoor, 2010; Kapoor, 2013). The integrated mode can enable a firm to benefit from coordination advantages especially when there are complementarities and synergies between the design and production functions (Monteverde, 1995). Although, by partnering (networked mode) with other players a firm can develop advanced technology, such organisational arrangement is unlikely to match the extensive internal (intra-firm) knowledge sharing and coordination that an integrated mode offers in organising interdependent production tasks (Kapoor, 2013).

In addition, an integrated mode can also offer advantages in terms of flexible as in this mode the firm mainly uses intra-firm design and manufacturing interfaces. Unlike in the networked and licensing mode, which are based on standardisation (slow and inflexible industry-wide standard), intra-firm interfaces can easily be adjusted to meet design and manufacturing needs.

However, despite the apparent advantages, the organisation mode also has some drawbacks. First, an integrated mode assumes that the firm has all the prerequisite technology in-house to design and manufacture a complete integrated circuit (chip). Even when a firm can develop an entire chip/technology in-house without infringing the intellectual property rights of other firms, the inefficiencies resulting from intra-firm coordination (duplicative re-engineering) may still be costly and time-consuming (Kapoor, 2013; Somaya & Teece, 2001). Second, an integrated mode sacrifices the benefits of modularisation (well-defined design rules), and experimentations that may result from accessing technology from other firms and using alternative approaches to develop new technology. Last, the internal stability and political status quo that underscore coordination across design and manufacturing domains in the integrated mode can become a liability in the long term, especially if managers and engineers are not in harmony with each other. This may block the adoption of best-in-class design elements from outside, which have a negative impact on the firm's performance.

3.4.2. Networked Mode

The networked mode consists of using the market to coordinate interdependent activities among partners. It enables firms to mitigate low-powered incentives of hierarchy associated with the integrated mode (Kapoor, 2013; Mahoney 1992; Williamson 1985). Most specialised firms in the semiconductor industry use the networked mode. They do not engage in manufacturing (do not own manufacturing facilities (fab)) but mainly use a network of partners to develop and commercialise their technology.

The networked mode offers firms with many advantages. Compare to the integrated mode, the networked mode enables firms to invest relatively less in terms of research and development (R&D) to develop an integrated circuit (IC). In a network mode because each partner specialises on a specific aspect of the value chain, this reduces the cost of R&D required to develop a complete silicon chip. In addition, similar to the cost of R&D, firms draw upon a broader set of capabilities (designing and manufacturing) from partners to manufacture chip (ICs) in the networked mode, which leads to a reduction in the cost of production (Langlois 1992, Kapoor, 2013; Sarma & li Sun, 2016; Sturgeon 2002).

However, the network or licensing mode is also plagued with many constraints resulting mainly from transaction cost associated with coordinating cooperative/licensing activities among partners. The first source of transaction cost results from technological interconnectedness. In a networked model, to produce a functional product requires partners to adapt and integrate each other technologies. When a firm licenses its technology to partners, they cannot foresee in advance all issues of integration that may occur in the licensing process. Despite modularisation and standardisation efforts that have taken place lately in the industry, technological interconnectedness risks resulting from incorporating partners' technology are still likely to occur, which in turn increases transactional costs associated with licensing.

The second source of transaction cost results from diffusion entitlement. Diffusion entitlement arises from the unclear nature in which IP rights are allocated to inventions in the semiconductor industry. Because of the cumulative nature of the industry technology and the complexity of uncovering firms patent rights especially when the relevant patents have not yet been issued, it is usually very difficult to identify beforehand all firms that own the IP rights to a given technology. The ambiguity in uncovering firms' patents means that in an event of a litigation parties are exposed to substantial liabilities, which enhances the transaction costs associated with licensing.

Another source of transaction cost relates to uncertainties associated with commercialising technology. In technology licensing, it can be difficult to determine in advance the true value of a technology as licensing parties may associate different value to the same technology (Merges and Nelson, 1990, 1994). The evaluation problem is even compounded in semiconductor because of the multi-invention nature in which innovation takes place in the industry - whereby a single product may contain technologies of many firms making it difficult to evaluate the contribution of a single or a firm technology to a product.

Finally, transaction costs also accrue from monitoring and metering needs of licensing agreements, which exacerbate the evaluation and contracting issues highlighted above. In technology licensing, it can be difficult to determine in advance how partners may use the firm (licensor) technology. Although 'field of use' (i.e. application, region, etc.) in the licensing contract may impose a restriction to the use of the licensed technology, licensees may still invariably use the licensor technology, which can cause unanticipated losses to the licensor.

Despite these drawbacks, in the last two decades, there have been huge efforts in the semiconductor industry to reduce transaction costs associated with licensing and make the networked mode works. Increased modularisation and standardisation efforts have led to well-defined rules in designing and manufacturing, which entail that firms can engage in other value chains tasks without requiring a significant adjustment in their production processes. These efforts have made it easier for firms to engage in licensing as partners can coordinate their licensing activities more efficiently and thus enhancing the viability and popularity of the networked mode.

Within the networked mode, there are two main models: Fabless and Chipless mode. In the Fabless model, firms design and outsource their technology (IPs blocks) to foundries (specialised manufacturers) who manufacture the technology for them. Chipless firms in contrast design and license their intellectual properties (IPs) to partners, who combine chipless firms' IPs with their own technologies to create a complete products (IC).

3.4.2.1. Chipless Firms and Value Chain Members

Chipless firms are principal innovators in the semiconductor industry. Compared to integrated firms, chipless firms are relatively smaller in size and younger as most of them entered the industry after 1980 when CMOS replaced PCB as the dominant design leading to increase specialisation (see table 3.2 below for more information). They do not engage in any manufacturing but mainly use licensing and ecosystem formation to create and capture value from their innovation. As specialised firms that do not possess manufacturing facilities, they invest hugely in R& D to innovate and develop new technologies. When chipless firms develop a new technology, they patent and license the rights to the intellectual property to other firms. Their partners then use chipless firms' IP blocks alongside their technology to develop advanced products that are suitable for many consumer electronics such as smartphones, laptops, tablets, computers, and most smart and wearable consumer electronics devices.

Licensing enables chipless firms to work with many partners and from the partnerships; they form an ecosystem of independent and interconnected firms (Moore, 1986). Licensing through ecosystem enables chipless firms' technology to reach a large number of customers/markets quickly. By working with a large number of partners, chipless firms access a broad range of market information and tap into complementary capabilities of partners. Accessing up-to-date market information quickly enables chipless firms to develop and maintain a valuable stream innovation. From their ecosystem of partners, they also gain insight into the unfolding technological roadmap in the industry, which in turn enables them to produce new product generations and also enable them to decide when and whether to shift into new technological areas.

Rather than designing and manufacturing products alone, chipless firms partnership model also enable them to reduce the cost of developing and marketing technology. Chipless firm partners invest in other areas of the value chain, which reduce the overall cost of R&D and production. Leading firms (in terms of size as a measure of revenues and number of employees) employing the chipless mode include Arm Limited, Rambus, Imagination Technologies, Synopsys, Mosaid Technologies, Virage Logic, Silicon Image, Achronix, Verisilicon and Ceva .

Table 3-2 : Firm Size and Establishment Date of Top 10 Firms in Each Organisational Mode.

Integrated Mode				Networked Mode							
Integrated Device Manufacturers				Fabless Firms				Chipless Firms			
Firm	Est. date	Rev Billion	No Emp.	Firm	Est. date	Rev Billion	No Emp..	Firm	Est date	Rev Billion	No Emp.
Samsung	1938	210.90	32,0671	Qualcomm	1985	22.73	11,750	Arm Limited	1993	1.61	6,250
Intel	1968	70.80	107,100	Broadcom	1961	20,84	35,400	Synopsys	1986	0.62	12,590
SK Hynix	1983	35.27	22,2254	Novatek	1994	10.00	11,528	Cadence	1988	0.18	7,600
Micron	1972	20.32	34,100	Nvidia	1993	9.71	7,000	Imagination Technologies	1985	0.12	1233
TI	1930	15.78	29,714	AMD	1969	6.48	10,100	Ceva	1999	0.07	313
Toshiba	1890	10.7	141256	Marvell	1995	2.86	5,200	Verisilicon	2010	0.04	275

NXP	1953	9.41	31,000	Xilinx	1984	2.53	4,014	Achronix	2004	0.02	200
Infineon	1999	7.59	40,100	Realtek	1987	1.51	5,997	Rambus	1990	0.05	819
Sony	1964	6.54	117,300	Dialog Semiconductor	1985	1.44	4,000	eMemory Technology	2000	0.04	500
Mitsubishi	1970	154	88,744	Media Tek	1997	0.27	1,850	Waves Computing	2008	0.04	254

Revenues and employees number in 2018. Source: IPnest (May 2018).

Chipless firms value chain members include partners such as EDA software suppliers, system integrators, specialised manufacturers - foundries, fabless firms and some integrated devices manufacturers. Chipless firms and partners work together to provide superior value to customers (see figure 3.2 below for information on chipless firms value chain).

Chipless Firms Value Chain Members

3.4.2.1.1. EDA Software Suppliers

EDA software providers are considered principal suppliers to chipless firms. The EDA segment emerges in the semiconductor industry at the same time that the system of chip movement (SoC) took off in the late 1980s (Linden & Somaya, 2003). EDA firms supply chipless firms with software that automates chip designing, simulation, verification and manufacturing and have been at the vanguard of promoting design methodologies that support licensing in the semiconductor industry. Their software or tool serves as a pre-test design element (basic building block) on which an entire chipset is constructed. The software makes it easy for partners to manufacture chips based on specification.

The early players in this segment include Mentor Graphics, Synopsys, Tality, and Cadence Design System. These firms are still the leading firms in the segment in terms of market share and mainly use licensing and subscription model to create and capture value from their innovation.

3.4.2.1.2. Foundries

Similar to chipless firms and EDAs, foundries are specialised manufacturing firms that entered the semiconductor industry in the late 1980s when complementary metal-oxide semiconductor (CMOS) and improvement in designed software facilitated licensing and manufacturing of standardised chip modules. Before the entry of foundries, early-networked firms depended on the vertically integrated firms, who only manufactured networked firms chips using their spare capacities.

The entry of foundries in the 1980s changed the competitive dynamic in the semiconductor industry. Foundries provide tight process integration and manufacturing services to networked firms and partners. Foundries possess more advanced and cutting edge manufacturing technology than many IDMs. Foundries and networked firms' partnership model has increased the competitive pressure of IDM firms as it takes away customers who might otherwise absorb IDMs extra manufacturing capacities or even buy IDMs technology (Fraone, 1999). These changes in market and technological landscape have driven some IDMs to use either fab-lite model (do not offer the full range of manufacturing services available from regular foundries) or create their own foundry services in order to stay competitive in the industry (Smith, 1999). For example, AMD has spun off a new foundry division as a stand-alone company under the name – Globalfoundries.

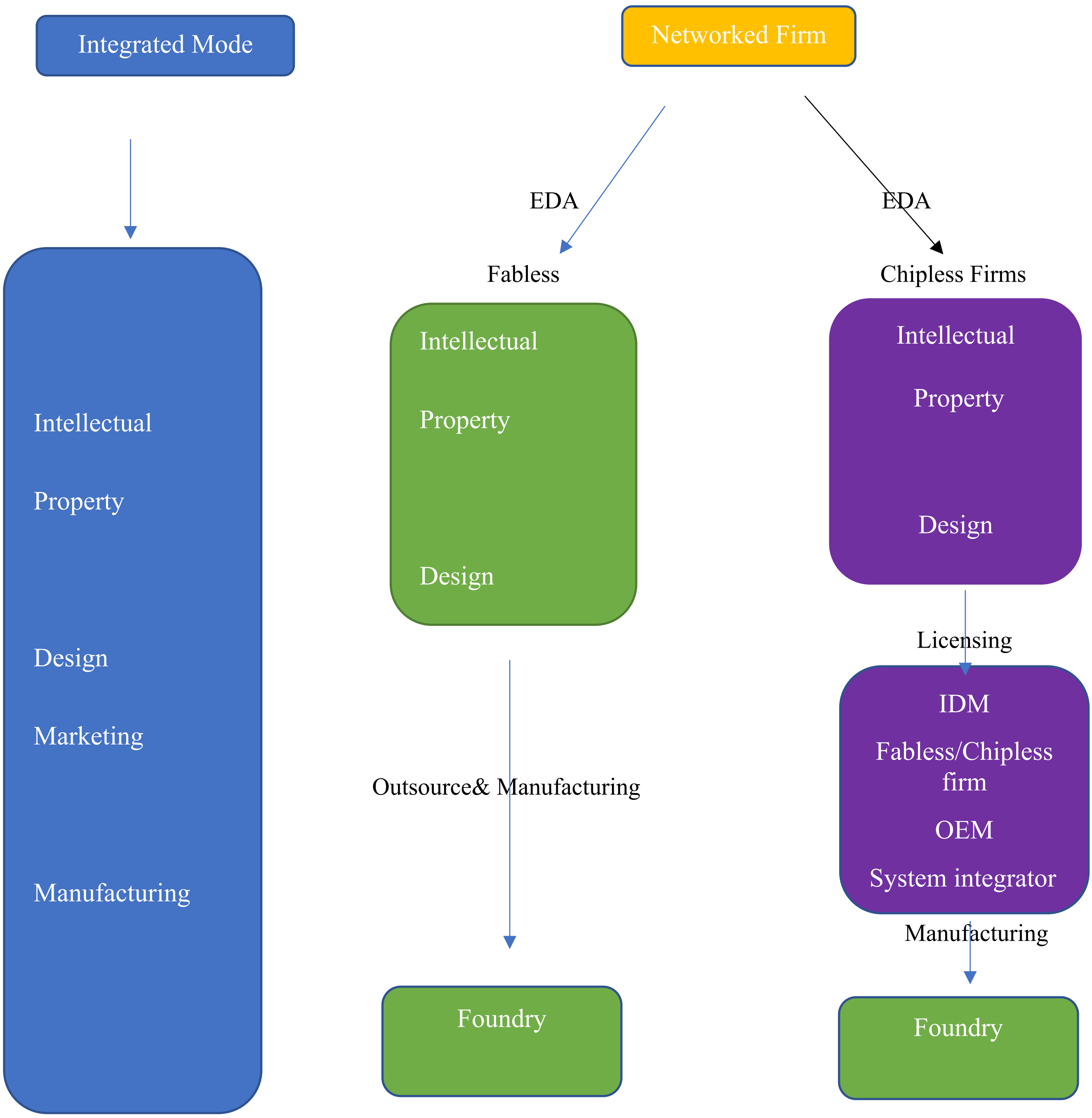
Firms from Far East Asia dominate the foundries segment. Leading firms in the segment include United Microelectronics (UMC) and TSMC both from Taiwan, Hua Hong Semiconductor and Dongbu Hitek (China) Samsung (Korea), Globalfoundries, Powerchip (USA) – IDM's and Foundries.

3.4.2.1.3. System Integrator Firms

System integrators are firms that assemble and market electronics end- products to consumers. Although some system firms possess their IC design and manufacturing facilities, they also exploit opportunities emerging from the networked side of the system of chips. System firms access IPs and software from chipless firms and EDA and manufacturing services from foundries. As system integrators, they used networked firms' services to save cost and to differentiate their products from those of other vertical integrated firms in the industry. Somaya & Teece 2001, describe how Quantum Corporation, the volume leader in hard disk drives (HDD) in 1999 licensed a microcontroller module from Arm, a DSP module from Rambus, and a 'read-channel' module from Lucent to create a single-chip solution for its drives. This enables Quantum Corporation to leverage its system-level understanding and dual-source fabrication to its advantage in products development and price negotiations.

Figure 3-2: Summary of Organisational Forms in Semiconductor Industry.

This figure summarises the two organisational modes that semiconductor firms use to develop and commercialise technology. In the Integrated mode, firms (IDMs) involve in the entire value chain (designing, marketing and manufacturing). The networked mode-partnership mode, firms either outsource manufacturing to foundries (fabless mode) or license IP to partners (chipless mode)



3.5. Drivers of Growth and Market Segments in the Semiconductor Industry

The demand for semiconductor industry products is mainly influenced by end-user needs. Increased global population and rising standards of living in many part of the world has led to growing demands for digital devices, which contain a vast amount of ICs. In addition, the increased pace of technological development in the electronics industry has further provided a rich and large market for semiconductor products. The desire for industry players to meet this growing demand has spurred innovation and led to the development of new products and new markets, which in turns has led to semiconductor firms generating more revenues. In 2017, the global semiconductor industry generated a revenue of over 463.41 billion U.S. dollars and the industry revenue is forecasted to be in the region of about 1trillion U.S. dollars by 2030.

Based on end-user needs and products, the modern semiconductor industry can be broadly classified into four main product categories (Gartner, 2017):

1. **Memory:** Memory chips comprises of chips that are used for information and data transmission. They are heavily used in industrial products such as power supply equipment, bar code scanners, medical devices such as patient monitors, ultrasound imaging. The memory market segment has consolidated over time, driving memory prices low such that only very large integrated firms such as Toshiba, Samsung and NEC are able to compete in the segment.

2. **Microprocessors:** Microprocessors are central processing units that contain the basic logic for performing computational tasks. They are found in many electronics products such as servers, computers, printers, cars, aircrafts and other related hardware. This segment is one the largest market segment in the semiconductor industry. It is dominated by Intel Corp. The domination of the microprocessor segment by Inter Corp

has forced most players out of the market or into different segments or small niches with the exceptions of Arm Limited, Advanced Micro Devices, Broadcom and Qualcomm

3. **Commodity Integrated Circuit:** Sometimes called "standard chips", these comprise chips that are used in household appliances, LCD TVs and washing machines. Large Far East Asian chip manufacturers such as TMSC, Foxconn and United Microelectronics (UMC) dominate this segment. The segment offers razor-thin profit margins that only the biggest semiconductor companies are able to survive in this market.

4. **Complex SOC:** This market segment revolves around the growing demand for small size consumer electronics products requiring huge power and low energy consumption. The production of these products takes advantage of the system on chips capability essentially these products are created based on integrating many integrated circuits on a single chip. This market is considered a growing segment of the semiconductor industry and it is dominated by networked or chipless firms such Arm Limited, MIPS, Synopsy, Imagination Technologies and RAMBUS producing low power and high battery life chips (RISC technology), which are suitable for small and smart electronics devices.

The semiconductor industry is a highly fragmented industry with firms occupying different market segments and positioning themselves differently in the market. Within each segment, there are sub and sub segments. Competition is fierce between players in the same segment and among firms operating within the semiconductor industry. Innovation is seen as a key source of competitive advantage and firms compete on technology rather than on price. They use R & D investment as a strategy to maintain their dominant position in their respective market segment (s) and also a mechanism to move into other market segments. Chipless firms invest hugely in R&D and are constantly innovating with the objective to move into other market segments where they possess lower market share. For example, Arm Limited, a leading chipless firm in the semiconductor industry has a market share almost 75% in the smartphones market segment but less than 5% market share in the servers and microprocessors segment. Arm is investing hugely into the development of chips that can serve the servers and microprocessors segment (www.arm.com).

The next section examines how chipless firms compete in the semiconductor industry. To capture how chipless firms compete, Arm limited is used as an example to illustrate how chipless position themselves in the different market segments. The rationale for selecting Arm is because it is the largest chipless firms in term size (employees and revenues) (see table 3.3 below)). The table illustrates that Arm Limited is the most profitable chipless firms as its revenues in 2018 is almost twice that of it is closest rivals Synopsys. As the world's leading intellectual property supplier, Arm Limited licensing and ecosystem strategy is of particular interest as it plays an important role in its ability to innovate and compete.

Table 3-3: Top Ten Chipless Firms Based on Revenues in 2018

Ranking (2018)	Company	Employees	Revenues (millions)
1	ARM	6,250	1610,9
2	Synopsys	12,590	629,8
3	Cadence	7,094	188,8
4	Imagination Technologies	1,008	119.7
5	Ceva (ParthusCeva)	313	77.9

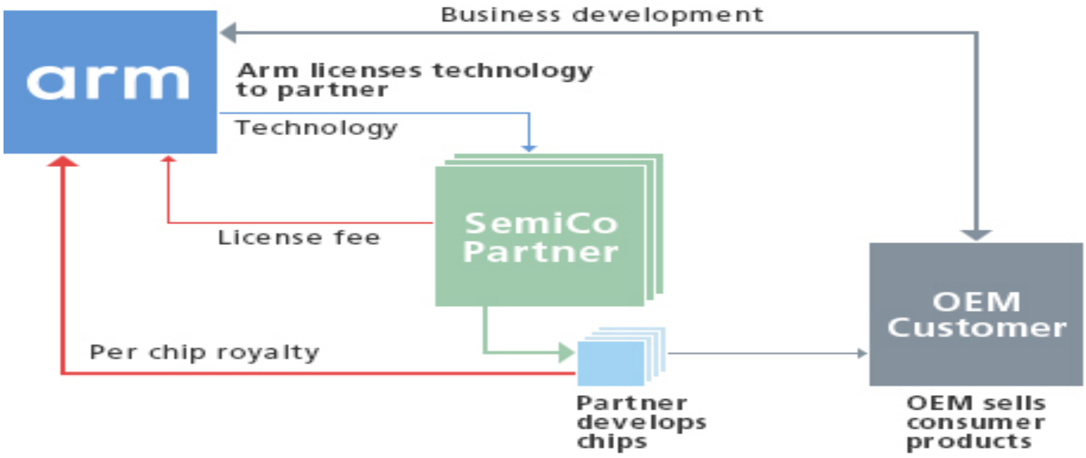
6	Verisilicon	420	66.3
7	Achronix	200	52.5
8	Rambus	819	52. 1
9	eMemory Technology	500	47.9
10	Waves Computing	233	41.1
	Top 10 Vendors		2,886.0
	Other		716.6
	Total		3602,6

Source: IPnest (May 2018)

3.6. Arm Limited

Arm Limited is one of the early players in the chipless space. It was created in Cambridge – UK in 1993 as a spin-off from Acorn Computer. It designs intellectual property and related technology and software and licenses them to other semiconductor firms. Its partners include most of the leading semiconductor companies (see table 3.4 below). From large integrated firms such as Intel, LSI Logic, Micron, Toshiba and Renesas to prominent OEMs such as Samsung, Apple, Huawei and other networked firms such as Qualcomm, Broadcom, Ceva, Rambus and Atmel, which entails that Arm's technology is present in most consumer electronics and semiconductor application products (smartphones, laptops, computers, tablets, wearable devices, televisions, internet of things, cars, aircrafts, etc). Arm's partners use Arm's IP blocks alongside their own technology to produce advanced electronics products. They pay an upfront licensing fees and royalties (that can go for up to 25 years) for each product that they produce using Arm's technology (see figure 3.4 below). The flexibility of Arm's licensing and ecosystem business model makes it highly profitable and cash generative (arm.com/ir).

Figure 3-3: Arm's Business Model



Source. www.arm.com/ir

Table 3-4: List of Arm Limited Key Partners and their Status.

Arm Limited Key Partners					
Partners					Status
Toshiba	NEC	Panasonic	Rohm Semiconductor	Renesas	1
Rhomb	On Semiconductor	NXP EDV Elektronik	Ltek Elektronica	Maxim Integrated	1
Oki Electric Industry Co Ltd	Lar Systems Hyundai Group	Avnet Texas Instruments Inc	Intel Corp	LSI Logic Corp	1
Samsung	Huawei	Apple	Nokia	Ericsson	2
Motorola Daliwork	Baidu 3Com Corp	Nuvoton	Express logic 3DO Co	Comtech Multitech	2
Realtex	Qualcomm	Analog Devices	Atmel Corp	Broadcom	3
Cirrus Logic Microsoft	Cross Products Ltd	Digital Semiconductor(Digital)	Embedded Performance Inc	Imagination Tech	3
United Microelectronics	Google	Alibaba	SEMTECH	BAI	3

Source: arm.com

(1) IDM (2) OEM (3) Networked firm.

From five forces of competition perspective, players trying to compete with Arm limited face high barrier to entry. To develop a new chip (the sort of chips develops by Arm) requires a huge amount of capital investments, which may be very expensive even for large chip manufacturers such as Qualcomm, Intel, Texas Instruments, Toshiba, Infineon and behemoth consumer electronics companies such as Samsung, Apple and Sony. Because of the huge up-front costs required to develop a new chip, rather than developing their own technology in-house, semiconductor firms (partners) prefer to use Arm's intellectual properties. The high cost for developing chips has made Arm to become almost a monopoly in the industry. As of 2018, Arm had more than 1650 partners and shipped over 130+ billion Arm-based chips (www.arm.com).

Similar to other chipless firms, Arm invests a huge amount of its licensing revenues into R & D and works closely with partners who shoulder some of the cost of developing its technology. By collaborating with ecosystem partners, Arm shares knowledge about its current and future technology, aligning its technological roadmaps with those of partners. This makes it easy for Arm to develop technology that is compatible with those of partners, which in turn ensures that Arm and partners are able to continue to build technology that is suitable for most consumer electronics products in the future. Arm's partnership model means that for an entrant to enter the market and compete effectively with Arm (chipless firms), the entrant needs to able to manufacture, advertise and distribute on a large scale, suggesting significant start-up costs for an entrant to gain a competitive position.

The bargaining power of Arm suppliers can be considered as low to medium. EDA software suppliers are chipless firms or Arm main supplier. EDA firms provided chipless firms with software that automates the designing, simulation and verification of chips. These tools or software makes it easy for Arm and partners to manufacture chip based on specifications.

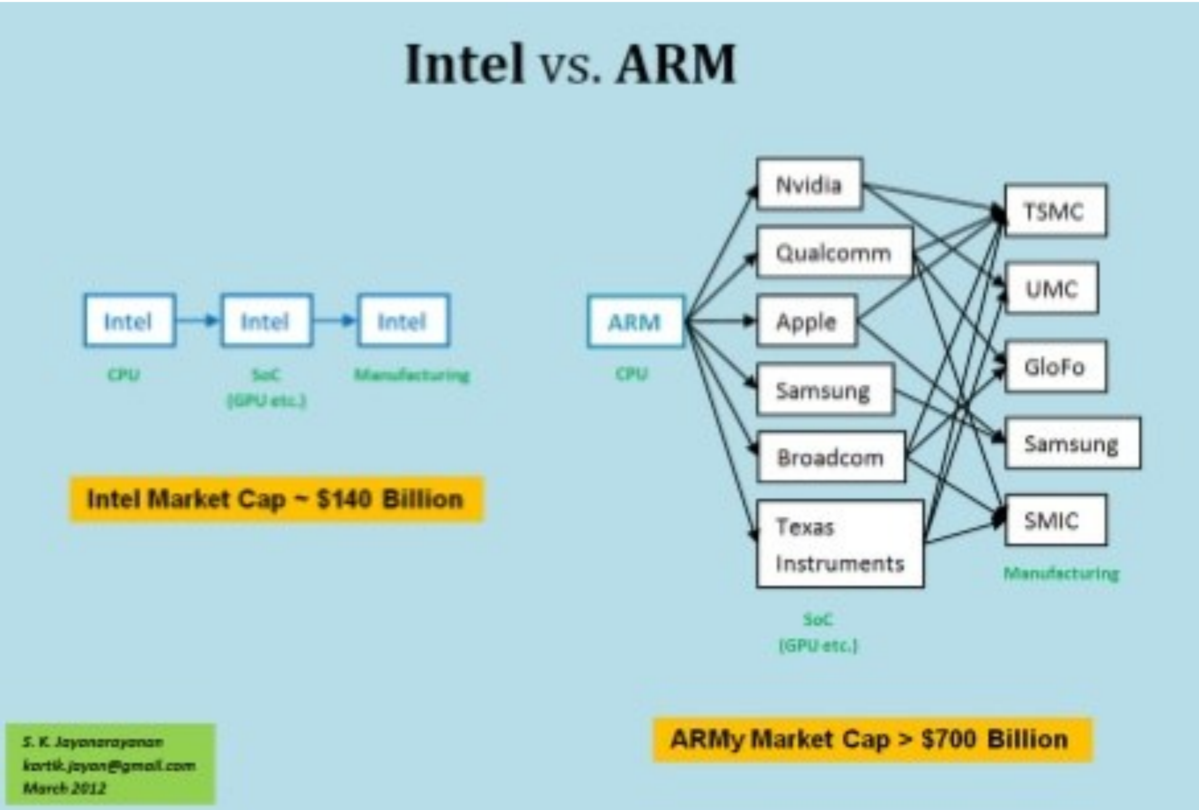
Although EDA software plays an important role for chipless firms' ability to license their technology, EDA firms are seen as complementors that work collaboratively together with chipless firms to provide superior value to customers. In the semiconductor industry, there are a large number of EDA suppliers and most of them are relatively small in size compare to Arm, which entails that Arm can easily switch from one supplier to another or even buy its suppliers if the need arises.

In the last five years, Arm has been building its capabilities in the area of tools and software automation. It has mainly built it capabilities through acquisition. In 2015, it acquired Sansa Security and Offspark, both providers of hardware security IP and software for advanced system-on-chip components deployed in Internet of Things (IoT) and mobile devices. Arm also bought Apical, a provider of imaging and embedded computer vision IP products and Allinea Software, a leading provider of software tools for HPC in 2016 (www.arm.com), thus lessening the bargaining power of its suppliers.

The bargaining power of chipless firms' customers is also low as there are a large number of customers for chipless firms and Arm low energy and high power technology, which provides Arm the leeway to determine its licensing and royalty fees. In terms of threats to substitute, although there are many copycat producers with the ability to introduce cheaper version of chips or alternative products into the market, however as a threat to substitute, this is mitigated by the short innovation cycle in the industry making it hard for these players to survive for a long time.

For the degree of rivalry, competition among firms in the semiconductor industry is extremely fierce. Chipless firms do not just compete among themselves (firms in the SOC market segment) but also with large IDMs, foundries, fabless and other electronics firms. From a competition perspective, one would have expected Arm main competitors to be other IP suppliers (chipless firms). However, Arm feistiest competitor is Intel, a large integrated device manufacturer (see figure 3.5 below). Unlike Arm and other chipless firms, who use a collaborative business model to develop and commercialise chips, Intel uses an integrated model designing, marketing and manufacturing its chips internally.

Figure 3-4: Illustration of Intel and Arm Business Model.



Arm competes with Intel in many different market segments of the semiconductor industry (see table 3.5 below). In the smartphones and smart devices segment, Arm it is a leader. It holds more than 75% of the market share in this segment as its low energy and high power chips seem to more suitable for these small devices. Arm's main rival, Intel holds less than 10

% of the market share. Other licensing and ecosystem players (chipless firms) also compete in this segment, however, together these firms hold less than 10% of the market share.

In the microprocessors segment, Intel is the run-away leader possessing more than 85% of the market share, with Arm and other players having less than 10% of the market share. The servers and microcontrollers markets are dominated by Intel and three other large firms AMD, QUALCOMM and Nvidia with Arm having less than 5% of the market share (www.arm.com).

As we can see from the analysis, Arm is a leader in one market and a follower in another market. Strategic rivalry between Arm and Intel is likely to intensity in the future as each firm try to expand into the other market segment. However, because of locked-in syndrome and network effect – firms (customers) are less likely to switch to competing technology- Arm and Intel are likely to maintain their dominant position in their respective core market segments in the long term. That said, going forward Arm and other chipless firms may gain market share especially in the servers' market. Most servers run on Intel x86 architecture, which is based on high energy and high performance technology and thus consumed a lot of energy. With increasing concerns over climate changes, Arm low energy and high performance chips are likely to be attractive for the servers and networking infrastructures market segment. If Arm can provide customers with a significantly better price/power/performance ratio in the future than Intel, Arm is likely to gain market share in the servers segment.

Another market area that Arm may grow its market share in the future is in the internet of things and artificial intelligence segment. Internet of things and artificial intelligence are seen as potential growth areas. To operationalise internet of things requires the use of a broad portfolios of products from different firms. Arm's and chipless firms' collaborative business model seems to be more suitable for these new growth areas, and are more likely to grow their market share in the long term. However, Intel as a large integrated firm with huge capital reserves has the innovative potential to compete head on with Arm. Intel is increasingly investing in the development of new processors (Atom) particularly targeting the smartphones market. It is also expanding into the wearable space with new chips, which are suitable for smart devices. Thus, how the rivalry between Arm and Intel places out in the long term cannot be determined with certainty.

Table 3-5: Summary of Comparison between Intel and Arm.

2018	Intel	ARM
Revenues	$ 70.0 billion	$ 1.41 billion
Employees	107,100	6,250
Market share	%	%
Smartphones	10	75
Microprocessors	85	10
Servers & Microcontrollers	30	4

3.7. Industry and Market Structure Conclusion

The technology of the semiconductor industry has evolved rapidly over time. Changes in technological development (CMOS replacing PCB as dominant designs) have facilitated the entry of specialised and networked firms - chipless firms. These small and innovative firms mainly use the licensing and ecosystem model to create and capture value from their innovation. Their collaborative business model enables them to reduce costs and also benefits from economics of scope and scale. Chipless firms mainly compete in the smartphones and smart devices market segments - where their low power and high performance technology is most suitable - in the semiconductor industry. Through their collaborative strategy, chipless firms have built their capabilities over time, as a result are more likely to move into other market segments such as the servers and network infrastructure segment that are currently dominated by large integrated firms. Chipless firms collaborative business model also seems to be suitable for the smart devices, artificial intelligent applications and internet of things, which are seen as major growth areas in the semiconductor. They are thus likely to be major players in the semiconductor industry in the long term.

4. RESEARCH METHODOLGY

4.1. Introduction

At the core of this thesis are three empirical-based studies/papers with each study responding empirically to a specific research question. The research methodology used in each study is described in details in the constituent paper. This chapter provides a general overview of the methodology and the basic philosophical assumptions underpinning the dissertation as well as depicting the link between the overall methodology of the thesis and its constituent papers. It also provides an explanation for the appropriateness of the research strategy and research design employed in the investigation.

In addition, it highlights how data for the research are collected and describes the analytical techniques and tools used for analysing the data. It annunciates the unit of analysis and observation, research setting and sampling mechanisms used in investigating each of the phenomena in the thesis. The different data sources that have been used by researchers to investigate similar phenomenon and the strengths and weaknesses of these databases are also discussed.

4.2. Philosophical Considerations in Choosing the Research Methodology

4.2.1. Methodological and Design Considerations

Before embarking on a description of the research method used in this thesis, it is essential to illuminate the methodological considerations that were taken in account in selecting the research method as that may affect the outcome of the study. According to Creswell (2014), in order to investigate a social phenomenon, the researcher requires a plan to guide him through the research process. Research approaches are detailed plans and procedures that incorporate the underlying philosophical assumptions underpinning the research, including data collection methods and how the collected data are analysed and interpreted.

Creswell (2014) and Bryman (2016) indicated that there are three main types of research approaches: quantitative, qualitative and mixed method. Unlike quantitative approaches, which are generally associated with measurements and statistical inference, qualitative approaches are broadly linked to research that does not use a statistical procedure or any form of quantification measure to produce findings (Strauss & Corbin, 1999). Qualitative and quantitative approaches are sometimes seen as rigid, distinct and polar opposing approaches; however, some social science practitioners argue that such classification may be too simplistic as both approaches have some commonalities. Mixed approaches, on the other hand, incorporate both elements of quantitative and qualitative approaches. Creswell (2012) argues that quantitative, qualitative and mixed approaches constitute a continuum with mixed approaches situated in the middle of the continuum.

From a philosophical perspective, the quantitative research approach engenders positivist epistemologies and ontologies (Crotty, 1998; Lincoln, Lynham, & Guba, 2011; Creswell, 2012) and employs a deductive theoretical framework (Lincoln, Lynham, & Guba, 2011). It incorporates the natural science research doctrines for which studying the relationship between and among variables is considered central to answering research questions (Crotty, 1998; Creswell, 2012). In this perspective, hypotheses are generated from theories and variables are typically measured using numbers that are analysed with statistical procedures (Lincoln, Lynham, & Guba, 2011).

In contrast, the qualitative research approach employs an inductive lens, which places emphasis on theory building. The approach aligns with the interpretative philosophical doctrine. It rejects the objectivist principles and norms of natural science and emphasises the need for the researcher to participate in the interpretation of the social phenomenon (Creswell, 2012). From this school of thought the research process, emerging questions and data are typically collected in the participant(s) setting with the researcher and participants playing an integral role in interpreting the meaning of the data.

Mixed method research approaches incorporate both inductive and deductive features of quantitative and qualitative approaches. The core rationale for a mixed approach is because both quantitative and qualitative approaches are plagued with flaws; combining both approaches eliminates some weaknesses of each approach and provides greater insights into the understanding of a social phenomenon (Creswell, 2012).

From a philosophical point of view, the research approach is closely associated with the critical realist perspective. Critical realists believe that there is neither pure objectivism nor pure constructionism. Unlike positivists who hold the view that the scientific representation of reality truly reflects that reality, realists argue that scientific conceptualisation is just a way of knowing that reality (Bryman, 2012). Lately the mixed approach has grown in popularity in the social sciences research sphere; however, some authors argue that the mixed method approach dilutes the core attributes and practices of quantitative and qualitative approaches. They assert that the use of this mosaic approach does not add much to the rigour and consistency of social science research (Stacey, 2007; Bryman & Bell, 2007).

In the field of social science, it is generally agreed that many factors influence the choice of research approach that the researcher employs to investigate a social phenomenon (Creswell, 2012; Bryman & Bell, 2016). The researcher's views on knowledge (epistemology or paradigms) and how he/she perceives the social world (ontology or world view) influence his choice of research approach. Other factors such as the nature of the research problem being investigated, the researcher's personal experience and values, and the research audience also play a role in the researcher's choice of research strategy (Bryman, 2016; Creswell, 2012).

This thesis is strongly grounded in the positivist sphere adopting a quantitative research approach and deductive lens for testing theories. The arguments for the appropriateness of using a quantitative approach are based on factors that influence the researcher's choice of research approach as highlighted above. The preceding sections describe the role of the researcher's philosophical position, the implications of his/her personal experience and values, and the research questions and audience on the choice of research approach used in the thesis.

4.2.1.1. The Researcher Philosophical Position

The researcher's philosophical worldview (Creswell, 2012) or what other authors describe as epistemological and ontological position (Crotty, 1998) or paradigmatic position (Lincoln, Lynham, & Guba, 2011; Mertens, 2010) influences the choice of research approach that he/she uses to investigate a social phenomenon. A worldview is a set of beliefs about the nature of knowledge and the social world that the researcher brings to the study. These beliefs are shaped by the norm of practices in the research field, supervisors' inclinations and researcher's past research experience (Creswell, 2012).

From an epistemological and ontological perspective, the positivist and interpretative view are considered the two main philosophical positions, although within these two main stands are many other variances (critical realism, phenomenological, constructivist and pragmatist, feminist, transformative and postmodern perspectives) (Bryman 2012). The interpretative view is typically associated with the qualitative research approach (Creswell, 2012). It adheres to the assumption that social phenomena exist within a social sphere with the researcher and research participants engaging in sense-making of the social experience (See Crotty, 1998; Lincoln & Guba, 1985; Merten, 2010; Lincoln et al., 2011). The sense-making process is based on their historical and cultural perspective, as human beings are influenced by the culture into which they are born, which means that our views of the world vary depending on our life experience. This suggests that the research questions or questioning should be broad and general to enable participants to make sense of the situation. Often subjective meanings are formed through social interactions, which is influenced by their cultural norms and historical connections. The role of the researcher from this view is to address and facilitate the interaction process between participants. Hence, in this worldview, the researcher and participants are seen as co-creators of knowledge and the subjectivity of the researcher is paramount to explaining the social phenomenon being studied. Studies from an interpretative perspective are usually context specific and do not seek to generalise to a broader audience. Rather, the objective of the interpretive approach is mainly geared towards theory building (see for example, Fincham et al., 2002; Huxham & Vangen, 2003).

The positivist doctrine, on the other hand, assumes that social phenomena are distinct from the individual (observer) who observes them (Huxham & Vangen, 2003). Advocates of this doctrine believe that knowledge should be gained in a way that is objective and free from the influence of the person or individual that conducted the research. This doctrine places greater emphasis on the natural sciences concept of control and uses nomothetic laws and cumulative evidence to examine social phenomena. Scholars with this perspective study a problem by identifying and assessing the causes that influence outcomes using a method similar to that in experiments. The knowledge that results from a positivist lens is based on careful observations and measurements (Creswell, 2012). Thus, from the positivist approach, the research process generally begins with theories, with the researcher developing hypotheses and collecting data to support or refute the theory, then makes necessary revisions and conducts a further test to confirm the final outcome (Hamel, 2000; Phillips & Burbules, 2000).

In this study, the researcher holds a positivist view and believes that the social world should be studied according to the same principles, procedures and ethos as that of natural science. He upholds the importance of testing theory as it provides materials and direction for the development of concrete and testable theories. These views stem from the fact that a large number of studies (more than 70% of published research) in the areas of knowledge sharing, ecosystem and inter-firm networks are positioned within the positivist sphere. Studies in these areas of management research are heavily influenced by doctrines from economics, in particular mathematical modelling, and the pure deductive approach used in industrial economics (contractual and governance) and behavioural economics (ecosystems and networks). This study is considered part of that same doctrine.

From an epistemological stand, unlike studies that are positioned within the interpretative space, the researcher assumes that objectivity is vital for knowledge creation and sees knowledge sharing between firms, ecosystems and inter-firm networks as objective subjects that can be studied irrespective of the view of the individual that observes or perceives them. According to the researcher, the subjectivity and bias of the observer are largely irrelevant and play absolutely no role in the research process, which are important criteria in qualitative and interpretative approaches.

In addition, in the inter-firm collaborations (licensing, ecosystem, alliance and network) research areas, extant literature is well developed as scholarly discourses have been unfolding for a long period. The links between the different constructs of technology/knowledge sharing, ecosystem and inter-firm network and performance outcomes – innovation, value creation and value capturing – have been formalised already, and the objectives of most current studies are geared towards testing of prior theories. The issues of theory development or theoretical diversity, which are important criteria of the qualitative approach, are almost inexistent in these areas of research. The current thesis is considered as part of that conversation and makes an incremental contribution to the scholarly discussion.

Furthermore, the inclinations of the researcher's supervisors for the use of robust scientific research approaches in investigating social phenomenon, and the support received from supervisors on the operationalisation of quantitative methods had a bearing on the researcher's choice of research method. In addition, the researcher's prior scientific and technical academic experience and familiarity with statistics and computation related programmes also influenced his choice of research approach. Hence, the combination of points highlighted above swayed the researcher towards the use of quantitative positivist approaches in investigating the role of knowledge sharing-licensing and networking in ecosystem development in an emerging high-tech industry.

4.3. Quantitative Research Designs

The quantitative research approach has naturally been categorised as either an experiment or a quasi-experiment design (Bryman 2016). Because a vast majority of variables cannot be manipulated, experimental research in social sciences has been considered as quasi-experimental design. It embodies most of the characteristics of experimental designs except for the lack of random assignment requirements. Bryman (2016) identifies a number of different types of quasi-experiment designs. One form of quasi-experimental design is the cross-sectional design often referred to as a social survey design. The cross-sectional design has much relevance in management and business studies. It is mostly used when the researcher wants to collect data or examine a phenomenon that cannot be directly observed (Bryant, 2011). It involves the use of many cases and the way the researcher institutes the research plan (respondent selection, conceptual design, administration of research instrument and analysis of data) is vital to the outcome of the survey.

Survey design mainly uses a questionnaire and structured or semi-structured interviews to examine the relationship between variables at a given point in time. Unlike the experimental design that involves the manipulation of variables, survey design does not result in the manipulation of any variables; inference between variables is based on the pattern of association. For the above reason, this type of design is more suitable for the examination of naturally occurring phenomenon in real-life conditions. Survey designs only show variation between variables and it can sometimes be difficult to infer the causative association between the variables. From a survey design, the researcher may be able to recognise the relationship between variables but cannot determine the cause of the variation. This weakness reduces the internal and external validity of the survey design (Strauss & Corbin, 1999).

Another form of quasi-experiment design is the longitudinal research design. Schvaneveldt et al. (1998) asserted that longitudinal design is an exceptionally suitable inquiry strategy for studying human development and social change. It typically takes place over a prolonged period, which enables the researcher to determine the pattern of change in business or phenomenon that is being investigated. The research design is very similar to classic experimental design as it involves pretesting and post-testing but without the manipulation of variables (experimental and control group).

Unlike the cross-sectional design, longitudinal design can provide causal inference between variables. Data for the research design are collected on at least two or more occasions enabling the researcher to identify potential changes that have occurred over time on the dependent variables. This allows a causative link to be inferred between the dependent and independent variables providing greater insight into the understanding of social events.

This current thesis (all the studies in the thesis) is modelled on a quantitative longitudinal research design with the main objective to investigate the causal relationship between technological sharing, ecosystem/networks and performance. The rationale for using a longitudinal panel data design approach is because the licensing, alliance and network fields are areas of research rich in quantitative data sources. Publicly and privately owned research organisations (e.g. SDC Thomson, National Bureau of Economic Research (NBER) database, Dataquest, REUTER, etc.) have been collecting firms' licensing and alliance data since the 1960s. Scholars can access these data free from publicly owned organisations and for a fee from commercial bodies. The availability of these multiple data sources makes it easier and appropriate to carry out longitudinal studies in these areas of research.

Using multiple data sources, especially combining multiple quantitative data sources, can facilitate the operationalisation of variables enabling the researcher to uncover some unique variances, which otherwise could not be captured from a single data source. In fact, many researchers have advocated the use of multiple data sources, commonly denoted through methods such as triangulation as this has the potential to increase the internal validity of the research (Bryman & Bell, 2007; Creswell, 2008). Using multiple sources for data can lead not just to more interesting results, but also more valuable insights as the finding from one data source can be used to complement another (Creswell, 2008). This thesis utilises various data sources – including licensing and alliance data, patenting data and firms' personal attributes data – in a complementary way. The data sources are described below and discussed in more depth in the constituent studies/papers.

4.3.1. Hypotheses Development and Operationalisation of the Dissertation

Although this dissertation takes a quantitative research approach, whereby hypotheses are developed and tested using quantitative data, the researcher recognised that information about firms, (social science data) are messy and data alone cannot provide a holistic picture of the phenomenon being studied. Unlike the linear process described above, quantitative research in social sciences is often based on a set of interactive processes.

The researcher began PhD or dissertation process first by carrying out in depth archival research on licensing. Next, the researchers discussed some key lines of inquiries (gaps on the topics) with the supervisory team. Then, he interviewed experts involved in licensing of technology. The interviewees constitutes seven licensing and corporate directors at Arm Limited and three at Imagination technology (two leading IP suppliers/chipless firms in the UK). The interviews mainly centred around the structure of semiconductor industry, chipless firms licensing strategy and how they manage their licensing contracts and partners. From the interviews, it was clear that nature of these firms' technology, type of licensing that they use to exchange their technology, and the composition of their ecosystem play a vital role to their performance and long-term survival. These inputs provide a thick description of the effect of licensing and ecosystem formation on firms' performance and reinforced the researcher desires to explore the phenomenon further.

After establishing the boundaries of the research in particular that of the first two studies of the dissertation, the researcher carried out follow up interviews with the directors. The hypotheses and data sources were also discussed with the licensing directors to ensure that data collected could provide a valid response to the research questions. Another round of interviews was also carried out to explore the implications of the empirical results.

4.4. Unit of Analysis and Observation

4.4.1. Unit of Analysis

Before describing the data source, it is essential to ascertain the unit of analysis and unit of observation from which the research data is collected. The unit of analysis in this research is the firm level rather than the network/ecosystem/industry level, as firms are the primary entities involved in technology sharing and ecosystem formation. Although cooperation between licensing firms led to the formation of ecosystems and it is through these networks that they innovate and generate value from technology, the dependent and independent variables are measured at the firm level. The variables constitute repeated measures of firms' data.

Further, the dependent variable (performance outcomes) do not vary within firms in the same ecosystem but rather across networks. Thus, employing a firm level analysis is considered appropriate for the research as aggregating technology sharing at an industry or network level may disguise significant differences in strategies used by firms. The propensity for the firm to engage in technological sharing and ecosystem formation may vary across industries due to the nature of technology and the strength of IP rights (Teece, 1987; Arora & Fosfuri, 2001; Cohen et al., 2001; Gans & Stern, 2001).

4.4.2. Unit of Observation

For the three studies/papers constituting this thesis, the unit of observation is either the licensor, that is, the firm offering its technology to others (licensees), or the licensee, the firm acquiring the licensor technology (for more details on the unit of analysis and observation see constituent studies).

4.5. Research Setting and Data Sources

4.5.1. Research Setting

The industry setting for this thesis is Chipless firms and partners operating within the semiconductor industry (SIC 3674). This setting is relevant to studying the implication of technology sharing and ecosystems and networks formation on firms' performance for the following reasons. First, the semiconductor industry is considered as a complex industry whereby technological development builds on prior knowledge (Eisenhardt & Schoonhoven, 1996; Hall & Ziedonis, 2001). The industry is also characterised by short product lifecycles with high levels of research and development (West, 2002), and patenting and innovation activities (Hall & Ziedonis, 2001), which entails that firms have to cooperate with each other in order to create and capture value from their technology (Adner & Kapour, 2010). Licensing of technology is seen as an essential component of technological development (Teece & Grindley, 1987). It facilitates the formation of ecosystems and networks (Macher et al., 2007; Hall & Ziedonis, 2001), and it is through these networks that firms innovate and capture value from their innovation (Teece, 1989; Linden & Somaya, 2003).

In addition to this competitive dynamic, in the last three decades, the semiconductor industry has also witnessed a significant shift from vertical integration to vertical disintegration (Macher et al., 2007), leading to increased levels of specialisation. Chipless firms are specialised firms at the forefront of the development of highly efficient microchips. Their low power technologies are essential core elements of connected devices such as mobile phones, tablet computers, flat screen monitors and smart television sets and play a significant role in the sophisticated car and aircraft industry and the internet of things.

Furthermore, chipless firms are considered as principal licensors in the semiconductor industry (Linden & Somaya, 2003). They do not engage in any manufacturing but mainly create value from their technology through licensing and ecosystem/network formation (Moore, 1996). Chipless firms' licensing choices and composition dynamic within their ecosystems and networks influence their performance. Hence, chipless firms and partners operating within the semiconductor industry provide us with a valuable setting in which to examine the roles that technology sharing, ecosystems and networks have on firms' performance outcomes.

4.5.2. Data Sources

The data for this thesis were collected from multiple data sources. The primary data source used in all three empirical studies was the Thomson-Reuter Financial SDC Platinum strategic alliance and joint venture database. The database was mainly used to retrieve firms' licensing and alliance activities. It is considered as one of the most comprehensive data sources for large base empirical studies (see Anand & Khanna, 2000; Siebert & Von Graevenitz, 2006; Siebert, 2010 ; Srivastava & Gnyawali, 2011) and has been widely used in the licensing, alliances and networks literature with reliable results (Ahuja, 2000b; Sampson, 2007; Hagedoorn et al., 2008; Parachuri, 2010; Singh et al., 2016).

Scholars have also used other databases such as MERIT- CATI, CORE, Recombination capital (RECAP), and BIOSCAN to investigate licensing and cooperative strategies of firms (e.g., Anand and Khanna, 2000; Beck- man, Haunschild, and Phillips, 2004; Folta and Miller, 2002; Gulati, 1999; Hagedoorn, 2002; Lavie and Rosenkopf 2006; Mowery, Oxley, and Silverman, 1996; Powell, Koput, and Smith-Doerr, 1996; Rothermael and Deeds, 2004; Sampson, 2005). Each of these databases has its own unique set of advantages and disadvantages that make it better suited to some types of research than others. It is very important for researchers to understand these advantages and disadvantages when selecting a database and creating a research design as this may influence the outcome of their research.

The coverage and completeness, in term of patterns in sectoral composition, temporal trends, and geographic patterns in inter-firms' activity vary across these databases. SDC, MERIT-CATI, and CORE cover multiple sectors. Whereas RECAP and Bioscan databases mainly specialise on alliances in the biotechnology sector. SDC captures and reports a very wide scope of alliances, including joint ventures, strategic alliances, research and development (R&D) agreements, sales and marketing agreements, manufacturing agreements, supply agreements, distribution pacts and licensing agreement (unilateral and cross licensing deals). A strength of the SDC is that it is very searchable, with over 200 data elements, including coded fields and keyword searches. It is very user friendly (has a user-defined output), which makes it easy to use in large-scale analysis. Although the SDC collects inter-firm collaboration activities on wide range of industries, research and technology alliances (those that entail some aspect of joint research or cross-technology transfer) account for roughly half of the alliances reported on the database including many in less developed countries from 1990-2005. One weakness of the SDC is that some data elements have many missing values and it very Anglo-Saxon oriented.

MERIT-CATI covers a fair number of sectors with the bulk of alliances being research and technology alliances. It utilises retrospective data collection method incorporating data as early as 1960. However, the database contains very limited information about the alliance deals and it is bias toward English-language source.

CORE is another multiple sectorial database. It contains a large population of the agreement filed under the NCRA Act. and highly reliable for this population. It is explicitly United State Focused. An advantage of the database is that if the researcher wants to cross check the information on the database with other sources it is possible to obtain the original documents filed with each agreement through the Federal Register. Although the data goes back to 1985, a disadvantage of the dataset is that NCRA collaborations are limited to very small subset of the collaboration activities struck between U.S. firms.

Recombinant Capital (RECAP) focuses solely on biotechnology and provides a great deal of information on individual alliance agreements. It reports alliances that go far back as 1973. It has a very searchability user-friendly interface with both keywords and coded fields. Some of the weaknesses of the database are that output options are limited, making it difficult to use for large-scale analyses. In addition, it is heavily focused on U.S. SEC filings, which may cause U.S. firms to be overrepresented on the database.

Bioscan also focuses only biotechnology alliances. It tracks activities of a stable set of firms, permitting better longitudinal assessments of the firm's behaviour. It also provides a detail profile of each firm, including key employees, major products, business strategy, and stock history. Patenting data also available on the database, which is helpful when researchers are analysing the performance outcome of firms. A disadvantage of the database is that it is searchable only with key words (not codes) - makes searching less reliable.

This dissertation uses the SDC database as main data sources. The database seems to be more appropriate for studying licensing as Anand & Khanna (2000) indicate that licensors and licensees are generally correctly identified in the database. Shilling, (2008) and Gilsing, Belderbos, & Jacob (2013) highlight that the SDC database codes more indicators on cooperative agreements and technology alliances than the MERIT-CATI and CORE databases. These indicators offer researchers with the opportunity to operationalise a large number of variables.

Shilling, (2008) also conduct a comparative analysis of these databases from 1990 to 2005 (similar to the period used in this dissertation), examining their coverage, trends in sectoral composition, alliance activities over time, and geographical participation of firms. She concluded these databases exhibit strong symmetries in factors and the results from these databases seem to be reliable for many—if not all—research purposes. The study also indicates that among these large databases, findings from studies especially those on technology alliances that use SDC seem to be more reliable. Empirical studies using the SDC as data source were most commonly published in top strategy journals (Academy of Management Journal, Administrative Science Quarterly, Management Science, Organization Science, or Strategic

Management Journal) followed by Bioscan, MERIT-CATI and RECAP. From a data perspective, Shilling (2008) study provides thus some assurance that findings from this dissertation are more likely to be reliable.

Another important source of data was the NBER patent database. The database was mainly used to retrieve firms' patents. Patent has been widely used as an indicator for the firm innovation performance in the licensing and network literature (Abuja, 2003; Sampson, 2005; Hagedoorn et al., 2008; Griliches; Parachuri, 2010; Phelps, (2010); Singh et al., 2016; Srivastava & Gnyawali, 2011; Lavie, 2007; Trajtenberg, 1987; 1990; Jaffe et al., 1993). The National Bureau hosts the NBER patent databases for Economics Research. The databases contain patent information from the US Patent and Trademark Office (USPTO), the European Patent Office (EPO), and other key patent jurisdictions in the world, such as Japan, China, South Korea and Australia. It provides information on the total number of patents granted to a firm, that is, the parent company including those of all its subsidiaries. It also reports the number of citation counts made and received by each patent, its technological class and subclass, as well as a wealth of other relevant information. For this thesis, the researcher mainly used the database containing patents' information from the USTPO only to measure the innovation performance of firms. This database comprises detail information of almost 26 million U.S. patents granted between January 1963 and December 2005, all citations made to these patents between 1975 and 2005 (over 36 million), and a reasonably broad match of patents to Compustat (the data set of all firms traded in the U.S. stock market). Many scholars have also used only US patents to capture firms' innovation performance. Similar to NBER, scholars have also used commercial databases that compiled patents from USTPO records including TotalPatent -LexisNexis, PatBase - Minesoft, Orbit- Questel, Derwent Innovation – Clarivate, WIPS Global -WIPS, Patseer – Gridlogics, Ambercite, PatSnap. Research has shown that these databases exhibit strong similarity in terms of coverage, patterns of sectoral composition and number of firms and the results from these databases seem to be reliable for many—if not all—research purposes. Some scholars have created their own patent datasets from the USTPO. Retrieving patents from the USTPO patent database yourself is laborious process with high risk of errors and mistakes. Commercial databases retrieve and clean patent data using sophisticated search and analysis tools. They provide a more enhanced and improved classification/indexing systems, which make it much easier for researchers to count and visualise patents.

In addition to central databases, firms' personal attributes data was also retrieved from DataStream, Compustat – Capital IQ, Amadeus, LinkedIn, Bloomberg, Bureau van Dijk, IHS Global Insight, Research Quotient and firms' websites, annual accounts and other web and business directories to complement the other data (for a detailed description of these databases, see the research method section in the constituent studies).

4.5.3. Description of the Data

The researcher initially retrieved 4,980 licensing deals of firms operating in the broader electronics industry (using the two digits SIC (36)) from 1985 to 2005. The researcher then refined the sample by focusing on licensing arrangements in which at least one of the principal participant lines of business is the semiconductor and related devices (SIC 3674) on the contextual description of the licensing deal. From this refinement, 3,231 semiconductor firms and 1,556 licensing agreements were obtained. From the list of semiconductor firms, the research focused on all licensing agreements signed by chipless firms and partners. From this selection, the researcher obtained 458 licensing agreements signed by 635 chipless firms from 2005. Of the 458 licensing agreements, approximately 91% were unilateral licensing, while the remaining 9% were cross licensing.

The research also used searched through almost 26 million patents on the NBER database to identify patents of chipless firms and partners (For further information on how the data was collected and refined, see constituent papers).

Table 4-1: Total number of Licensing deals and Patents Granted to Top 10 Chipless firms.

Chipless Firm	No of Licensing	No of patents 1985–2005
ARM Holdings PLC	30	1770
MIPS	30	599
DSP Group Inc	25	321
Rambus Inc	20	3152
LSI Logic Corp	18	13132
SRS Labs Inc	15	78
General Instrument Corp	12	1796
Silicon Storage Technology In	11	67
Tessera Technologies Inc	11	248
Synopsys Inc	10	659
Aware Inc	10	142
Cyrix Corp	10	209

Silicon Image Inc	9	67
Atmel Corp	9	2048
Integrated Silicon Solution	8	130

4.6. Data Analysis Technique

With regard to data analysis and interpretation, before collecting data it is essential for the researcher to consider the analytical approach/technique to be used in analysing said data as this could affect the interpretation of data and thus the outcome of the research (Bryman, 2016). Each of the empirical studies in this dissertation investigates a unique phenomenon in its own right and uses a specific statistical tool or analytical technique to make sense of the collected data. Analytical techniques are based on specific assumptions and procedures, which influence how data is analysed and results are interpreted.

Study/paper 1 examined the conditions under which firms prefer to exchange technology through either cross or unilateral licensing. A logistic regression technique was employed to determine the likelihood of licensors choosing between unilateral and cross licensing to exchange technology. Other contingency techniques such as Probit could have been used to analyse the licensors licensing choices; however, Probit and Logistic models rest on similar assumptions and generally lead to the same outcomes. The Probit method was used to check the robustness of the research findings and results seem to be consistent with those of the Logistic regression model.

Study 2 investigated how actors and technological ecosystem complexity influence focal firms' value creation. The random effects panel negative binomial regression model was used to analyse the data. Other count specific models, such as the Poisson regression models could have been used to analyse the data but were not deemed suitable because of overdispersion in the dependent variable (resulting from excess zero in the independent variable) (Baltagi, 2005). Study 3 explored how the quantity and quality of ties affect the innovative performance of firms. It measured the innovative performance of firms using their citations weighted patent counts. As the dependent variable is count variable it uses the random effects panel negative binomial model to analyse the data. All the statistical analyses were carried out using procedures in Stata. The data collection mechanisms and analytical techniques are described in details in each empirical study, and a summary is provided in the following section. (For details of the analytical techniques, see constituent papers in chapter 5, 6 & 7)

5. INTER-FIRM TECHNOLOGY EXCHANGE THROUGH UNILATERAL OR CROSS LICENSING: EVIDENCE FROM CHIPLESS FIRMS IN THE SEMICONDUCTOR INDUSTRY[1]

5.1. Abstract

The characteristics of firm and those of partners are important factors for the firm's preference for either cross or unilateral licensing. In this paper, we investigate the impact of the licensor's absolute and relative technology and market diversification, past licening experience and firm size the licensor's licensing preference. Using data of Chipless firms operating in the semiconductor industry from 1985 to 2005, we find that with higher levels of diversification, licensors tend to prefer to engage in bilateral exchange rather than unilateral licensing. When licensors are less diversified than licensee, licensors are more likely to prefer to engage in cross licensing as the licensing mechanism enables them to alleviate the effect of increased competition. The study also shows that licensors' experiences in cross and unilateral licensing are important determinants for the licensing agreement that licensors prefer to use for exchanging technology in the future. Moreover, the licensor's licensing preferences is shaped by the magnitude of competition that it faces from licensing its technology to partners of different sizes. These findings have important managerial implications as the licensing choice that licensors use to exchange technology influences the amount of rents they can extract from their technology and the competitiveness or the very survival of licensors.

[1] As mentioned in the Introduction, the paper on which this chapter is based received a best paper award at the 2017 British Academy of Management Conference at the University of Warwick.

Keywords: Technology licensing preference, unilateral licensing, cross licensing, partnership, learning, and competition.

5.2. Introduction

In the latter half of the twentieth century, firms (especially those in high-tech industries) used their technology in-house to gain competitive advantages vis-à-vis their competitor. In more recent decades, cost, complexity and speed of technology development have dramatically changed the way firms organised their R&D and related innovative activities (Dyer & Singh, 1998; Grant & Baden-Fuller, 2004). These changes have led an increasing number of firms to bring in new technologies from outside the firm boundary (Chesbrough, 2003) and have broadened the market for intellectual property (IP) (Arora & Forfuri, 2003). Firms increasingly use many third-party arrangements, such as mergers and acquisitions, strategic alliances, joint ventures, and R&D collaborations but also licensing which is considered one of the most important business arrangement that firms utilise to transfer and generate rents from their technology through IP (Anand & Khanna, 2000; Teece, 1986).

Licensing agreements are widely categorised into unilateral and cross licensing (Anand & Khanna, 2000). Unilateral licensing occurs when a licensor offers its technology to a licensee (s). It enables the licensor to raise revenues from technology, but also expose its technology to other firms. Cross licensing is a bilateral exchange between two firms; it enables both licensing parties to access each other's technology and provides both licensor with the opportunity to restrict the number of firms with access to its technology to a single partner. Given these options, from the licensor's perspective, in order to maximise the value of its technology and to stay competitive, it is important to select the appropriate licensing agreement to exchange its technology (Nagaoka & Kwon, 2006; Teece, 1986).

Given the risks and potential benefits of unilateral and cross licensing, several studies have empirically examined the determinants for firms to engage in the different types of licensing agreements (Kim & Vonortas, 2006; Nagaoka & Kwon, 2006). Earlier studies explained the licensing preference of firms based on either the variation in the characteristics of licensors (Kim & Vonortas, 2006a; Motohashi, 2006; Somaya et al, 2010) or the characteristics of licensees (e.g Atuahene-Gima, 1993; Laursen et al, 2010; Lowe & Taylor, 1998). However, Kim and Vonortas, (2006b) argue that many of these earlier studies adopt a rigid firm level perspective, which assumes that the characteristics of licensing partners are constant across firms and have no effect on the licensor/licensee's licensing preference.

More recently, researchers have challenged this rigid firm level focus by suggesting that firm characteristics and licensing partner characteristics together determine licensing preference and call for a better understanding of these characteristics (Arora & Gambardella, 2010; Kim & Vonortas, 2006b; Nagaoka & Kwon, 2006). For example, Siebert and Von Graevenitz (2010) show that with increasing rivalry in the technology marketplace, firms tend to prefer to cross license their technology as this enables them to alleviate the effect of competition and uncertainty in the long term. Nagaoka and Kwon (2006) find that the licensing contingency between two firms is mainly influenced by the size of the potential licensor and the larger the licensor size in terms of its technological capabilities, the higher the licensor preference for cross licensing.

In this paper, we extend these studies on pair level characteristics along the following dimensions. First, we investigate how the degree of diversification from the perspective of a focal licensor and the differences between the licensor and its licensee influence the licensing preference of a licensor. The degree of diversification offers firms a different advantage that is considered of greater importance and a more informative determinant for their licensing preference than the firm size that has previously been examined in much of the literature (Markides & Williamson, 1994). A large firm may operate in a single market whereas a multi markets presence enable a firm to produce patents in a broad range of industries and enhance the quality (breadth and depth) of its patents that can be used for both cross and unilateral licensing. Further, the number of markets and field of technology in which firms operate accelerates their learning potential (ability to absorb externally acquired knowledge and develop new products (Cohen & Levinthal, 1989)), which shorten the time to market and competitive advantages vis-à-vis other firms (Gimeno & Woo, 1999). We argue that at the firm level (the licensor characteristics), the capabilities that firms accrue from operating in multiple markets and field of technology and the imperative to capitalise on the benefits of these capabilities determines their licensing preference. At the pair level, we highlight that differences in the licensing pair degree of diversification (in terms of markets and technology) determine the magnitude of competitive pressure that licensors face and subsequently the licensing type that they choose to capture value from their technology.

Second, we examine the effect of the licensor's prior cross and unilateral licensing experiences and differences in the licensing pair experiences for both types of licensing agreements on the licensor's licensing preference. Earlier studies on licensing have traditionally conceptualised the firm licensing experience at a broader level (Anand & Khanna, 2000; Kim & Vonortas, 2006; Nagaoka & Kwon, 2006). Although this traditional characterisation of experience in terms of knowledge that firms gain from engaging in licensing is useful, it is incomplete as cross, and unilateral licensing are different focal activities and the experience that firms accrue from both licensing types varied. We provide an explicit explanation for the roles that the licensor prior cross and unilateral licensing experience play on licensing agreement that it uses in the future. Lastly, we re-visit the effect of the firm size to ascertain the findings in prior literature (Kim & Vonortas, 2006; Nagaoka & Kwon, 2006), by adding a new dimension to the analysis, i.e., the implication of the licensor size relative to the licensee. In contrast to prior works, our study indicates that the licensor size vis-à-vis the licensee may be a better predictor for the licensor's licensing preference than the licensor/licensee absolute firm size per se.

We explore a set of hypotheses related to the above, using Chipless firms operating in the global semiconductor industry from 1985 to 2005. Chipless firms setting provides an ideal setting to examine the effect that the licensor's characteristics and licensing pair differential contingencies have on the licensor's licensing preference. They are considered principal licensors in the semiconductor industry. Chipless firms do not engage in any manufacturing but primarily use cross and unilateral licensing as the primary mechanisms to capture value from their innovation. As specialised firms that depend solely on cross and unilateral licensing, the licensing type that they select to exchange their technology is critically important. It influences the amount of value that they capture from their innovation and hence has a profound implication on their very survival.

The remainder of the paper is structured as follows. The next section briefly describes the major features of unilateral and cross licensing. Then we provide the theoretical background for explaining the effect that the firm's characteristics and licensing pair or contract level contingencies have on the licensor licensing preference and formulate our testable hypotheses. The following section describes the empirical setting, data collection methods and statistical model used in analysing the data. The last section deals with the discussion of the results and conclusion with possible areas of future research.

5.3. Theoretical Background and Hypotheses Development

5.3.1. Major Features of Unilateral and Cross Licensing

In most high-tech industries, firms can choose either unilateral or cross licensing to exchange and capture value of their technology (Anand & Khanna, 2000; Arora, & Fosfuri, 2003; Arora & Gamberdella, 2010; Ruckman & McCarthy, 2016; Teece, 1986). Unilateral and cross licensing offer the licensor's the opportunity to capture value from its technology but also entail a certain degree of risks. The risk arises mainly from the possibility of licensees assimilating the licensor technology and developing products that can better serve the need of the licensor's customers (Fosturi, 2006; Nagaoka & Kwon, 2006; Sibert & Von Graevenitz, 2010), and from opportunistic behaviours of licensees (Teece, 1986). This has the potential of increasing the number of players with similar technologies and intensify competition in the relevant markets. However, as the nature of unilateral and cross licensing differs and they carry different degree of risks and benefits to the licensor's, this impacts the amount of rents that a licensor's can extract from its technology.

Unilateral licensing constitutes a one-way transfer of technology from a licensor's as the owner of technology to the licensee (s) as acquirer of technology. When a licensor unilaterally licenses its technology to a licensee, the licensing arrangement offers the licensor with the option to gain revenues in the form of a fixed fee and/or royalty depending on the codified legal term of the contract (Hagedoorn et al., 2008). As the supplier of technology, the licensor can opt for a fixed fee only option or it can choose a mixed licensing fee option containing a lump sum and royalties based on the sale of the licensee final product to which its technology has contributed. A firm may unilaterally license its technology to instate it as the defacto standard, especially in industries where externality is important for commercialising technology (Gallini, 1994). By working with many partners, the licensor's can reap greater rewards and installs its technology as the defacto standard especially in the industries where externality is important for commercialising technology (Gallini, 1994). By working with many partners, the licensor can reap greater rewards and install its technology as the defacto standard in the industry.

However, unilateral licensing with a large number of partners has the downside of bolstering the technological capabilities of these partners (Movery, Oxley & Silverman, 1996). Through working with the acquired technology, licensees can gain valuable knowledge and develop new products and processes that can rival the licensor's technology. This has the potential of increasing the intensity of competitive pressure in the relevant technology markets (Fosfuri, 2006) especially if licensees operate in multiple markets or are larger players capable of quickly assimilating the acquired technology speedily.

Cross licensing agreement occurs when two firms grant each other the right to access the other's technologies (Gallasso, 2012). Cross licensing usually involves the exchange of a portfolio of patents between the licensing parties. It can be a mutual exchange when both parties' patent portfolios are considered equal enough not to require any extra compensation or royalty fee. It can also be accompanied by a fixed fee and royalty depending on the relative strength and quality of the patent portfolio of the engaging parties (Anand & Khanna, 2000; Telsio, 1979).

Cross licensing enables the engaging parties to broaden their technological base and enhances their knowledge of the state of the art of technology in the industry. In a complex industry setting, whereby technological development is based on fast-moving knowledge and diffusion, cross licensing is of strategic importance (Grindley & Teece, 1997). It provides both partners with the freedom to use their partners' technology, avoiding the risk of lengthy negotiation and costly litigation. In terms of competitive risks, unlike unilateral licensing that contains the risk of bringing in a number of new players in the market, through reciprocity in cross licensing agreement resulting in effect a situation hostage, each licensor's can curtail the number of firms with access to its technology through cross licensing (Fosfuri, 2006). Bilateral exchange of technology through cross licensing provides an equal chance for the engaging parties to learn from each other reducing the risk of the licensor losing out to its licensing partners.

5.4. Determinants of Licensor's Licensing Preference

To disentangle the relationship between the licensor characteristics, the licensing pair characteristics and licensor's licensing preference; we draw knowledge from the technology licensing literature, resource-based theory, and absorptive capability (AC) literature. In most high-tech industries, variations in firms' licensing preference have been attributed to the characteristic of the firm (Gambardella et al., 2007; Kim & Motohashi, 2012; Kim & Vornotas, 2006; Nagaoka & Kwon, 2006). In addition, the licensor internal resources and the absorptive potential of the licensee have been shown to influence firms' licensing decisions (Arora et al., 2003; Fosfuri, 2006).

Regarding the licensor characteristics, larger firms and firms that operate in multiple markets benefit from several advantages such as a steep learning curve, substantial market power, and complementary resources, which enhance their ability to exploit technology (Walter, 2012). However, large firms also suffer from several disadvantages such as core rigidities, highly complex managerial control system and bureaucratic inertia that compared to small and less diversified firms can constrain their ability to successfully explore innovation (Gambardella et al., 2007; van Wijk, Walter, 2012). These advantages and constraints that are associated with firms of different sizes, different degree of diversifications and also diverse experiences influence the licensing preferences of firms.

Based on a firm's internal capability and absorptive potential, the licensee's ability to absorb and utilise externally acquired knowledge facilitates the ease at which it can generate new technology from the licensed technology and enter the licensor's market (Cohen & Levinthal, 1990). Whereas the licensor's internal capabilities facilitate its ability to generate new products in a timely fashion, the speeds at which the licensor can generate new technology can mitigate the adverse effect of new players entering its market. Hence, the joint effect of the licensee's absorptive capabilities and strength of the licensor's internal capabilities determine the potential benefits and risks that the licensor's will face through licensing. Drawing on these insights in terms diversifications, size, and experience and its relative characteristics vis-à-vis its partners (licensor/licensee) play in shaping the licensor's licensing preference.

5.4.1. Licensor Absolute and Relative Technology Diversification

Diversification is generally referred to as the number of technologies, product lines or markets that a firm operate in (Ansoft, 1966; Gimeno & Woo, 1999; Porter, 1985). Many prior studies in strategic management have highlighted the benefit that firms accrue from operating in multiple markets (Gimeno & Woo, 1999; Penrose, 1959; Porter, 1985). According to this body of literature, firms that operate in multiple markets can exploit synergies across markets by consolidating business activities in manufacturing, raw material purchases, marketing, and distribution, thus achieving both economies of scale and scope (Amit & Livnat, 1988; Rumelt, 1982). In addition to cost saving and learning efficiencies, compared with single market firms, firms with multiple markets presence, generally possess superior market power and resources, which enable them to create new markets, manufacture and sell their products quickly (Amit & Livnat, 1988)

From a technological perspective, Freeman and Hannan (1983) point out the advantages that firms gain from operating in multiple technological areas. Firms with diverse technological resources are more likely to develop more advanced capabilities and novel technologies than those operating in a narrow technological space. Merges and Nelson (1990) indicate that more technologically diverse firms often engage in riskier projects than those with a single technological scope, which enriches their chances of developing new and innovative technology.

Scholars have also highlighted that firms with multi-markets presence firms invest more in basic research than applied research, which enhances their possibility to develop the sort of advanced technology that other firms may seek to license (Ahuja & Lambert, 2001; Hill, 1992; Markides & Williamson, 1994). In a similar line of thought, compared to less diversified firms, more diversified firms engage in multiple networks and are often at the nexus of these networks. The network position or network structure of more diversified firms enable them to access a vast range of knowledge and information, which they can use to innovate (Freeman & Soefe, 1997; Miller, 2006).

These different literatures suggest that firms accrue advantages from operating in multiple markets and using diverse knowledge and technology sources. Compared to less diversified firms, technology from more diversified firms is more likely to provide greater exploration and exploitation opportunities to licensing partners (Markides & Williamson, 1994; Merger & Nelson, 1990; Sears & Hoetker, 2014). In comparison, unilateral licensing from more diversified licensors to other firms will only help to strengthen the technological capabilities of these licensees and apart from generating additional income, will contribute little or no potential value to the licensor with multi-markets presence licensors. Cross licensing, however, will offer diversified licensors the opportunity to share and access new external knowledge and technologies that enhances their ability to reap more value in combination with their existing technology (Chatterji, 1996). Given the different benefits and potential damages of unilateral licensing and cross licensing, we expect more diversified firms that act as licensors to have a higher preference for cross licensing rather than for unilateral licensing. Hence:

Hypothesis 1a: The higher the levels of diversification for the licensors, the more likely these licensors prefer cross licensing to unilateral licensing.

To understand how licensing pair technology diversification differentials affect the licensor's licensing preference, we confine our analysis on the competitive risks that the licensor's run when its partners assimilate its technology and enter into its market (Arora & Fosfuri, 2003; Fosfuri, 2006; Motohashi, 2006; Nagaoka & Kwon, 2006). According to Fosfuri (2006) and Nagaoka & Kwon (2006), the magnitude of the competitive pressure that the licensor will face in licensing varies depending on the absorptive capability of its licensing partners. In addition, Motohashi (2006) asserts that differentials in licensing pair's absorptive capabilities shape the amount of the value that the licensor can capture from licensing.

From an organizational learning perspective, the number of technologies and markets that firms operate in affects their learning and absorptive capabilities (Levinthal & March, 1993; March, 1991; Katila & Ahuja, 2002; Laursen et al., 2010). Increased levels of diversifications can positively affect new technology development or the firm's absorptive potential in a number of ways. Increased levels of diversification can positively affect new technology development or the firm's absorptive potential in a number of ways. First, learning from multiple sources and using the same knowledge repeatedly in multiple markets increases firms learning cyclical learning and enables them to develop more reliable routines and efficient innovative structures (Levinthal & March, 1993). By developing organisational routines that are more efficient, firms that are present in multi-markets can more easily assimilate externally acquired knowledge and later on develop their own proprietary knowledge (Katila & Ahuja, 2002). Second, using similar technology repeatedly in multiple markets enables more diversified firms to develop a deeper understanding of their knowledge base.

The above highlights that with increasing levels of diversification, firms become more efficient in absorbing and utilizing external acquired technology. It also suggests that when firms with different levels of diversification enter into a partnership, more diversified firms as licensors are less likely to suffer greater competitive risks from partners using their technology as a springboard to generate products and/or technologies that can better serve the needs of their customers (Laursen et al., 2010; Arora et Forfuri, 2003). In that context, a licensor and its licensee(s) are less likely to be in direct competition across the board (Tripsas, 1997).

In an alliance context, the extent to which a firm's technological resources are diverse may influence the behaviour of its alliance partner. It is argued that asymmetric learning between a firm and its partner about each other's resources and technologies may increase uncertainty of partner behaviour and influence alliance performance (Khanna et al., 1998). For instance, when a partner can learn more quickly about a focal firm's technological knowledge than the focal firm can absorb its partner's knowledge, the focal firm is likely to be cautious about transferring its technology to its partner (Khanna et al., 1998). Hamel (1991) argues that the potential for increased competition among partners raises concern for firms to transfer their technology to partners for fear of making them strong competitors.

When a more diversified firm is a licensor to a less diversified firm, we expect the licensor to face less competitive risk in the marketplace from unilateral licensing. Although one-way technology transfer from a more diversified licensor to a less diversified firm may upgrade the licensee's technological knowledge base, the latter may not be able to generate a broad range of new products from the licensed technology in a speedy manner because of its limited breadth in absorptive capability. When compared to its licensee, more diversified licensor has a greater incentive to engage in unilateral licensing, as before its less diversified licensee partner can integrate the licensed technology into its production structure, the more diversified licensor can take full advantage of its technology (Zhang & Baden-fuller, 2010) and reduce the potential negative effect of unilateral licensing (Arora et al., 2001).

On the other hand, unilateral licensing to a more diversified partner may be considered a riskier strategy for the licensor. A more diversified licensee can easily utilize the licensed technology to develop products and services that are similar to those of the licensor, enhancing competition in the marketplace. Thus, to avoid the risk of creating a stronger potential competitor and losing out its competitive edge when the licensing agreement expires (McDonald and Leahey, 1997), the licensor may be better off to enter into a cross licensing agreement. Unlike unilateral licensing, bilateral exchange provides equal opportunities for the licensing partners to learn from each other's technological knowledge base, neutralising the risk for the licensor to lose out to the licensee. Thus:

Hypothesis 1b: In the context of licensing pair diversification differentials, when licensors are more diversified than licensees, the more likely licensors prefer unilateral license to cross licensing.

5.4.2. Licensor's Experience with Cross and Unilateral Licensing

In prior licensing literature, a firm's licensing experience is considered as a critical determinant for its licensing preference (Gambardella et al., 2010; Kani & Motohashi, 2012, Kim & Vornotas, 2006; Motohashi, 2008; Nagaoka & Kwon, 2006;). However, the analysis of the firm licensing experience has mostly been carried out in the context of licensing in general. In this study, we delve a bit deeper in analysing the impact of licensors' prior cross and unilateral licensing experience on their licensing preference. Cohen and Levinthal (1989) argue that firms learn or build their experience through repeated engagements in similar focal activity over many years. Through cumulative involvements in an activity, firms develop efficient organisational routines and standard operating procedures (Pisano, 1996) and consequently gain specific knowledge and skills on how to execute a particular activity. The accumulated knowledge greatly simplifies the coordination of that activity and reduces costs, especially in managerial attention and resources needed to carry out the focal activity (Rothaemel & Thursby, 2005). Because of the acquired knowledge, firms are more likely to draw on the accumulated experience for future engagements (Cohen &Levinthal, 1989).

Unilateral and cross licensing are considered unique focal activities and firms use each of the licensing agreement for specific reasons. As seen in the above, the characteristics of cross licensing differ from that of unilateral licensing in many respects: the mode of governance, control of partners and long-term risks and contribution to profit. As a specialised focal activity, this implies firms' that engage extensively in cross licensing would have developed more in-depth knowledge for the licensing type and are more likely to prefer to choose the licensing arrangement in the future. For example, because of the complexity in assessing the value of different patent packages of partners, especially in complex technology industries whereby technological development builds on prior activities, firms that frequently engage in cross licensing would have built up managerial capabilities and expertise needed to assess partners' patents. These firms are more likely to have a greater cross licensing experience as the licensing and when faced with the prospect of future licensing; these firms are more likely to use the licensing type for which they possess extensive experience.

Licensors with greater cross licensing experiences would have a higher preference for that licensing type, as they are likely to face fewer difficulties in coordinating the licensing arrangement in the future than licensors with less experience. In a similar vein, licensors' that have used unilateral licensing extensively would have a higher preference to license their technology unilaterally. Moreover, we expect that when licensors possess greater cross or unilateral licensing experience than their licensees, i.e. when the licensor is the more experienced partner, these licensors are more likely to prefer the licensing type for which they possess greater experience. The above suggests the following hypotheses:

Hypotheses 2a: The greater the unilateral licensing experiences of licensors, the more likely licensors prefer unilateral licensing to cross licensing.

Hypotheses 2b: The greater the cross licensing experience of licensors, the more likely licensors prefer cross licensing to unilateral licensing.

Hypotheses 2c: In the context of licensing differentials, the greater unilateral licensing experience of licensors, the more likely licensors prefer unilateral licensing to cross licensing.

Hypotheses 2d: In the context of licensing differentials, the greater cross licensing experience of licensors, the more likely licensors prefer cross licensing to unilateral licensing

5.4.3. Licensor's Absolute and Relative Size

Extant literature suggests that firm size and in particular the differentials in licensing partners size, influence the type of the licensing arrangement that licensors' prefer to use to exchange their technology (Ceccagnoli et al., 2010; Fosfuri, 2006, Kim & Vonortas, 2006; Motohashi, 2008; Nagaoka & Kwon, 2006;). To understand how the size of firms shape their licensing preference, the resource dependence view and related perspectives in the licensing literature heavily emphasise the role of specialised downstream capabilities such as distribution channels, marketing capabilities and regulatory skills (Cavas et al., 1983; Ceccagnoli et al, 2010; Teece, 1986). According to this body of literature, for firms to capture the highest returns from their proprietary assets, the licensed technology must be bundled with other complementary resources (Teece, 1986). These resources enable firms to take their technology to the market in a speedy manner.

In general, compared to smaller firms or start-up firms, larger firms are more likely to own more complementary assets (Teece, 1986), which enable them to take their technology to market alone (Shane, 2001). Smaller firms, on the other hand, must either incur substantial capital investments or enter into collaborative agreements with competitors or owner of complementary assets in order to build their complementary asset stocks. In addition to complementary assets, larger firms are also more likely to possess a more significant pool of managerial expertise, sales force and technical capabilities required for technological exploitation. Unlike larger firms, even the most technologically savvy smaller firms may not possess all the technical competencies and managerial resources required to take their technology to market (George, 2005).

Furthermore, the market-based perspective of the licensing literature indicates that the size of firms is an essential source of market power (Schmalensee, 1989). Market power provides firms with legitimacy and other advantages such as economies of scope and scale (Stuart et al., 1999). Smaller firms generally lack reputation and legitimacy (Barla, 2000), which they could mitigate by collaborating with more established firms (Teece, 19876). Due resource constraints and lack of legitimacy, smaller licensors are more likely to have a higher preference for the licensing arrangement enables them to access complementary resources. Unilateral licensing provides firms access to necessary complementary resources (Bianchi et al., 2010), thus, we expect that with decreasing size of licensors they are more likely to have a higher preference for unilateral licensing as the licensing type would enable them to gain access to complementary resources and also enhance their reputation in the market. On the other hand, because larger licensors generally own significant financial, marketing and manufacturing resources, they are better able to commercialize their technology (Lowe & Taylor, 1988). Hence, we expect that with increasing firm size of licensors, they are more likely to have a higher preference for cross licensing, as bilateral exchange would enable them to broaden their technological base, enhancing their ability to explore and exploit their resources. Hence:

Hypothesis 3a: With increasing firm size of licensors, licensors prefer cross licensing to unilateral licensing.

Turning onto the licensing pair size differentials, it is argued in the literature that when firms of different sizes engage in technological exchange; the size of the licensor relative to the licensee can influence the degree of risks that the licensor faces from the partnership (Nagaoka & Kwon, 2006). It is suggested that the smaller the licensor's vis-à-vis the licensee's, the more likely the licensor's would face increasing risks (Hagedoorn et al., 2008). This is mainly because larger firms are more capable of extracting value from externally acquired technology than smaller firms. Due to slacked resources and higher internal capabilities, larger licensees are able to quickly integrate and generate a new product from externally acquired knowledge (Cohen & Levin, 1989).

Because smaller licensors face higher risks when they offer their technology to larger licensees, they would have a higher preference to cross license their technology. Unlike unilateral licensing, a bilateral exchange would enable licensing parties to mutually access each other's technologies, where mutual access to partner's technologies mitigate the effect of smaller licensors losing out to larger partners. Therefore:

Hypothesis 3b: In the context of licensing pair size differentials, when licensors are smaller than licensees, it is more likely that licensors prefer cross licensing to unilateral licensing.

5.5. Method and Data

5.5.1. Research Setting

The empirical setting for this research refers to Chipless firms operating in the global semiconductor industry as the research context. The chipless firms' setting is hugely relevant to our study as they are considered leading licensors in the semiconductor industry. They do not engage in any manufacturing, but mainly use cross and unilateral licensing to capture value from their technology and to access the state of the art of technology developed by rivals in the industry. As specialised firms that depend solely on licensing, the licensing type that chipless firms select to exchange their technology is critically important. It influences the amount of value that they capture from their innovation and has a profound implication on their very survival (Davis, 2008; Linden & Somaya, 2003).

In addition, chipless firms operating in the global semiconductor industry differ significantly in size, licensing experience, and technology market diversification (Linden & Somaya, 2003). These firms vary from smaller firms operating in a single market to large firms with multiple markets presence and licensing experiences. As principal licensors with unique characteristics, chipless firms provide us with an interesting setting to study the effects that the licensor's diversification, size and licensing experience play on its preference for either cross or unilateral licensing.

Furthermore, from chipless firms licensing activities, we can capture the effect that the licensor's characteristics vis -à- vis the licensee has on the licensor's licensing preference. Chipless firms license their technology to partners operating in a broad range of industry settings but are more likely to suffer the adverse effects of increased competition from partners, which are capable of entering their marketplace. Licensees that are larger and highly diversified than Chipless firms can easily assimilate chipless firms' technology and develop products that can better serve the need of their customers.

5.5.2. Sample and Data

To test our hypotheses, we built a novel dataset from chipless firms licensing activities from 1985 to 2005. The rationale for using the time frame was because a large number of Chipless firms operating in the semiconductor industry entered the industry in the late 1980's. The sample period coincides with a paradigmatic shift in the industry whereby complementary metal-oxide semiconductor (CMOS) replaced bipolar technology as the dominant design. Before the introduction of CMOS technology, bipolar technology or PCB generated too much heat and consumed too much power as more chips were added to transistors (Jian et al., 2011; Linden & Somaya, 2000). The introduction of CMOS made it possible for a large number of chips to be inexpensively placed on a single transistor (Garnsey et al., 2008). This miniaturisation of chips or system on chip (SOC) created a more significant division of labour in the industry and facilitated the entry of new and specialised firms (Linden & Somaya, 2000).

We collected data on chipless firms licensing activities from Thomson-Reuter Financial SDC Platinum strategic alliance and joint venture database. For every licensing agreement recorded in the database, SDC database reports information on the date the licensing deal is announced, the name of licensing partners participating in the licensing arrangement, licensor and licensee public status, partners' industry affiliations and countries in which they are headquartered. It also provides a brief description of the purpose of the licensing agreement, type of technologies involved in the licensing deal, mode of contracts (unilateral licensing, cross licensing and other contractual types) use in the technology transfer and primary SIC code of the engaging parties.

To build our sample, we carried out the following steps. First, we selected from the SDC alliance database all licensing deals from the broader electronics industry using the two digits

SIC (36) from 1985 to 2005. From this data extraction, we obtained a sample of 4980 licensing agreements. We refined the sample by focusing on licensing arrangements in which at least one of the participant principal lines of business is the semiconductor and related devices (SIC 3674) on the contextual description of the licensing deal. From this refinement, we obtained 3231 semiconductor firms engaged in 1556 licensing agreements. From the list of semiconductor firms, we focused on all licensing agreements signed by chipless firms. According Linden and Somaya (2003) firms in the semiconductor industry use two main organisational governance modes to create and capture value from their innovations: integrated device manufacturers (IDMs) and networked firms (IP suppliers, fabless, foundries, EDA software suppliers). IDMs are firms that engage in the entire value chain designing and manufacturing integrated circuits in house using very limited licensing or external resources. Although IDMs may engage in some licensing, they mainly bring external technology through mergers and acquisition (Linden & Somaya, 2003).

Networked firms on the other hand either outsource (fabless model) or license (chipless model) their technologies to third parties. Chipless firms are networked firms that design technology and license the right of their IP blocks to other firms. Their partners use chipless firms' technology alongside their technology to develop advanced consumer electronics products (manufactured using their fab (manufacturing facilities) or external manufacturers – foundries)

We identified chipless firm by checking on its website if it is exclusively mentioned that the firm is a chipless firm. We also searched news wires and archival sources on the internet for the firm's history paying specific attention to its business model to confirm its status. Firms that we could not determine their status from both their website and other data sources were deleted from the dataset. From this selection procedure, we obtained 458 licensing agreements signed by 635 chipless firms from 1985 to 2005. Of the 458 licensing agreements, approximately 91% were unilateral licensing, while 9% of all the licensing agreements were cross licensing agreements.

Next, we compiled patent information for chipless firms – licensors and their partners in our sample. The patenting data was retrieved from the patent databases compiled by the National Bureau of Economic Research (NBER). NBER databases contain patent information from the US Patent and Trademark Office (USPTO), the European Patent Office (EPO), and other key patent jurisdictions in the world such as Japan, China, South Korea, and Australia. The NBER databases provide information on the total number of patents granted to a firm - ultimate parent including those of all its subsidiaries. They also report the number of citation counts made and received by each patent, its technology class and subclass, as well as a wealth of other relevant information (for a detailed description of the databases, see http://eml.berkeley.edu//~bhhall/patents.html). For our study, we mainly used the information of firms' patent technology classes to measure technology diversification (Sampson, 2007; Jaffe et al., 1993).

Furthermore, based on the variables to be tested in the research, we complemented our dataset by collecting data on licensors and licensing partners' size and age from multiple databases such as Compustat, DataStream, Amadeus, LinkedIn, and Bloomberg. For those that we could not find their age and size on these databases, we searched their company website, annual reports, the internet and other firm directories to confirm these details.

5.5.3. Operationalisation of Variables

5.5.3.1. Dependent Variable

The dependent variables in this study are alternative licensing options (cross and unilateral licensing) that the licensor can choose from to exchange its technology. We construct a dummy variable and code it as 1 if the mechanism of technological exchange used in the licensing agreement is unilateral licensing and 0 if it is cross licensing.

5.5.3.2. Independent Variables

To gain a specific understanding of the effect of diversification on the licensing preference of licensors, we measured diversification in terms of both market and technology diversification. Following prior studies by Hagedoorn et al., (2008) and Sear & Glenn Hoetker, (2013), we identified *licensor market diversification* using the industry SIC code assigned to firm in the Thomson SDC Reuters database. To measure the licensor's product market diversification, we counted all the SIC codes assigned to the licensor's in the licensing agreement.

We captured *licensor absolute technology diversification* using their patent technology classes. Similar to Jaffe et al. (1993), we measured licensor technology diversification as a count of the number of different technology classes of a licensor's patents assigned to the observation year t.

Licensor relative market diversification is measured as the difference in the number of SIC codes of the licensing pair. We captured this by using a dummy. Based on the licensing pair SIC codes differential, we identified a market diversification differentials dummy as 1 if the licensor operates in more markets than the licensee, 0 otherwise.

For *licensor relative technology diversification*, we took the diversity of the licensing pair patents across their different technology classes (Rivkin, 2000; Rumelt, 1974; Sampson, 2007). In the NBER database, firm patents are categorized under different technology classes. Through partners' patents technology classes, we can capture the similarities as well as the technology differences among their patents (Jaffe et al., 1993). Licensing partner technologies are considered similar when their patents are allocated to the same patent technology class (Jaffe et al., 1993).

To construct licensor relative technology diversification, we, first of all, generated the licensing pair patent portfolios. Then we computed the distribution of the licensing pair patents across the different technology classes using the multidimensional vector applied by Sampson (2007). This multidimensional vector takes the form $(F_i) = (F_i^1 \ldots F_i^s)$, where F_i^s symbolizes the number of patents allocated to partner firm i in patent class s (Sampson, 2007).

$$\text{Technology diversity} = (F_i) \quad = \quad 1 \quad - \quad \frac{(F_i F_j^1)}{\sqrt{(F_j F_i^1)\,(F_j F_j^1)}}$$

Where $i \neq j$. Technology diversity varies on a continuum from 0 to 1 with a value of 1 representing the highest possible level of technology diversification among partners (for more details on the operationalization of the vector, see Sampson (2007))

Licensor absolute cross and unilateral licensing experience are measured as counts of cross or unilateral licensing that the licensor's has engaged in within five years before the licensing announcement date. A five years' window is used as the timeframe to operationalize the variable because prior research indicates that firms build their licensing experience over time and the benefit from the accumulated experience sharply depreciate over time, losing significant value within 3 - 5 years approximately (Ahuja & Katila, 2001).

Licensor relative cross and unilateral licensing experience vis-à-vis its licensing partner is operationalised as the difference in the licensing pair experience for the specific licensing type.

To capture the impact of the licensor's relative licensing experience for cross or unilateral licensing, we create two dummy variables (CR & UL). The variables are assigned a value of 1 when the licensor possesses greater licensing experience for the specific licensing type than the licensee, 0 otherwise.

Licensor absolute size is measured as the number of corporate employees that the licensor employed at a given time t (observation year). For the sample firms, the total number of employees fluctuates between 1 and 196200, following prior literature, we controlled for non-linearity and statistical skewness by transforming the count variable using natural logarithm (Hagedoorn et al., 2008; Walter, 2012).

To measure *licensor relative size,* we followed the procedures used in prior studies by Barla, (2000) and Hagedoorn et al., (2008). The licensing pair size differential is measured as the difference between the number of employees employed by the licensor and licensee at given time t. Similar to other relative variables, we constructed a dummy variable to capture the impact that the licensor/licensee size differential has on the licensor licensing preference. Based on the number of employees of the licensing pair, we assigned a value of 1 when the licensor is larger than the licensee, 0 otherwise.

5.5.3.3. Control Variables

The technology licensing literature has identified a number of firm levels and pair level factors that can affect the choice of the licensor licensing preferences. We controlled for these effects by including the following variables.

Following Hagedoorn et al., (2008) and Siebert and Von Graevenitz (2010), we used a *time* trend variable to account for the impact that variation in time may have on the licensor's licensing preference. We assigned a value to each year for the time frame of our study and the time trend variable starts at 1 for the year 1985 and runs up to 21 for 2005.

Licensor age is measured as the number of years that had elapsed from when the licensor was established to date of the announcement of the licensing deal. A logarithm form is used to remove the skewness in the data.

To control for the impact that the licensing pair technology similarity may have on the licensor's licensing preference, we constructed a *technology market similarity* variable. Following Hagedoorn et al. (2008); Karim & Mitchel (2000) and Markri et al. (2010), we operationalised the licensing pair technology overlap at the primary industry SIC codes level. We constructed a linearly ranked variable base on the similarity of the licensing pair primary SIC code. We assign a value of '4' when the licensor and licensee operate in the same fourth digit SIC code, '3' for similarity at the third digit SIC code level, '2' for the second digit SIC code similarity and value '1'when there is no product market similarity between the pair (Haleblian & Finkelstein, 1999).

To control for cross-country heterogeneity and geographical explanations in the attitude of firms towards unilateral and cross licensing, we constructed a *global licensing* participant's distribution dummies. We partitioned the licensing partners into geographical regions and constructed six global, regional dummies. Each dummy captures the proportion of the licensor partners in its home region. We used the firm's parent firm headquarter to classify the licensing partner into one of the following five regions: *USA, Europe, Japan and South Korea, Other developed nations, Fast East Asia and Rest of the world.*

We also control for exclusivity in the licensing deals as prior research has indicated that scope restrictions (products & geography) may impact on licensors' licensing choice (Kim & Vonortas, 2006; Somaya, Kim & Vonortas, 2011).

5.6. Econometric Specification

We used the logistic regression model to estimate the likelihood that the licensor will select either cross or unilateral licensing to exchange its technology. The logistic model has been well established in prior literature as an appropriate approach for modelling firms' strategic decision-making based on binary alternatives (Hagedoorn et al., 2008; Siebert & Von Graevenitz, 2010, Walter, 2012; Kim & Vornotas, 2006). A fundamental assumption underlying this model is that any pairwise comparison is unaffected by the characteristics of other licensor partners other than the pair under consideration (Ruckman & McCarthy, 2016). We estimated the logistic regression specification using the logistic command in Stata 14.

5.7. Findings

Table 5.1 presents the descriptive statistics and the Pearson correlation coefficients for the market diversification (absolute and relative) variables and all the other explanatory variables. Table 5.2 reports similar descriptive statistics and correlation coefficients and includes the technology diversification variables. Given the high correlation coefficient between the licensor absolute and relative market diversification (0.4884) and the licensor absolute and relative cross licensing experience (0.5300), multicollinearity could have influenced our findings. We checked the influence of multicollinearity on our results using mean - variance inflation factor (VIF) scores. The VIF scores for all of the independent variables were all around 3.43, which is far below the critical value of 10 for multicollinearity to be considered a problem (Belsley, 1980; Cohen et al., 2003).

--------- Insert Tables 5.1 and 5.2 about here --------

Table 5.3 and Table 5.4 display the logistic regression results with market and technology diversification variables in separate regressions. We used a stepwise procedure; whereby we first introduced the control variables, followed by the licensor absolute characteristics and the licensor relative characteristic variables. In both tables, Model (1) contains only the control variables. In model (2) we incorporated two licensor absolute diversification, in model (3) we introduced licensor absolute cross or unilateral licensing experience. Model (4) contain licensor size and (5) include the licensing pair characteristics. The addition of the licensing pair variables greatly improves the baseline model (1), and the examination of the statistical difference in the pseudo R squared value for all the models suggests that model (5) provides the best fit for the data.

----------- Insert Tables 5.3 and 5.4 about here -----------

To report our findings, we organised the results in function of the order of the hypotheses. Hypothesis (1a), states that with increasing levels of diversification, licensors tend to prefer to engage in bilateral exchange rather than unilateral licensing. In support of this hypothesis, licensor absolute market diversification (Table 5.3, models 2 and 5) and technology diversification (Table 5.4, models 2 and 5) have the expected negative (significant) signs ($p < 0.01$ and $p < 0.05$). We also hypothesized that the more diversified licensors are relative to licensees, the higher the likelihood licensors prefer to engage in unilateral licensing rather than in cross licensing (hypothesis 1b). Both relative market diversification (Table 5.3, model 5) and technology diversification (Table 5.4, model 5) have the expected signs. However, while the relative market diversification is significant ($p < 0.05$), technology diversification is only marginally significant ($p < 0.10$).

In hypotheses 2a and 2b, we stated that with increasing levels of licensors' prior unilateral or cross licensing experience, they tend to prefer the licensing type for which they possess greater experience. Both hypotheses are supported (Table 5.3 and Table 5.4, models 4 and 5) with significant values ($p < 0.01$ or $p < 0.05$). For the licensing pair experience differentials, see hypothesis 2c, we predicted that when licensors possess more prior unilateral licensing experiences than licensees licensors prefer to engage in unilateral licensing. Hypothesis 2c is not supported as $p > 0.05$ in both Table 5.3 and Table 5.4, model 5. Hypothesis 2d proposes that when licensors have greater cross licensing experiences than licensees, licensors are more likely to prefer cross licensing to unilateral licensing. This hypothesis is supported with a highly statistically significant value $p < 0.01$ in Table 5.3 and $p < 0.05$ in Table 5.4, model 5. Tuning onto the hypotheses on the licensor's size and licensing pair size differentials. Hypothesis 3a proposes that with increasing firm size, licensors are more likely to prefer to cross license their technology to licensing them unilaterally. In hypothesis 3b, we predicted that when licensors are smaller than licensees, licensors tend to prefer to cross licensing their technology as opposed to unilateral licensing them. Hypothesis 3a is not supported in either model (4) and (5), whereas hypothesis 3b is supported ($p < 0.05$ in table 3 and marginal support of $p < 0.10$ in table 5.4).

In addition to the core effects, we also examined the marginal effect. We estimated the effects that a predicted change in the probability of explanatory variables would have on the dependent variables (Green, 2003). The findings of the marginal effects are reported in Table 5.5 and Table 5.6. The results indicate that each additional market and technology space that a licensor entered (i.e., increased in diversification) decreases the probability of unilateral licensing by 19%. Also, an increase in the licensor's cross licensing experience of 1% increases its preference to engage in cross licensing in the future by 31%, whereas an increase of the licensor's unilateral licensing experience of 1 % leads to 25% increase for the use of unilateral licensing.

----------- Insert Tables 5.5 and 5.6 about here -----------

5.7.1. Robustness Checks

To confirm the accuracy of our finding, we carried out several sensitivity tests. First, for the hypotheses on the impact of licensor cross and unilateral licensing experiences, the variables (absolute and relative effect) are operationalised using a 5 years' time window. We also estimated the models using 4 and 6 years' window. However, using both timeframes yield almost similar results in terms of direction and significance, which reinforces the validity of our findings.

Second, for the firms' size, we also transformed the size variable into a categorical variable. Information on size (in terms of the number of employees) for publicly owned firms was collected from Bloomberg, Reuter database and firms' annual accounts. Size information for private firms was mainly retrieved from the Internet and other sources that might be less reliable. Following OECD classification, we considered small and medium size firms as firms with the total number of employee's equal or less than 500 and assigned a value of 0 to these firms, whereas large firms were considered as a firm with total number employees greater than 500 and were given a value of 1. The estimated regression coefficients from the analysis using these dummy variables were qualitatively similar to those in the full model, lending support to our hypotheses.

Further, in line with debate on the effect of firms' size in the licensing literature, we also test the impact of the licensee's absolute size on the licensor licensing choice. Similar to the licensor's absolute size, the size of the licensee (alone) has no implication on the licensor's licensing preference.

5.8. Discussion and Conclusions

Our study extends prior studies and contribute to the literature on the determinants of the firm's licensing preference from a pair level perspective (Kim &Vonortas, 2006b; Nagaoka & Kwon, 2006; Arora & Gambardella, 2010; Siebert & Von Graevenitz, 2010). Its theoretical and empirical contributions lie in understanding of how degree of licensor technology and market diversifications and differentials in licensing pair diversification influence the licensor's licensing preference. Our empirical study shows that diversification (in terms of both market and technology) is arguably the most important determinant for the licensor's licensing choice. Our study also shows that the licensor prior in cross and unilateral licensing play an important role in the preference for either cross or unilateral licensing. In contrast to the assumptions in the literature on the firm size, the study also indicates that the size of licensor relative to its licensee may be a better predictor of licensor licensing preference than licensor or licensee size per se. Our findings illustrates the importance of incorporating both the firm characteristics and pair level differential characteristics in the examination of firms' licensing preference.

Our study offers the following theoretical insights. First, the degree to which licensors are diversified influence the licensing agreement that they prefer to use to transfer technology. Our finding supports the view that the desire to exploit the advantages of capabilities that firms accrue from operating in multiple markets influence their licensing preference. As more diversified licensors engage in a number of technology market areas and they are generally multidimensional in scope (Freeman & Soefe, 1997), they tend to prefer to cross license as opposed to unilaterally licensing. Learning from partners is more important to diversified firms than just accruing revenue from arm length or market based transfer of technology. Bilateral exchange enables more diversified firms to access advanced technologies of partners, enhancing their ability to benefit from their technology (Nagaoka & Kwon, 2006) and also develop new knowledge they can exploit in the future. Licensors that operate in a single market are more likely to prefer to transfer their technology through unilateral licensing because they lack the technological competencies and patent stocks required for cross licensing. To the best of our knowledge, this relationship has not been formalised in prior licensing literature, which may be an important contribution of our study.

Regarding the effect of licensing pair diversification differential, our research suggests that the degree to which the licensor is diversified relative to the licensee has a very significant effect on the licensor's licensing preference. This supports the view that increasing technology market diversifications significantly enhance the firm's learning and absorptive potential and more diverse firms are better able to absorb externally acquired technology (Cohen & Levinthal, 1990; Teece, 1986). When faced with licensees that are more diversified, licensors are more likely to prefer to use the licensing type that will shield them from the risk of increasing competition. The more diversified the licensees are, the more they can quickly utilise the licensor's technology as a springboard to generate new products that can better serve the need of licensors' customers, which enhances the degree of competition. This finding is concurrent with prior licensing studies from the competitive perspective (Arora et al., 2003; Fosturi, 2006; Siebert & Von Graevenitz, 2012), which showed that with increasing competition firms tend to be more cautious in their licensing decision and tend to select the licensing type that will guard them against the adverse effect of increasing competition.

The second finding refer to the effect of licensors' prior cross and unilateral licensing experience. In earlier licensing literature, firm experience has been examined general licensing experience (Hagedoorn et al., 2008; Kim & Motohashi, 2012; Kim & Vonortas, 2006; Motohashi, 2006; Ruckman & McCarthy, 2016). Our result adds to these studies by examining the implication that licensors' prior cross and unilateral licensing has on its specific licensing preference. Our finding indicates that the knowledge that firms gained from engaging repeatedly in a specific activity dramatically enhance their ability to implement the activity in the long term (Pisano, 1996). It supports the view that the ease at which the licensor can orchestrate a specific licensing type significantly increases its preference to use that licensing type in the future.

Turning onto the licensing pair experience, according to our theory, heterogeneity in the licensing pair experience for both licensing type is expected to influence licensors' licensing preference. Our results indicate that while differences in licensor and licensee's cross licensing experience is an important predictor for the licensor preference for cross licensing, this not the case for unilateral licensing. The positive relationship between licensing pair cross licensing differentials and licensor' preference for cross licensing may be related to the latter's need to be assured that their partners possess the relevant technologies and patent portfolios. Moreover, cross licensing is also used as a mechanism to deal with issues of patent infringement, which requires a considerable amount of specialized knowledge, which in turn implies that the sort of experience that firms gained from engaging in cross licensing may have a more profound impact on the licensor than the experience gained from unilateral licensing.

Another important insight from this study relates to the effect of the licensor's size and the size of the licensor relative to the licensee. Our findings suggest that the size of the licensor vis - à - vis its licensing partner may be a more important predictor for its licensing preference than the licensor or the licensee size per se. Some previous research (e.g., Kim & Vonortas, 2006; Nagaoka & Kwon, 2006) find that large firms are more likely to prefer to exchange technology through cross licensing, while other researchers (Gambardella et al., 2010; Kim & Motohashi, 2012) find no effect or the opposite on the implication of firm size on licensing preference (Motohashi, 2006). However, most of these studies did not examine the effect of the licensor size relative to the licensee size. Our research provides some answers to this debate. It shows that when the licensor size is examined alongside the licensee size, the licensor size seems to have a significant effect on licensor's preference. The finding supports the argument that the degree of competition that a licensor will face from licensing its technology to licensees of different sizes is the determining factor for its licensing preference rather that the size of the licensor or the licensee per se. With increasing size, firms generally tend to possess more resources and can use these resources to extract value from externally acquired technology. Larger licensees can readily use licensor technology as a catalyst to generate new products. When these products are somewhat similar to those of the licensor, these partners become direct competitors. When licensors are smaller than licensees, to minimise the adverse effect of increased competition, licensors will have higher preference for cross licensing as this licensing type protects them from losing out to larger partners. This finding concurs with prior licensing literature from the competitive perspective (see also Arora & Fosfuri, 2003; Siebert & Von Graenenitz, 2010).

Our study also have some important managerial implications. Given the risks and rewards that unilateral and cross licensing bring to licensors, understanding under what conditions firms' managers should select a specific licensing agreement is of critical importance. Based on the licensor characteristics and licensing pair differential characteristics uncovered in this study, a licensor can optimise the amount of value of it captures from its technology by selecting the appropriate licensing agreement to exchange its technology. Our findings indicate that when operate in multiple markets, they should exchange their technology through cross licensing as that would enable them to capitalise on the capabilities they accrue from operating in multiple markets. Licensor should consider how diversified they are relative to their potential partners. When the licensor operates in fewer markets than their potential licensee, they are likely to suffer more risk in partners who are able to assimilate their technology quickly. Under such circumstance, they should select cross licensing as a mechanism to exchange their technology as that would shield them from the adverse effect of increasing competition from new players entering their marketplace.

Regarding the licensors prior cross and unilateral licensing experience, our finding indicates that, given the conditions mentioned in the above, licensors should also consider utilising the licensing type for which they possess greater experience. In this way, they are able to reap the advantage of efficiently implementing the licensing type with which they are most familiar.

Our study is also subjected to some limitations that provides directions for future research. The first limitation of this study is related to its research setting. The study is operationalised within a single industry (semiconductor industry), which implies the findings may not be easily generalised. Although the theoretical background and hypotheses are not based on the distinctive features of the semiconductor industry, we are conscious of the fact that although the characteristic of licensors and partners in the semiconductor industry may be similar to those in other architecture industries such as computers, software, and electronics, they may vary significantly from those of other high-tech industries such as pharmaceutical, chemical, and telecommunications industries. A logical step forward to deal with the issue of generalisation is to broaden the scope of future studies by incorporating data from other high-tech industries. Second, our data is based solely on publicly announced agreements, which is limited in terms of information on the licensor motives to use a particular licensing agreements. Understandably, more information is needed on the motives of firms in order to gain a full picture their licensing preference. Other research designs such as case studies and survey designs, which offer the researcher the potential to ask more in-depth questions, could generate greater insight and broaden our understanding on the conditions under which firms' prefer to engage in cross or unilateral licensing

However, despite these limitations, we believe this study makes a significant contribution to our understanding of the preference of licensors for particular licensing types as they engage in the exchange of their technology in knowledge intensive industries amid fierce competitions in a globalized market.

Figure 5-1: Cross Licensing versus Unilateral Licensing in Technology Transfers

Variable	Description	Expected effect	
Dependent variable			
Licensing choice	1 if the mechanism of technological exchange is unilateral licensing and 0 if it is cross licensing		
Independent variables		**Cross**	**Unilateral**
Licensor absolute market diversification	Number of SIC codes assigned to the licensor in licensing agreement	+	−
Licensor absolute techno-logy diversification	Number of different technology classes of the licensor patents	+	−
Licensor relative market diversification	Difference in the number of the licensor and the licensee SIC	− −	+ +
Licensor relative techno-Logy diversification	Difference in the number technology of licensor and the licensee patents	−	+
Licensor absolute size	Log number of employees employed by licensor at time t	+	−
Licensor relative size	Log difference in the licensor and the licensee employees number at time t	−	+
Licensor absolute unilateral licensing experience	Number of unilateral licensing deal engaged in within 5 years of the licensing announcement date	0	+
Licensor absolute cross licensing experience	Number of cross licensing arrangements engaged in within 5 years of the licensing announcement	0	+

	Date		
Licensor relative unilateral Licensing experience	The difference in the number of the licensor licensee unilateral licensing deals	0	+
Licensor relative cross Licensing experience	The difference in the number of licensor and licensee cross-licensing	0	+
Time	Time trend starts at 1 for the year 1985 and runs up to 20 for 2005		
Licensor age	Log number of years between licensor date of establishment and date of announcement of the licensing deal		
Product market similarity	The closeness of the licensor and licensee primary industry SIC codes		
USA	Licensing partner parent headquarters, coded 1, if the pair operates in USA and 0 otherwise		
Europe	Licensing partner parent headquarters, coded 1, if the pair operates in Europe, and 0 otherwise.		
Exclusivity	Scope (products & geography) of the licensing deal		

Table 5-1: Descriptive Statistics and Correlation Matrix - Market Diversification

Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13
Form of licensing	.8682927	.3385855													
1Licensor abs size	3116.259	12063.75	1.000												
2Licensor abs market diversification	3.221951	2.447893	0.1735*	1.000											
3Licensor abs unilateral licensing	4.148148	5.781473	-0.0603	0.0940	1.000										
4Licensor abs cross licensing	.191358	.6344146	0.0167	0.0794	-0.0765	1.000									
5Licensor rel size	.1902439	.392973	0.1374	0.0805	-0.0388	0.0963	1.000								
6Licensor rel market diversifications	.2942387	.4561693	0.0340	0.4884	0.1012	0.0344	0.2467*	1.000							
7Licensor rel unilateral licensing	.2901235	.4542868	0.0121	-0.0268	0.1083	0.0228	0.2099*	0.1859*	1.000						
8Licensor rel cross licensing	.5164609	.5002439	0.0400	0.0419	-0.0199	0.5300*	0.1237*	0.1522*	0.2663*	1.000					
9Time	11.51852	5.043999	-0.1366*	- 0.0385	0.2389*	-0.0917	0.0796	0.0932	-0.1879*	-.00500	1.000				
10Licensor age	3.447144	.3332618	0.1982*	0.2644	0.0219	0.1709*	0.0463	0.1206*	0.0096	0.1355	-0.3608*	1.000			
11Technology market similarity	3.109053	1.195542	-0.0570	- 0.0789	0.1358*	0.0338	0.0559	-0.1069*	-0.0783	- 0.1355*	0.5008	-0.0114	1.000		
12USA	.4053498	.4914655	-0.0103	0.0344	-0.0775	0.0704	0.2053	0.01268*	.0022	0.1006*	-0.0002	-0.0015	-0.1380*	1.000	
13EUROPE	.00226337	.1488861	-0.0071	0.0377	-.0.0145	0.0079	0.0234	-0.0073	-0.0119	0.0445	0.1339*	-0.0143	0.0048	-0.1169*	1.000

Table 5-2: Descriptive Statistics and Correlation Matrix - Technology Diversification

Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13
Form of licensing	.8682927	.3385855													
1Licensor abs size	3116.259	12063.75	1.000												
2Licensor abs techn diversification	2.015464	.0955853	0.3622*	1.000											
3Licensor abs unilateral licensing	4.148148	5.781473	-0.0895	0.0416	1.000										
4Licensor abs cross licensing	.191358	.6344146	-0.0666	0.1006*	-0.3781*	1.000									
5Licensor rel size	.1902439	.392973	0.1384*	0.1995*	-0.0713	0.0359	1.000								
6Licensor rel techn diversifications	.6514515	.0198671	0.0059	-0.2901	0.0151	0.0373	0.0903	1.000							
7Licensor rel unilateral licensing	.2901235	.4542868	0.0216	-0.0164	0.0808	0.0915*	0.2083	0.1954*	1.000						
8Licensor rel cross licensing	.5164609	.5002439	0.0606	-0.0179	-0.01028*	- 0.0179	0.1241*	0.0278	0.2746*	1.000					
9Time	11.51852	5.043999	-0.1579*	- 0.0236	0.2319*	-0.2342*	0.0776	0.1287*	-0.16793*	-.00402	1.000				
10Licensor age	3.447144	.3332618	0.3136*	0.1874 *	-0.0216 *	0.0527	0.0741	0.0859	0.0136	0.1180*	-0.0240*	1.000			
11Technology market similarity	3.109053	1.195542	-0.0605	- 0.0108	0.1313*	0.1355 *	-0.0575	-0.1816*	-0.1134 *	- 0.1426 *	0.0203	0.0240	1.000		
12USA	.4053498	.4914655	-0.0449	0.0930	-0.0567	0.0575	0.2082*	0.0007	0.0064	0.0771	0.0148	-0.0318	-0.1421*	1.000	
13EUROPE	.00226337	.1488861	-0.0142	-0.0677	-.0326	0.0317	0.0295	-0.0689	-0.0119	0.0427	0.1079*	-0.0065	0.0602	-0.1256*	1.000

Table 5-3: Estimation Results of Logit Regression Predicting the Preference of Firms for Unilateral or Cross Licensing - Market Diversification

Variables	Model1	Model 2	Model 3	Model 4	Model 5
Constant	2.268797*** (0.6450944)	2.599317*** (0.6754461)	2.612895*** (0.6930385)	3.295398*** (0.8487388)	2.477314*** (0.6540704)
Licensor abs market diversification		-0.1277262** (0.054139)	-0.113751** (0.0554734)	-0.1086203* (0.0578739)	-0.199999*** (0.0707729)
Licensor abs size			-0.1297042 (0.0855717)	-0.1394595 (0.0844314)	-0.1209742 (0.010251)
Licensor abs unilateral licensing experience				0.1559336*** (0.0569469)	0.2298651*** (0.0823471)
Licensor abs cross licensing experience				-0.1709345*** (0.0346873)	-0.3245673*** (0.0334117)
Licensor rel market diversification					0.9987705** (0.4755887)
Licensor rel size					0.8536406** (0.4481019)
Licensor rel unilateral licensing experience					0.004893 (0.0053946)
Licensor rel cross licensing experience					-0.811332*** (0.0899245)
Time	0.0798202** (0.0320498)	0.0841625** (.0325317)	0.0810257** (0.032962)	0.0448059 (0.0328044)	0.049215 (0.018228)
Licensor age	-0.0129933 (0.0091222)	-0.059188 (0.0096755)	-0.0082174 (0.0100088)	-0.0029575 (0.0104149)	-0.0043933 (0.0133172)
Technology market similarity	-0.1576593* (0.1294261)	-0.1929996* (0.1317657)	-0.1965253* (0.13461)	-0.2370364* (0.1370684)	-0.2792441* (0.1514823)
USA	-0.6894751** (0.2976353)	-0.6757908** (0.2989667)	-0.6458874** 0.123781	-0.5530811* (0.3089779)	-0.3758968 (0.3452162)
Europe	-0.631228 (0.115786)	- 0.625173 (0.114789)	-0.6338505 (0.133473)	-0.2187368 (0.146703)	0.2675408 (0.192705)
Exclusive licensing	Included	Included	Included	Included	Included
Japan and South Korea	Included	Included	Included	Included	Included
Other developed nations	Included	Included	Included	Included	Included
Far East Asia	Included	Included	Included	Included	Included
Rest of the world	Included	Included	Included	Included	Included
Number of obs	410	410	410	410	410
Log likelihood	-165.60786	-163.0082	-157.61322	-157.61222	-125.77245
Pseudo R2	0.0463	0.0613	0.0662	0.1027	0.1427

Standard errors are in parentheses *p < 0.10; **p <0.05; ***p < 0.01

Table 5-4: Estimation Results of Logit Regression Predicting the Preference of Firms for Unilateral or Cross Licensing -Technology Diversification

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	2.268797*** (0.6450944)	2.280547*** (0.7363712)	2.391971*** (0.7544056)	2.5696567** 0.813414	2.2817799** 0.7955845
Licensor abs technology diversification		-0.16728** (0.0815623)	-0.1700470** (0.0853778)	-0.117216* (0.019323)	-0.1341145** (0.0868547)
Licensor abs size			0.0118347 (0.0116973)	-0.0110433 (0.011528)	-0.0113456 (0.0010234)
Licensor abs unilateral licensing				0.2394468** (0.274567)	0.4393807** (0.065577)
Licensor abs cross licensing				-0.8733923*** (0.278697)	-0.6325674*** (0.0745632)
Licensor rel technology diversification					-0.1456965* (0.0584512)
Licensor rel size					-0.1604595* (0.051678)
Licensor rel unilateral licensing					0.1998545 (0.0592345)
Licensor rel cross licensing					-0.5484508** (0.3514123)
Time	0.798202** (0.0320498)	0.091772** (0.0385751)	0.0904242** (0.038964)	0.1219936 (0.1523591)	0.2588175 (0.2465345)
Licensor age	-0.0129933 (0.0091222)	-0.0119509 (0.0111909)	-0.016474 (0.0114244)	0.0181415 (0.013336)	0.0136889 (0.043757)
Technology market similarity	-0.1576593* (0.1294262)	-0.1593798* (0.1479582)	-0.1701754 (0.1548115)	-0.844987 (0.6821232)	-0.6682022 (0.339567)
USA	-0.6894751** (0.2976353)	-0.5858017* (0.334446)	-0.5256211* (0.3344690	-0.2239495 (0.215734)	0.416678 (0.362189)
EUROPE	-0.622800 (0.115786)	-0.336345 (0.118346)	-0.338645 (0.190954)	0.344291 (0.221225)	0.3536233 (0.218659)
Exclusive licensing	Included	Included	Included	Included	Included
Jap & S. Korea	Included	Included	Included	Included	Included
Other Dev. Nation	Included	Included	Included	Included	Included
Far East Asia	Included	Included	Included	Included	Included
Rest of World	Included	Included	Included	Included	Included
Number of obs	410	410	410	410	410
Log likelihood	-165.608	-131.134	-127.781	-111.763	110.567
Pseudo R2	0.046	0.0513	0.0532	0.0928	0.0938

Standard errors are in parentheses $*p < 0.10$; $**p < 0.05$;

Table 5-5: Predicted Probability for the Licensor Prefer a Unilateral or Cross Licensing - Market Diversification

Variables	Model1	Model 2	Model 3	Model 4	Model 5
Constant	9.667766*** (6.236621)	13.45454*** (9.087819)	26.01541*** (21.565)	26.98816*** (22.9059)	11.90923*** (11.36224)
Licensor abs market diversification		1.2800943** (0.0476475)	1.209037* (0.0518972)	1.297071* (0.051917)	1.3187315*** (0.057944)
Licensor abs size			0.8783552 (0.0751624)	0.8698282 (.0734408)	0.9792442 (0.0981547)
Licensor abs unilateral licensing				0.88749*** (.0665567)	0.81843*** (.036281)
Licensor abs cross licensing				1.253546*** (0.069648)	1.315673*** (0.634562)
Licensor rel market diversification					1.314942** (0.1.291196)
Licensor rel size					0.4258617** (0.1908294)
Licensor rel unilateral licensing					1.004905 (0.0054211)
Licensor rel cross licensing					0.2969408*** (0.0781233)
Time	1.083092** (0.0347129)	1.087806** (0.0353882)	1.082314** (0.0354528)	1.045825 (0.0343076)	1.050447 (0.0391027)
Licensor age	0.9870908 (0.0090045)	0.9940985 (0.096184)	0.9966771 (0.0103598)	-0.9970469 (0.0103841)	0.7563552 (0.0133758)
Technology market similarity	0.8541407* (0.1105481)	0.8244823* (0.1086385)	0.8284057* (0.111227)	0.7889626* (0.1081419)	0.7563552* (0.1145744)
USA	0.5018394** (0.1493651)	0.5087539** 0.1521005	0.5379961** 0.1631366	0.5751749* (0.1777163)	0.6866732 (0.2370508)
EUROPE	0.5319382 (0.5935293)	0.5351688 (0.5966003)	0.5451917 (0.61796)	0.8035332 (0.9214142)	0.306747 (0.258564)
Exclusive licensing	Included	Included	Included	Included	Included
Jap & S. Korea	Included	Included	Included	Included	Included
Other Dev. Nation	Included	Included	Included	Included	Included
Far East Asia	Included	Included	Included	Included	Included
Rest of World	Included	Included	Included	Included	Included
Number of obs	410	410	410	410	410
Log likelihood	-165.60786	-163.008	-157.61322	-157.61322	-125.77245
Pseudo R2	0.0463	0.0613	0.0662	0.1027	0.1427

Standard errors are in parentheses *p < 0.10; **p <0.05; ***p < 0.01

Table 5-6: Predicted Probability that the Licensor Prefer a Unilateral or Cross Licensing - Technology Diversification

Variables	Model1	Model 2	Model 3	Model 4	Model 5
Constant	9.667766*** (6.236621)	9.782029*** (7.203204)	10.9359*** (8.24944)	13.0609* (8.3.933)	19.12547** (13.69232)
Licensor abs technology diversification		1.1459627** (0.069986)	1.14362** (0.07202)	1.124706* (0.4414448)	1.1745426** (0.5958915)
Licensor abs size			0.9900006 (0.000019)	0.9999557 (0.0000528)	0.99993 (0.0000964)
Licensor abs unilateral licensing				.839546** (0.4758992)	0.881682** (0.58489)
Licensor abs cross licensing				1.231095*** (0.002315)	1.240611*** (0.00186)
Licensor rel technology diversification					1.366528* (0.010781)
Licensor rel size					0.627289* (0.0765692)
Licensor rel unilateral licensing					0.829525 (0.0602041)
Licensor rel cross licensing					1.36061*** (0.018622)
Time	1.083092** (0.0347129)	1.096115** (0.042827)	1.094638** (0.0426524)	1.129747 (0.1721272)	1.294943 (0.3181546)
Licensor age	0.9870908 (0.0090045)	0.998051 (0.042827)	0.9935464 (0.011350)	1.008175 (0.538039)	1.002857 (0.0439155)
Technology market similarity	0.8541407 (0.1105481)	0.8526724 (0.1261599)	0.8435269 (0.1305861)	0.4295629 (0.2930148)	0.1885601 (0.1959983)
USA	0.501839** (0.1493651)	0.5566594* 0.186173	0.5906562 0.199724	1.251008 (0.771094)	1.32121 (0.976446)
EUROPE	0.5319382 (0.5935293)	0.1675504 (0.2007711)	0.1313753 (0.162845)	0.412706 (0.03828)	0.45105 (0.0449)
Exclusive licensing	Included	Included	Included	Included	Included
Jap & S. Korea	Included	Included	Included	Included	Included
Other Dev. Nation	Included	Included	Included	Included	Included
Far East Asia	Included	Included	Included	Included	Included
Rest of World	Included	Included	Included	Included	Included
Number of obs	410	410	410	410	410
Log likelihood	-165.60786	-131.134	-127.7810	-111.7634	-110.567
Pseudo R2	0.0463	0.0513	0.0532	0.0928	0.0938

Standard errors are in parentheses *p < 0.10; **p <0.05; ***p < 0.01

Table 5-7: Summary of Hypotheses and Findings

Hypotheses	Outcome	Key Implications
Diversification absolute effects - 1a	P < 0.05	-Learning with and from partners (Soet, 1997) -Cross licensing enables access to advanced knowledge (Hagedoorn et al., 2008)
relative effect - 1b	P < 0.05	-Springboard to generate new products (Teece, 1986, Cohen & Levinthal, 1990) -Cross licensing serves as a shield to competition (Arora & Fosturi, 2006; Siebert & Von Graevenitz, 2012)
Experience absolute cross and unilateral effect; 2a & 2b	P < 0.01	-Development of reliable routines and processes (Cohen & Levinthal, 1987) -Facilitates the implementation of licensing in the future (Pisano, 1996
relative unilateral effect; 2c	P > 0.05	-Licensor unilateral experience relative to partners have no impact on the licensor licensing preference
relative cross licensing effect; 2d	P < 0.05	-More specialised knowledge gained from cross licensing and has a profound impact on the licensor preference
Firm size absolute size: 3a	P > 0.05	-Has no significant effect alone (Kim & Vonortas, 2006; Nagoaka & Kwon, 2006; Kim & Motohashi, 2012; Gambardella et al., 2010)
relative size: 3b	P < 0.05	-Indicates that the degree of competition rather than the size per se determines the licensor licensing preference

6. HOW DO FOCAL FIRMS' TECHNOLOGY AND ACTOR ECOSYSTEM COMPLEXITY AFFECT VALUE CREATION? EVIDENCE FROM THE SEMICONDUCTOR INDUSTRY

6.1. Abstract

In this paper, we investigate the heterogeneity in the performance of licensors in the context of contingencies that influence focal licensors' ecosystem complexity. We differentiate licensors' ecosystem complexity into technology and actor complexity, which are the key architectural components that determine the functionality of the ecosystem. We develop a set of measures for quantifying technology and actor complexity and develop a framework relating technology and actor ecosystem complexity to focal licensors performance. Using data of licensing and ecosystem activities of 115 Chipless firms from 1985 to 2005, we find that increased levels of technology and actor ecosystem complexity enable focal licensors to generate superior value from their ecosystems. In addition, we find that the joint effects of technology and actor complexity augment the amount of value that focal licensors generate from licensing within ecosystems. These findings contribute to the emerging ecosystem literature and have significant managerial implications.

Keyword: Ecosystem, Ecosystem architecture, technological and actors' ecosystem complexity, value creation, licensing performance

6.2. Introduction

Increased competition and the rapid pace of technological development, however, have dramatically changed the way firms organised their R&D lately (Giachetti & Dagnino, 2014). Firms have engaged in the formation of ecosystem (Adner, 2017), as a strategy to create and appropriate value from technology (Gawer & Henderson, 2007). Ecosystem enables the focal firm to share the risk and cost of developing new technology with partners(Jacobides et al., 2015), or for its technology to interact with partners' technologies (components and complementors), increasing the overall value that is generated from focal firms technology (Adner, 2017, Jacobides et al., 2015; Kapoor & Agarwal, 2016).

Prior literature has acknowledged that focal firms or ecosystem orchestrators often experience considerable differences in their performance outcomes (Gawer & Henderson, 2006; Jacobides et al., 2015). Such heterogeneity in the performance of focal firms has been explained in terms of either the nature of relationships among actors within ecosystems (Autio & Thomas, 2014; Rong & Shi, 2014; Jacobides et al., 2015), or the structural aspects of ecosystems (Adner & Kapoor, 2010; Kapoor & Lee, 2013). Despite the rich insights gained from these studies, our understanding of why some focal firms outperform others remains incomplete (Adner, 2017).

In this study, we offer a slightly different explanation for heterogeneity in the performance of focal firms, which hinges on the architectural components of their ecosystems. We base our explanation specifically, on the degree of interactions in key architectural components (technology and actor) that shape the functionality of the ecosystem. We argue that the number and magnitude of interactions among technologies and actors within focal firm ecosystems which we characterise as focal firms' technology and actor complexity determine the amount of value they generate from their ecosystems. To theorise how the focal firm technology and actor ecosystem complexity influences its performance, we draw knowledge from complexity theory, especially from Kauffman's NK model (1993). Complexity of a system increases with the number of unique subcomponents within the system, which creates a rich interconnectivity among them that together produces a higher outcome than would be achieved from a slightly lower variation in the activity sets (Cockburn & Henderson, 1996). Based on the number of unique actors and technologies within focal firm ecosystems, we contend that, at the technology level, as the number of technologies and interdependency among them grow, the bond between the partners' technologies becomes more solid (Rivkin, 2000). This makes it more difficult for rival firms to access the focal firm partners and imitate its technology Kapoor & Agarwal, 2016), enhancing for the focal firm's ability to gain from synergetic advantages (Davis & Thomas, 1993). Hence, focal firms that operate within the ecosystem with higher levels of technology complexity are more likely to generate superior value from their ecosystems than those with low levels of technology ecosystem complexity.

Likewise, because of knowledge sharing and learning resulting from increased actor complexity, focal firms that operate within ecosystems with higher levels of actor complexity are more capable of coordinating the ecosystem/licensed technology, which in turn, enhances their chances of creating superior value from their ecosystems (Autio & Thomas, 2014; Rong & Shi, 2014; Jacobides et al., 2015).

In addition, we also argue that technology and actor ecosystem complexity jointly augment the performance effect of the focal firm. While the focal firm's technology ecosystem complexity enhances its performance due to the richness of the technological interconnectivity ((interdependent among partner technologies) (Rivkin, 2000)), actor complexity serves as the channel through which these advantages are realised. A focal firm that operates within an ecosystem with high levels of technology complexity would generally require a higher level of actor complexity to coordinate the ecosystem technology. Hence, the focal firm's technology and actor complexity jointly improve its performance significantly.

We test our arguments using the licensing and ecosystem activities of chipless firms operating within the semiconductor industry from 1985 to 2005. Chipless firms are highly specialized firms and do not engage in any manufacturing but mainly create value from their technology through licensing and ecosystem formation (Linden & Somaya, 2003, Moore, 1993). The degree of technology complexity and actor complexity within chipless firm ecosystems varies from one chipless firm ecosystem to another. Hence, chipless firms provide us with a valuable setting to examine the effect that the focal firm's technology and actor ecosystem complexity have on its value creation.

Our study makes a number of contributions. First, it examines a particular type of ecosystem resulting from the licensing of technology. By so doing, it contributes to the empirical literature on the interplay between licensing, ecosystem formation and firms' performance (Davis, 2001; Kollmer & Dowling, 2004). Second, it contributes to the ecosystem literature by introducing the notion of complexity in the analyses of interdependences among partners. It conceptualises the architecture of focal firm ecosystems into technology and actor and highlights how interactions among the different architectural components can help us better explain who benefits more from their ecosystem. Finally, our study complements the actor-centric approach (e.g. Autio & Thomas, 2014; Jacobides et al., 2015; Iansiti & Levien, 2004;; Rong & Shi, 2014) and activity or technology-centric view (e.g., Adner, 2006, 2013; Adner & Kapoor 2010; Kapoor & Agarwal, 2016), which so far have been studied separately, by examining focal licensors' performance from both the technological and the actor perspective.

6.3. Theoretical Background and Hypotheses Development

6.3.1. Components of Ecosystems

In technology management literature, an ecosystem is referred to as a network of interconnected firms that interact to take the focal technology to end users (Moore, 1993;

Adner, 2017). Ecosystems generally vary in terms of their scope, size, shape, structure, the number of partners and the nature of the relationships between them (Williamson & De Meyer, 2012). Some ecosystems evolve through serendipity (Santos & Eisenhardt, 2009), while others emerge from self-organisation (Hannah & Eisenhardt, 2016). However, most ecosystems are created by a "focal or lead firm'' (Jacobides et al., 2015; Iansiti & Levien, 2004). As the orchestrator of the ecosystem, the focal firm generally sets the rules and provides the platform or architecture under which the ecosystem operates (Gawer & Cusumano, 2002)

In the licensing context, a licensor can catalyse the development of an ecosystem by licensing its technology to partners, who may operate in the same industry or different industry settings. Although the licensor's partners may have different business models and technologies (Casadesus-Masanell & Yoffie, 2007), they are linked together by the licensor's architecture. Because of the commonality in their architectural base and the interdependence between the licensor and licensees, they are embedded in a network of interconnected and interdependent firms (Adner & Kapoor 2010; Kapoor & Agarwal, 2016).

According to Baldwin and Clark (2000) and Baldwin (2014), the architecture of an ecosystem constitutes a technological structure and an actor/social structure. The technological structure describes the design elements of the licensor technology and specifies how the focal technology could be linked to other firm technologies (Baldwin & Clark, 2000). It defines the interface between the licensor's and licensee (s)' technologies and the procedures or technical tasks required licensees to incorporate the licensed technology into their production structure. The design elements typically constitute blueprints of the technology and are generally conveyed through pictures, diagrams, and words. Thus, to bring the design elements together and to carry out the task specified in the technological structure, social interactions must occur between the licensing partners. These social interactions create what is called the social/actor structure of the ecosystem architecture (Baldwin, 2014), which enables knowledge and resources to flow between actors (Baldwin & Clark, 2000). Knowledge sharing among actors' harnesses learning through knowledge recombination (Cohen & Levinthal, 1990) and assists the assimilation of the licensed technology. Hence, the actor structure facilitates the building and coordination of the technological structure of the ecosystem. Although the actor structure is sometimes considered as an integral part of the technological architecture, the technological and actor structures are conceptually different, and each plays a distinctive role in the functionality of the ecosystem (Baldwin, 2014). The two structures complement each other and together contribute to the overall performance of the ecosystem (Arthur, 2009).

6.3.2. Architectural Approach to Value Logic

The theoretical ecosystem literature has evolved in four main streams: (1) value creation, (2) value capturing, (3) actor-centric – the network theory application approach and (4) technology/activities centric – the structuralist approach (Autio & Thomas, 2014; Adner, 2017). Although these streams of literature have significantly enhanced our understanding of the ecosystem, they fall short of fully accounting for the contributions that the key architectural components that constitute the ecosystem make to the focal firm's performance.

When considering prior works on the focal firm's performance, the value creation and value-capturing stream offer complementary insights into the rationale for differentials in the performance of focal firms. The value creation stream has focused on understanding the strategies that focal firms institute to encourage partners to join their ecosystems and the cooperative dynamics within ecosystems (Gawer & Henderson, 2007; Hannah & Eisenhardt, 2016). This stream has explained the rationale for heterogeneity in focal firms' performance based on the incentives that focal firms offer partners to participate in their ecosystems (Jacobides, Cennamo & Gawer, 2015), the timing of entry (Adner & Kapoor, 2010), knowledge and capabilities sharing (Jacobides et al., 2016) and strategic and organisational alignments between partners (Hannah et al., 2016). The key insight from this stream is that an increase in the number of partners that the focal firm interacts with significantly contributes to its performance.

On the other hand, the value capturing stream has sought to understand how ecosystem orchestrators, also known as ‘keystones’ (Iansiti & Levin, 2004) or ‘kingpins’ (Jacobides et al., 2015), emerge and how they capture a disproportionate amount of value from their ecosystem through exploiting their dominant position. The stream highlights that heterogeneity in focal firms’ performance is shaped by the levels of control (bargaining position vis-à-vis their partners) that have over their partner (Jacobides et al., 2015; Jacobides & MacDuffie, 2013). Although these streams have offered rich insights into how and why some focal firms are more successful than others are, they do not incorporate in their analysis degree of interactions of architectural components in focal firms’ ecosystems and the implications that this may have on their value creation and value appropriation. Heterogeneity in the amount of value that focal firms generate from their ecosystems may influenced by not just how they motivate partners to join their ecosystem (alignment of incentives), but also the ease with which the partners technologies interconnects and the flow of activities within their ecosystem (Adner, 2017). Interactions among actors (actor complexity) facilitate the coordination of partners’ technologies and enable the focal technology to reach a large number of customers quickly. Further, the ease with which the licensed technology interconnects with those of partner technologies provides reassurance to partners that they will extract value from the licensed technology, which can play an important role in attracting other firms to join the ecosystem. Thus, the level of focal firms’ technology and actor complexity can affect their bargaining power and position within their ecosystems (Brandenburger & Nalebuff, 1996).

Originating from the networking discipline, the actor-centric approach regards firms as independent social actors and focuses on the nature of the relationships among them (Autio &

Thomas, 2014; Jacobides et al., 2015; Jacobides et al., 2016). This stream emphasises access and openness between actors and how social relationships among actors create opportunities and constraints. Social interactions facilitate strategic alignments and enable partners to deal with coordination challenges that arise when partners' strategic incentives are not aligned (Adner 2017; Autio & Thomas, 2014). They may also encourage partners to act favourably vis-à-vis the focal firm and contribute positively to its value creation (Jacobides et al., 2016). The last perspective, the ecosystem as a structure, explores the set of activities that need to occur for the focal value proposition to reach the end user (Adner & Kapoor, 2010). This activity-focused stream places more emphasis on the flow of activities among partners and on the position of the focal firm vis-à-vis to partners where coordination challenges occur within the ecosystem. The alignment of activities and the coordination of partners' technologies is seen as a key to unlocking value creation (Adner, 2017; Adner & Kapoor, 2010).

However, as we can see, the last two streams focus on the role of relationship building, co-specialisation and coordination among partners' activities but do not consider the role that the architecture of the ecosystem plays in shaping focal firms' performance. These streams tend to assume that the amount of value that focal licensors generate from cooperating with partners is the same regardless of the number and magnitude of technological and actor interactions within their ecosystems. Within an ecosystem, the focal firm's technology only creates value when it interconnects seamlessly with those of partners. Interactions among a large and diverse set of actors' harness learning and facilitate coordination of partner technologies. In this sense, the amount of value that focal licensors generate from their ecosystem is contingent on the level of technology complexity and actor complexity within their ecosystems. In this study, we focus on these key contingencies, which we consider as important sources of heterogeneity in focal firms' performance.

6.3.3. Technology Ecosystem Complexity

Our theoretical predictions are based on the aggregate complexity (Kauffman, 1993; Simon, 1963), which is concern with how individual elements of a system work in concert to create a system with complex behaviour. The benefits of a complex system results from the fact that interactions between components within the system leads to improvement that enables the system to mitigate constraints imposed by any of the components. Here we consider the ecosystem as a complex system, in which the focal firm and partners are components of the system. Focal firm ecosystems may be subject to varying degrees of complexity dependent on the number of unique components interacting within the ecosystem (Kauffman, 1993). The greater the number of unique components interacting within the focal firm ecosystem, the greater the complexity of its ecosystem. From an architectural perspective, whereby the ecosystem is partitioned into technology and actor, licensing within an ecosystem setting constitutes the focal licensor technology interacting with those of partners (Adner & Kapoor, 2010; Movery et al., 1985). The focal firm technology ecosystem complexity increases when its technology interacts with a large and diverse number of partner technologies, which creates a rich technological interconnectivity (Kauffman, 1993). Greater levels of technological complexity solidify the link between the partner technologies and reinforces the focal licensor's architectural structure. This offers the licensor greater control over its technology and drives the emergence of what Ethiraj (2007) describes as strategic bottlenecks. Strategic bottlenecks occur when barriers are erected around critical components or when a firm controls the critical components (licensing partners) where the value is accrued (Jacobides et al., 2006). The formation of strategic bottlenecks makes it more difficult for rival firms to access the focal licensor’s partners, thus enables the focal firm to continue to interact with a large pool of partners. This increases the likelihood of the focal firm or its technology to reach a large number of customers and also enhances the potential to gain valuable information for new product development (Ethiraj, 2007; Baldwin, 2014).

Research and empirical evidence from different industry contexts seem to provide some support for these arguments. For example, Ethiraj and Posen (2013), in their study of the PC ecosystem, reveal that firms that control complex architectural ecosystem create more patents and generate a higher amount of value from their ecosystem. In line with Ethiraj and Posen's (2013) study, Jacobides et al., (2015) also find that in the automotive industry, original equipment manufacturer (OEM) automaker firms, which control complex R&D architecture, generate more amount of value from their ecosystem compared to those with less complex architectural structure. Similarly, Lavie (2007) in his study of networks in the US software industry also shows that focal firms whose partner technologies are strongly linked to the focal technology generate a superior value from their network than those with less integrated partners.

In addition to the advantages of strategic bottlenecks, evolutionary economists have also shown that technological complexity can serve as a barrier to imitation (Bresnahan et al., 2002; Rivkin, 2000). Imitation is considered one of the primary factors that prevent licensors from creating value from licensing (Cava et al., 1983; Teece, 1989). Rich technological interconnectivity makes it much more difficult for would-be copycats to decipher the exact configuration of the licensor's technology (Kapoor & Agarwal, 2016). Rivkin (2000) illustrates that while it may be easy to imitate isolated activities, competitors will find it much more difficult to understand and imitate an entire system of mutually enhancing components without some errors. In a similar vein, Milgrom and Roberts (1995), in their empirical study of fit and complementarity demonstrate that rich interactions among a firm's activities and resources curb would be imitators' ability to copy the firm's practices effectively. The authors attribute the inability of rivals to copy the firm's activities in part to complex complementarities among its practices.

Although these studies are based on the firm's internal activities, the findings also apply to loosely and tightly coupled systems such as the ecosystem (Glassman, 1973; Weick, 1976), since the barriers to imitation are based on the underlying logic of complexity resulting from rich interconnectivity between subcomponents.

Furthermore, increased technological complexity may also enhance the licensor's ability to derive more value from its technology because of switching costs. Switching costs occur when licensees whose technologies are highly interwoven within a focal licensor's technology want to switch to another licensor; they must de-integrate their technologies from that of the focal licensor's system and integrate them into a rival system. Unlearning an old system and learning a new system is an expensive and time-consuming process. The network externalities created by the focal licensor's technology ecosystem complexity increases switching costs (Farrell & Saloner, 1986), rendering substitution an expensive proposition (Williamson & De Meyer, 2012). The difficulties for partners to switch quickly to complementary systems when their technologies are interwoven within a complex system of technologies enables the focal licensor to continue to interact with a large number of partners (Williamson & De Meyer, 2012), which in turn enhances its exploitative and explorative potential.

In contrast, when the licensor's technology interacts with a limited number and less diverse set of partner technologies or operates in a less technologically complex ecosystem setting, the linkages among partner technologies are relatively weak. As a result of weak bonds between partner technologies, rival firms can easily access the licensor partners, and licensees can quickly switch to other complementary systems, which reduces the capacity for the focal licensor to generate superior value from its technology.

In summary, higher levels of the focal firm technological complexity make it more difficult for rivals access to the licensor's partners and to imitate its technology. Increased technological complexity also increases the cost for licensees to switch to complementary systems, thus enhancing the licensor's ability to generate superior value from licensing. Based on the above arguments, we propose the following hypothesis:

Hypothesis 1: The higher the focal licensor's technology ecosystem complexity, the higher the likelihood it will create more value from its ecosystem.

6.3.4. Actor Ecosystem Complexity

In technological licensing, the potential outcome of a licensing deal is contingent on the ease with which the licensee (s) can incorporate the licensed technology into its production structure (Motohashi, 2008). When a licensor licenses its technology to partners, for the licensor technology to create value, it must work seamlessly with those of partners (Iyer et al., 2006; Walter, 2012). There must be some degree of interactions between the licensor and licensees to facilitate the flow of information and knowledge sharing between them, which helps the coordination of the licensed technology (Cohen & Levinhal, 1990; Coleman, 1990).

Generally, when licensors license technology to licensees, they do not just supply tools, software and maintenance systems to licensees but also provide technical support in the form of making their technical team available to licensing partners (Macho-Stadler et al., 1996). Interactions between licensing partners allow knowledge to flow backwards and forwards between them (Grant, 1996). Knowledge sharing between licensing partners opens up new potential for learning and enables the licensor to gain vital knowledge and develop new ways on how to reconfigure the licensed technology (Zahra & George, 2002). However, the quality knowledge gained varies depending on the number and diversity of licensors partners (Sampson, 2007).

When an actor interacts with a large and diverse set of actors or operates in a more complex ecosystem setting, it gains new knowledge and perspectives from multiple sources. Exposure to a diverse pool of knowledge broadens the range of ideas from which the licensor can tap new insight from, enhancing its ability to develop more reliable processes and routines (Cohen & Levinthal, 1987). The development of more innovative routines makes the focal licensor more efficient in coordinating the licensed technology (Rothaemel & Thursby, 2005), which in turn reduces the time needed for its partners to internalise its technology (Pisano et al., 1988) and enables the focal technology to reach a large number of customers quickly.

In addition to the advantages of developing more reliable internal routines, when a licensor operates in a more complex actor ecosystem setting (interacts with a wide range of different actors), it is exposed to new ways of reasoning and develops unique communication skills, which makes the licensor more competent in dealing with a broad range of licensees (Sampson, 2007). In technology licensing ‘‘the not invented here'' syndrome, which refers to the internal barriers that firms face when they attempt to incorporate a licensed technology into their manufacturing structure is considered one of the factors that prevent licensors from generating a large share of value from licensing (Caves et al., 1983). The ability of the focal licensor to communicate effectively with a large set of partners can enable to deal not just with the ‘not invented here syndrome' issues but also to overcome adoption issues prevalent in technology licensing (Ahuja & Katila, 2003). In ecosystem settings, adoption is of particularly importance as firms’ benefit more when a critical mass of other firms adopts their technology. The licensor’s ability to communicate effectively with partners can stimulate co-investment and encourage partners to act cooperatively, enhancing potential for the focal licensor to create more value from its ecosystem.

In contrast, when a licensor operates in a less complex actor ecosystem setting, critical information about the licensed technology is shared only with a few and a similar set of actors. Some scholars have argued that under such circumstances, licensees may easily assimilate the licensor’s knowledge because of the similarity in their knowledge base (Cohen & Levinthal, 1989). However, in the licensing context, where the principal goal for the focal licensor to interact with other actors to gain valuable knowledge, interacting with a limited and less diverse set of partners may contribute very little in terms of new knowledge as a significant amount of partners' knowledge may already be known by the licensor ((Ahuja & Katila, 2003). In contrast, when a licensor operates in a more complex actor setting, it is more likely to access a broad pool of knowledge, which facilitates the development of reliable routines and processes, which in turn enhances its ability to create superior value from its ecosystem.

Hypothesis 2: The higher the focal licensor's actor ecosystem complexity, the higher the likelihood it will create more value from its ecosystem.

6.3.5. The Joint Effect of Technology and Actor Complexity

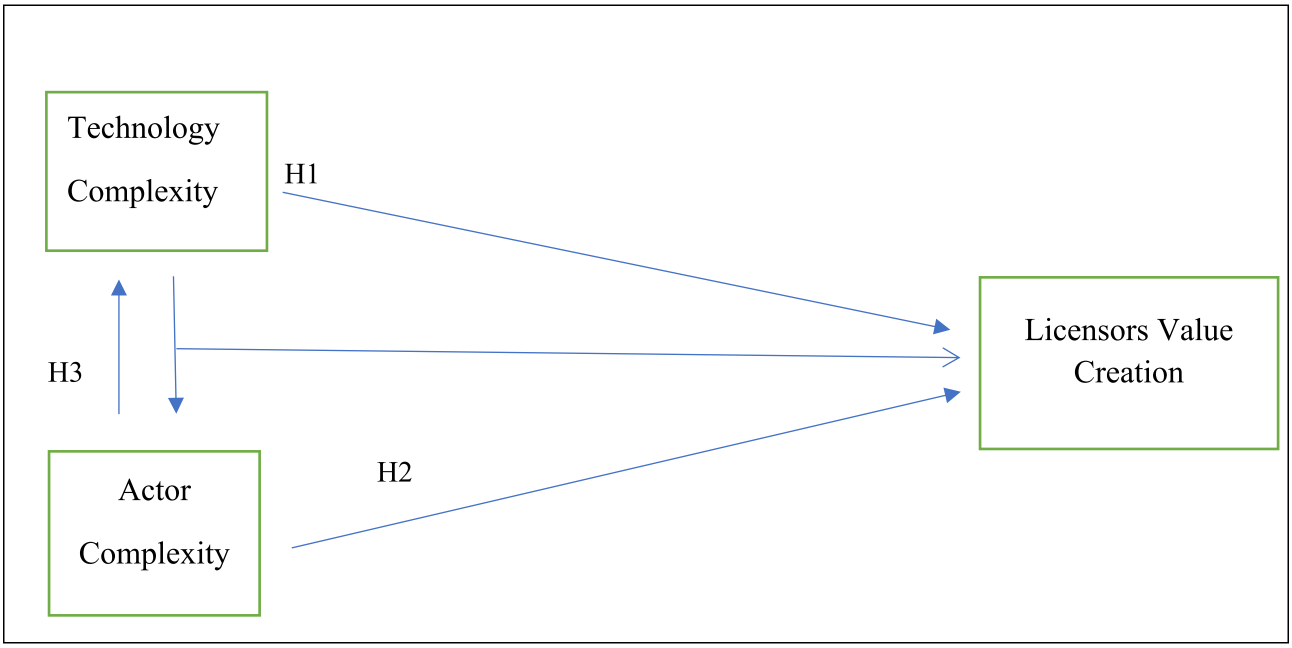
While focal firms' technology ecosystem complexity, specifically the number and diversity of technologies within their ecosystems, enhance their performance due to the richness of the technological interconnectivity (Rivkin, 2000), actor ecosystem complexity could serve as a mean through which these advantages are realised. Higherr levels of the focal technology ecosystem complexity reinforce its technological architecture and drive the emergence of strategic bottlenecks. The formation of strategic bottlenecks makes it more difficult for rival licensors to access the focal licensor’s partners ((Ethiraj, 2007; Jacobides et al., 2006; Hannah & Eisenhardt, 2015). Higher levels of technology complexity may also serve as a barrier to entry by raising the cost of imitating the focal firm’s technology and the cost that partners incur for switching to complementary systems (Willamson & De Meyer, 2012), thus enhancing the focal licensor’s ability to create superior value from its ecosystem.

However, the ease with which partner technologies link together within an ecosystem may be assisted by the ecosystem actor’s complexity. A licensor that operates in an ecosystem with high levels of technology complexity would require more efficient routines and skills to facilitate the interoperability of the ecosystem technology. Increased levels of the focal firm's actor complexity allow access unique knowledge and information from multiple sources. Access to novel information broadens the licensor's problem-solving arenas and enables the formation of more reliable innovative routines (Ahuja & Katila, 2003). The development of more efficient routines facilitates the interoperability and coordination of the licensor and licensees' technology. Thus, higher level of the focal firm's actor ecosystem complexity enhances the chances of a focal technology that integrated within a complex technological to reach a large number of customers quickly, increasing the potential for the focal licensor to create superior value from its technology.

A good illustration of how higher levels of the focal firm's technology and actor ecosystem complexity lead to greater value creation can be seen with Arm Limited, a leading intellectual supplier in the semiconductor industry. Arm's ecosystem constitutes more than 1100 partners originating from a broad range of industry and market settings (https://www.arm.com/company). Because of the number and diversity of technologies and actors within Arm's ecosystem, the firm has been able to benefit from stickiness resulting from rich technological interconnectivity and gained access to a vast pool of resources and knowledge, which has enabled the firm to develop more cutting-edge technology quickly and cheaply. Arm's high level of technology and actor ecosystem complexity is considered as one of the main reasons why the firm has been hugely successful in the competitive semiconductor industry (Willamson & De Meyer, 2012).

Hypothesis 3: The higher the levels the focal firm actor ecosystem complexity, the higher the positive impact of its technology ecosystem complexity on its value creation.

Figure 6-1: Conceptual Framework



6.4. Methodology

6.4.1. Research Setting

The empirical setting for this research is Chipless firms operating within the semiconductor industry. We selected this setting for the following reasons. First, the semiconductor industry is considered the epitome of a complex industry in which ecosystems are pronounced (Eisenhardt & Schoonhoven, 1996). It is characterised by short product lifecycles with high levels of research and development (West, 2002) and patenting and innovation activities (Hall & Ziedonis, 2001), which require firms to cooperate and compete in order to create and capture value from their technology (Adner & Kapour, 2010). The formation of ecosystems enables the focal technology to interact with those of partner, enhancing the overall value generated from the focal technology (Adner, 2017; Kapoor & Agarwal, 2016).

In addition to this competitive dynamic, in the last three decades, the semiconductor industry has also witnessed a significant shift from vertical integration to vertical disintegration (Macher et al., 2007), leading to an increased level of specialisation. Chipless firms are specialised firms at the forefront of the development of highly efficient microchips based on low power and high performance technology. Their technologies are essential core elements of connected devices such as mobile phones, tablet computers, flat screen monitors and smart television sets and play a significant role in the sophisticated car and aircraft industry and the internet of things.

Furthermore, chipless firms are principal licensors in the semiconductor industry that do not engage in any manufacturing but mainly create value from their technology through licensing and ecosystem formation (Moore, 1996; Davie, 2010). Ecosystem formation enables their technologies to interact with those of partners technologies, and within each focal firm, ecosystem actors interact to facilitate the coordination of the licensed technology. The degree of actors and technological complexity within chipless firm ecosystems varies considerably from one focal firm ecosystem to another. Hence, chipless firms provide us with a valuable setting in which to examine the impact that the focal firm's technology and actor ecosystem complexity have on value creation.

6.4.2. Data and Sample

To test our hypotheses, we assembled licensing and patenting data of chipless firms operating in the semiconductor industry from 1985 to 2005. We used patenting data to measure licensors' or focal firms' value creation, their technology ecosystem complexity and partners' pre-ecosystem innovativeness, whereas licensing information was mainly used to capture focal licensor's actor ecosystem complexity and to measure some control variables of the research (more details on the rationales for using patent and licensing data are discussed later in the operationalisation of variables). We collected chipless firms' data over a 21-year period, from 1985 to 2005. We started our data collection from 1985 because a large number of chipless firms entered the semiconductor industry in the late 1980s. This was facilitated by the introduction of Complementary Metal Oxide Semiconductor (CMOS) technology, which made it easier for a large number of chips to be inexpensively placed on a single chip (Garnsey et al., 2008). The miniaturisation of chips enabled the creation of what is called in the industry a system on chip - SOC (Linden & Somaya, 2000). The SOC movement led to a significant shift in the industry from vertical integration to vertical specialisation (Macher et al., 2007) and facilitated the entry of Chipless firms. We ended our data collection in 2005 because the licensing and alliances' coverage in our primary data source – the SDC Thompson Reuter database is less comprehensive after this date (Lahiri, & Narayanan, 2013). Constraining our study period to these dates enabled us to collect appropriate and reliable data to test our hypotheses.

To generate our sample firms, we adopt the following procedure. First, we retrieved licensing deals of firms operating within the broader electronic industry (SIC 36) from the Thompson Reuter Platinum - SDC Strategic Alliance and Licensing database. This database is considered as one of the most comprehensive data sources for large-scale empirical studies and has been widely used in the alliance; ecosystem and licensing literature with reliable results (see Anand & Khanna, 2000; Kim & Vonortas, 2006; Sampson, 2007 and Siebert & Von Graevenitz, 2010 for most recent commentaries).

From this data extraction, we selected licensor firms, whose main line of business was described in the licensing agreement as semiconductors and related devices (SIC 3674). From the list of semiconductor firms, we focused on the licensing agreements signed by Chipless firms. According Linden and Somaya (2003) firms in the semiconductor industry use two main organisational governance modes to create and capture value from their innovations: integrated device manufacturers (IDMs) and networked firms (IP suppliers, fabless, foundries, EDA software suppliers). IDMs are firms that engage in the entire value chain designing and manufacturing integrated circuits in house using very limited licensing or external resources.

Although IDMs may engage in some licensing, they mainly bring external technology through mergers and acquisitions (Linden & Somaya, 2003).

Networked firms on the other hand either outsource (fabless model) or license (chipless model) their technologies to third parties. Chipless firms are networked firms that design technology and license the right of their IP blocks to other firms. Their partners use chipless firms' technology alongside their technology to develop advanced consumer electronics products (manufacture the products using their fab (manufacturing facilities) or external manufacturers – foundries). Chipless are considered as principal licensors in the semiconductor industry and license their technology broadly to partners operating within and outside the semiconductor. Through their broad licensing strategy, they form ecosystems, which depending on the number and diversity of technology and actors they create varying levels of value from their ecosystems. We identified a chipless firm by checking on its website if it is exclusively mentioned that the firm is a chipless firm. We also searched news wires and archival sources on the internet for the firm's history, paying specific attention to its business model to confirm its status. Firms whose status could not be determined from both their website and other sources were deleted from the dataset. Our final sample comprised 115 chipless firm ecosystems that engaged in 465 licensing agreements from 1985 to 2005.

Second, we compiled patent information for each chipless firm and its partners in our sample. The patenting data was retrieved from the patent databases compiled by the National Bureau of Economic Research (NBER). NBER databases contain patent information from the US Patent and Trademark Office (USPTO), the European Patent Office (EPO), and other key patent jurisdictions in the world such as Japan, China, South Korea, and Australia. The NBER databases provide information on the total number of patents granted to a firm - ultimate parent including those of all its subsidiaries. They also report the number of citation counts made and received by each patent, its technological class, and subclass, as well as a wealth of other relevant information (For a detailed description of the databases, see http://eml.berkeley.edu//~bhhall/patents.html).

For our study, we mainly used the database containing patents information from the USTPO only, which is consistent with other large-scale studies on licensing and ecosystem formation (e.g., Anand & Khanna, 2000; Siebert & Von Graevenitz, 2006, 2010). Drawing patenting information from only the USPTO is considered appropriate for the following reasons. First, because of the sheer size of the US market and the strength of its patent regime (Almeida, 1996; Lim, 2004), most semiconductor firms are likely to register patent with the regime in order to stay competitive in the marketplace (Hall & Zienonis, 2001). Second, different patent jurisdictions in the world use different standards and methods to assign patents to innovators. Using patents from a single regime reduces the likelihood of biases and inconsistency that could result from using patents from different jurisdictions.

Finally, we collected data for our control variables (the licensor's and licensees' size, age and status) from Compustat, DataStream, NBER, Amadeus, LinkedIn, and Bloomberg. We also consulted the firms' websites, annual accounts and other web and business directories in cases where we could not find reliable data from the above databases.

6.4.3. Operationalisation of Variable

Dependent Variable

Our dependent variable, the licensor’s or focal firm’s value creation is measured using its citations weighted patent counts. Measuring the firm value creation using its patenting activity is considered appropriate for the following reason. First, patents are closely correlated with sales growth (Scherer, 2007), new products development (Comanor & Scherer, 1969), profitability, research and development intensity (Griliches, 1990) and literature based invention counts (Adner & Kapoor, 2010). Second, patents capture better the collaborative aspects of the ecosystem settings (Sampson, 2007). In the ecosystem, the performance of the firm depends not only on its actions but also on those of partners (Adner & Kapoor, 2010). We can easily track and capture the contribution of partners to the focal firm performance from patents than other economic and financial measures such as sales growth, profitability, and new product development (Lahiri & Narayanan, 2013; Griliches, 1990). Thus, in collaborative settings, patents are considered more reliable tools for measuring the focal firm's value creation.

Following prior work by Ahuja and Katila (2000) and Narin et al. (1987), we measure the value that a focal licensor/firm creates from its ecosystem by first counting the number of patents granted to the licensor within five years post the observed licensing deal. Then, for the granted patents, we count the number of forward citations received within the timeframe. We add a weight to each patent as research suggests that firms that create superior values from patents are cited more (Sampson, 2007; Jaffe et al., 1993). In addition, we use a five-year window to operationalise the variable because empirical evidence also suggests that when firms license technology it takes around 3-5years to create value from their technology and that patents that are not cited within the timeframe are less likely to be cited again (Jaffe et al., 1993). Finally, we multiplied the patent count figures by the total number of citations received by the granted patents.

6.4.3.1. Independent Variables

Licensor technology ecosystem complexity

Following studies from the complexity theory tradition (Kauffman, 1993, Rivkin, 2000, Ethiraj & Levinthal, 2004), we capture the focal firm's technology ecosystem complexity from the number and the diversity of technologies within its ecosystem. We measure the focal firm's technology complexity from the number of its patents and similarities/differences in licensing partners' patent classes. On the NBER database, each patent is categorised under a specific technology class. Through the patent technologies classes, we can capture the similarities in partners' technologies within an ecosystem as well as technological differences among them (Jaffe et al., 1993). Licensing partner technologies are considered similar when their patents are allocated to the same patent technological class and vice versa (Jaffe et al., 1993).

To construct the licensor's technology ecosystem complexity, we first generated the licensing pair patent portfolios five years after they engaged in a licensing deal. Then we computed the distribution of the licensing pair patents across different technological classes year by year using the multidimensional vector applied by Sampson, (2007). The multidimensional vector takes the form $(F_i) = (F_i^1 \ldots F_i^s)$, where F_i^s symbolises the number of patents allocated to partner firm i in patent class s (Sampson, 2007). Diversity of partner firm technologies is then:

$$\text{Technological diversity} = (F_i) = 1 - \frac{(F_i F_j^1)}{\sqrt{(F_j F_i^1)(F_j F_j^1)}}$$

Where $i \neq j$. The technological diversity varies on a continuum from 0 to 1 with a value of 1 representing the highest possible level of diversity between partners (for more details on the operationalisation of the vector, see Sampson, (2007)).

Next, we multiply the average value of the multidimensional vector (technological diversity) with the total number of the focal firm patents to get the technological complexity of its ecosystem.

Licensor actor ecosystem complexity

Similar to technology ecosystem complexity, actor ecosystem complexity relates to the number of unique actors in the licensor ecosystem, which affects the richness of partner interactions in its ecosystem (Ethiraj & Levinthal, 2004; Kauffman, 1993). We captured the focal actor ecosystem complexity from the licensor's licensing records and the nature of the relationships among licensing partners in its ecosystem. The number of licensees with that the focal licensor interacts with and the nature of the licensing deals (technological agreement) they engage in (cross or unilateral licensing) can serve as an indicator of the degree of interactions among actors (Gulati, 1995). In high-tech settings such as the semiconductor industry, firms generally use cross-licensing and unilateral licensing to exchange technology and the licensing type they use in exchanging technology can influence the level of interactions between partners. Because of its bilateral or reciprocal nature, cross licensing offers the focal licensor a more significant opportunity to interact with partners than unilateral licensing (Gallasso, 2012). For the above reason, we assigned a higher weighting (4) when licensing partners engaged in cross licensing, and a lower weighting (2) when they use unilateral licensing.

As a multidimensional variable, we computed the focal firm complexity using the following procedures. First, we counted the number of unique partners that the licensor interacts with within five years post the observed licensing deal. Then, we multiplied the number of partners with the sum of the number of the cross and unilateral licensing deal that they engaged within the timeframe. Thus, the licensor actor ecosystem complexity is measured as the sum of the number of different partners and number of cross and unilateral licensing deals among them.

6.4.3.2. Control Variables

Licensor pre – ecosystem patents.

To control for factors that may affect the value that the firm creates from its ecosystem, we include variables that capture the firm and partners' inputs before they engage in the ecosystem. The firm's pre-patenting activities are used to capture its inputs as past research suggests that the firm's prior knowledge has a significant impact on the value it creates in the future (Cohen & Levinthal, 1990). A firm that has superior capabilities is likely to continue to generate more patents or maintain its stock of knowledge over time (Katila & Abuja, (2003). Following studies by Katila & Abuja (2003) and Cloodt et al. (2006), we measured the licensor's pre – patent stocks as the number of patents assigned to the firm within five years before the observed licensing deal

Partner pre – ecosystem patents

Because inputs into the ecosystem include not only the focal firm's inputs but also its partner inputs, we also included partner pre- ecosystem capabilities (Sampson, 2007). Although the licensor may not own its partner resources, it can easily access them through interacting with partners. Similar to the licensor's pre – ecosystem value creation, we measured partner's pre – ecosystem patents as the number of patents obtained by partners five years prior to the observed licensing deal.

Firm and partner size

As a standard indicator in performance studies, we also controlled for the firm size as research indicates that larger firms are more likely to possess greater resources and generate more patents from their ecosystem than smaller firms (Scherer, 1986). We measured the firm size as the total number of employees employed by the firm at the observed time.

Firm and partner age

We also controlled for the firm's age, as prior research shows that older firms generally possess a higher stocks of knowledge/resources (Gittelman & Kogut, 2003), which they can use to generate more patents from their ecosystem. We measured the firm's age as the time that elapsed from the date when the firm was incorporated to the date of the observed licensing deal.

Partners' status

We also controlled for the public/private status of partners within the focal licensor's ecosystem as research highlights that the relational benefits that a focal firm accrue from partners may vary depending on whether its partners are privately or publicly owned firms (Lavie, 2007). Publicly traded firms are often seen as key influencers in the industry, and their association with an ecosystem can encourage other firms to join or adopt the focal technology. We captured this variable using a dummy, which takes a value of 1 when a partner is a publicly traded firm and 0 otherwise

Location variables

In the licensing and ecosystem literature, the inability for the licensor to find suitable partners for its technology may inhibit its ability to create an ecosystem (Caves et al., 1993; Zuniga & Guellec, 2008; Kani & Motohashi, 2012). The licensor can easily license its technology or enters into the ecosystem with partners that are geographically closed to the licensor (Zuniga & Guellec, 2008). To account for cross-country and geographical heterogeneity in focal firm ecosystem activities, we constructed five regional licensing partners' distribution dummies; 'USA', 'Europe', 'Japan and South Korea', 'Other developed nations', and 'Fast East Asia and the rest of the world'. Based on the firm parent headquarters, we classified the licensing partner into one of the five regional dummies.

6.5. Statistical Analysis

The objective of our empirical analysis is to explore how the focal firm technology and actor ecosystem complexity affects the amount of value it generates from its ecosystem. Although the unit of analysis is the ecosystem, our dependent variable is the firm's citation weighted patent counts, comprises of multiple observations for the firm over time. As a result of these structural features in our data and the fact that our independent variable is a count (only non-negative integer) variable, we used the Panel negative binomial model to analyse our data.

Other count specification models such as the Poisson regression model could have been used to analyse the data but were not deemed suitable because of overdispersion resulting from excess zero in the dependent variable.

For our analysis, we used the random effects panel specification rather than the fixed effects panel specification. This is because our interest is in the variation of performance between focal licensors (Baltagi, 2005) and our key independent variables (technology and actor complexity) do not vary within focal firms. Random effects specification accounts for unobserved heterogeneity and firm-specific error terms and is deemed more appropriate than the fixed effects. We carried out our analysis using the random effects panel negative binomial procedure in STATA 15.

--------- Insert Tables 6.1 and 6.2 about here --------

6.6. Findings

Table 6.1 represents the descriptive statistics of all the variables, which includes the means, standard deviations and bivariate correlations between all the explanatory variables. In general, the correlation coefficients among the independent variables are low except for a few variables that deserve our attention. First, the focal firm size is correlated with its pre-ecosystem creation (0.5195) and the partner size variable is correlated with the partner pre-ecosystem creation (0.5168). However, robustness tests indicate that our findings are consistent and unaffected by the moderate correlations among these variables. Furthermore, the mean-variance inflation factor (VIF) score for all of the independent variables is around 3.43, which is far below the threshold value of 10 for multicollinearity to be considered an issue (Cohen et al., 2003).

Table 6.2 reports the random effects panel negative binomial regression results. For the analysis, we followed a hierarchical approach, whereby we introduced the control variables first and then the independent variables in the subsequent models. Model (1), our baseline model, contains only the control variables. In models (2) and (3), we introduced the focal firms' technology and actor ecosystem complexity respectively to assess its effect on the focal firm value creation. In model (4), we incorporated the focal firm's technology, and actor complexity onto control variables, while in model (5), we introduced the interaction term to test the joint effects on the focal firm value creation. We discussed the findings of our hypotheses based on the full model (model 5) as changes in model fit statistics (Δx^2) show that adding our explanatory variables significantly improve the models fit over the baseline model (1). We summarised our findings as follows.

First, in hypothesis 1, we proposed that when a focal licensor operates within an ecosystem with higher levels of technology ecosystem complexity, it is more likely to generate superior value from its ecosystem. This hypothesis is supported in model 2 & 5 with a positive coefficient and statistically significant p-value.

Second, in hypothesis 2, we predicted that focal firms that operate within ecosystems with higher levels of actor complexity ecosystem are more likely to generate superior value from their ecosystem. The positive coefficient and statistically significant p-value in model 3 & 5 supports the hypothesised relationship.

Third, in hypothesis 3, we predicted that the joint effect of the focal firm technology and actor complexity amplify its performance in terms of value creation. The interaction term in model 5 has a positive coefficient ($\beta = 0.00234$) and a highly statistically significant p-value ($p < 0.0001$). The changes in model fit (Δx^2) statistic between model 5 & 4 indicate that adding the interaction term significantly enhanced the fitness of the models (i.e., Δx^2 (5-4) = 12.45, df = 3, p < 0. 01), leading full support to hypothesis 3.

Besides our key explanatory variables, the findings of our control variables are also worth reporting. In line with the underlying theories, our findings highlight that the focal firm and partner pre-ecosystem capabilities have a positive impact on the value the focal firm creates from its ecosystem and this finding is consistent throughout the models. However, although both variables (the focal firm and partner pre-ecosystem capabilities) positively affect the focal licensor performance, the focal firm pre-ecosystem resources seems to have a more significant effect ($\beta = 0.0003$, $p < 0.001$) than licensees'/partners' pre-ecosystem innovativeness ($\beta = 0.0008$) and ($p < 0.01$). A possible interpretation for this result is that rather than just the capabilities that partners bring to the ecosystem, the focal firm's ability to exploit capabilities play a more critical role in the amount of value it creates from its ecosystem.

The focal firm partner size is also seems to have a positive and significant effect on the focal firm's performance. This finding indicates that the focal firm's technology and actor ecosystem complexity is enhanced when their partners are larger firms than when they are smaller firms.

In addition, our findings also show that partners' location matters to the focal firm's value creation. The location variable -USA – where most of the ecosystem partners are located seems to be consistently positive and significant in all the models. It highlights that the closer the geographical proximity among partners the easier it is for them to share resources, which in turn enhances the focal firm's ability to create value from its ecosystem.

6.6.1. Robustness Tests

We carried out a number of sensitivity tests to check the robustness of our findings. First, since we measured our dependent variable (forward citation weighted patent count) using a 5year moving window. We explored alternative specifications using a 4 and 6-years window. In additional, we also explored alternative models using other performance measures - simple patent counts and backward citation counts - that have been used in prior studies to measure the firm's performance or value creation. The overall outcomes from these models are consistent with those reported in our findings, which reinforces our predictions.

Second, to compute the focal firm's actor ecosystem complexity, we assigned different weights to the licensing type that the focal firm uses to exchange technology (unilateral licensing = 2 and cross licensing = 4). We also run robustness checks using different weighted values (1 for unilateral licensing & 3 for cross licensing), and the outcomes from these models indicate that our empirical results are not sensitive to the weighted value used.

Third, given the moderate correlation coefficients between the focal firm's size and its pre-ecosystem resources (0.5195) and the partner's size variable and the partner pre-ecosystem resources (0.5168), our findings may be influenced multicollinearity. To check that multicollinearity has not influenced our results, we, first, mean centred the variables and created a grand variable for both set of variables and run new models. In addition, we checked the mean-variance inflation factor (VIF) score for the variables. The VIF, for all of the independent variables, is around 3.43, which is far below the critical value of 10 for multicollinearity to be considered an issue (Belsley, 1980; Cohen et al., 2003). The results from these robustness tests indicated that our findings were consistent and unaffected by correlations among these variables.

Finally, we also check the amplification effects (interaction between technology complexity and actor complexity) on the focal firms' performance using their marginal effects. The results of the marginal effects indicate the interaction term contributes more to the focal firm's performance than the individual effect of the focal technology and actor ecosystem complexity, which ascertains the hypothesised relationship that the interactions between the focal firm technology and actor complexity augment value firm creation. For brevity, the robustness results are not reported here but are available from the authors upon request.

6.7. Discussion and Conclusions

Despite the recent surge in the number of studies on the ecosystem strategies of firms, our understanding of why some ecosystem orchestrators outperform others remain incomplete (Adner, 2017). Prior studies have traditionally explained the performance of focal firms from the perspective of either the structural aspect (flow of activities) of the ecosystem (structuralist perspective) or the relational embeddedness of partners within the ecosystem (actor-centric perspective). In this study, we provide an alternative explanation for heterogeneity value creation of focal firms by using a simple framework that highlights the roles of architectural components of the ecosystem.

Our key theoretical and empirical contributions lie in conceptualising the ecosystem architectural in terms of the technology and actor ecosystem complexity and how this characterisation explains which focal firms will create superior value from their ecosystems. On the one hand, technological bonds between the focal firm technology and those of partners augment the technology complexity of its ecosystem and offer the focal firms with synergetic advantages in R & D and production. On the other hand, the focal firm actor ecosystem complexity harnesses within its ecosystem and facilitates its ability to coordinate the ecosystem technology. The magnitude of the focal firm actor and technological ecosystem complexity augment the amount of value it creates from its ecosystems significantly.

The architectural approach we put forward in this study complements both the structuralist and actor-centric approaches. It enriches our understanding of the structural aspects of ecosystems and their contribution to superior performance. Traditionally, scholars with a structuralist view of the ecosystem have emphasised the importance of managing interdependency among partner inputs and outputs and how this may affect the focal firm's ability to create value from its ecosystem (Adner & Kapoor, 2010). By distinguishing the components within an ecosystem into technology and actor, this study offers an additional lens for understanding how the coordination of activities within an ecosystem contributes to the focal firm's value creation. In line with our hypotheses, this study reveals that higher levels of the focal firm's technology complexity reinforces the architecture of its ecosystem and drives the emergence of strategic bottlenecks, which in turn enhances its ability to create superior value from its ecosystem. This finding is consistent with prior works such as those of Ethiraj (2007), Adner & Kapoor (2010), and Ethiraj & Posen (2013), who find that controlling bottlenecks – key components where value is accrued can significantly enhance the focal firm performance. Our findings add to these studies by showing that rich technological interconnectivity among partner technologies within ecosystem offers the focal firm greater control over its technology and makes it much more difficult for rival firms to access its partners. This finding also supports Jacobides et al.'s (2014) argument that controlling strategic bottlenecks that resulting from supply limitation, when reinforced with architectural control and legal protection such as patents significantly, enhances the focal licensor ability to create value from its ecosystem.

In addition, this study advances the actor-centric perspective of the ecosystem literature (Rong & Shi, 2014; Jacobides et al., 2015) by considering not just how the attributes of the focal partner but also how the type of licensing deal it uses to exchange technology influences its performance. In particular, the findings suggest when a focal firm interacts with a large and diverse set of partners its gains new knowledge and perspectives from multiple sources. Exposure to a diverse pool of knowledge spurs creativity and make the focal licensor more efficient in coordinating the licensed technology (Cohen & Levinthal, 1987; Pisano et al., 1988).

Finally, the findings also indicate that the focal firm's technology complexity and actor complexity jointly augments its performance. This finding highlights that the focal firm's ability to reap superior benefits from its ecosystems depends not just on the alignment of technologies/inputs within its ecosystem, but also on the degree of interactions among actors in the ecosystem. For the above reasons, perhaps, some prior studies (e.g., Adner and Kapoor, (2010), Boudreau. (2010), which emphasise the effects of the flow of activities (technologies) within the ecosystem on the focal firm performance without fully accounting for the role of actor interactions, might over report the contribution of technological alignment on the focal firm's performance. Similarly, other studies (e.g., Autio and Thomas, (2014), Jacobides et al., (2015), which consider actor interactions as a key contingency for value creation, but ignore the role of technological alignment, may not be discerning the adverse effect that the focal firm's inability to coordinate the licensed technology may have on its performance. Our current study juxtaposes the technology and actor aspects of the ecosystem, thus avoiding such under or over-specification regarding the degree to which technology and actor interactions may have on the focal firm's performance.

This study also has some important managerial implications. Our findings suggest that focal firms should build their architectural capabilities, as these alongside their patents' and other organisational resources can enable them to create superior value from their ecosystems. This study indicates that when attracting partners, ecosystem managers should consider their partner attributes in terms of the nature of their technologies as ecosystem orchestrators turn to perform better when technologies within their ecosystems originate from a broad and diverse set partners.

In addition, the characteristics of actors that the focal firm interacts with and the type of the agreement used in collaborating with partners should be well thought as this has a tremendous implication on the focal firm's value creation. The findings highlight that the focal firm's ability to create value from its ecosystem depends heavily on the quality of interactions and degree of learning within its ecosystems. Focal firms that operate in ecosystems with higher levels of actor ecosystem complexity tend to enjoy superior learning, which in turn enhances their value creation.

Despite the theoretical and managerial contributions, this research also has many shortcomings that serve a basis for future research. First, this research is operationalised within a single industry setting, which means that the findings cannot be easily generalised. The ecosystems examined in this study originate from the licensing activities of chipless firms operating within the cumulative semiconductor industry. Although the drivers of performance in this industry may broadly apply in other high-tech settings, the ecosystem dynamics in less cumulative industry settings such as the pharmaceutical and chemical industry may be slightly different to those in the cumulative industry, and orchestrators may face different coordination challenges in these industries. Broadening the scope of this study to other high-tech industry settings may provide us with useful insights into the effect that the focal firm ecosystem complexity may have on its performance.

Second, in this study, we characterise the complexity of the focal firm ecosystem based on two components – technology and actor. However, besides these two principal components, other factors such as the level of technological change and uncertainty regarding the demand for the focal technology may affect how partners interact within the ecosystem. Further research could address how these factors influence the complexity of the ecosystem and hence the focal firm's performance.

Another possible weakness of this research relates to the fact that in our theorisation we assume that partners within the ecosystem always behave cooperatively, which may not often be the case. Researchers could also examine how the competitive actions of partners within the ecosystem may affect the focal firm's ecosystem complexity and the implication that such behaviour may have on its performance.

Table 6-1: Descriptive Statistics and Pairwise Correlations

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1.Technology ecosystem complexity	1.0000											
2. Actor ecosystem complexity	0.0237	1.0000										
3.Interaction Techn comp * actor comp	0.1979*	0.3170*	1.0000									
4. Licensor pre-ecosystem patents	-0.0463	0.0198	0.0271	1.0000								
5. Partners pre-ecosystem patent	-0.1454*	0.0876	0.0274	-0.0000	1.0000							
6. Licensor size	-0.0115	-0.0460	-0.0369	0.5159*	0.0664	1.0000						
7. Partners size	-0.2599*	-0.0691	-0.1083*	-0.0283	0.5168*	-0.0446	1.0000					
8. Licensor age	-0.1240*	-0.0710	-0.0689	0.2707*	0.380*	0.2380*	0.0538	1.0000				
9. Partners age	-0.1959*	-0.0305	-0.0606	-0.0586	-0.41680	-0.1391*	0.5945*	0.0431	1.0000			
10. Partners status	-0.2312*	0.0141	-0.0408	-0.1283*	-0.1535*	-0.1553*	0.2476*	0.0061	.03250*	1.000		
11.USA	-0.0092	-0.1351*	-0.1418*	-0.0032	-0.0718	-0.0296	-0.1452*	0.0099	-0.2034*	-0.0628	1.000	
12.EUROPE	0.0726	0.1121*	0.1139*	-0.0211	0.0066	-0.0153	0.0032	-0.1090	-0.0030	0.0530	-0.1041*	1.000
Mean	.638232	131.877	86.7371	89.3903	1374.436	3235.59	70972.8	18.25765	57.28316	0.846939	0.410714	0.15306
Standard Deviation	.394057	275.270	232.388	291.180	2434.19 0	11334.6	106600	11.41484	39.65676	0.360506	0.492592	0.22924

Table 6-2: Random Effects Panel Negative Binomial Estimates for Technology Complexity and Actor Complexity on Focal Firm Performance

Variables	Model1	Model 2	Model 3	Model 4	Model5
Constant	-1.31268***	-0.71523**	-1.27051***	-0.71746**	-0.94922**
Technology Ecosystem Complexity		0.92389*** (0.15160)		0.91680*** (0.15376)	0.63608*** (0.16290)
Actor Ecosystem Complexity			0.00076*** (0.00026)	0.00047** (0.00019)	0.00184*** (0.00039)
Interaction Technology comp * Actor comp					0.00234*** (0.00002)
Licensor pre-ecosystem patents	0.00029 *** (0.00017)	0.00001*** (0.00017)	0.00357*** (0.00015)	0.00002*** (0.00017)	0.00003*** (0.00017)
Partners pre-ecosystem patents	0.00012*** (0.00002)	0.00007 ** (0.00003)	-0.00111** (0.00003)	-0.00007** (0.00003)	-0.00008** (0.00002)
Licensor size	0.00005*** (0.00001)	0.00001 (7.58000)	0.0001*** (9.4600)	0.00001 (7.60006)	0.00001 (7.60000)
Partners size	2.51000*** (26.6407)	1.35000* (6.53000)	2.20000*** (6.6700)	1.34000** (6.55000)	1.38000* (6.51000)
Licensor age	0.00444* (0.00175)	0.01368† (0.00708)	0.00465*** (0.00136)	0.01361* (0.00709)	0.01566* (0.00727)
Partners age	0.00182 (0.0018)	0.00019 (0.00175)	0.00090 (0.00178)	0.00015 (0.00176)	0.000433* (0.00174)
Partners status	-0.05279 (0.12712)	-0.13399 (0.15617)	-0.12843 (0.12184)	-0.12759 (0.15830)	-0.12105 (0.15866)
USA	0.66728*** (0.11790)	0.63836*** (0.11547)	0.59234*** (0.11831)	0.63508*** (2.11615)	0.58592*** (0.11422)
EUROPE	0.22520 (0.51801)	0.44737 (0.51992)	-0.49153 (0.53898)	0.47254 (0.53135)	0.37867 (0.53642)
Jap & S. Korea	Include	Include	Include	Include Include	Include Include
Others Dev. Nation	Include	Include	Include	Include	Include
Far East Asia	Include	Include	Include	Include	Include
Rest of World	Include	Include	Include	Include	Include
Number of obs	465	465	465	465	465
Log likelihood	-4196.38	-4177.08	-4190.48	-4177.06	-4167.31
Df	14	18	16	20	24
Wald chi square	87.55***	126.27***	97.06***	126.04***	148.84***
Models Δx^2		(4) – (2) 6.86***	(4) – (3) 12.342***	(4) – (1) 38.68***	(5) – (4) 12.54**

Standard errors are in parentheses. † P < 0.10; * P < 0.05; ** P < 0.01; *** P < 0.001

7. INNOVATION PERFORMANCE: THE EFFECT OF THE QUANTITY AND QUALITY OF BOTH DIRECT AND INDIRECT NETWORK TIES

7.1. Abstract

This research examines the effects of the quantity and quality of network ties on firms' innovation performance. It addresses the theoretical and empirical puzzle why firms with similar patterns in their direct and indirect network ties may exhibit heterogeneous innovation performance outcomes. Using licensing and patenting data of firms operating in the semiconductor industry, we find that both the quantity and quality of direct ties of the firm have a positive impact on their innovation performance, but the quality of ties seems to have a more significant effect than the quantity of these ties. Our findings further show that the effect of the quality of ties is more significant at the level of direct ties than at the level of indirect ties. Our research adds new insights to the body of literature exploring the implications of the quantity and quality of direct and indirect partners' resources on innovation performance.

Keywords: Networks, direct and indirect ties, quality and quantity ties, innovation performance

7.2. Introduction

There is a growing recognition in the network literature that the position of firms in their networks of direct and indirect ties to other firms convey them with different advantages (Ahuja, 2000b; Paruchuri, 2010; Podolny & Stuart, 1995; Powel et al., 1996; Salma & Savies-Laura,, 2005; Shan et al, 1994; Singh et al., 2016; Zaheer & Bell, 2005). Because direct ties serve as pools of resources and knowledge (Tortoriello et al., 2014) and indirect ties as pipes through which knowledge flow in networks (Podolny, 2001), connecting to a large number of partners enable firms to access a large quantity of new resources and knowledge, which they can recombine and reconfigure to innovate (Fleming, 2001; Rodan & Galunic, 2004; Mors 2010). For example, in his study of the chemical industry, Ahuja (2000b) finds that the number of a firm's direct and indirect ties significantly improved its innovation performance. For a sample of Canadian biotechnology firms, Salma and Savies – Laure (2005) establish that firms that are connected to a large number of indirect ties are more innovative than those with a small number of indirect partners.

Interestingly, Gulati et al. (2011) argue that many of the studies that have examined the implications of network ties on innovation performance have primarily concentrated on the structural features of networks such as the position and centrality of firms. While the quantity of resources that firms accrue from the different parts of their networks impact their innovation performance, the quality of resources is to be seen as another important facets of inter-firm networks (Gulati et al., 2011; Madhavan & Prescott, 2017; Sarkar, Aulakh & Madhok, 2009). Studying the effects that the quantity of external resources has on innovation performance without accounting for the quality these resources, does not provide us with a full picture of how network ties affects innovation performance (Gulati; 2007; Gulati et al., 2011; Sarkar, Aulakh & Madhok, 2009).

Gulati et al. (2011) in their conceptualisation of the underlying mechanisms driving performance within networks argue that the quality of partners' resources (richness of resources) enables firms to identify complementarity (potential synergies) between their resources and those of partners, thus enhancing their innovative potentials. Sarkar, Aulakh, and Madhok (2009) also suggest that firms with similar positions in networks, in terms of the quantity of their ties may accrue heterogeneous levels of network external resources due to variances in the quality of these resources. In other words, the quality of resources that firms accrue from their partners may distinguish firms that are otherwise structurally equivalent, i.e., – occupy similar network positions (Wang & Rajagopalan, 2015). However, the focus of most of these studies has mainly been theoretical, and scholars have not systematically measured the quality of ties at the inter-firm network level.

In this study, we empirically explore how the quantity and quality of resource that firms access from the different parts of their networks affect their innovation performance. We examine the effects of the quantity and quality of ties of firms on their innovation performance using patent data and licensing agreements signed between firms operating within the semiconductor industry. Firms often license in and out technology from multiple partners, partners that themselves also act as licensors and licensees to others, and as such find themselves situated within a network of relationships. Through these networks firms learn to innovate and capture value from external technology (Hall & Ziendonis, 2001). Depending on the number direct and indirect of partners in their networks and the quality or richness of their resources, firms exhibit heterogeneous innovation outcomes. Our research indicates that both the quantity and quality of direct ties have a positive and significant impact on innovation performance, but the quality of ties seems to have a more significant effect than the quantity of ties per se. Our findings further show that the effect of the quality of ties is more significant at the level of direct ties than at the level of indirect ties. As such, our research indicates that firms that occupying the same network position may exhibit different innovative outcomes based on the quality of their partners' resources. Accordingly, our research adds new insights to the body of literature exploring the implications of the quantity and quality of direct and indirect partners' resources on innovation performance (Ahuja, 2000b; Gulati et al., 2011; Madhavan & Prescott, 2017; Salma & Savies-Laura, 2005; Sarkar, Aulakh & Madhok, 2009).

7.3. Theoretical Background and Hypotheses

7.3.1. Licensing and Network Formation

The alliance and network literatures are replete with the view that the network in which the firm is embedded is an important source of competitive advantage (Ahuja, 2000b; Gnyawali & Madhavan, 2000; Kim & Lee, 2007; Gulati, Nohria & Zaheer, 2000; Podolny, 2001; Zaheer & Bell, 2000). This assertion is based on understanding that valuable resources do not only reside within the firm’s boundary but can also be accessed through ties to other organisations (Baum et al., 2000; Gulati, 1990; Kim & Lee, 2007; Podolny, 2001). In that content firms use many mechanisms such as mergers & acquisitions, alliances, R&D collaborations and also licensing that is considered as one of the most important mechanisms that firms use to share and to access externally developed resources (Grindley & Teece, 1989; Leone & Reichstein, 2012).

Although licensing of technology entails the transfer of technology from the licensor (owner of technology) to the licensee (s) (buyer of technology), it also enables firms' to access relevant partners' resources, skills, knowledge, and capabilities**.** Firms often license in and out technology from multiple partners (Anand & Khanna, 2000; Arora et al., 2003; Hagedoorn et al., 2008) and based on their network of partners and partners of their partners (direct and indirect ties) they build networks (Freeman & Hagedoorn, 1994; Ahuja, 2000b). From their direct ties network of partners, firms access resources, knowledge, and capabilities (Powel et al., 1996) and also gain valuable information about the state of art of technologies in their industry from their indirect network ties (Gnyawalli & Madhaven, 2001; Powell, 1990; Powell et al., 1996). Since innovation results from the recombination and reconfiguration of multiple resources, networks play a crucial role in harnessing the capabilities of firms to develop new products, technologies and serve new markets. In this light, as a mechanism that facilitates learning and the formation of networks, licensing can be conceived as a springboard for enhancing innovative capabilities (Grant, 1996; Leone & Reichstein, 2012; Powell et al., 1996; Tsai & Wang, 2009).

7.3.2. Network Resources and Their Origins

The emerging research on networks suggests that network resources constitute resources that are accessible to a firm through its ties with partners (Jensen, 2003; Gulati et al., 2011; Lavie, 2006; Singh et al., 2016; Zaheer & Bell, 2005). According to this recent stream of literature, network resources can be conceptualised into two main types, i.e – tangible and intangible resources (Ahuja, 2000b; Hansen, 1992; Nonaka, 1994; Salman & Savies- Laure, 2005; Singh et al., 2016) that can be accessed from different locations of the network (Paruchuri, 2010; Salman & Savies- Laure, 2005; Singh et al., 2016). Tangible resources constitute resources such as partners' intellectual property (e.g., - patents), tools and instruction manuals, financial assets, distribution and marketing channels, and personnel. These resources are mainly accessed through partners that the firm is directly connected to, that is, through a dyadic ego-alter relationship or the firm's direct ties (Ahuja, 2000b; Salman & Laure-Savies, 2005; Singh et al., 2016).

On the other hand, intangible resources, including resources such as knowledge, information, and skills, are gained through social interactions between and among network partners. Intangible resources are tacit and non-codifiable and play an important role in the integration and assimilation of tangible resources (Singh et al., 2016; Rodan & Galunic, 2004). They are impacted by the indirect relationship of a firm with other firms through its primary partners (Podolny, 2001; Tortoriello et al., 2014), described in the network parlance as friends of friends or indirect ties (Ahuja, 2000b; Salman & Savies- Laure, 2005; Singh et al., 2016). Indirect ties enable firms to access knowledge not just held by their direct partners but also held by their partners-partners' (Freeman, 1991; Singh et al., 2016). As channelling devices, indirect ties enable firms to access new and useful knowledge flowing through networks (Leonard-Barton, 1984; Powell et al., 1996; Salman & Savies- Laure, 2005; Singh et al., 2016). Because innovation is conceived as a combination of diverse resources, knowledge, and skills (Henderson & Clark, 1990; Fleming, 2001), both direct and indirect ties can be significant sources of innovation (Ahuja, 2000b; Hargadon & Sutton, 1997; Salman & Savies- Laure, 2005).

In this light, both direct ties and indirect ties are expected to have an impact on firms' innovation performance (Ahuja, 2000), as they influence the amount and sort of capabilities (quantity and quality) that they access from their network of partners and also their ability to recombine and reconfigure externally acquired capabilities. Although prior research has examined the effects of firms' ties on innovation performance, most of these studies have exclusively focused on either the effects of the quantity (number) of direct ties (dyadic interactions) (Rodan & Galinic, 2004; Mor, 2010), or the effects of quantity of indirect ties (Gulati, 1995; Salman & Savies-Laure, 2005). For instance, Ahuja (2000b) and Singh et al., (2016), do explore the implications of the quantity of resources and knowledge that firms accrue from their direct and direct ties, but do not examine the role of the quality or richness of partner resources as a predictor of innovation performance.

Some prior research, however, suggests although the quantity direct and indirect ties contribute to performance innovation of firms, the quality of these ties is also an important facets of networks (Gulati et al., 2011; Madhavan & Prescott, 2017; Sarkar, Aulakh & Madhok, 2009; Wang & Rajagopalan, 2015). This entails that to understand the role of network ties on innovation, research has to examine not just the implications of the quantity (number) of direct ties and indirect ties but also how the quality/richness of resources that direct and indirect partner possess influences their innovation performance. In this study, we examine the effects of the quantity of direct and indirect ties alongside the quality of these ties on innovation performance. By so doing, we deepen the understanding of the heterogeneity in innovation performance of firms that occupy rather similar network positions in terms of their direct and indirect ties.

7.3.3. Direct Ties and Innovation Performance

Through direct ties, firms can access both tangible resources (Baum et al., 2000; Gulati, 1990; Koput & Smith-Doerr, 1996; Podolny, 2001; Lee, 2007; Stuart et al., 1999; Salman & Saives-laure, 2005, 2005) that when recombined with firms' internal capabilities can positively enhance their innovativeness (Fleming, 2001; Henderson & Clark, 1990; Kim & Lee, 2007; Levin et al., 1987; Powel et al., 1996; Venkatraman & Lee, 2003).

However, the potential benefit that firms accrue from their networks of direct contacts may vary depending on the location/position they occupy within inter-firm networks (Powell, 1990), different structural positions (Ahuja, 2000; Gulati.1995) offer them access to different set of resources and capabilities (Ahuja, 2000; Baum et al., 2000; Gulati, 1995; Koput & Smith – Doer, 1996; Tsai & Wang, 2007). Highly centrally positioned firms are more likely to have access to a large pool of external resources as centrality has been shown to be positively associated with the availability of information (Bonacich, 1987; Gulati, 1995; Podolny, 2001; Nerkar & Parachuri, 2005). As innovation results from the recombination of new and existing resources (Levin et al., 1987; Henderson & Clark, 1990; Fleming, 2001), firms that have access to a large pool of resources are more likely to generate more cutting edge innovations (Henderson & Clark, 1990; Fleming & Sorenson, 2001; Katila & Ahuja, 2001).

A number of prior studies provide supporting evidence that more centrally positioned firms generate more significant benefits from their network of direct ties than less central firms do. For example, Tsai (2000 and 2002) shows that network centrality increases firm's innovative potential. Ahuja (2000) also shows that firms that occupy a more central position are more innovative when measured by the number of patents and new products generated. In line with the above studies, Baum, Calabrese, and Silverman (2000) and Hagedoorn et al., (2016) indicate that the number of partners of new biotechnology firms' partners at founding is positively related to their performance measured by the multiple indicators, such as – revenues, R&D spending, and patent generation.

Furthermore, since ties to other organisations are seen as pipes through which information flows within networks, more centrally positioned firms are more likely to be aware of development in their networks (Podolny, 1993). They can also easily communicate and promote their technology to a large pool of firms, which enhance the chances for their technology to reach a large number of players and increases the likelihood for their technology to become the standard in an industry (Katz & Shapiro, 1986). Firms whose technology is industry driver are more likely to gain new information from a broad range of customers, which they can use to generate new products and technologies (Podolny, 1993; Stuart et al., 1993).

Hence, given the vast amount of resources and knowledge spill-overs and externalities resulting from connecting with a large number of partners, more centrally positioned firms are more likely to outperform those occupying less central positions (Freeman, 1991; Pologny, 1993; Bonacich, 1997; Baum et al., 2000; Ahuja, 2000b). In line with the above literature, licensees that license in technologies from many partners can be viewed as occupying more central positions. More centrally positioned licensees have access to a large pool of technologies with which they can experiment and generate more novel products and technologies. This suggests that more central positioned licensees are more likely to benefit in terms of innovation performance through externally acquired technology than less central positioned licensees. Hence:

H1a: The more firms (licensees) are centrally positioned in a network of direct ties, the higher their innovation performance.

In addition to the number of partners from which firms license in new technologies, the innovation performance of firms may also be affected by the quality of the source of the licensed technologies (Lavie, 2006; Gulati et al., 2011). Firms accrue differential benefits from their network of direct ties based on the attribute of their partners (Lavie, 2006; Madhavan & Prescott, 2017; Sarkar, Aulakh & Madhok, 2009). More specifically, Gulati et al. (2011) argue that firms occupying similar central positions may achieve different innovation performances because of the differences in the characteristic of their direct partners. The attributes of a firm's partners strongly influence the quality of resources and the inherent value a firm can accrue from its direct networks ties (Gulati et al., 2011; Madhavan & Prescott, 2017).

The notion of the quality of ties relates to technologies and resources of a firm's partners are reconfigured (Gulati, 1995b; Gulati et al., 2011). From an innovation perspective, the benefits of the quality of firms' ties or richness of partners' resources arise from learning options and the possible recombination that firms can generate from partners' resources (Gulati, 1998; Henderson & Clark, 1990). According to Fleming (2001) and Fleming & Sorenson (2001), access to partners with high-quality resources augments the potential for firms to find more relevant knowledge. Thus, firms that have access to a set of partners with superior technological capabilities are more likely to develop breakthrough innovations (Cohen &

Levinthal, 1989), which are novel to the market and difficult to copy by competitors (Ahuja & Katila, 2001; Rosenkopf & Nerkar, 2001).

In the context of licensing, high-quality technologies refer to sophisticated technologies, cutting-edge technologies (Hagedoorn et al., 2008). Firms (licensees) that have access to partners with highly sophisticated technologies are more likely to find relevant knowledge sources through their partners. This increases the likelihood they can generate new products or processes (Fleming & Sorenson, 2001; Nerkar & Parachuri, 2005), and enhance their innovativeness (Gulati & Singh, 1998).

In addition, firms that are tied to partners with more sophisticated technologies can easily find complementarity between their technologies and those of partners through effective triangulations (Podolny, 2001; Gulati et al., 2011). By collaborating with partners with high-quality resources, licensees can verify the value of one partner's technology by consulting with other partners (Podolny, 2001; Singh, 2005), which may be more difficult for licensees that are tied to partners with low-quality technologies. The possibility of cross-checking partners' technology against other high-quality technologies enhances firms' learning ability and increases their innovative potentials (Stuart et al., 1999; Singh, 2005; Nerkar & Parchuri, 2005; Lavie, 2006).

Given the evidence from the above literature, firms (licensees) that are tied to partners with high-quality resources are more likely to generate more innovative ideas than those that are connected to partners with lower - quality resources. The former enjoys more advantages from their position due to new insights they can derive from their partners' resources. Hence:

H1b: The higher the quality of firms' (licensees') direct ties, the higher their innovation performance.

7.3.4. Indirect Ties and Innovation Performance

While occupying a central position and receiving rich resources from direct ties are expected have a positive impact on innovation performance, firms' indirect ties may also be significant sources of innovation (Ahuja, 2000b; Salman & Savies-Laure, 2005). Firms' indirect ties are generally referred to as their partners' partners (Gulati. 1995; Sorenson et al., 2006). Indirect ties can serve communication channels through which firms access knowledge of their partners'- partners (Salman & Savies- Laure, 2005). Through indirect ties, firms' can access knowledge that is new or unfamiliar to them (Gulati, 1995; Davis, 2004), as firms may have a good understanding of their partners' knowledge base but may be unfamiliar with the knowledge base of their partners' partners. The number of a firm's indirect ties increases the pool of new knowledge from which it can derive new insights. Thus, being well located within a network with indirect ties situates the firm favourably to access a large quantity of new and useful knowledge (Sorenson et al., 2006; Salman & Savies-Laure, 2005), and provides the firm with many innovation benefits (Ahuja, 2000b; Powell et al., 1996).

As an information gathering device (Leonard-Barton, 1984; Freeman, 1991; Powell et al., 1996; Salman & Savies- Laure, 2005), indirect network ties enable firms to gather information and to access knowledge about a range of activities which their partners' partners engage in, which enables them to be in tune with what is going on in the industry (Roger & Larsen, 1984; Sorenson et al., 2006)

Indirect ties can also serve as a valuable source of combinatory knowledge (Dyer & Singh, 1998; Singh et al., 2016), useful in recombining internal and externally acquired knowledge (Cohen & Levinthal, 1990). Combinatory knowledge is generally gained through experience (learning by doing) or from interactions with network partners (Argote & Guo, 2010). Interactions between partners enable firms to share their experience and knowledge they accrued from their interactions with other partners and with each other (Gulati & Garguilo, 1999). Firms that interacts with a large number of other firms are more likely to have routines and processes in place for coordinating their network activities (Kim & Kogut, 1996; Argote & Ingram, 2000). They are more likely to possess more significant experience in recombining externally acquired knowledge (Cohen & Levinthal, 1990; Lane et al., 2001).

In the context of licensing, when licensees acquired technology from licensors in order for licensees to integrate the licensed technology, the must be some degrees of communicating between them. Communication between the licensing partners' enhances licensee's licensing experience, which in turn, facilitates its abilities to integrate the licensed technology. Firms that themselves license in technology or interact with other firms are more likely to have processes and routines in place for reconfiguring and recombining externally acquired knowledge. When these firms act as licensors and interact with their partners, they are more likely to pass useful knowledge, insights, experience, routines, and processes to their partners (Tortoriello et al., 2014; Singh et al., 2016). Thus, firms (licensees) which are linked to partners that are themselves are connected to many other firms' partners are more centrally positioned in a network with indirect ties. These licensees are more likely to access a larger pool of new and combinatory knowledge, which in turn, increases their propensity to recombine and reconfigure externally acquired knowledge and improve their innovation performance (Hansen, 2002; Sorenson, Rivkin, & Fleming, 2006). Hence:

H2a: The more firms (licensees) are centrally positioned at the network of indirect ties the higher their innovation performance.

The degree to which focal firms benefit from indirect ties, however, may also be influenced by the quality of their indirect partners' resources (Lavie, 2006; Gulati et al., 2011; Madhavan & Prescott, 2017). The quality of firms' indirect ties may affect the value of these ties as the inherent value that firms accrue from their indirect ties depends on the attributes of their partners-partners' resources (Gulati et al., 2011). Firms that are tied to partners whose partners possess higher quality resources are more likely to find potential synergies and/or complementarities between their resources and those of their partners than firms whose indirect ties possess lower quality resources (Lavie, 2006; Gulati et al., 2011).

From a licensing perspective, licensees that have indirect ties to higher quality partners, i.e. partners' partners that possess more sophisticated technologies, are likely to enjoy more benefits from their network of indirect ties than those whose partners' partners have a lower quality, i.e. indirect ties with a less sophisticated knowledge base. Hence:

H2b. The higher the quality of firms' (licensees') indirect ties, the higher their innovation performance.

7.4. Method and Data

7.4.1. Research Setting

We tested our hypotheses on a sample of firms (licensees) operating within the semiconductor industry (SIC 3674). We study firms operating in the semiconductor industry because the industry is considered a complex industry whereby technological development builds on prior knowledge (Teece & Grindley, 1987; Hall & Ziendonis, 2001; Linden & Somaya, 2003). In this context, in order to innovate, firms have to gain access to other firms' (partners) technology, and licensing is seen as an essential component of technological development (Teece & Grindley, 1987). Technology licensing facilitates the emergence of networks (Powell et al., 1996) and it is through these networks that firms innovate (Hall & Ziendonis, 2001; Linden & Somaya, 2003). Licensees occupy varying positions within their networks and depending on the number and quality of their direct and indirect network ties; they access differential levels of knowledge, information and resources.

In addition, because we measured firms' innovation performance using their patenting frequency, this requires us to select an industry where patents are a meaningful indicator for new inventions. Firms in the semiconductor industry routinely and systematically patent their invention and patents are seen as an efficient mechanism for protecting and generating value from innovation (Stuart, 2000; Hall & Ziendonis, 2001; Srivastava & Gnyawali, 2011). Thus, using firms operating within the semiconductor industry provides an appropriate setting to test the implications that the quantity and quality of direct and indirect ties have on innovation performance.

7.4.2. Data and Sample

We assembled data on the licensing and patenting activities of focal firms and their partners. Patent data was used to measure the innovation performance of firms and their pre-network innovativeness, whereas licensing information is mainly used to capture firm networks and to measure some control variables (the rationale for using patenting and licensing data is explained in the operationalisation of variables below)

We collected longitudinal data of the patenting and licensing frequency of firms. The panel used in the analysis contains yearly licensing data for the period of 1985 to 2005 and patenting data from 1980 to 2010, reflecting a five-year lead and lag period between licensing and patenting data. We employ a five-year lead and lag period in order to provide enough time for all firms' patents to go through the patent examination process and to collect the forward citation counts for granted patents and measure firms' pre-network innovativeness. Prior research suggests that when firms license in technology, it takes 3 to 5 years for them to develop new patents (Jaffe et al., 1993). Research also indicates that patents generally take 3 to 5 years to be granted (Griliches, 1990) and a patent is normally cited within 5 to 7 years (Trajtenberg, 1987; Griliches, 1990; Jaffe et al., 1993), thus using a 5-year's lead and lag period provides sufficient time to collate the forward citation records for all the sample firms' patents and their level of innovativeness before engaging in networks.

We collected licensing data of focal firms and their partners from Securities Data Company (SDC) Thomson Reuter database. The database is considered as one of the most comprehensive data sources for large base empirical studies (e.g., Anand & Khanna, 2000; Phelps, 2003, Srivastava & Gnyawali, 2011) and has been widely used in the licensing, alliances and networks literatures with reliable results (Ahuja, 2000b; Sampson, 2007; Hagedoorn et al., 2008; Parachuri, 2010; Singh et al., 2016). The database provides information on the name of licensing partners participating in the licensing arrangement, their public status, industry affiliations and countries in which they are headquartered. It also provides a brief description of the purpose of the licensing agreement, type of technologies involved in the licensing deal and primary SIC code of the engaging parties. We constructed each firm's network by collecting licensing agreements signed between the firm and its partners and built a firm-firm network with firms serving as nodes and licensing agreements as ties through which resources, information and knowledge flow within networks. Following prescriptions from prior literature for establishing network boundaries (Laumann et al., 1993; Schilling & Phelps, 2007), we restricted firm networks to licensing deals that occurred within the semiconductor industry. Recent network studies have also used similar network construction criteria (e.g., Rowley, Behrens & Krackhardt, 2000; Schilling & Phelps, 2007; Phelps, 2010; Parachuri, 2010; Singh et al., 2016). Further, because our hypotheses require us to test for heterogeneity between focal firms, we selected only firms that have at least two or more licensing partners during the timeframe of the study and used the random effect specifications to account for these selection criteria as explained in the statistical technique section below. From these data sampling procedures, we obtained a sample of 64 firms engaging in 342 licensing deals.

Next, we compiled patents information for each sample firm and its partners. We retrieved firms' patent data from the patent databases compiled by the National Bureau of Economic Research (NBER). NBER databases contain patent information from the US Patent and Trademark Office (USPTO), the European Patent Office (EPO), and other key patent jurisdictions in the world, such as Japan, China, South Korea, and Australia. The databases provide information on the total number of patents granted to a firm - ultimate parent including those of all its subsidiaries. They also report the number of citation counts made and received by each patent, its technological class, and subclass, as well as a wealth of other important information (for a detailed description of the databases, see http://eml.berkeley.edu//~bhhall/patents.html). For the current study, we mainly used the database containing patents information from the USTPO only. This is consistent with other large-scale studies on the effects of network ties on firms' innovativeness (Ahuja, 2000b; Parachuri, 2010; Phelps, 2010; Singh et al., 2016). Drawing patenting information from only the USPTO is considered appropriate for the following reasons. First, because of the sheer size of the US market and the strength of its patent regime (Almeida, 1996; Lim, 2004), in order to stay competitive in the industry, semiconductor firms are more likely to patent their inventions with that regime (Hall & Ziendonis, 2007). Second, since different patent jurisdictions in the world use different standards and methods to assign patents to firms, using patents from a single regime reduces the likelihood of biases (inconsistency and comparability) in the independent variable that can result from using patents from different jurisdictions (Stuart & Podolny, 1996; Stuart, 1998; Ahuja, 2000b).

Finally, we collected data for the control variables (firms and partner's size, age and status) from Compustat, DataStream, NBER, Amadeus, LinkedIn, and Bloomberg. We also consulted firm websites, annual accounts, and other web and business directories in cases where we could not find reliable data from the above databases.

7.4.3. Operationalisation of Variables

7.4.3.1. Dependent Variable

We measure the firm innovation performance using its citations weighted patent counts (Ahuja, 2000b; Phelps, 2010; Sampson, 2007). This measure has been extensively used in prior network and alliance studies to analyse the implications of network ties on firms' innovation outputs (Ahuja, 2000b; Katila & Srivastava & Gnyawali, 2011; Parachuri, 2010; Phelps, 2003; 2010; Nerkar & Parachuri, 2005; Singh et al., 2016). Patents are a valid and robust indicator of innovations (Griliches, 1990). They represent a codifiable portion of firm's technical (tangible) knowledge (Griliches, 1990; Trajtenburg, 1987), and have been shown to correlate with its tacit (intangible) knowledge (Brouwer & Kleinkneckt, 1998; Phelps, 2010).

Following prior work by Sampson (2007) and Phelps, (2010), we constructed the innovation performance of each firm by first counting the number of patents granted to the firm within five years after the observed licensing deal. Then, for each of the firm patents, we count the number of forward citations received within the timeframe. A five-year window is used to operationalise the variable because research suggest when firms engage in alliances it takes 3-5 years for them to develop new patents. Prior research also shows that patents are generally cited within a five-year window, and patents that are not cited within this timeframe are less likely to be cited at a later date (Jaffe et al., 1993).

7.4.3.2. Independent Variables

Direct ties - centrality (Hypothesis 1a) refers to direct contacts (firms) that are directly linked to the focal firm, that is, those that are within a path distance of 1 in the firm's network (Freeman, 1979). In prior literature, the firm's network centrality has been operationalised using many different measures such as degree centrality, closeness and betweenness centrality (Wasserman & Faust, 1994). As the most used centrality measure, we operationalised the quantity of the firm's direct ties using its degree centrality. Following Freeman (1979) and Wasserman and Faust (1994), we measure a firm 's degree centrality as the total number of unique partners that a firm licenses technology from during the observed time t.

The quality of direct ties (Hypothesis 1b) to partners is strongly linked to the sophistication of its partners' technological resources (Gulati et al., 2011). Following Lavie (2006) and Singh et al. (2016), we measure the richness of the firms' direct ties as the total the citation counts of at firm's direct partners' patents.

Indirect ties centrality (Hypothesis 2a) represent the extent to which a firm direct partners are linked to other partners, that is, the number of that firm's partners-partners' (Ahuja, 2000b; Moran, 2005; Singh et al., 2016). The firm's indirect ties have commonly been captured at the ego – alters - alters or whole network level (Burt, 1992a; Stuart & Podolny, 1996; Podolny & Baron, 1997). Following Freeman (1979) and Wasserman and Faust (1994), we measure a firm's indirect ties degree centrality as the total number of unique partners that a firm's partners'- partners engage in licensing deals with at the observation year t.

Similar to the quality or richness of direct ties, we measured the quality of the firms' indirect ties (Hypothesis 2b) as the total the citation counts of a firm's partners-partners' patents.

7.4.3.3. Control Variables

To isolate the effects of the explanatory variables, we controlled for a number of factors at the firm and partner level that may influence the innovative performance of firms.

Focal firms' pre-network innovativeness accounts for the level of that firm's innovativeness before engaging in a licensing deal as prior research suggests that the knowledge that firms accumulate in the past may have a significant impact on their degree of innovativeness in the future (Cohen & Levinthal, 1990). Firms with a high level of innovativeness are likely to continue to generate more patents or maintain their stock of knowledge over time (Katila &

Abuja, 2003). Following studies by Katila & Abuja (2003), and Cloodt et al. (2006), we measure the firm pre-network innovativeness as the number of patents assigned to the firm within five years before the observed licensing deal.

Partners' pre-network innovativeness is relevant as a control variable, as research shows that the amount of prior knowledge that partners bring to the network may also influence the focal firm's innovation performance (Sampson, 2007). Although the focal firm does not own its partners' resources, it can access them through its ties to partners. Similar to firms' pre–innovative network potentials, we measured partners' pre–network innovativeness as the number of patents obtained by the firm partners within five years before the observed licensing deal.

As a standard indicator in performance studies, we also controlled for firms' size as research indicates that larger firms are more likely to possess greater resources, which enable them to generate more patents than smaller firms (Scherer, 1986). We measured the firm size as the total number of employees employed by the firm at the observed time t.

We also control for firms age, as prior research shows that older firms are more likely to possess a higher stock of knowledge than younger firms (Gittelman & Kogut, 2003). This can influence the number of patents that they generate from their network resources. We measure the firm age as the time that elapsed from the date it was incorporated to the date of the observed licensing deal.

The public/private status of a firm partners within its network is relevant, as research highlights that the relational benefits that focal firms accrue from network partners may vary depending on whether their partners are privately or publicly owned (Lavie, 2007). Publicly traded firms are often seen as key influencers in the industry, and their association with a particular network can encourage other firms to join or adopt the focal firm's technology. We captured this variable using a dummy, which takes a value of 1 when a partner is a publicly traded firm and 0 otherwise.

Finally, the licensing literature mentions the difficulties that firms face in finding suitable partners for their technology, which may constrain their ability in forming or engaging in networks (Caves et al., 1993; Kani & Motohashi, 2012; Zuniga & Guellec, 2008). The geographical location where the firm is situated may influence its abilities to join a network(s) (Ahuja, 2000b). To control for cross-country heterogeneity and geographical explanations for firms' network activities, we constructed a global network partner distribution dummies. We partitioned network partners into geographical regions and constructed five global, regional dummies. Each dummy captures the proportion of the focal firm and partners in a given region. We used the location of the firm's parent headquarter to classify the firm and network partner into one of the following five regions: 'USA,' 'Europe,' 'Japan and South Korea,' 'Other developed nations,' and 'Far East Asia and the rest of the world.'

7.5. Statistical Analysis

Our dependent variable is the annual firms' citation weighted patent counts and the data for the explanatory variables comprises of multiple observations per firm over time. As a result of these structural features and the fact that our dependent variable is a count (only non-negative integer) variable, we used a panel negative binomial model to analyse our data. Other count specification models such as a Poisson regression models could have been used to analyse the data but were not deemed suitable because of overdispersion in the dependent variable (resulting from excess zero in the independent variable).

For our analysis, we used the random effects panel specification rather than the fixed effects as the key explanatory variables (the quantity and quality of direct and indirect ties) do not vary within firms in the same network and our interest is in the variations in performance between focal firms (Baltagi, 2005). Under these conditions, the random effect specification accounts for unobserved heterogeneity, as it incorporates a firm's specific error term and is deemed more appropriate than the fixed effect. Our analysis uses the random effects panel negative binomial (xtnbreg) procedure in Stata15.

7.6. Findings

Table 7.1 represents the descriptive statistics, which includes the means, standard deviations and bivariate correlations between all the explanatory variables. In general, the correlation coefficients among the independent variables are very low except for a few variables that deserve our attention. First, the quantity of direct ties – centrality measure is relatively highly correlated with the number of indirect ties (0.5976) and the partner size variable is also correlated with the partner age (0.5137). However, multicollinearity does not seem to present any problem to the analysis, as the mean-variance inflation factor (VIF) score for all of the independent variables is around 4.43, which is far below the critical value of 10. The robustness tests indicate that our findings are consistent and unaffected by the high correlations among these variables.

Insert tables 7.1 and 7.2 about here

In table 7.2, we report the results of random effects panel negative binomial regression. For the analysis, we followed a hierarchical approach, whereby we introduced the control variables first and then the independent variables in the subsequent models. Model (1), our baseline model, contains only the control variables. In models (2) and (3), we added the centrality and richness of direct ties measure to assess the effects of direct ties. In model (4) and (5) we introduced the centrality of indirect ties and quality of indirect ties, while in model (6), we incorporated all of the independent variables along with the control variables.

For direct ties, as predicted, hypothesis 1a is supported in models 2 and 6. In each of these models, direct ties centrality exhibited a positive and statistically significant effect on firms' innovation performance. Hypothesis 1b is also supported, see models 3 and 6. The positive coefficients and statistically significant p values in models 3 and 6 lend support to the hypothesis that the quality of firms' direct ties has a significant and positive effect on their subsequent innovation performance.

For indirect ties, see hypothesis 2a, we proposed that the more a firm is centrally located in its network of indirect ties, the higher its innovation performance. This hypothesis is supported in model 4 with a positive and statistically significant p-value but becomes insignificant in the full model 6. In hypothesis 2b, we proposed that the richness of indirect ties has a positive and statistically significant effect on the innovation performance of firms. The estimated positive coefficient of the quality of indirect ties in models 5 and 6 lends support to this hypothesis.

We performed likelihood ratios tests to examine whether adding our independent variables significantly improved the explanatory power of the models over the baseline model 1 with only the control variables. The resulting chi-squares $\Delta\chi^2$ are statistically significant indicating that adding the key independent variables significantly improves the explanatory power of the model. Model 6 includes both the centrality and quality of direct and indirect ties. Comparing the p-values in model 6 indicates that the effects of the quality of direct ties ($p < 0.0001$) are statistically more significant than the effect of the quantity of direct ties ($p < 0.05$). Similarly, at the indirect ties level, unlike the quantity of indirect ties, the quality of indirect ties ($p < 0.05$) seems to have a statistically significant effect on innovation. The findings further indicate that the effect of the quality of ties is more significant at the direct ties level ($p < 0.0001$) than at the indirect ties level ($p < 0.05$).

Some findings on our control variables are also worth reporting. In line with prior research, our findings highlight that the size of firms has a positive and significant impact on innovation performance and this is consistent throughout the models. This indicates that the focal firms' innovation performance increases with the size of the firm. Our findings also show that focal firms and their partners' pre-network have a negative and significant effect on innovations innovation performance. Although both variables have a significantly negative impact on innovation performance, focal firms' pre-network innovativeness seems to have a stronger effect ($\beta = 0.0001$ and $p < 0.001$) than partners' pre-network innovativeness ($\beta = 0.0009$ & $p < 0.01$). This suggests that, rather than just using the capabilities that firms access from partners, their ability to recombine and reconfigure these capabilities plays a more important role in increasing in their innovation performance. In addition, our findings indicates that partners' location also matters to the focal firm's innovation performance. The location variable USA, where most of the network partners are located, seems to be consistently positive and significant in all the models. This highlights that the closer the geographical proximity among partners, at the global scale, the easier it is for them to access and share resources, which subsequently enhances their innovation performance.

7.6.1. Robustness Tests

We carried out a number of sensitivity tests to check the robustness of our findings. First, while we measured our dependent variable using five-year moving windows and we believe that it is a reasonable proxy for innovation performance, we also tested a number of alternative specifications to check that our results are not influenced by the selected timeframe. We measured the dependent variable using 4 and 6 - year windows. Additionally, we explored alternative models using other performance measures, patent counts and total citation counts (backward and forward citations), that have been used in the prior literature to measure firms' innovation performance. The overall outcomes from these models were largely consistent with those reported in our findings, which reinforces our predictions.

Second, we hypothesised in this study that the quantity and quality of ties enhanced firms' innovation performance, however, both innovation and network ties may be influenced by unobserved factors of firms. This entails that endogeneity may be an issue in this study. Although our statistical approach controlled for unobserved heterogeneity, we also tested for the implication of endogeneity by first of all isolating the effects of the quantity and quality of direct and indirect ties using firms' prior innovativeness (Schiling & Phelps, 2007; Phelps, 2010). Then, we used the approach proposed by Reagan and McEvily (2007) to establish exogeneity for cooperation in the network context. The results for these alternative analyses are qualitatively similar to those reported in the main findings.

Finally, given the high intercorrelation between the quantity of direct ties and the number of indirect ties (0.5976) and the partner size variable with the partner age (0.5137), multicollinearity may have influenced our findings. We checked the effect that multicollinearity might have on our results by first of all mean centring these variables. Then we created a grand variable for both set of variables and ran the different models. In addition, we checked the mean-variance inflation factor (VIF) score for all explanatory variables. The VIF for all the independent variables is around 3.43, which is far below the critical value of 10 (Belsley, 1980; Cohen et al., 2003). The results from these robustness tests indicate that our findings are consistent and unaffected by correlations among these variables.

7.7. Discussion and Conclusions

To understand how network ties affect innovation performance, prior literature has mostly concentrated on the effects of the quantity or number of direct ties and indirect ties (Ahuja, 2000b; Parachuri, 2010; Mor, 2010; Salman & Savies-Laure, 2005; Singh et al., 2012). While the quantity of resources that firms accrue from direct and indirect ties contribute to their innovation, the quality of the resources is also an important facet regarding the impact of networks (Gulati et al., 2011; Madhavan & Prescott, 2017; Sarkar, Aulakh & Madhok, 2009). Studying the benefits of the quantity of resources that firms accrue from the network of partners without accounting for attributes or quality of these resources cannot sufficiently explain innovation (performance) differential (Sarkar, Aulakh & Madhok, 2009).

Our results suggest that firms benefit from both the quantity and quality of their direct and indirect ties and that the nature of these benefits varies significantly depending on the quality of their partners' resource. Our research also indicates that the quality of resources possessed by partner firms that firms access through direct ties have a stronger impact on their innovation performance than the quantity of resources in terms of the number of direct ties. Similarly, the quality of resources that firms can access through indirect ties has stronger impact on their innovation performance than the benefits they accrue from the quantity of partners' resources through indirect ties. These findings lend support to the ideas that firms occupying the same structural position may benefit differently from their network centrality depending on the attributes of partners that they are connected to (Gulati et al., 2011).

The theoretical implications of these findings suggest the need to simultaneously explore the effects of the quantity and quality of resources. Thus, our study contributes to the recent body of literature that explore the roles that the attributes of partners or the quality of network resources has on firms' (innovation) performance (Gulati, 2007; Gulati et al., 2011; Lavie, 2006; Madhavan & Prescott, 2017; Madhavan et al., 2008; Sarkar, Aulakh & Madhok, 2009).

In addition, our study contributes to both the social capital perspective and social embeddedness stream of the network literature (Granovetter, 1985, 1992; Uzzi, 1996; 1997; Gulati, 1997; Lavie, 2007). It explores the effects of centrality, a structural feature of network, alongside the quality of ties to partners, a relational aspect of network (Gulati et al., 2011) and hence it goes beyond the dominant logic in most prior studies that have exclusively relied upon either the structural (Coleman, 1988; Portes, 1988; Burt, 1992; Putnam, 1993; Adler & Kwon, 2002) or relational embeddedness perspective in studying the effect of network ties. By simultaneously considering the structural, relational, and actor attributes as determinants of innovation performance, our study offers additional insights into the role of network ties on firms' performance.

Finally, our research enriches the extant literature by showing that the number of partners from which firms' license technology, the quality of their partners' resources and the ability to reconfigure and recombine this technology through their own innovative capabilities contribute significantly to their innovation performance.

Besides these theoretical and empirical contributions, our findings also have some interesting managerial implications. When firms act as licensees, they should not only focus on creating a broad portfolio of licensing agreements with a diversity of licensors. It is crucial for them to connect to licensors that are able to give them access to cutting-edge technologies. In addition, in this context, to increase innovation performance, the quality of partners is more important than their quantity. The quality of licensing partners is also apparent in the impact of the quality of a firm's indirect partners, i.e. the quality of the licensing partners of your own partners. In essence, this suggests that managers should not just connect to a large number of licensing partners to get access to a variety of technological insights but should strategically evaluate the technological capabilities of both their direct and indirect partners as this enhances the quality of resources they can accrue from their broader licensing network and improve their innovation performance.

As with all empirical studies, this study also has several limitations, which provide potential avenues for future research. First, the findings of this study are based on the patenting and licensing data of firms operating within the semiconductor industry. The implications of market and technological dynamics within the semiconductor industry may vary from those of other high-tech industries, such as pharmaceutical, chemical, and telecommunication industries and industries that are characterized as medium or low-tech. Further studies are needed to investigate whether our findings are also relevant in a much wider variety of industry settings. The second limitation of this study is the use of patent data as a measure of innovation. As it is well known in the literature, not all innovations are patented, and some innovations are not patented for strategic reasons (Trajtenberg, 1987; Griliches, 1990; Jaffe et al., 1993). Future studies could use other kinds of innovation data related to new product and process development and to the actual market success of new products. Qualitative data could also be used as this could provide us with more insights into social interactions between partners and the implications that this may have on innovation outcomes.

Next, in this study, we presented and explored the effects of two key aspects of networks (centrality and quality of ties) on firms' innovation performance. However, we did not explore the substitution effects at either the direct ties or the indirect ties level. Different combinations of the quantity and quality of ties at the direct and indirect ties level may lead to different innovation performance outcomes. Future research could examine the substitution effects between the quantity and quality of network ties as this could provide additional insights into the effects that network ties have on innovation.

Despite these limitations, this study makes a number of contributions to our understanding of the effects of network ties on innovation performance. By showing that firms occupying similar network positions may exhibit different innovation performance outcomes depending on the quality of their direct and indirect partners' resources, this paper contributes to the research on networks, alliances, and innovation. we hope that this study will spur further research exploring the combined effects of the quantity and quality of network ties and the attributes of partners on innovation performance.

Table 7-1: Descriptive Statistics and Pairwise Correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
Direct ties centrality	1.0000												
Quality of direct ties	0.4437*	1.0000											
Indirect ties centrality	0.5976*	0.2340*	1.0000										
Quality of indirect ties	0.3578	0.23476	0.4114*	10000									
Firms pre-network innovativeness	0.0216	0.0050	0.0304	0.0145	1.0000								
Partners pre-network innovativeness	0.3975*	0.3961*	0.3565*	0.2345*	0.0288	1.0000							
Firms size	0.2346*	-0.0268	0.0712	0.3453	0.4334*	-0.0654	1.0000						
Partners size	0.2346*	0.3776*	0.2070*	0.0123	0.0143	0.4591*	-0.0204	1.0000					
Firms age	0.0167	0.0070	-0.0038	0.0043*	0.3654*	-0.0618	0.3030*	0.0767	1.0000				
Partners age	0.2608*	0.2131*	0.2436*	0.1456	-0.0066	0.3356*	-0.0924	0.5137*	0.0009	1.0000			
Partners status	-0.0289	0.0595	-0.0214	0.0874	-0.1038	-0.0081	0.0329	0.1270*	0.0460	0.1295*	1.0000		
USA	0.0123	0.1885*	-0.0556	0.1944 *	-0.0535	0.0094	0.0040	-0.0497	-0.0748	0.1631*	0.0157	1.0000	
EUROPE	-0.0968	-0.0422	-0.0850	-0.1234	-0.0228	-0.0357	-0.0293	-0.0081	0.1840*	0.0560	0.0267	-0.0802	1.0000
Mean	3.6859	101362	11.735	322790	2226.6	2147.4	100962	2552.2	70.467	33.401	19.462	0.3388	0.0124
Standard Deviation	1.9560	263201	11.532	1551755	2834.3	2810.2	119044	7586.1	39.004	13.668	0.2259	0.4742	0.1109

Table 7-2: Random Effects Panel Negative Binomial Estimates for Direct Ties and Indirect Ties on Focal Firms Innovative Performance

Variables	Model1	Model2	Model 3	Model 4	Model5	Model6
Constant	-0.5447** (0.8171)	-1.3495*** (0.6295)	-1.3234** (0.6718)	-1.7094** (0.7211)	-1.6904** (0.7016)	-1.9721** (0.7278)
Direct ties centrality		0.1202*** (0.0054)				0.1399 * (0.0739)
Quality of direct ties			0.0661*** (0.0035)			2.13e6*** (2.84e-0)
Indirect ties centrality				0.0301*** 0.0065		0.0103 (0.0114)
Quality of indirect ties					0.0185** (0.0094)	0.0264* (0.0078)
Firms pre-network innovativeness	-0.0003*** (0.0015)	-0.0002*** (0.0003)	-0.0001*** (0.0003)	-0.0001*** (0.0002)	-0.0001*** (0.0003)	-0.0001*** (0.0002)
Partners pre-network	-0.0017** (0.0756)	-0.0012 *** (0.0003)	-0.0011** (0.0004)	-0.0020** (0.0006)	-0.0021** (0.0006)	-0.0009* (0.0005)
Firms size	3.30e-0 *** (8.99e-0)	6.13e-1*** (5.24e-1)	4.66e-3*** (5.82e-1)	5.44e-0 *** (8.36e-0)	5.44e-0*** (8.36e-0)	4.83e0*** (8.24e-0)
Partners size	0.0002 † (0.0001)	0.0002** (0.0001)	0.0031* (0.0032)	0.0001* (0.0001)	0.0001* (0.0001)	4.44e-0 (0.0001)
Firms age	0.0030 (0.0023)	0.0001 (0.0120)	0.0011 (0.0011)	0.0001 (0.0020)	0.0011 (0.0010)	0.0009 (0.0021)
Firms age	0.0100 † (0.0053)	0.0012 (0.0042)	0.0055 (0.0035)	0.0066 (0.0052)	0.0056 (0.0042)	0.0078 (0.0050)
Partners status	-0.6284 (0.3995)	-0.5344 (0.4471)	-0.3123 (0.3225)	-0.4132 (0.3477)	-0.3164 (0.3223)	-0.3360 (0.3534)
USA	0.6271 *** (0.1690)	0.3463** (0.1944)	0.2323* (.2215215	0.3332** (0.1491)	0.3297** (0.1389)	0.1859** (0.1563)
EUROPE	-0.5798 (1.2233)	-0.7566 (1.250)	-0.4439 (1.0230)	-0.4132 (0.3477)	-0.4523 (0.3347)	-0.5255 (1.0170)
Jap & S. Korea	Include	Include	Include	Include	Include	Include
Others Dev. Nation	Include	Include	Include	Include	Include	Include
Far East Asia	Include	Include	Include	Include	Include	Include
Rest of World	Include	Include	Include	Include	Include	Include
Number of obs	342	342	342	342	342	342
Log-likelihood	-3966.84	-3949.41	-3923.35	-3922.61	-3922.24	-3921.51
Wald chi-square	72.51***	108.24***	108.77***	109.06***	109.47***	298.59***
Models Δx^2		(2) – (1) 35.73***	(3) – (1) 36.26***	(4) – (1) 36.55***	(5) – (1) 36.96***	(6) – (1) 72.51***

Standard errors are in parentheses. † P < 0.10; * P < 0.05; ** P < 0.010; *** P < 0.001

8. CONCLUSION

This thesis has dealt with one of the most critical management issues of our time, that is, collaboration among firms. In recent years, increasing pace in technological development and interdependence among firms and their activities have led to an increase in collaboration among firms. Collaboration involves the sharing and exchange of resources and capabilities among partners, at times even between competitors, which entails new requirements for the management of firms' activities.

The thesis has examined the collaboration strategy of firms from three critical perspectives – technological sharing (licensing), ecosystems and networks. In each perspective, it has responded to a pressing question in the areas of research, thus advancing our understanding of how licensing (technological sharing) through networks and ecosystems shape organisational outcomes.

From a licensing perspective (study 1/chapter 5 of this thesis), it provides empirical evidence on the conditions under which firms prefer to exchange their technology through cross and unilateral licensing. It investigates the firms' licensing preference from both the characteristics of the firm and those of its partners. As a result of far-reaching influences of diversification, the thesis argues that market diversification may be a more informative determinant for a firm's licensing preference than the firm size that has been examined in the prior literature. A large firm may operate only in a single market and technological space, whereas operating in multiple markets and multiple technological spaces enhance firms' learning potential enabling them to develop more critical assets, which in turn, strengthens their bargaining position and competitive advantages.

The finding shows that at the firm level, firms or licensors' licensing preference is shaped by the capabilities that firms accrue from operating in multiple markets and multiple technological spaces, and the imperative to capitalise on the benefits of these capabilities determines firms' licensing preference. This finding suggests that because more diversified firms possess more capabilities (patents) they tend to prefer cross licensing as this licensing type offers them the opportunity to access and share advanced knowledge of partners enhancing their ability to benefit from their technology. Less diversified firms may prefer unilateral licensing because they lack the technological competencies and patent stocks required for cross licensing.

At the pair level, the finding reveals that the licensing preference of firms is based on the magnitude of the competitive risks that they face from licensing their technology to partners. When licensors operate in fewer markets and technological spaces than licensees do, the former tend to prefer to engage in cross licensing rather than unilateral licensing. The finding suggests that because increasing market and technological diversification significantly enhances a firm's learning and absorptive potential when less diverse licensors are faced with more diversified licensees; they are more likely to prefer the licensing type that will shield them from the risk of increasing competition. This finding is consistent with prior licensing studies from the competitive perspective (Arora et al., 2003; Fosturi, 2006; Siebert & Von Graevenitz, 2012), which show that with increasing competition firms tend to be more cautious in their licensing decision and they tend to prefer the licensing type that will guard them against the adverse effects of increased competition.

The findings from this study also show that as distinctive focal activities, the experience that firms' possess in cross and unilateral licensing influences their licensing preference. The finding suggests that the development of reliable routines and processes facilitates the ease with which licensors can orchestrate a specific licensing type and significantly increases their preference to use that type of licensing agreement in the future.

Lastly, the findings also indicate that the size of the licensor vis-à-vis its licensing partner may be a more important predictor for the licensor's licensing preference than the licensor size. The results suggest that licensors' licensing preference is influenced not just by the resources that they possess but also by the degree of competition that they would face from using a particular licensing type.

For managers, based on the licensor characteristics and licensing pair differential characteristics uncovered in this study, the findings suggest that by selecting the appropriate licensing agreement IP managers can optimise the amount of values they can capture from their technology. The findings also suggest that based on their capabilities firms should select the licensing type that would enable them to capitalise on these resources. It demonstrates that licensors should factor in how diversified they are relative to their partners in their licensing decision. When licensors operate in fewer markets and technological spaces than licensees, licensors face a higher risk in the partnership and should select the licensing type that would shield them from the adverse effect of increasing competition in the marketplace.

From an ecosystem perspective (study 2/chapter 6), the thesis provides an alternative explanation for heterogeneity in focal firms or ecosystem orchestrators' performance, which hinges on the roles of the architectural components of the ecosystem. By distinguishing the components within an ecosystem into technology and actors, this study offers an additional lens for understanding how interaction among actors (cooperation) and the coordination of technologies (coordination of activities) within ecosystems contribute to performance outcomes. It argues that the degree of technological interconnectedness (technology complexity) and the level of actors' interactions (actor complexity) within ecosystems influence the amount of value that firms generate in their ecosystems. In line with these hypotheses, this study reveals that increased level of technology and actor ecosystem complexity enhances the amount of value that firms accrue from their ecosystem. The findings suggest that increased level of technology complexity reinforces the architecture of focal firms' technology and leads to the emergence of bottlenecks. It supports the view that controlling strategic bottlenecks that result from supply limitation – when reinforced with architectural control and legal protection such as patents – enhances focal licensors' capacity to generate value from ecosystems. The findings also suggest that when actors interact with a large and diverse set of actors (increased actor ecosystem complexity) because of increased knowledge that focal actor gained from the interaction, they are more efficient in coordinating the ecosystem technology thus enhancing their ability to generate superiority from their ecosystem.

Finally, the findings also indicate that the focal firm's technology complexity and actor complexity jointly augment the focal firms' performance. This finding illustrates that focal firms' ability to reap superior benefits from their ecosystems may depend not just on the alignment of technologies within their ecosystem, but also on the degree of interactions among actors in the ecosystem

These findings have important implications for the ecosystem literature. Unlike prior studies that have traditionally explained the performance of focal firms from either the structural properties of the ecosystem (structuralist perspective) or the relational embeddedness of actors within the ecosystem (actor-centric perspective), the architectural approach proposed in this thesis complements both the structural and actor-centric approaches. The findings add to the structural approach by showing that rich interconnectivity among partner technologies offers the focal firm greater control over its technology and makes it much more difficult for rival firms to access its partners (Adner & Kapoor, 2010; Ethiraj, 2007; Ethiraj & Posen, 2013). It also advances the actor-centric perspective of the ecosystem literature (Jacobides et al.,2015; Rong & Shi, 2014;) by considering not just how the attributes of partner firms contribute to focal firms' value creation but also how the licensing deal in which they engaged (mechanism) influences the degree of interaction within their ecosystem and performance.

For managers, the findings suggest that when constituting their ecosystems, managers should consider the attributes of their partners in terms of the number and diversity of actors and technologies as ecosystem orchestrators tend to perform better when the technologies and actors within their ecosystems originate from a broad and diverse range of industry settings.

From the last perspective, networks – study 3/chapter7 - the thesis provides empirical evidence on how the effects of the quantity and the quality of direct and indirect network ties affect firms' innovative performance. This study aligns with prior literature on the relational aspect of networks and argues that while the number of resources that firms accrue from direct and indirect ties contributes to innovation, the source of these resources also matters. The findings indicate that the quality of resources and capabilities that firms access from direct ties and indirect ties have a much stronger impact on their innovative performance than the quantity of resources. The results suggest that while connecting to a large number of partners enables firms to access a large quantity of resources, the quality of partners' resources enables them to find complementarity between their resources, enhancing their innovation potential.

These findings have important theoretical implications for the literature on network ties and innovative performance. First, they contribute to the recent body of literature exploring the roles of partners' attributes or the quality of network resources on firms' innovation performance (Gulati et al., 2011; Lavie, 2006; Madhavan & Prescott, 2017; Madhavan et al., 2008; Sarkar, Aulakh & Madhok, 2009). The findings lend support to the idea that firms occupying the same structural position may benefit differently from their network centrality depending on the attributes of partners to which they are connected (Gulati et al., 2011; Madhavan & Prescott, 2017; Sarkar, Aulakh & Madhok, 2009). In addition, the findings also contribute to both the social capital perspective (Adler & Kwon, 2002; Burt, 1992; Coleman, 1988; Portes, 1988; Putnam, 1993;) and social embeddedness stream of network literature (Granovetter, 1985, 1992; Uzzi, 1996; 1997) as the study explores the effects of centrality – a structural aspect of network – jointly with the quality of ties to partners, a relational aspect of network (Gulati et al., 2011).

For managers, these findings suggest that they should not simply connect to too many partners but should strategically evaluate the capabilities of partners before collaborating with them as firms that are connected to partners with more cutting-edge technologies accrue more significant benefits from their networks than those that are connected to partners with fewer quality technologies.

8.1. Limitations and Suggestions for Future Research

The three empirical studies constituting this thesis are subject to several common limitations, which could serve as possible avenues for future research. The first limitation of this thesis relates to its research setting. The three studies of the thesis are all operationalised within a single industry (semiconductor industry), which implies that the findings may not be easily generalised. Although the theories and hypotheses developed in the studies may not depend on the distinctive features of the semiconductor industry, we are conscious of the fact that the characteristics of firms in other high-tech industries such as pharmaceutical, chemical and telecommunications industries may vary significantly from those of semiconductor industry. A natural way forward to deal with the issue of generalisation is for researchers to broaden the scope of these studies by incorporating data from other high-tech industries.

The second limitation of this thesis is its use of patent data as a measure of innovative performance. Not all innovations are patented, and some innovations are not patented for strategic reasons (Griliches, 1990; Jaffe et al., 1993; Trajtenberg, 1987). Patents may therefore not account for all firm innovation outputs. In addition, patents do vary across industries (Hall et al., 1986). Although in this thesis patent data are collected from the semiconductor industry – an industry with a high level of patenting and R&D activity – which minimises sectorial differences in patenting activities, patent counts are still an imperfect measure of innovation (Hall et al., 1986). Future studies could use other kinds of performance data such as financial ratio-based measures – profitability, return on equity, return on investments and sales growth – and economic or market-based measures – new product generations, market entry and failure rates. Qualitative data could also be used as this could provide more insight into the collaborative strategies of firms and its implications on innovation outcomes.

The last limitation of this thesis relates to the sources of data. The findings of this thesis are based on licensing and patenting data collected from the SDC Thompson Reuter and NBER databases, respectively. The licensing data on SDC databases are compiled from alliances that are publicly announced by the alliance parties, and are therefore highly skewed towards alliances in the US and the Western world. This means that data of alliances that are not publicly published as well as alliances elsewhere may be lacking, which may provide a distorted picture of the number of alliances that occurred during the sample period. In addition, the patent data used in this thesis originates only from the USPTO in the NBER database. Although using patents from a single regime may reduce issues of comparability, reliability and consistency resulting from using patent data from many different jurisdictions, it may also lead to bias, especially towards non-Western firms. Thus, researchers may seek appropriate methods and mechanisms to calibrate patents from different jurisdictions as this may enable the measurement of innovative performance in a more reliable manner enhancing the quality of findings in this area of research.

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