BORROW AND BUY: COMPLEMENTARITY AND SUBSTITUTABILITY OF ACQUIRERS' ALLIANCES AND TECHNOLOGY ACQUISITIONS

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To my parents, who sacrificed so much to give me a better life.

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ABSTRACT

What is the relationship between a firm's alliances and its acquisition choice and performance? In this dissertation, I argue that alliances may not only substitute for, but also be complementary to technology acquisitions. I also propose that acquirer's alliances and how they relate to the target have an important effect on that acquirer's acquisition performance. I highlight the role of distinct components of the acquirer's alliance portfolio – its functional and technological alliances in, or outside of its core business – for that firm's technology acquisition choice and performance. When it comes to choice, I show that a higher number of functional alliances is correlated with a higher number of technology acquisitions in same business segments, and with a lower number of technology acquisitions in other business segments where the firm may not have functional alliances. At the same time, technological alliances generally substitute for technology acquisitions, but may be complementary to technology acquisitions within strategically important markets outside of the acquirer's core business. Building on my investigation into acquisition choice, I show that both functional and technological alliances are an important factor in performance outcomes of technology acquisitions following these strategic choices. I find evidence supporting my claims using a sample of 208 large, public, high-tech US firms from 1996-2010, with their 13,074 total unique alliances and 5,215 unique acquisitions, as well as over 1.4 million unique patents. I contribute to corporate strategy and technology and innovation management research by showing how firms' boundary choices, specifically when it comes to technology acquisitions, as well as the performance outcomes of these choices, are influenced not only by internal, but also by external resources and capabilities accessible through their alliance portfolios. I also address the enduring puzzle of why firms engage in seemingly unrelated acquisitions by showing that sometimes, such transactions may in fact be indirectly related and complementary to the acquirer through its alliance portfolio.

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1. INTRODUCTION

What is the relationship between a firm's alliances and its acquisition choice and performance? Despite the considerable volume of recent alliance- and acquisition-related studies, not much research exists that looks beyond a single dyad or a transaction and explores in detail the way a firm's alliances influence both the way that firm chooses to engage in acquisitions, as well as these transactions' resulting outcomes. When it comes to academic thinking about alliances and acquisitions taken together, with the exception of a few studies looking at some relationships between whole portfolios of transactions (Hernandez and Shaver, 2017; Stettner and Lavie, 2014), in strategy literature these are most often considered as alternatives to each other (Capron and Mitchell, 2009; Villalonga and McGahan, 2005; Lungeneau, Stern, and Zajac; 2016); or analyzed in the context of how learning from one may influence the other (Zaheer, Hernandez, and Banerjee, 2010; Zollo and Reuer, 2010). I argue that alliances may not only substitute for, but also be complementary to technology acquisitions, and that there is much to be gained by thinking more carefully about the relationships between these external transaction modes.

In this study, I describe how functional alliances may actually be complementary to technology acquisitions within the business segments where these transactions occur, while serving as disincentives to technology acquisitions in other business segments. I also propose that technological alliances are generally substitutes to technology acquisitions, but may also be complementary to technology acquisitions in those strategically important segments outside of the acquirer's core business where the acquirer accumulates technological capabilities through alliances. I then explore acquisition choice as well as the performance implications of these choices given the acquirer's alliance portfolio.

I argue that there is much to be learned from understanding firms' entire mixed portfolios of transactions, where resources and capabilities[1] concurrently sourced from alliances and acquisitions may be not only substitutable, but also complementary to each other. This is supported by recent work pointing out that not only are governance choices interdependent (Argyres and Liebskind, 1999; 2002; Leiblein, 2003; Leiblein and Miller, 2003), but also that especially in knowledge-intensive industries, firms often need access to whole bundles of co-specialized, interdependent resources and capabilities that may require for the focal firm to engage in more than one transaction (Argyres and Zenger, 2012; Kaul, 2013). I propose that under certain conditions, some resources and capabilities may be best accessed through alliances, while other complementary resources and capabilities may be best internalized through technology acquisitions, and the resulting bundles of capabilities may be recombined to create value and to improve firm performance. As I will elaborate in more detail later, observational data indeed shows that firms like Apple, EMC, Cisco Systems, and Intel tend to engage in both acquisitions and alliances, often concurrently and in pursuit of the same strategic goals (CB Insights, 2016; SDC Platinum, 2017). After theorizing about firms' acquisition choice, I then

[1]Concepts of resources and capabilities are often debated and, at least to a degree, often conflated (Amit and Schoemaker, 1993; Makadok, 2001). In this study I use both terms interchangeably largely in the same spirit (Madhok, 2002), but rely conceptually more on capabilities as a shorthand to discuss bundles of both capabilities and the resources orchestrated through these capabilities, presumably with a degree of at least basic competence (Capron and Mitchell, 2009; Helfat and Peteraf, 2003; Helfat and Lieberman, 2002; Kaul and Wu, 2015), most closely resembling key "strategic assets" that are the determinants of economic rents, as discussed by Amit and Schoemaker (1993).

discuss performance implications of firms' acquisition choices given their alliance portfolios.

I explore my theory using a sample of 208 large, public, high-tech US firms from 1996 through 2010, complete with their 13,074 total unique alliances and 5,215 unique acquisitions, as well as over 1.4 million unique patents in portfolios of all of these firms, whether a focal firm, an alliance partner, or a target. In estimating both acquisition choice and performance, I try to account for endogeneity of a firm undertaking any acquisition by incorporating a two stage selection adjustment, and making the type of an acquisition and its performance conditional on that firm engaging in any acquisition at all, as well as by using matched treatment and control groups. I employ alternative model specifications, including panel fixed effects, and investigate not only firms' acquisition choices, but also performance implications of these strategic decisions. I refrain from making the strongest causal claims, but intend for this study to be a meaningful first step towards investigating complex and endogenous underlying relationships between transaction modes, as well as corresponding strategic choices that firms make.

I set out to make three distinct contributions. First, I contribute to understanding corporate scope and boundary decisions, specifically core and non-core technology acquisition choice, in knowledge-intensive settings (Argyres, 1996; Helfat and Eisenhardt, 2004; Helfat and Peteraf, 2003; Kaul, 2012; Penrose, 1959; Silverman, 1999). I elaborate how resources and capabilities accessible through the firms' alliance portfolios may influence the likelihood of firms to engage in core or non-core technology acquisitions. As firms in knowledge-intensive industries often engage in both alliances and acquisitions concurrently and sequentially, I try to untangle complex interdependence between technology sourcing modes, adding nuance to scholarly understanding of strategic fit and complementarity (Capron and Mitchell, 2009; Hitt *et al*., 1996; Lee and Lieberman, 2010; Zaheer, Castaner, and Souder, 2013). I find evidence for a multifaceted relationship between alliances and acquisitions, where alliances may serve as substitutes or be complementary to technology acquisitions, as I explore distinct influences of core and non-core, functional and technological components of the alliance portfolio on acquisition choice.

Second, I contribute to understanding the <u>performance</u> implications of these technology acquisition choices given the focal firm's choice in the context of its external portfolio of resources and capabilities accessible through alliance partners, adding a new dimension to prior literature on acquisition performance that until now largely focused on the role of the acquirer's internal resources and capabilities, or spillovers with respect to corporate development experience and specific prior dyadic relationships (Ahuja and Katila, 2001; Cloodt *et al*., 2006, King *et al*., 2008; Lavie and Stettner, 2014; Zaheer *et al*., 2010; Zollo and Reuer, 2010). Although assessing acquisition performance is complex and requires further investigation, I find encouraging evidence that the composition of the firms' alliance portfolios has a distinct influence on both financial and innovative performance of acquisitions given the acquisition choices that they make, and, given tradeoffs between different aspects of performance that firms may face as they make their acquisition choices, that performance generally follows patterns I theorize with respect to acquisition choice.

Third, I contribute by proposing that if we pay attention to these external resources and capabilities that firms may access through their alliances, we can move towards resolving the long-standing puzzle of why firms engage in acquisitions that seem to be unrelated to their core business, as well as address the mixed findings with regard to performance of such transactions (Harrison *et al*., 1991; King *et al*., 2004; Park, 2003; Seth, 1990). I find support for my assertion that what are often assumed to be unrelated non-core acquisitions may in fact be indirectly related and strategically coherent from the focal firm's perspective (Teece *et al*., 1994) when they are complementary to the capabilities and resources in the acquirer's alliance portfolio, and I find strong evidence that these acquisitions are often among the best performing deals compared to all other transactions.

2. THEORY AND HYPOTHESES

2.1 GENERAL THEORY AND RELEVANT LITERATURE

2.1.1 General Assumptions

In this dissertation, I proceed from certain assumptions which are generally in agreement with those in the relevant literature. In modern markets, technological complexity, uncertainty, and pace of change make competition in most prominent industries especially challenging, and access to external resources and capabilities becomes one of the key considerations for firm survival and performance (Bourgeois and Eisenhardt, 1988; Brown and Eisenhardt, 1997; Eisenhard, 1989; Helfat and Eisenhardt, 2004; Madhok, 2002). Much of competition revolves around changing complementarities and technological resources and capabilities as some of the main differentiators (Lee *et al*., 2010). It is specifically these systems of complementarity and capabilities that are the focus of my research.

Firms in today's dynamic settings are in general more likely to remain involved in ongoing technological development, and potentially reconfiguration, renewal, and redeployment of resources and capabilities over time (Agarwal and Helfat, 2009; D'Aveni, 1994; Helfat and Eisenhardt, 2004; Galunic and Eisenhardt, 2001; Karim and Mitchell, 2000; 2004). Few, if any, firms can integrate every part of the value chain and the relevant business ecosystem and operate completely autonomously. Instead, these firms are induced to continuously search externally for technologies, partners, suppliers, and new distribution channels, leading to increased inter-organizational interdependence in these settings (Adner and Kapoor, 2010; Ireland *et al*., 2002; Langlois, 1992; Jacobides and Winter, 2005).

However, external partnering for capability sourcing is by no means a straightforward task, for two related reasons. First, modern high-velocity environments imply a higher degree of technological uncertainty, making technological development or assessment of future technological states more difficult, and resulting in a premium placed on knowledge breadth of, as well as the ability to recombine and use both internalized and external resources and capabilities (Eisenhardt, 1989; Eisenhardt and Martin, 2000; Jacobides and Winter, 2005; Leiponen and Helfat, 2010; Nelson and Winter, 1992). Moreover, as it is especially challenging to predict the outcome of technological collaborations or the direction of technological trajectories in these settings, returns to redundancy and optionality and depth, whether as the ability to conduct multiple experiments, or to collaborate with multiple partners in same area, may increase (Brown and Eisenhardt, 1997; Dosi, 1982; Helfat and Raubitchek, 2000; Leiponen and Helfat, 2010). Second, these dynamic nature and uncertainty combine to make it more challenging to find, develop, and contract outside partners and suppliers. Complementarities between products, technologies, and firms change over time (Langlois, 2002; Lee *et al*., 2010; Teece, 1986; 2006), and the average stability of partnerships in the focal firm's alliance portfolio may then end up lower on average in more uncertain settings. This may lead firms to be more proactive in a constant search for new partners and for access to new external resources (Heide and John, 1990; Perry, Sengupta, Krapfel, 2004; Stump and Heide, 1996).

At the firm level, I assume that managers operate under conditions of bounded rationality, but have a degree of basic strategic foresight as they seek to balance both costs and benefits of their existing and potential heterogeneous resource endowments in pursuit of and in an attempt to balance both short- and long-term performance (Ahuja, Coff, Lee, 2005; Amit and Schoemaker, 1993). However, given high level of uncertainty in dynamic settings, managers, even if they have complete information about the current state of the firm and the industry, will not always be able to clearly assess what the best strategic decision is in every situation. This will lead to heterogeneity in firms' strategic actions and resulting outcomes. Existing alliance portfolios are then both the path-dependent result of prior strategic decisions, as well as a source of accessible external capabilities that may influence future strategic decisions[3] given environmental uncertainty. So firms may rely not only on internalized resources, whether internally developed or acquired, but also on those accessible through alliances (Capron and Mitchell, 2009; Das and Teng, 2000; Grant and Baden-Fuller, 2004; Lavie, 2006), and which can be recombined with other externally or internally sourced capabilities (Wassmer and Dussauge, 2011). Although I acknowledge internal research and development as important (Cassiman and Veugelers, 2006), I focus on the role of firms' portfolios of external relations, and so I hold constant the focal firm's internal capabilities (and control for them in my empirical analysis) as I develop my theory[4].

I also assume that when firms make strategic decisions, they do so in a coherent, non-random manner, pursuing opportunities and markets that they perceive as complementary and compelling in light of their own existing capabilities and aspirations (Breschi, Lissoni, Malerba, 2003; Foss and Christensen, 2001; Penrose, 1959; Teece, *et*

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[3] This approach to looking at interdependence of resource and capability endowments, strategies, boundary choice, and resulting performance outcomes is largely in line with contemporary strategy literature (Argyres and Zenger, 2012; Jacobides and Winter, 2005; Madhok, 2002).

[4] To further clarify, I assume that at the baseline, all firms engage in some kind of internal capability development, and then may choose to access additional external capabilities through alliances, acquisitions, or both.

al., 1994). This complementarity[5] is dynamic, that is changing both over time, as well as through market space as industries, markets, and firms' own capabilities and resources evolve (Foss and Christensen, 2001; Jacobides and Winter, 2005; Zaheer *et al.*, 2013).

Finally, I also assume that although firms may have a stated or modal preference for either alliances, acquisitions, or corporate venture capital investments (Capron, 2015; Capron and Mitchell, 2009; 2012, Villalonga and McGahan, 2005), firms are generally aware that all of these strategic choices exist, and so these are not mutually exclusive choices as some of the literature occasionally assumes. A firm may then simultaneously or sequentially engage in all types of external transactions, or none at all, limited only by its available resources. From a theoretical perspective, I treat factors related to both transaction costs and resources as at least partially interdependent, and allow that due to both exogenous and endogenous factors, such as firm-level capability development or industry evolution, different firms may face heterogeneous transaction costs in otherwise similar positions (Argyres and Zenger, 2012; Jacobides and Winter, 2005; Langlois, 1992; Leiblein, 2003).

2.1.2 When are Alliances and Acquisitions Complementary or Substitutable?

Researchers already know that firms may source capabilities externally through either alliances, which may allow for greater optionality and flexibility, but potentially lower appropriability (Gulati, Lavie, and Singh, 2009; Lavie, 2007); or through acquisitions,

[5] It is important to highlight here that the nature of complementarity is complex and still actively debated, resulting in concurrent use of different terms, for example relatedness, which in my definition is subsumed under complementarity (Breschi *et al.*, 2003; Harrison *et al.*, 1991; 2001; Teece, 1986; 2006; Teece *et al.*, 1994; Zaheer *et al.*, 2013).

which may increase appropriability and improve integration of complex knowledge, but are generally assumed to be more costly and to imply lower flexibility (Capron, 2015; Higgins and Rodriguez, 2006; Kaul and Wu, 2015). Consequently, when it comes to connecting the two transaction modes, in contemporary literature these are most often viewed as substitutes and alternatives to each other (Capron and Mitchell, 2009; Villalonga and McGahan, 2005; Lungeneau *et al*; 2016), sometimes allowing for limited spillover of experience or learning from one mode to another (Zaheer *et al*., 2010; Zollo and Reuer, 2010).

The main underlying mechanisms are subsumed under complementarity and substitutability. When it comes to **complementarity**, I include all information-, knowledge-, and resource-related mechanisms that may contribute to additional synergistic value creation when resources and capabilities are combined. The general complementarity that is central to both mechanisms can be articulated with the assistance of Milgrom and Roberts (1995): possessing specific accessible types of capabilities and resources in the alliance portfolio may lead to additional value creation, through the means listed above, when combined with resources and capabilities assimilated from the acquisition in question (Lien and Klein, 2008).

Substitutability is related to complementarity but concerns the nature of underlying redundancy: are the resources and capabilities already accessible through the alliance portfolio and those acquired substitutable, and is the nature of this substitutability value-destroying or value-creating? Is there a payoff to this substitutability, for example, where an ability to experiment is valuable, and does that added value exceed the costs of redundancy? If the net effect is positive, then substitutability in fact leads to complementarity. However, if the costs of redundancy exceed value created, the net performance effect is negative, becoming an inverse of Milgrom and Roberts' (1995) complementarity: when the firm possesses resource *A*, the value of adding resource *B* would be less than if the firm only had *B* without *A*. The key to my theory is that both complementarity and substitutability factors related to any technological acquisition matter not only when it comes to the combined resources and capabilities of the target and the acquirer, but also complementarity and substitutability of the capabilities from the acquirer's alliance portfolio with those of the target.

So in settings where knowledge and governance choice are not independent (Kapoor and Adner, 2012), firms may treat alliances and acquisitions as not just substitutes, but also as potentially complementary to each other within the firm's whole portfolio of transactions, engaging in both and internalizing some sets of capabilities through acquisitions, while relying on partners for others. I propose that some technology acquisitions may become more valuable in presence of alliances that give the firm access to bundles of complementary resources, and vice versa, that some technology acquisitions may similarly enhance the value of the firm's alliances.

For example, a firm may choose to internalize some knowledge resources or a part of an activity through an acquisition, even at a higher relative cost, in order to better manage another distinct set of alliance activities, or in order to create valuable and uniquely complementary bundles of resources (Argyres and Zenger, 2012; Kapoor and Adner, 2012). Internalizing some key set of technological capabilities in one area may also increase the firm's ability to integrate knowledge in a new market, or to better appropriate value created in a technological collaboration in the same area. At the same time, using alliances concurrently with acquisitions allows for additional flexibility and optionality that may be necessary when facing technological uncertainty. Anecdotal evidence indeed suggests that firms often have to rely on combining alliances and acquisitions to access bundles of complementary resources and capabilities that they may need[6]. Consider the following two examples.

First, from a product family perspective, Apple's iPhone is often discussed colloquially as a proprietary, Apple-specific product, assumed to be designed almost entirely by Apple's own engineers. Yet the iPhone product line draws heavily on resources obtained from both alliances and acquisitions (See Figures 1a and 1b). Each major software or hardware component of the iPhone has been developed and improved through the use of multiple alliances and technology acquisitions (SDC Platinum, 2016; Techninsights, 2017). For example, to be able to design and to externally manufacture Apple's industry-leading[7] custom "*A*"-series chipsets, the "brains" of iPhones and iPads, Apple not only acquired semiconductor firms *P.A. Semi* (2008), *Intrinsity* (2010), *Anobit* (2012), *Passif* (2013), and *Primesense* (2013), but also entered partnerships with semiconductor development and manufacturing partners like *ARM*, *Imagination Technologies*, *Intel*, *Samsung*, and *TSMC* (SDC Platinum, 2016; Stone *et al*., 2016). I argue that such complex configuration of external capability sourcing activity is not merely an artifact of independent dyadic transaction choices, but rather an indication of

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6 This may be the case even if firms are thought to have a preferences for one type of transaction over the other. Consider that Cisco Systems, generally described as a serial acquirer, also engages in many technological and functional alliances, while Hewlett-Packard, often said to prefer alliances, engaged in at least ten acquisitions in 2007 alone (SDC Platinum, 2016). This is generally a consistent pattern for firms in my own data.

7 For example, Apple's A7 was industry's first 64-bit smartphone processor in 2013, surprising industry analysts, and putting Apple well ahead of semiconductor powerhouses like Samsung and Qualcomm (Bauder, 2013; Stone *et al*., 2016).

existence of complex underlying complementarity and interdependence that may lead firms to concurrently access some capabilities through partnerships, and others through acquisitions.

Figure 1A: Apple's Select Technology Acquisitions Related to iPhone Components

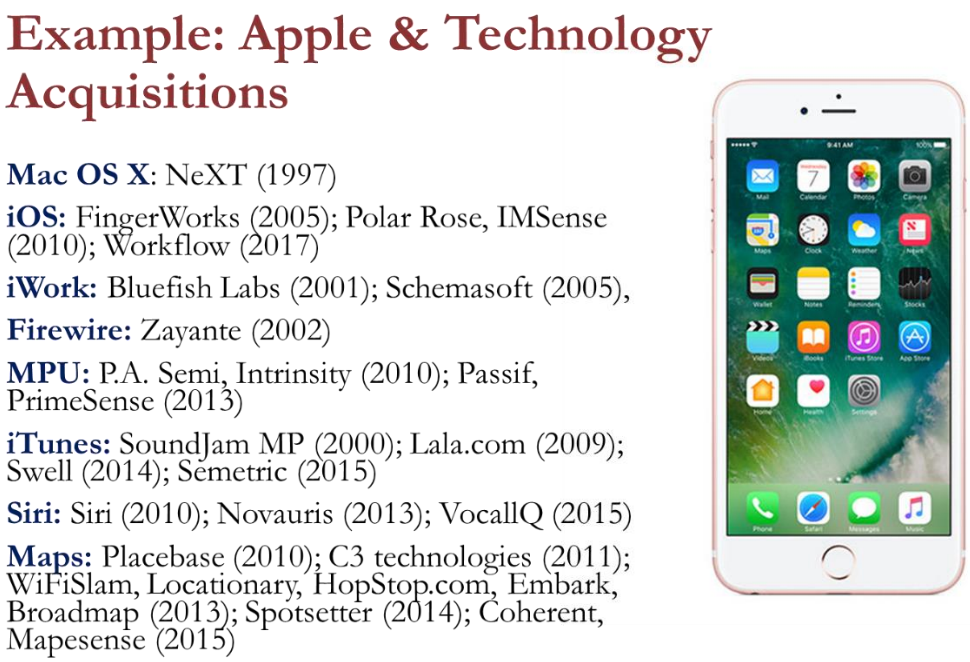

Figure 1B: Apple's Major Technological and Functional Alliance Partners Important to the iPhone

Second, if we were to take a business-level perspective in the context of co-evolution of capabilities and transaction costs, and firms and industries over time (Argyres and Zenger, 2012; Jacobides and Winter, 2005; Langlois, 1992), EMC Corporation provides a good example. In the last two decades, as information technology and industry co-evolved, EMC augmented its core business in enterprise data storage hardware and expanded its reach into new market segments like data security and cloud storage by using both alliances and acquisitions, often concurrently. EMC used acquisitions to gain access to new technologies, while also relying on a variety of partners across market segments for projects ranging from technology development to marketing and distribution. "Frankly, we have always built through a combination of acquisition, partnership, and internal development", explained an EMC vice president in one of the interviews (Kane, 2003). For example, in the storage virtualization segment, from 2001 through 2015, EMC entered alliances with *Cisco*, *Juniper Networks*, *Oracle*, and *Wyse Technology*, and acquired *VMware*, *Rainfinity*, *Acxiom*, *Akimbi*, *YottaYotta*, and *Syncplicity*. Similar patterns are present in most of the segments in which EMC operates, for example, in Information Security and e-Documents markets, as Figure 1c below elaborates (See Appendix I for a detailed listing of EMC's alliances and acquisitions in all segments for 2001-2016). I argue that this pattern where firms may engage in both alliances and acquisitions, some of which may be complementary to each other, and often in the same markets, is common in knowledge-intensive settings, and that to understand these firms' strategic choices and outcomes, we should pay attention to their entire mixed transaction portfolios.

Figure 1C: EMC's Alliances and Acquisitions in InfoSec and eDocs Segments

Years	Form	Security+	eDocs
2001-2005	ALLIANCE	Mobius Management, Surety LLC	Document Sciences, Thunderhead, Adobe Systems
	ACQUISITION		Documentum, Ask Once, Acartus, Captiva
2006-2010	ALLIANCE	McAfee, Neoscale, Verint	Microsoft, NEC Corp, Arcot Systems, Oracle
	ACQUISITION	RSA Security, Authentica, Network Intelligence, Valyd, Verid, Tablus, Archer Technologies	Pro Activity, X-Hive, Document Sciences, Kazeon
2011-2016	ALLIANCE	Zscaler, Fortinet	Adobe Systems
	ACQUISITION	Netwitness, Silicium Security, Silver Tail Systems, Aveksa	Syncplicity

Apple’s and EMC’s concurrent alliance and acquisition moves provide support for the general logic of this study. First, these firms often use multiple alliances and acquisitions in the same business segments, supporting my assertion that especially in knowledge-intensive settings, firms may use different transaction modes to access multiple complementary or co-specialized capabilities concurrently in same market segments (Argyres and Zenger, 2012; Kaul, 2013). Second, this anecdotal evidence also bolsters my argument that this accumulation and recombination of complementary or substitutable technological and functional capabilities through both alliances, which provide optionality, flexibility, and access to a variety of unique resources, and acquisitions, which allow firms to internalize and control key strategic assets, may result in unique firm specific bundles of resources and capabilities (Argyres and Zenger, 2012) that improve that firm’s ability to create and appropriate value beyond what’s possible with just alliances or just acquisitions. For example, both Apple and EMC were engaged in key alliances with IBM and Cisco Systems, which possess functional and technological resources that were important to the two firms (Bradshaw, 2016; SDC Platinum, 2017). On one hand, both Apple and EMC may have to be wary of appropriability concerns in alliances with such large, powerful partners (Lavie, 2007). These concerns may not be simply resolved through acquisition of IBM or Cisco as a substitute to partnering because such a large transaction may be an impractical option. However, an acquisition of another firm in order to internalize some key technological capabilities may increase the focal firm’s ability to appropriate value created in alliances with such powerful partners. According to industry insiders, Apple’s previously discussed technology acquisitions in the semiconductor space significantly increased its ability to create and to appropriate value there while collaborating with potential rivals and large partners like Samsung and Qualcomm (Bauder, 2013; Stone, Satariano, and Ackerman, 2016). On the other hand, even where acquisitions are possible, relying only on internalizing capabilities may be both costly and risky in dynamic knowledge-intensive settings as it may lead to missed opportunities, technological lock-in into a wrong trajectory, and lack of flexibility or of access to key unique resources (Brown and Eisenhardt, 1997, Van de Vrande, Vanhaverbeke, and Duysters, 2009).

So to understand how firms manage their boundaries and create value by combining internal and external capabilities and resources in knowledge-intensive settings, we have to pay closer attention to firms' entire sets of externally sourced capabilities, not only as distinct transaction choices, but as also as portfolios of potentially interdependent bundles of capabilities within and across transaction modes. We should also pay attention to how firms balance external sourcing decisions across modes and contexts. First, to understand the mechanisms that influence whether some combinations of alliances and acquisitions are complementary or substitutable, we should consider the difference between both the specific transaction modes, as well as what firms may get through different types of alliances or acquisitions, and the difference between potential partners, targets, and capabilities that they may offer. Second, we should consider that when firms increase depth of their capabilities in one business segment, they may gain greater knowledge, and strength and productivity of their resources may improve (Capron and Mitchell, 2009), but this can be costly financially, and when it comes to opportunity and redundancy costs, and risky when uncertainty is high. Conversely, increasing breadth of capabilities across many markets may increase optionality and the total set of recombinatory opportunities, but may also lead to a lack of focus, high management and attention costs, and lower strength of capabilities in specific business segments.

To explore further and to investigate the underlying mechanisms and relations, I first categorize alliances and acquisitions. Alliances can be non-technological **functional**, where the focal firm gets access to, for example, a partner's marketing or manufacturing capabilities, or **technological**, where technologies are exchanged or co-developed by partners. In addition to substitutability, I look at complementarity of alliances and acquisitions in **core** and **non-core** settings, from the perspective of the focal firm's core industry (Capron and Mitchell, 2009; Kaul, 2012). Complementarity in core settings has been referred to as relatedness, similarity or as related or horizontal complementarity (Zaheer *et al*., 2013). Earlier work on relatedness in acquisitions focused on this type of complementarity (Harrison *et al*., 1991; 2001), that suggests a higher likelihood of closeness between the focal firm's own capabilities and those of the target or a partner (Capron and Mitchell, 2009).

Complementarity of assets in non-core areas, which may include complementarity between vertically-related, seemingly unrelated, or even dissimilar resources and capabilities (Teece, 1986; Zaheer *et al*., 2013), works through synergies between sets of resources or capabilities either upstream or downstream in the value chain, or across market spaces in which complementary resources and capabilities coevolve (Langlois, 1992; Teece, 1986). Non-core complementarity may be especially important in knowledge-intensive contexts where firms may have to depend on complementary resources of firms from other industries (Teece, 1986). Such complementarity may change over time as industries and technologies evolve (Jacobides and Winter, 2005; Langlois, 1992), and firms then may need to renew their capabilities, and to redeploy them between markets, leading them to seek access to new complementary non-core capabilities (Helfat and Eisenhardt, 2004; Helftat and Lieberman, 2002; Sakhartov and Folta, 2014). Access to these non-core resources driven by inter-firm interdependence may have a significant influence on firms' ability to create and to capture value (Adner and Kapoor, 2010; Kapoor, 2013; Kapoor and Furr, 2015; Teece, 1986).

When firms engage in **core** technology acquisitions, they may do so to deepen their core technological resources and capabilities, whether to augment them, or to close core capability gaps (Capron and Mitchell, 2009). When firms engage in **non-core** technology acquisitions, they may do so to broaden or to extend their technological capabilities, often facing different contexts from that of their core knowledge domains (Argyres, 1996; Argyres and Silverman, 2004; Capron and Mitchell, 2009; Karim and Mitchell, 2000; Kaul, 2012; Kaul and Wu, 2015; Lee and Lieberman, 2010). Here I also argue that when we pay attention to the externally accessible capabilities of the acquirer, some of these seemingly non-core, often discussed elsewhere as unrelated acquisitions should actually be considered **indirectly related non-core** technology acquisitions, as opposed to what would be conventionally considered an **unrelated non-core** acquisition, as the focal firm may have already accumulated complementary capabilities in a non-core segment through its alliance partners.

In the theory development that follows, I will first discuss acquisition choice in the context of acquirer's alliance portfolio, where I theorize that a higher number of functional alliances is correlated with a higher number of technology acquisitions in same business segments, and with a lower number of technology acquisitions in other business segments where the firm may not have functional alliances. At the same time, I propose that while in general technological alliances substitute for technology acquisitions, they may also be complementary to the indirectly related non-core technology acquisitions, which are acquisitions within strategically important markets outside of the acquirer's core business.

Second, having developed my theory of acquisition choice given the acquirer's alliance portfolio, I then focus on investigating performance of these acquisition choices, from the focal firm's perspective. I generally follow the logic of my hypotheses on acquisition choice with respect to complementarity or substitutability, but given that transaction and firm-level performance are complex concepts, and that there is a large divide between managerial decisions (and intentions) and their results, I focus on dissecting different aspects of performance outcomes in my empirical analysis, and then reconcile the results of my empirical analysis of choice and performance. Ultimately, I offer that both functional and technological alliances are important factors that should be considered when researchers explore performance outcomes of technology acquisitions following firms' strategic choices.

2.2 INFLUENCE OF FIRMS' ALLIANCE PORTFOLIOS ON ACQUISITION CHOICE

2.2.1. Functional Alliances as Complementary to Technology Acquisitions

In assessing the role of the acquirer's functional alliances, the relevant mechanisms described in prior literature are those of capability deployment (Helfat and Lieberman, 2002; Kaul and Wu, 2015). Combinations of compatible functional and technological capabilities are likely to be complementary, as technological capabilities can generally only be deployed when combined with appropriate functional capabilities (Helfat and Lieberman, 2002; Teece, 1986), forming bundles of financially productive synergistic resources. The value-creating mechanism in this case is combining acquired technological capabilities with partners' functional capabilities (i.e. marketing or manufacturing) that are necessary to capture value[9] from these technologies (Helfat and Lieberman, 2002; Teece, 1986). These cross-functional[10] complementary combinations of functional and technological resources have been shown to correlate with acquisition performance (King *et al*., 2008).

There are three general reasons why potential for cross-functional complementarity may be high when combining functional and technological capabilities. First, functional and technological capabilities are distinct, complementary, and non-substitutable by definition. Second, the chances of negative spillovers of complex knowledge in functional alliances may be lower than those associated with, for example, technological collaborations, due to these functional alliances' non-technological

[9] Consider again Apple's acquisitions of technological capabilities in the semiconductor space to deploy in its manufacturing relationships with the likes of Samsung and TSMC.
[10] That is combining distinct functions – i.e. marketing capabilities and technological capabilities.

purpose. Third, functional alliances may not require potentially difficult transfer of sticky, tacit knowledge to create value (Szulanski, 1996). So given availability of partners' functional capabilities, a focal firm may be induced to engage in technology acquisitions to obtain and deploy technological capabilities in order to take advantage of available cross-functional complementarities.

In addition, when it comes to markets outside of the focal firm's core business, as the focal firm gains access to functional capabilities of its partners in non-core settings, it may be induced to engage in complementary non-core technology acquisitions. Since functional capabilities may not "travel" as well between dissimilar contexts, access to partners' functional capabilities in non-core markets may prove especially valuable and meaningful as an incentive to deploy technological capabilities there (Capron and Mitchell, 2009; Helfat and Raubitschek, 2000; Sakhartov and Folta, 2014). Even if the focal firm already possesses some compatible technological capabilities, as it deploys these existing capabilities in unfamiliar settings, it may find them lacking in this new context. Research also shows that firms may realize better innovative performance when possessing both high-performing R&D function and downstream, more likely to be functional, alliances (Hess and Rothaermel, 2011). Becoming aware of technological capability gaps and opportunities for capability expansion through these functional alliances in non-core businesses may then serve as an inducement for the focal firm to acquire new or additional non-core technological capabilities in those areas.

For example, a high-tech firm may enter into a marketing alliance to sell its product in a new market segment only to find its existing technological capabilities deficient when deployed there, encouraging it to acquire additional technological capabilities in this non-core space. Moreover, as the firm would have accumulated some knowledge and experience in non-core domains while working with non-core partners, it may also develop stronger integrative capabilities in non-core contexts (Helfat and Lieberman, 2002; Helfat and Raubitscheck, 2000; Mitchell and Shaver, 2003). So when firms may choose to acquire non-core technological capabilities, they may be more likely to acquire these capabilities in those areas where they already possess access to complementary functional capabilities through their partners, as well as the resulting knowledge and experience (Wu, Wan, and Levinthal, 2014), without the need to acquire functional capabilities of their own.

So when it comes to deployment of technological capabilities both in core and non-core settings, *ceteris paribus*[11] it then generally may make more sense for the focal firm to engage in technology acquisitions in market segments, core or non-core, where it has access to partners' functional capabilities, and less sense to engage in technology acquisitions where it does not have access to such capabilities, especially if they are available elsewhere. So in addition to being incentives to acquire in markets where they can be accessed through partners, complementary functional capabilities may also serve as cross-functional disincentives[12] to technology acquisitions in segments with fewer or no such accessible functional capabilities when other more attractive opportunities for

[11] As previously outlined in my assumptions, I assume that all firms are simultaneously continuing to develop and deploy their internal resources and capabilities, but I hold this constant given that it is not the focus of my analysis. It may also be important to consider here that the relationship may be somewhat different when it comes to core vs. non-core alliances, as by definition of a core business, a firm is already presumed to have access to some internal core functional capabilities, but may not be presumed to have such internalized functional capabilities in all of its non-core segments. This presents an interesting theoretical question, but I do not address it theoretically within the bounds of this dissertation, but revisit it in my empirical analysis.

[12] These disincentives are not direct substitutions, as by definition although functional and technological capabilities may be complementary, they are distinct, and cannot directly substitute each other.

taking advantage of complementarity exist. The more alliance partners' functional capabilities the focal firm can access in its core domain, the less likely it will be to engage in technology acquisitions in non-core areas, and vice versa, the more non-core functional capabilities of alliance partners it can access, the less likely it will be to engage in core technology acquisitions.

> ***Hypothesis 1a:*** *The higher the number of functional alliances in a core or a non-core area, the more likely the focal firm is on average to engage in technology acquisitions in that area.*
>
> ***Hypothesis 1b:*** *The higher the number of functional alliances in a core or a non-core area, the less likely the focal firm is to engage in technology acquisitions in other areas.*

2.2.2. Technological Alliances as Complementarities or Substitutes to Technology Acquisitions

In assessing the role of the acquirer's technological alliances, I focus on the mechanisms of capability development (Helfat and Lieberman, 2002; Kaul and Wu, 2015). Technological capabilities from the focal firm's alliance portfolio may be combined with the acquired technological capabilities to develop, rebuild, or renew the focal firm's own technological capabilities[13]. The key mechanism here is value creation through technological development by capability recombination (Helfat and Peteraf, 2003). To deepen their core technological capabilities and to plug technological gaps at the core

[13] E.g. Apple developed technological capabilities in semiconductor space through acquiring, licensing, and collaborating.

(Lee and Lieberman, 2010), firms may engage in core technology acquisitions or technological alliances. Engaging in only core technology acquisitions or only core technological alliances to develop and augment core technological capabilities may both be effective strategies (Kamuriwo and Baden-Fuller, 2016; Lee and Lieberman, 2010, Yu *et al*., 2016).

However, if the focal firm already has access to core technological capabilities in its alliance portfolio in addition to its own internal core resources and capabilities before engaging into such acquisitions, that firm is already more likely to reach a higher degree of substitutability, and potential redundancy between core technological resources and capabilities, due to some combination of the following three fairly well-known reasons. First, a firm is most likely to have developed its most substantial knowledge base, by definition, in its core business, where it should be most efficient learning, transferring knowledge, and integrating capabilities compared to non-core segments (Saxton, 1997). Second, value created through recombination of related knowledge may be outweighed by costs of redundancy faster than when recombining knowledge with less of an overlap (Ahuja and Katila, 2001; Sears and Hoetker, 2013). Third and final, the more core technological capabilities the focal firm has access to through its alliances, in addition to the core internal technological capabilities it already has by default, still higher the chance that these capabilities will be substitutable and redundant. This explanation is also consistent with the earlier discussion of balancing appropriability and uncertainty, as on average the focal firm is already most likely to possess internal technological capabilities in its core business that it can use to increase value capture when recombining with core technological alliances without the need to acquire more core technological capabilities, which may otherwise lead to redundancy.

In non-core contexts, sourcing technological capabilities broadly through acquisitions may be costly from a different perspective, due to high uncertainty of broad technological search in general, higher costs of participating in less familiar contexts, and the focal firm's likely lack of substantial knowledge in non-core markets, as well as higher demands likely placed on the firm's resources and total absorptive capacity (Jiang, Tao, and Santoro, 2010; Sampson, 2007; Vasudeva and Anand, 2011). Such constraints are especially likely if the focal firm already possesses many diverse non-core technological alliances, which can be effectively used for broad exploration (Lavie, Kang, Rosenkopf, 2011; Stettner and Lavie, 2014). So especially when it comes to overall breadth of non-core technological capabilities a firm can access, engaging in many non-core technology acquisitions while simultaneously maintaining many diverse non-core alliances may quickly lead to decreased payoffs for three reasons. First, there are significant resource costs to engaging in an excessive number of both non-core acquisitions and non-core technological collaborations at the same time. Second, these costs and resource requirements of learning, monitoring, and integrating in non-core domains are higher than the same costs and requirements in the core business of the acquirer. Third, engaging in many acquisitions and alliances in non-core business segments also places higher demands on managerial attention and focus. So broadly engaging in costly, less flexible non-core technology acquisitions when the firm already possesses a broad portfolio of non-core technological alliances that could be used to explore distant markets and technologies may not make sense, unless the firm focuses its non-core technology acquisitions in those strategically important and coherent non-core domains which will be discussed in the next subsection (Makri, Hitt, and Lane, 2010, Srivastava and Gnyawali, 2011; Yamakawa *et al*., 2011). So both in core and non-core settings, generally, technological alliances and technology acquisitions are likely to be substitutable.

Hypothesis 2a: *The higher the number of core* <u>*technological*</u> *alliances, the less likely the focal firm is on average to engage in core technology acquisitions.*

Hypothesis 2b: *The higher the number of non-core* <u>*technological*</u> *alliances, the less likely the focal firm is on average to engage in non-core technology acquisitions.*

2.2.3 Indirectly Related Non-Core Acquisitions

Firms tend to be at least somewhat strategically coherent in their moves across markets (Teece *et al*, 1994), and broad exploration and experimentation aside, in non-core settings firms may focus significant attention on a few strategically important business segments. I propose that when a firm enters into non-core alliances, some of these alliances will likely cluster in business segments that are complementary and strategically important to the focal firm. Such accumulation of alliances will be a signal of higher importance and complementarity of that sector to the focal firm, an indicator of its commitment and likely sunk costs, as well as an indicator that the focal firm is potentially obtaining access to and developing stronger capabilities in that sector (Helfat and Lieberman, 2002; Lieberman *et al*., 2016; Teece *et al*, 1994). In these markets, a degree of indirect relatedness and stronger potential non-core complementarity *vis-à-vis* the focal firm and its already present commitments in form of alliances there may serve as inducement for that firm to expand its technological capabilities in those areas through complementary technology acquisitions (Penrose, 1958; Sakhartov and Folta, 2015). So the focal firm may be more likely to engage in seemingly “unrelated” non-core technology acquisitions in business segments where it has accumulated more technological capabilities through its alliances, and these indirectly related non-core technology acquisitions may outperform genuinely unrelated acquisitions in other non-core business segments.

I suggest that as the number of technological alliances, which are more likely to be substitutes for technology acquisitions elsewhere, increases in a strategically important non-core area, it leads to accumulation of technological capabilities complementary to non-core technology acquisitions in that same area. Prior literature provides strong support. In unfamiliar settings, technological alliances may provide low cost probes and ways to experiment and to learn in novel, uncertain contexts (Brown and Eisenhardt, 1997). With more such alliances and resulting focus in strategically complementary non-core areas may come improved context-specific knowledge to recombine, more absorptive capacity, experience, and better knowledge transfer and integration capabilities (Grant and Baden-Fuller, 2004). Not only are capabilities in novel contexts more useful as they accumulate (Capron and Mitchell, 2009; Karim and Mitchell, 2000), there is also evidence that when firms venture out from their core business, it may pay to take a “telescopic” approach, focusing efforts in fewer complementary non-core markets providing best opportunities to recombine capabilities and to create value (Kaul, 2012; Kaul and Wu, 2015; Vasudeva and Anand, 2011). So as firms gain capabilities and manage uncertainty and appropriability in these complementary, strategically important non-core areas through technological alliances, they become more likely to benefit from internalizing key complementary non-core technological capabilities to increase their ability to create and to capture value from alliances in those segments.

The overall logic of this argument is similar to that in Hypothesis 1a and in agreement with contemporary literature on capability development and deployment. Technology acquisitions in non-core markets with more technological alliances will be the type of strategically coherent acquisitions that firms may use to close capability gaps between their own internal capabilities, and their desired capabilities in these markets with the help of capabilities accessible and developed from these non-core technological alliances (Capron and Mitchell, 2009; Helfat and Lieberman, 2002; Lieberman *et al*., 2016; Kaul, 2012; Teece *et al*., 1994). So in fact, in these non-core areas of focus where there is an accumulation of alliances, what seems like a non-core, conventionally labeled as "unrelated" technology acquisition, may actually be a complementary <u>indirectly related non-core</u> acquisition, which may lead to better acquisition performance compared to other non-core transactions.

In addition to the example of Apple's semiconductor moves (p. 6), I illustrate the potential importance of focusing on a few strategically important non-core markets with two more distinct cases of seemingly unrelated acquisitions by Intel Corporation and Cisco Systems. From 2004 to 2009, Intel engaged in several functional and technological alliances[14] in the information security space, focusing some of its attention on that

[14] Intel entered into a software development alliance with *Cybergard*, in 2004 and a marketing alliance with a network security firm *Interlink* in 2005. In 2007, Intel entered into a marketing alliance with security firm *PGP*, a global alliance to market network security solutions and services with *Nokia* and *CheckPoint Software*, an alliance to provide enterprise data protection and encryption management with *Credant Technologies*, and an alliance to develop software and hardware security and protection with *ARM Ltd*. In

market. Initially, security may have been a strategic concern for Intel, but it was not yet a business segment in which Intel had serious presence. That changed when in 2010, Intel announced a $7.7 billion acquisition, its largest at the time, of *McAfee, Inc*., the world's biggest security software firm (Intel Corporation 2010; 2011). As the acquisition closed in 2011, security became one of the key non-core business segments for Intel (Intel Corporation, 2012). Having initially gained access to partners' capabilities in the security space through alliances, Intel significantly added to its resources in this sector with this major acquisition that may have complemented Intel's already accessible capabilities in this indirectly related area. Without considering Intel's alliances in this space, McAfee may have seemed like a wholly unrelated acquisition for Intel, when I propose that it was in fact an indirectly related non-core acquisition.

Conversely, in 2009, Cisco Systems entered consumer digital device space with its acquisition of Pure Digital, the maker of then popular *Flip* video camera, for $590 million (Grobart and Rusli, 2011). Cisco had little experience with consumer electronics prior to Pure Digital, lacking both internal capabilities in this space, as well as access to partners' functional or technological capabilities there (as it did not have any alliances in the consumer electronics space). Cisco's management allegedly saw the consumer space as the new market for the firm (Grobart and Rusli, 2011), and chose to enter directly with an unrelated acquisition, without accumulating additional complementary capabilities through alliances (SDC Platinum, 2017). Two years later, Cisco withdrew from this

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2008, Intel entered into an alliance with *Absolute Software* to distribute anti-theft, protection, and data recovery services for laptops (SDC Platinum, 2016).

market, shutting down Pure Digital and writing off this entire unrelated transaction (Grobart and Rusli, 2011).

Hypothesis 2c: *Ceteris paribus, the focal firm will be more likely to engage in indirectly-related non-core technology acquisitions in non-core segments strategically important to it (where it also accumulates alliances), relative to other non-core segments.*

Figure 2A: Theorized Effects of Functional Alliances on Capability Deployment through Technology Acquisition Choice

		Technology Acquisitions in:		
		Core Market	Non-Core Unrelated Market	Non-Core Indirectly Related Market
Functional Alliances in:	Core Market	Combining functional and technological capabilities in same business segment, whether core or non-core, increases opportunities for value creation and capture. (**Hypothesis 1a**).	Capabilities accessible in some business segments disincentivize firms from investing in acquiring technological capabilities elsewhere (**Hypothesis 1b**).	
	Non-Core Market	Capabilities accessible in some business segments disincentivize firms from investing in acquiring technological capabilities elsewhere (**Hypothesis 1b**).	Combining functional and technological capabilities in same business segment, whether core or non-core, increases opportunities for value creation and capture. (**Hypothesis 1a**).	

Figure 2B: Theorized Effects of Technological Alliances on Capability Development through Technology Acquisition Choice

		Technology Acquisitions in:		
		Core Market	Non-Core Unrelated Market	Non-Core Indirectly Related Market
Technological Alliances in:	Core Market	Technological capabilities acquired through alliances or acquisitions may be substitutable, reducing this to a mode choice. (**Hypothesis 2a**)	Effects Not Theorized	Effects Not Theorized
	Non-Core Market	Effects Not Theorized	Technological capabilities acquired through alliances or acquisitions may be substitutable when it comes to broad non-core exploration (**Hypothesis 2b**).	Combining tech capabilities from alliances and acquisitions in same non-core businesses may be complementary and increase likelihood of value creation and capture. (**Hypothesis 2c**)

2.2.4 Summary of Choice Hypotheses

To briefly summarize, in this section, I theorize how alliances may either be complementary to, or may substitute for technology acquisitions. Figures 2a and 2b illustrate the structure of my key points. First, I elaborate how functional alliances may be complementary to technology acquisitions in same business segments (Hypothesis 1a, Figure 2a), but may also serve as disincentives to technology acquisitions in other business segments (Hypothesis 1b, Figure 2a). Second, I explain how technological alliances may generally substitute for technology acquisitions in core or non-core segments (Hypotheses 2a and 2b, Figure 2b), but may also be complementary to technology acquisitions within specific strategically important non-core business segments (Hypothesis 2c, Figure 2b). I also address the longstanding puzzle of why firms engage in seemingly unrelated non-core technology acquisitions by showing that some of these non-core transactions may in fact be indirectly related non-core technology acquisitions complementary to the acquirer through its alliance portfolio (Hypotheses 1a (non-core only) and 2c, Figures 2a and 2b). Next, I consider the more nuanced implications of acquisition choice in the context of alliance portfolios for acquisition performance.

2.3 INFLUENCE OF FIRMS' ALLIANCE PORTFOLIOS ON ACQUISITION PERFORMANCE

So far, the focus of this study has been on the effects of the firm's alliance portfolio on its acquisition choice. Here I will discuss the effects of the firm's alliance portfolio on its acquisition performance when the focal firm chooses to engage in in different types of acquisition(s) given the specific configurations of its alliance portfolio components.

My approach to understanding the performance effects of alliance portfolio composition with respect to acquisition performance of the acquirer somewhat deviates in its logic from theorizing related to acquisition choice. While the choice to acquire can ultimately be abstracted to a binary outcome, acquisition performance may be considered across distinct and different dimensions, which may in fact differ from each other (Cording *et al*., 2010). In strategy literature, performance is most commonly considered as a type of financial performance or innovative performance.[15] Performance is multifaceted, and different dimensions of organizational performance provide different information that speaks to theory in distinct ways, and as such acquisition performance requires a more nuanced approach in this context if we are really to understand the effects of acquisition choices firms make given their portfolios of external relations (Chakravarthy, 1986; Cording *et al*., 2010). For example, following a transaction, a firm may realize an increase in innovative performance and a decrease in financial performance, due to different mechanisms (which may or may not be interdependent) operating at the same time.

[15] In addition to, potentially, social or other kinds of performance, which are outside the scope of this study.

Before proceeding with the rest of this section, I will first briefly discuss different approaches to assessing and understanding acquisition performance as financial performance and innovative performance. I will then explain how different aspects of performance may differ with regard to acquisition choices of the focal firm in the context of this study, and explain how I approach and investigate the performance effects of firms' acquisition choices.

2.3.1 Assessing and Measuring Acquisition Performance

Financial and Accounting Performance

Financial performance as financial (stock) markets' reaction to specific events like acquisitions or other types of deal announcements have long been used in accounting, finance, and management literatures (Cording *et al*., 2010; MacKinlay, 1997). The common approach here is to measure short-term (Capron and Pistre, 2002; Kim and Finkelstein, 1997; MacKinlay, 1997; Zaheer *et al*., 2010) or long-term performance effects (Chatterjee *et al*., 2003; Laamanen and Keil, 2008; Rabier, 2017) of a specific public announcement as abnormal stock market returns to the focal firm's equity, compared against some general equity index. This approach to assessing performance has two key advantages. First, it provides a way to assess specific financial performance of a single discrete event, and has been shown to be effective in assessing value of even less prominent announcements, such as those with regard to a granting of a patent (Kogan *et al*., 2017). Second, it provides a way to assess a performance of an event in the short term, potentially eliminating many of the other confounding factors (McWilliams and Siegel, 1997), or in the long-term (Rabier, 2017), after the transaction had been consummated and the acquired firm has been integrated with the acquirer, and all related information, including that related to overall success of the acquisition, had been disseminated in the stock market.

Accounting performance, which is related to financial performance, is tied to measures of profitability derived from a firm's accounting statements and public disclosures, such as return on assets or change in goodwill (intangible assets) associated with acquisitions. Accounting performance has long been a staple of strategic management and accounting literatures (Chakravarthy, 1986; Cording *et al*., 2010). Since all public US firms have to abide by SEC rules and accounting standards, such measures provide a degree of comparability, especially when they are adjusted for industry differences. However, since firms generally file their financial statements on a quarterly and annual basis tied to their specific fiscal year, which varies among firms, these measures should be primarily considered long-term, firm level measures, and can be somewhat noisy and difficult to implement across a sample of heterogeneous firms. Moreover, it is difficult to estimate when and how we will see performance outcomes of an acquisition reflected in a specific firm's accounting performance, especially when it comes to a single specific transaction, as firms generally aggregate their financial statements at the firm level, and make idiosyncratic choices with respect to when and how to report or to amortize certain costs or profits, Nonetheless, accounting performance measures have been shown to be a potentially effective way to see at least one dimension of acquisition performance (Cording *et al*., 2010), and so will be considered as one of the main components of this analysis. In this analysis, I start with assessment of financial performance at the transaction level, but include accounting performance as an alternative measure at the firm level.

Innovative Performance

Innovative performance of the firm is yet another way to assess acquisition performance, especially in industries where technology and innovation are important. Moreover, it is even more important to assess innovative performance in this study, where the main focus is on technology acquisitions specifically. Finally, it is important to note that while innovative and financial performance may be correlated, it is not always the case. A firm may invest in an acquisition with a goal of increasing its innovative output and not, at least not directly or in the foreseeable future, its profitability. Pecuniary results of such a transaction may be more difficult to track considering both the technological uncertainty and the difficulty of predicting timing of payoffs to innovating. Consequently, studies of firms' innovative performance, mostly focusing on these firms' patenting with respect to their strategic choices have become an important part of research in strategic management (Ahuja *et al*., 2008; Ahuja and Lampert, 2001; Valentini, 2012). This approach allows researchers to understand the implications of acquisitions not only for overall innovative activity of the firm, but also its quality and value, for example when it comes to production of particularly valuable or truly innovative patents (Ahuja *et al*., 2008; Ahuja and Lampert, 2001; Kogan *et al*., 2017; Valentini, 2012). As technological development, innovation initiatives, and patenting all may take a long time (Ahuja *et al*., 2008), innovative performance should generally be considered from a longer-term perspective, usually across spans of multiple years as there is much uncertainty with respect to the timing of innovation activity and of technological breakthroughs.

2.3.2 Does Choice Lead to Predictable Performance Outcomes?

It depends. One of the reasons why assessing performance outcomes is difficult is because firms may make various heterogeneous tradeoffs with respect to their strategic choices. First, acquisitions may result in distinct costs, ranging from transaction fees and integration costs, to indirect but real costs related to managerial attention and stakeholder reactions (Hitt *et al*., 1990; King *et al*., 2004; Morck *et al*., 1990). Second, much like an athlete considering different competitive sports and events and the potential course of their athletic career, a firm may make a decision to sacrifice one aspect of its performance to improve another both when it comes to a chosen performance measure, as well as its temporal nature, for example when it chooses to increase the number of new product introductions despite resulting lower margins, or if it invests its earnings into yet uncertain innovation initiatives which may take several years to produce any results, if at all, instead of maximizing short term financial performance. Assessing these and other factors related to different dimensions of performance together can help develop a more complete understanding of performance outcomes that firms derive from strategic choices that they make, given that these are interdependent.

Other potential factors may make reconciling choice and performance outcome difficult. First, some acquisition choices may be a consequence of poor or misinformed or irrational managerial decisions, inability to execute complex strategies, empire-building behavior, bandwagon effects, or other similar reasons (Benner and Zenger, 2016; Duchin and Schmidt, 2013; Gu and Lev, 2011; Jensen, 1993; Morck, Shleifer, and Vishny, 1990; Zhao, 2002; Zollo, 2009). Moreover, the most basic intent behind many acquisitions is often hard to determine, as firms may enter even technological acquisitions for many different reasons, including acquiring purely to internalize specific human or intellectual or product capital, to achieve operational or financial synergies, to foreclose competition or to develop a stronger competitive "moat", to get access to specific markets or customers, and so on (Barkema and Schijven, 2008; Hitt *et al*., 1998; Rabier, 2017; Western and Halpern, 1983). Second, even "good" acquisition selection choices may lead to a poor performance outcome because of factors impeding acquisition performance, for example unforeseen integration challenges (Datta, 1991; Puranam *et al*., 2009; Zollo and Singh, 2004).

Third, the levels of risk and reward may vary significantly between rational acquisition choices. Some acquisitions may be low-risk endeavors, for example a transaction aimed to acquire specific key resources that the firm requires and values objectively, while others may be more akin to purchasing a lottery ticket with a high risk and a high reward potential, and both may be rational decisions given some objective valuation approach. A firm may simultaneously pursue two distinct technological paths through series of acquisitions, with an expectation that only one of the technological trajectories will lead to commercial success. Fourth, technological uncertainty plays a key role in the context of this study, and even well-planned acquisitions may fail simply due to an unlucky technological bet that only becomes clear ex post (Eggers, 2012; Makri *et al*., 2010). Fifth, competitive dynamics are also important when we consider firm strategies, and competitive reactions and strategies may play an important role in performance outcomes of acquisitions. For example, a firm entering a new product market with an “optimal” acquisition strategy may be met with an overwhelming competitive response, or an acquisition may be prevented by a higher competing bid from another firm. Sixth, it may still be difficult to judge the performance of any single transaction ex post, given inability to precisely predict when (time) and where (performance dimension) we may observe its effects, and whether they will be permanent, and second, because in some cases it may be specific combinations of acquisitions or even other strategic actions that lead to firm or market-level effects. So it may be difficult to predict whether to expect results at the transaction level, a program level, or a firm level.

Seventh and final, when considering acquisition performance in the context of externally accessible resources and capabilities owned by alliance partners, it is also important to remember that both alliances and alliance partners, and the resulting outcomes of each individual alliance, vary widely in their characteristics. These characteristics may have an important effect on acquisition performance when considered in the context of a firm’s relationships, where firms worry not only about value creation, but also value capture (Arora, Belenzon, Patacconi, 2017; Dussauge, Garrette, Mitchell, 2000; Yang, Zheng, anZaheer, 2015; Zanarone, Lo, Madsen, 2016). All of these reasons taken together make it difficult to be precise and exact, much less claim causality, with respect to specific effects of specific transactions given the acquirer’s alliance portfolio.

In a general investigation that follows, I hope to help shed further light on acquisition performance and to provide a roadmap for future research endeavors. *In investigating performance effects of acquisition choice, I choose not to make multiple* *specific hypotheses with each addressing distinct and different aspects of performance. Instead, I follow theory developed earlier in this paper to explain acquisition choice in the context of the firm's alliance portfolios, assuming that* <u>*on average*</u>*, firms make these choices with bounded rationality and with expectations of positive performance benefits when it comes to at least one dimension of performance. Following my empirical analysis, I reconcile the results with the choice hypotheses, and address inconsistencies.*

Thus, expecting performance to generally reflect my theory on acquisition choice in the prior sections, I will test predictions with respect to how a firm's acquisition choices may influence its financial and innovative performance following different acquisition types (that is core, non-core, and focused non-core acquisitions) with respect to the specific configuration of that firm's alliance portfolio components. Moreover, one of the more intriguing opportunities of this study is to expand our understanding of whether the firms generally seem to make right or wrong strategic choices compared to theorized prescriptions, and whether these result in positive or negative performance in the context of other factors.

2.3.3 Summary of Proposed Performance Effects

Figures 3a and 3b below illustrate the structure of my key points in this section, which follows choice theory and the same mechanism and does not require additional hypotheses. First, following logic of **Hypothesis 1a**, I elaborate how functional alliances may be complementary to technology acquisitions in the same markets, and expect positive performance effects of functional alliances in markets where those are present. I do not investigate the performance effects of **Hypothesis 1b** as it is not possible to test performance of a potential acquisition that did not occur in this context. Second, following logic of **Hypotheses 2a** and **2b**, I expect that technological alliances may generally substitute for technology acquisitions in core or unrelated non-core segments (Figure 3b), leading to negative performance in core and unrelated non-core settings if a firm chooses to engage in core or non-core unrelated acquisitions given a higher number of core or non-core technological alliances respectively. Finally, in line with **Hypothesis 2c**, I propose that indirectly related non-core technology acquisitions complementary to the acquirer through its technological and functional alliance portfolios are more likely to lead to positive performance outcomes than truly unrelated non-core acquisitions (Figures 3a and 3b). I do not theorize about whether the effect of each type of a strategic choice will be of a specific magnitude with respect to financial or innovative performance, but rather look to empirical analysis to tell the story of where and how firms may trade off one kind of performance for another, or whether specific choices lead to specific types of performance outcomes. I will discuss and reconcile the implications of the combined results of choice and performance analyses in detail at the end of the fourth chapter.

Figure 3A: Proposed Performance Effects of Functional Alliances on Technology Acquisitions

		Technology Acquisitions in:		
		Core Market	**Non-Core Unrelated Market**	**Non-Core Indirectly Related Market**
Functional Alliances in:	**Core Market**	FINANCIAL PERFORMANCE: Positive effects due to value creation opportunities resulting from complementarity in core markets INNOVATIVE PERFORMANCE: Positive effects due to recombination opportunities and knowledge spillovers, less chance of knowledge leakage due to functional nature of alliances	Effects Not Theorized	Effects Not Theorized
	Non-Core Market	Effects Not Theorized	FINANCIAL PERFORMANCE: Positive effects due to value creation opportunities resulting from potential complementarity in other markets INNOVATIVE PERFORMANCE: Positive effects due to recombination opportunities and knowledge spillovers, less chance of knowledge leakage due to functional nature of alliances	FINANCIAL PERFORMANCE: Positive effects due to value creation opportunities resulting from complementarity in same markets INNOVATIVE PERFORMANCE: Positive effects due to recombination opportunities and knowledge spillovers, less chance of knowledge leakage due to functional nature of alliances

Figure 3B: Proposed Performance Effects of Technological Alliances on Technology Acquisitions

		Technology Acquisitions in:		
		Core Market	**Non-Core Unrelated Market**	**Non-Core Indirectly Related Market**
Technological Alliances in:	**Core Market**	FINANCIAL PERFORMANCE: Negative effects due to higher chances of redundancy and substitutability INNOVATIVE PERFORMANCE: Negative effects due to higher chances of redundancy and substitutability	Effects Not Theorized	Effects Not Theorized
	Non-Core Market	Effects Not Theorized	FINANCIAL PERFORMANCE: Negative effects due to diverse redundancy, lack of knowledge and high resource demands INNOVATIVE PERFORMANCE: Negative effects due to lack of knowledge and high resource demands, lack of focus	FINANCIAL PERFORMANCE: Positive effects due to increased potential for value creation and value capture opportunities INNOVATIVE PERFORMANCE: Positive effects due to more recombination opportunities, higher likelihood of radical innovation, and increased value creation and value capture opportunities

3. RESEARCH DESIGN & METHODS

3.1 SAMPLE AND DATA

My sample of acquirer firms consists of publicly-traded US companies in high-technology industries. For my sampling frame, I start with all firms that have appeared at least once on the *Fortune 1000* list of the largest (by revenue) firms in the United States within the timeline of my main analysis, from 1996 to 2010. This allows me to include all relevant incumbent firms, not only those that have persisted through the entire 15 years, limiting the chance of survivorship bias (Ahuja and Katila, 2001). Addressing survivorship bias is particularly important here because high-velocity settings often feature high churn of firms, as well as vertical integration and disintegration, intra-industry M&A, and divestment activity (Bourgeois and Eisenhardt, 1988; Brown and Eisenhardt, 1997; Langlois and Robertson, 1992). My sample is restricted to publicly-traded focal firms only, as both transaction- and firm-level data is generally unavailable, inconsistent, or non-standardized for many private firms (Ahuja and Katila, 2001; Makri *et al*., 2010).

I limit my sample to firms that have their core business in high-technology industries. In order to select high-technology firms only, I cross-reference as my selection criteria Organization for Economic Cooperation and Development's (OECD) high-tech classification ranking (Godin, 2004; Hatzichronoglou, 1997), National Venture Capital Association's (NVCA) and *VentureXpert* database's high-technology industry classification scheme (Bertoni, Colombo, Grilli, 2011), as well as classifications used in relevant literature (Benson and Ziedonis, 2009; 2010; Dushnitsky and Lavie, 2010; Powell, Koput, and Smith-Doerr, 1996; Wadhwa and Kotha, 2006). What constitutes high-technology is occasionally debated by researchers, but the core group of high-tech segments is relatively consistent across representative classifications. The included industries defined as high-tech[17] across various classifications are biotechnology and pharmaceuticals; computing equipment; telecommunications equipment; semiconductors, electronic circuitry, and magnetic storage media; aerospace, guidance, and navigation systems; scientific instruments; specialized medical instruments and equipment; optical equipment; and computer software, data, and programming services[18]. I confirm the primary industry as an SIC code for each firm in my sample through the Standard and Poor's *CompuStat* database and crosscheck with Securities and Exchange Commission's (SEC) *EDGAR* corporate filings database, defaulting to *EDGAR* when there is a conflict. Acquirer and target names are also cross-referenced from *CompuStat* to Thomson Reuters' *SDC Platinum* database to *EDGAR*.[19] The final sample includes 208 high-tech firms, 3,701 (out of 5,215) in-sample acquisition transactions, 13,074 total unique alliances, and 2,101 in-sample panel firm-year observations. List of all firms in the original sample and the years in which they appear could be found in Appendix III.

Defining what constitutes a *technology acquisition* has also been a point of debate in this literature. I define an acquisition as technology-motivated based on a set of

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[17] The resulting high-tech industries selected through these methodologies largely overlap when "medium-high" technology industries, such as machinery, automobiles, and industrial chemicals are excluded, with scientific instrument sector being the only contested industry, because it is much closer to the next industry in OECD's high-tech group than it is to the next industry in its designated medium-high tech group when it comes to its measured research intensity (Godin, 2004; Hatzichronoglou, 1997). I include it in my sample with an appropriate control, but exclude the rest of the "medium-high" tech industries as they do not generally appear in other high-tech classifications.

[18] SIC codes 2833, 2834, 2835, 2836, 3570, 3571, 3572, 3575, 3576, 3577, 3578, 3579, 3661, 3663, 3669, 3672, 3674, 3679, 3695, 3720, 3721, 3724, 3728, 3760, 3812, 3841, 3842, 3843, 3844, 3845, 3861, 7370, 7371, 7372, 7373, and 7374.

[19] Any firm relying on outside funds through issuance of any securities, whether equity, warrants or debt, even if it is a private entity, is required to register with SEC and to electronically file required forms made available online.

decision rules grounded in prior work (Ahuja and Katila, 2001; Desyllas and Hughes, 2008; Makri *et al*., 2010; Puranam and Srikanth, 2007). I begin with all acquisitions of targets in high-tech industries (Desyllas and Hughes, 2008), and any acquisitions of firms that had patenting activity in the past five years (Ahuja and Katila, 2001). I then <u>exclude</u> any targets where the primary motive for the acquisition is described in the media as to "access distribution, to gain market entry, to obtain financial synergies, or to increase market power" (Makri *et al*., 2010, p. 609) since these are not acquisitions aimed just to obtain technological capabilities, as so fall outside of the scope of my study. The one point of contention with some prior work may be that my sample includes acquisitions of large targets, whereas some studies do not (Makri *et al*., 2010; Puranam and Srikanth, 2007). Because these researchers had concerns that larger acquisitions may occur for motives other than technological, I address this by checking the motives behind the acquisition as described above, and by including a control for these large acquisitions.

My data is aggregated from multiple sources. Firm-level and industry-level financial data comes from the *CompuStat* database, and when necessary is confirmed and augmented with data from *EDGAR* public filings database, where the required electronic filings become available beginning in 1994 for most publicly-traded firms. For data on acquisitions and alliances, I start with *SDC Platinum* database, which I augment and cross-reference with Dow Jones' *Factiva* database, as well as data available from *EDGAR*, and occasionally *PrivCo*, *Crunchbase*, and *CB Insights* databases, and other data sources. For patent-based measures, I use raw granted patent data originating from the U.S. Patents and Trademarks Office, but I confirm some of my data processing with, and incorporate parts of relevant algorithms and data provided by National Bureau of

Economic Research (NBER) *Patent Project*, Harvard Business School's *Patent Network Dataverse*, UC Berkeley's Fung Institute for Engineering Leadership *Patent Database*, as well as US patent data collected for a recent study (Kogan *et al*., 2017) and made available through Indiana University. I also incorporate some industry-level data made available by National Venture Capital Association (2016), and IPO data collected and made available by Jay Ritter at the University of Florida (2017). For financial performance, I rely largely on equity pricing information from the Center for Research in Security Prices (CRSP) and additional tools from Wharton Research Data Services (WRDS). Although my core in-sample panel spans 1996-2010, consistent with prior work (Lavie, 2007; Cui and O'Connor, 2012, Zaheer *et al*., 2010), I construct a larger dataset starting five years earlier in 1991 and ending in 2014 in order to properly model prior acquisition and alliance experience, as well as to aggregate the focal firms' pre-existing external corporate development and patent portfolios, and to include variables lagged over multiyear periods. My actual sample includes 3,701 technology acquisitions within the estimation window. The data used to construct that sample, accounting for proper lags and aggregating the portfolio variables spans 1985-2015, and includes 4,193 firm-year observations, 13,074 total unique[20] alliances and 5,215 acquisitions, as well as over 1.4 million unique patents in portfolios of all of these firms, whether a focal firm, a partner, or a target.

[20] Less than 10% of alliances appear in the data more than once if more than one focal firm participates in an alliance. Similarly patents may be used multiple times as a part of the focal firm's own or alliance portfolio, or as a part of the target's patent portfolio.

3.2 MEASURES

Dependent Variables - Choice

For my dependent variables, I first operationalize a *Core Technology Acquisition* as a technology acquisition of a firm operating in the same industry as the acquirer. Second, in a *Non-Core Technology Acquisition*, the target and the acquirer are from different industries. I also control for the overlap of technological knowledge between the two firms' patent portfolios as described later. When I model whether the firm engages in acquisitions in non-core business segments where it has accumulated a significant number of alliances, I estimate the likelihood of such an acquisition occurring in a non-core market where the focal firm had accumulated the number of alliances that is higher than the median number across all non-core markets in that firm's alliance portfolio. I define this *Non-Core Alliance Focus Area* based on the number of non-core alliances all from the same business segment. I designate whether markets and industries are the same by using either 2 digit SIC codes, or the roughly equivalent but more technologically granular 3 digit NVCA high-technology industry classification (VEIC)[21].

Dependent Variables – Performance

My intent with measuring the performance outcomes of the technology acquisitions themselves is to pay attention to different aspects of acquisition performance. As such, I use several dependent variables to capture different dimensions of acquisition performance.

[21] I use multiple approaches to operationalize relatedness, relying on VEIC for main analysis due to its greater granularity in technological market space, although the results are generally similar if I rely on SIC codes instead, or change the granularity level.

Financial Performance

Short Term Cumulative Abnormal Return[22] is the first of my performance measurements. I follow prior literature by modeling cumulative abnormal returns (CAR) on acquirer's equity around the time of the acquisition event as a proxy of the markets' expectation of the transaction's future performance. I calculate CAR using a common approach based on the efficient market structure model reaction to new information (Fama *et al*., 1969; MacKinlay, 1997; Strong, 1992). I set the event date at [t = 0], and use the 150 day initial model estimation period of [t-165, t-15] to estimate the baseline market model where I calculate the common stock return of each firm in my sample on each specific date within the 150 day period, which falls well within the 60-600 day period common in literature (MacKinlay, 1997; Strong, 1992) and based on the corresponding market return on equal-weighted index. This estimated model is then used to predict daily returns for each of the acquirer firms in the short-term window surrounding the event itself. I then calculate the daily abnormal returns as the difference between actual returns of each firm's stock and those predicted by the model, and sum up this difference as a cumulative abnormal return on that stock within a short window surrounding the event. I focus on the five-day [-1, +3] window as shorter windows are generally preferable for this type of an event when it comes to identification and eliminating confounding events (McWilliams and Siegel, 1997), but I also intend to test alternative windows as a part of my future robustness checks (Capron and Pistre, 2002; Kim and Finkelstein, 2009; McWilliams and Siegel, 1997; Strong, 1992, Zaheer *et al*., 2010).

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[22] Recent work suggests that CAR valuation applied to these types of events might actually be a good proxy for economic value of innovative potential of a transaction, which here may provide a more focused, transaction-specific measure of potential innovative performance (Kogan, *et al*., 2017).

Buy and Hold Abnormal Return (BHAR) is another measure popular in finance and strategy literatures that is used to measure market's assessment of acquisition performance. While BHAR also uses cumulative abnormal returns on acquirer's equity similar to Short-Term CAR, it measures cumulative abnormal returns to an acquisition over a long period of time, as more information is received and incorporated by the market participants (Chatterjee, *et al.*, 2003; Loughran and Vijh, 1997; Rabier, 2017). Following state of the art practices from recent prior work (Rabier, 2017), I measure BHAR over a 24 month period from the date of the acquisition announcement, using firms' monthly cumulative abnormal returns adjusted against a corresponding return on an equal-weighted index.

Accounting Performance

I also use two measures of firm-level performance in my analysis. *Goodwill Impairment* occurs when firms negatively adjust the value of intangible assets associated directly with acquisitions, and is a measure shown in accounting literature to be associated with negative acquisition performance and decreased profitability (Gu and Lev, 2011; Li *et al*., 2011). As acquisition performance is generally revealed over the long term, I use likelihood of goodwill impairment over five years following the acquisitions as one of my acquisition performance measures. *Return on Assets (ROA)* is a common firm-level measure often used broadly in the strategy literature, and oftentimes in studies analyzing acquisition performance (Cording *et al*., 2010). Following prior work (Cording *et al*., 2010), I measure ROA as the difference in average, industry-adjusted return on assets in 2 and 3 years prior to the acquisitions, and the 2 and 3 years following an acquisition.

Innovative Performance

Measuring innovative performance as innovative output of firms (as opposed to their innovative efforts) is a complex endeavor (Ahuja *et al.*, 2008; Ahuja and Katila, 2001). Although patents have generally been used as one of the common proxies for a firm's innovative activity, even among patent-based measures, there are multiple distinct variables that measure differing aspects of innovation (Ahuja *et al.*, 2008; Ahuja and Lampert, 2001; Valentini, 2012). Number of patent applications is one such measure, but not all of such applications may be ultimately granted. Moreover, the value of patents varies dramatically. Some patents are granted and never put to use, while other novel patents may lead to an opening of a whole new area of research and be followed by thousands of other patents. I choose three distinct patent-based measures of innovative activity to attempt to capture different aspects of that activity within a firm after an acquisition occurs: total patent output, external citations to those patents, as well as the number of highly novel patents.

Post-Acquisition Annual Patent Output is measured as a number of ex-post successful patent applications filed at various time intervals after an acquisition. *Post-Acquisition Citations* are then external citations to these post-acquisition patents. *Post-Acquisition Annual Breakthrough Patent Output* measures the number of post-acquisition granted patents that are in the top 95% of all cited patents within the USPTO registry because these patents are most likely to be more valuable and ground-breaking (Ahuja and Lampert, 2001).

Independent Variables - Choice

For my independent variables, I test several ways of portfolio level aggregation discussed in prior literature (Ahuja and Katila, 2001; Cui and O'Connor, 2012; Harrison and Klein, 2007; Lavie, 2007; Makri *et al*., 2010; Mouri *et al*., 2012; Vasudeva and Anand, 2011; Wadhwa *et al.*, 2016). I define a *Technological Alliance* as one where at least a partial purpose of the alliance is technology transfer or technology development. *Functional Alliance* is then an alliance where the primary purpose is non-technological, for example a marketing or a manufacturing agreement. In order to determine the nature of an alliance, I first look for an indication of a technological transfer or collaboration for each alliance, and then where unclear, I review the alliance announcement to confirm the type of the alliance from the focal firm's perspective and cross-reference across data sources. Similarly to distinguishing core from non-core acquisitions, I define a *Core Alliance* as an alliance with the firm in the same industry as the acquirer, whereas a *Non-Core Alliance* would be an alliance with a firm in a different industry. I test both 2-digit level VEIC and 3-digit level SIC classifications as multiple measures of relatedness while controlling for cosimilarity of the focal firm's, its partners', and its targets' patent portfolios. My alliance portfolio measures and all patent portfolio measures are aggregated in moving lagged five year windows [i-6, i-1].

Additional Independent Variables – Performance

In my performance analysis, I use additional binary independent variables to model acquisition performance of specific acquisition types, that is as either a *Core Acquisition, Indirectly Related Non-Core Acquisition,* or an *Unrelated Acquisition* , where some non-core acquisitions may be considered I*ndirectly Related* if they are acquisitions in an alliance focus area. I also interact these variables with portfolio composition variables in my analysis. In my supplementary firm-level analysis, I measure a total annual number of each type of these acquisitions.

Table 1: Select Summary Statistics (Focal firm statistics reported at firm-year level)

Variable	Mean	Median	Min	Max
Core Acquisition	0.32	0.00	0.00	1.00
Non-Core Acquisition	0.68	1.00	0.00	1.00
General, Non-Focused Non-Core Acquisition	0.45	0.00	0.00	1.00
Non-Core Acquisition in Area of Focus	0.23	0.00	0.00	1.00
Tech. Core Alliances - 5yr	2.66	0.00	0.00	102.00
Tech. Non-Core Alliances - 5yr	10.13	3.00	0.00	376.00
Funct. Core Alliances - 5yr	2.39	0.00	0.00	97.00
Funct. Non-Core Alliances - 5yr	10.12	3.00	0.00	292.00
Cosimilarity Target to Allies	0.03	0.00	0.00	1.00
Cosimilarity Target to Acquirer	0.08	0.00	0.00	1.00
Allies' Core Tech. Patent Portfolio	1.03	0.00	0.00	10.01
Allies' Non-Core Tech. Patent Portfolio	2.10	0.00	0.00	10.43
Allies' Core Tech. Pat Portf. Proportion	28.68	0.00	0.00	1002.32
Allies' Non-Core Tech. Pat Portf. Proportion	41.98	0.20	0.00	1044.14
Tech. Core Alliances - 5yr Proportion	0.10	0.02	0.00	1.00
Funct. Core Alliances - 5yr Proportion	0.11	0.05	0.00	1.00
Tech. Non-Core Alliances - 5yr Proportion	0.32	0.31	0.00	1.00
Foreign Target	0.29	0.00	0.00	1.00
Public Target	0.13	0.00	0.00	1.00
Large Target	0.05	0.00	0.00	1.00
Cash Consideration	0.26	0.00	0.00	1.00
Target a Public Parent Divestiture	0.33	0.00	0.00	1.00
Target's Patent Portfolio Size - 5yr	0.28	0.00	0.00	7.91
Prior Alliance	0.04	0.00	0.00	1.00
Focal Firm Acquisition Experience	10.90	6.00	0.00	101.00
Focal Firm Patent Portfolio Size - 5yr (log)	4.32	4.66	0.00	9.32
Focal Firm Diversification	0.18	0.00	0.00	0.82
Focal Firm R&D ratio	0.13	0.10	0.00	9.51
Focal Firm Size - Employees (log)	2.39	2.17	-1.66	6.06
Focal Firm Size - Revenues (log)	8.04	7.78	0.99	11.74
New CEO in past 3 years	0.43	0.00	0.00	1.00

Table 2: List of all Control Variables

Level	Control	Brief Description
Firm	Focal Firm Acquisition Experience	Acquisitions in past 5 years
	Focal Firm Patent Portfolio Size	Number of patents granted to focal firm in prior 5 years (log)
	Focal Firm Diversification	1-HHI of businesses
	Focal Firm R&D ratio	R&D expense/Total Revenues
	Focal Firm Financial Constraint	Debt to Equity Ratio
	Focal Firm Size	Number of Employees (log)
	Focal Firm Divestiture Experience	Divestitures in past 5 years
	New CEO	CEO change in prev. 3 years
Alliance Portflio	Allies' Core Tech. Patent Portfolio	Number of Core Allies' Patents (log)
	Allies' Non-Core Tech. Patent Portfolio	Number of Non-Core Allies' Patents (log)
	Allies' Core Tech. Pat Portf. Proportion	Proportion of Core Allies' Patents to Focal Firm's
	Allies' Non-Core Tech. Pat Portf. Proportion	Proportion of Non-Core Allies' Patents to Focal Firm's
	Tech. Core Alliances - 5yr Proportion	Number of Core Tech Alliances to Total Alliance Portf. Size
	Funct. Core Alliances - 5yr Proportion	Number of Core Funct Alliances to Total Alliance Portf. Size
	Tech. Non-Core Alliances - 5yr Proportion	Number of Non-Core Tech Alliances to Total Alliance Portf. Size
Target	Foreign Target	Target from outside US
	Public Target	Target publicly traded
	Large Target	Deal size over $1 billion
	Target a Public Parent Divestiture	Target a division of public firm
	Target's Patent Portfolio Size - 5yr	Number of patents granted to target in prior 5 years (log)
Transaction	Co-similarity Target's Patents to Allies	Patent co-similarity target to allies
	Co-similarity Target's Patents to Acquirer	Patent co-similarity target to acquirer
	Cash Consideration	Acquisition paid for in cash
	Target Industry M&A Activity	Number of acquisitions t-1
	Competing Offer	Whether there was a competing bid
	Prior Alliance	Acquirer & target had alliance in prior five years

I control for variables at the industry, firm, and transaction level that may or have been shown to have an effect on acquisition selection or performance (See Table 2). Considering that much of the effort of this study is focused on understanding dynamics of multimode portfolios of resources and capabilities, I control for *Size* and *Proportions of the Alliance Partners' Patent Portfolios* with respect to the focal firm's patent portfolio, and for the *Proportions of the Alliance Portfolio Components* with respect to each other in the context of the entire portfolio, although my findings are not significantly affected by excluding these variables. As industries may go through occasional boom and bust cycles (Eisenhardt, 1989; Brown and Eisenhardt, 1997), I control for *Industry* and *Year*.

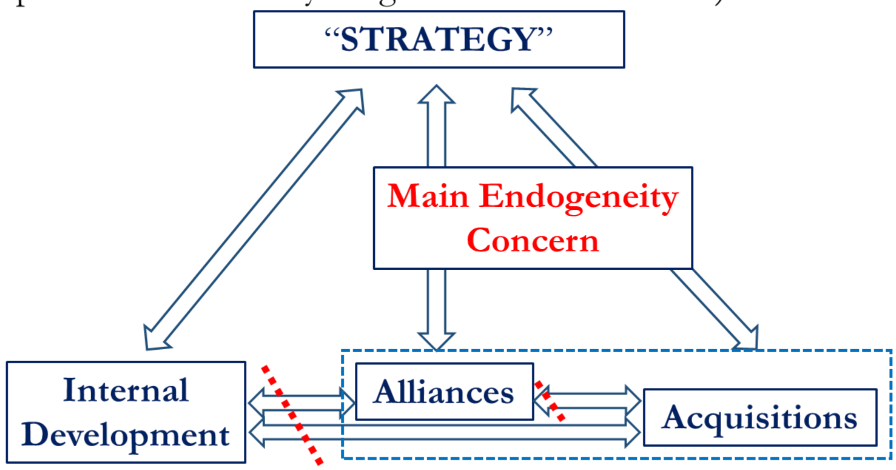
At the level of the focal firm, I control for *Size* as its number of employees, or, in robustness checks, its annual revenues, both logged. Since acquisitions often require a significant resource commitment, I also control for the level of *Financial Constraint* at the focal firm as its debt to equity ratio (Campello, Graham, Harvey, 2010; Kaplan and Zingales, 1997). I also control for a *CEO Change* in the prior three years that may indicate a change in a firm's strategic direction (Feldman, 2013; Walters, Kroll, Wright, 2006), *Diversification Level* as one minus the Herfindahl-Hirschman Index of the firm's business segments, focal firm's own *Patent Output* (logged) over the previous five years, as well as the firm's R&D function and absorptive capacity as the *R&D Intensity* of the firm as the proportion of its R&D expense to its total revenues (Cohen and Levinthal, 1990). I also control for the focal firm's *Acquisition Experience*, as the total number of its acquisitions over the prior five years, as well as for its *Divestiture Experience* (Hayward and Shimizu, 2006; Zollo and Singh, 2004). All firm-level variables are lagged one year and standard errors are clustered at the firm level. When it comes to transaction-specific controls, I measure *Patent Cosimilarity* in granted patent portfolio proportional composition by International Patent Classification section and class, and I measure this similarity between the target and both the acquirer, as well as acquirer's alliance partners' pooled patent portfolio (Ahuja and Katila, 2001; Jaffe, 1986; Makri *et al*., 2010). In order to eliminate potential order selection bias in measuring similarity of patent portfolios, for patent section and class data, I use all classes listed for each patent when I construct my measures (Benner and Waldfogel, 2007). I also control for *Target's Total Patent Output* in the prior 5 years. I pay attention to whether the target was a *Public Firm*, *Divestiture* of a public firm, or a *Foreign Firm*, whether this was a *Large Transaction* (over $1 billion), and for whether the transaction was a *Cash Deal*. I control for competitive dynamics of the transaction by including *Target Industry M&A Activity* in the prior year, and whether there was a *Competing Offer (*Bradley, Desai, Kim, 1988; Fishman, 1989; Loughran and Vijh, 1997; Ruback, 1983*).* Finally I control for a *Prior Alliance* between the target and the acquirer (Zaheer *et al*., 2010). Select summary statistics can be found in Table 1, and detailed description of the control variables can be found in Table 2. Although some of the correlations in my data are high (not shown for space considerations, available upon request), Variance Inflation Factor (VIF) analysis was used to investigate the possibility of multicollinearity. Mean VIF is no higher than 5 for any model, and individual VIF for any of the variables does not exceed 12, which is well below the threshold that might signal that there is a serious multicollinearity issue[23] (Greene, 2012).

[23] This is notwithstanding the fact that multicollinearity and VIF analysis can be rather complex in nonlinear models.

3.3 METHODS

Figure 4: Endogeneity Concerns and Tools

- **Reverse Causality:** (Address with Lags and Panel)
- **Self-Selection:** Acquisition is a choice (Address with Two-stage Model and Matching)
- **Unobserved Variable Bias:** Alliances and Acquisitions codetermined by overarching Strategy (Assume Incumbents' portfolios reasonably exogenous in the short run)



Methods – Acquisition Choice

In addition to using pooled logistic and OLS estimations while accounting for selection with a two stage Heckman-type selection model (Heckman, 1977; Shaver, 1998) where I condition the estimation on the initial choice to engage in any acquisition, I also use a panel Quasi Maximum-Likelihood (QML) Poisson specification that allows for using counts of core or non-core acquisitions in a panel fixed effects specification with correctly adjusted robust errors (Greene, 2012; Hagedoorn and Wang, 2012, Wooldridge, 1999). This method does not allow to control for selection into acquisition, but provides a useful alternative specification. Understanding choices of acquirer firms is key to my research question, as well as an important way to address endogenous multi-stage selection choices of firms (Shaver, 1998, also see Figure 4 above). I model the acquisition choice[24] first as a pooled, selection-adjusted probit with firm, year, and industry effects, where in each model, *1* stands for whether the firm engaged in a core or, respectively, a non-core technology acquisition that year, and *0* if otherwise.

Alternatively, the panel QML Poisson (*xtpqml* package in Stata) model uses a count of all core or non-core acquisitions in a year. For the first stage of the two stage Heckman model, I estimate the likelihood of the firm engaging in any acquisitions at all. Ideally, it would be desirable to account for endogeneity of alliance portfolio composition as interdependent with acquisition choice, but I currently have no feasible way of accomplishing this given my data and its structure. I add three instruments to the first stage that should not influence the choice of a type of an acquisition or performance of a single acquisition to estimate selection into any, core only, or non-core only acquisition at all: acquirer's *Annual Change in Core Industry Diversification*, *Industry Average Retained Earnings*, and *Industry IPO Activity.* All of these instruments exclude the focal firm. The logic behind the choice of these instruments is as follows. As other firms in the industry diversify, the focal firm may choose to expand, either in its core or non-core businesses. Higher industry retained earnings proportion may signal increase in slack and amassing of capital, which may lead to increased competition for resource accumulation through acquisition. On the other hand, increase in IPO activity of rivals may induce the firm to invest in internal rather than external capabilities, lowering the likelihood of

[24] When firms engage in core or non-core acquisitions, these choices may not be competing choices, as the firm can choose to engage in either or both types, or none at all.

acquisitions. I then construct inverse Mill's ratios (IMR) to use as regressors in the 2nd stage choice (probit) and short- and long-term transaction performance (OLS) models.

Methods – Acquisition Performance

Matching

Estimating acquisition performance is further complicated by the multi-stage selection processes described above. A firm first self-selects in being an acquirer, and then makes a choice with respect to what target it is going to acquire, and then realizes its performance outcome. A potential way to address some of these endogeneity challenges in this context at the transaction level is to use a matching estimator. In matching, each treated observation can be compared to a specific control observation or a synthetic counterfactual untreated control observation that closely matches the treated unit on all relevant categories but the treatment itself. Since using an exactly matched control observation is not always possible, following prior research I use a bias-correcting propensity-score matching (PSM) estimator that utilizes five most closely matched nearest neighbor observations, with replacement (Abadie and Imbens, 2009; Imbens and Wooldridge, 2012; Valentini, 2012), and estimates the variable of interest as average treatment effect on the treated (ATT). Observations are matched based on their characteristics at the year, industry, firm, and transaction levels. I use additional treatment effects specifications (coarsened exact matching, different PSM specifications and additional tests, and inverse probability weighting regression adjustment) and other additional tests to then scrutinize the results from PSM models.

Linear Regression

Another way to address some of the aforementioned endogeneity challenges is by using a two stage selection corrected linear regression. When estimating acquisition performance at the transaction level, similar to the models used to estimate acquisition choice, I run a selection-adjusted[25] OLS regression within a pooled data set that includes all relevant controls as previously discussed for each of the performance models.

Firm Level Panel Analysis

An alternative approach to understanding acquisition performance is to consider firm-level performance based on the number and type of all acquisitions a firm has entered into over a period of time, here a year, and to analyze the resulting aggregated firm-level performance. There are several resulting changes in methods that are important to note here. First, at the firm level it is possible to employ a panel specification, utilizing panel regression (*xtreg* in Stata 15) for continuous variables, as well as appropriate discrete variable specifications (such as *OML Poisson*) where necessary. While this approach allows for a true panel fixed effects specification, it is important to note that this is a fundamentally different specification from a two stage Heckman selection adjustment approach or the matching approach used at the transaction level. Second, since it is near impossible to properly specify a financial performance model at the firm-year level using either the short- or long-term models described above, I instead use an alternative measure of accounting performance, in addition to measures of innovative performance.

[25] For the performance analysis, I use inverse Mills' ratios (IMR) constructed using the first stage model described earlier in the paper, where I first estimate the likelihood of the firm engaging in any acquisitions at all. Additionally I use alternative IMRs for selection into core or non-core acquisition.

4. RESULTS

4.1 DESCRIPTIVE STATISTICS AND FREQUENCIES

Some descriptive statistics are worth mentioning before proceeding to the core analysis. The number of acquisitions by the firms in the sample varies by year, with the low of 179 during the "Great Recession" in 2009 and the high of 293 preceding that downturn, as well as preceding the technology boom and bust of 2000-2001. As discussed previously, most firms in the sample engage in both alliances and acquisitions. Only 8.02% of firm-year observations are of firms with no alliances at all, and only 36.6% have five alliances or fewer. Firms engage in no acquisitions at all in 32.2% of in-sample firm-year observations. As expected, level of overall acquisition activity among the firms in my sample varies across the years, with acquisition peaks around 1999-2000, 2006, and 2010-2011 (See Figure 5). An average firm in the sample entered into 15 alliances and 11 acquisitions in the prior five years, with these numbers skewed by more active firms from the median of 6 alliances and 6 acquisitions. An average firm in the panel was granted 504 patents over the prior five years, with the median at 105. Focal firms are likely to have more non-core than core alliances, and non-core acquisitions outnumber core acquisitions roughly two to one. Only about 4% of all acquisitions are of prior alliance partners.

Figure 5: Frequency of Acquisitions by Year

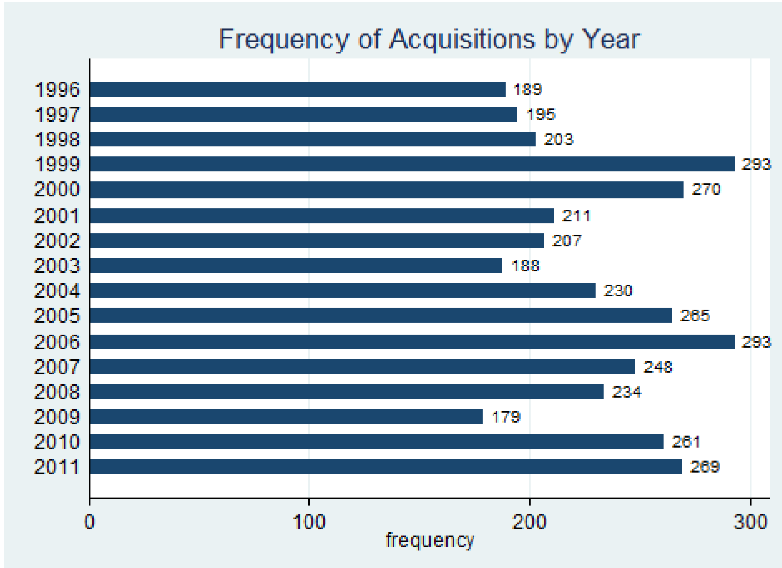


Figure 6 below summarizes frequencies of when specific types of acquisitions occur given the acquirer alliance portfolio. Core acquisitions when the focal firm has only a high number of core technological alliances or core functional alliances, and non-core unrelated acquisitions when a firm has many non-core technological alliances are relatively rare (3.43%, 4.66%, and 3.59%), while core acquisitions when a firm has many core functional and technological alliances, non-core unrelated acquisitions when the firm has many non-core functional alliances, and indirectly related non-core acquisitions in markets where the focal firm has many functional alliances are most common among all acquisition configurations (18.05%, 15.82%, and 14.30% respectively). I will revisit these numbers in my discussion of whether firm behavior matches the optimal choice (as offered in the hypotheses).

When it comes to financial performance of acquisitions, average cumulative abnormal returns over a five day period surrounding the acquisition announcement are close to zero, while average 24 month buy and hold returns are 4.23%. There are significant differences between partners and targets. Partners are more likely to be larger firms and more than twice as productive in median patent output, and seven times as productive in average patent output as the targets.

Figure 6: Frequency of Acquisition and Alliance Configuration Types

	Frequency in Sample	Percentage
Core Acquisition and Many Core Tech Alliances	128	3.43%
Core Acquisition and Many Core Functional Alliances	174	4.66%
Core Acquisition and Many Core Alliances	674	18.05%
Core Acquisition and Few Core Alliances	259	6.93%
Unrelated Non-Core Acquisition and Many Non-Core Tech Alliances	134	3.59%
Unrelated Non-Core Acquisition and Many Non-Core Funct. Alliances	336	9.00%
Unrelated Non-Core Acquisition and Many Non-Core Alliances	591	15.82%
Unrelated Non-Core Acquisition and Few Funct. Alliances	416	11.14%
Number of N/C Acq. in areas with Tech and Funct. All. Focus	334	8.94%
Number of N/C Acq. in areas with Tech All. Focus Only	333	8.93%
Number of N/C Acq. in areas with Funct Alliance Focus Only	534	14.30%

Table 3: First Stage (Selection) into acquiring

Model:	I	II	III
Likelihood of the focal firm engaging in :	**Any Acq.**	**N/Core Acq.**	**Core Acq.**
Annual Change in Industry Diversification	**8.273*** **(0.042)**	**11.793**** **(0.001)**	0.947 (0.795)
Industry Average Retained Earnings	**0.434**** **(0.009)**	**0.410†** **(0.051)**	0.266 (0.188)
Industry IPO Activity	**-0.001*** **(0.027)**	-0.0101 (0.485)	**-0.001**** **(0.010)**
Core Tech Alliance Portfolio	-0.010 (0.178)	-0.009 (0.180)	-0.001 (0.925)
Non-Core Tech Alliance Portfolio	**0.018**** **(0.010)**	**0.020**** **(0.008)**	0.004 (0.414)
Core Functional Alliance Portfolio	0.014 (0.125)	0.005 (0.461)	0.001 (0.889)
Non-Core Functional Alliance Portfolio	-0.004 (0.529)	-0.004 (0.612)	-0.006 (0.358)
Allies' Core Tech. Pat Portf. Proportion	0.001 (0.905)	-0.001 (0.539)	0.002 (0.117)
Allies' Non-Core Tech. Pat Portf. Proportion	-0.001 (0.363)	**-0.001†** **(0.052)**	0.001 (0.313)
Allies' Core Tech. Patent Portfolio	-0.001 (0.993)	-0.003 (0.852)	0.001 (0.958)
Allies' Non-Core Tech. Patent Portfolio	**0.034†** **(0.066)**	**0.042*** **(0.008)**	0.014 (0.414)
Tech. Core Alliances - 5yr Proportion	-0.209 (0.306)	**-0.796***** **(0.000)**	**0.959***** **(0.000)**
Funct. Core Alliances - 5yr Proportion	**-0.529*** **(0.018)**	**-0.637*** **(0.012)**	**1.696***** **(0.000)**
Tech. Non-Core Alliances - 5yr Proportion	-0.128 (0.461)	0.018 (0.922)	**0.435*** **(0.023)**
Focal Firm Acquisition Experience	**0.044***** **(0.000)**	**0.027***** **(0.000)**	**0.022***** **(0.000)**
Focal Firm Divestiture Experience	-0.002 (0.805)	0.013 (0.179)	-0.010 (0.283)
Focal Firm Patent Portfolio Size - 5 yr (log)	0.005 (0.824)	-0.014 (0.539)	-0.004 (0.874)
Focal Firm Diversification	-0.192 (0.313)	0.170 (0.391)	**-0.481*** **(0.012)**
Focal Firm Financial Constraint	**-1.272***** **(0.000)**	**-1.044***** **(0.000)**	**-1.248***** **(0.000)**
Focal Firm R&D Intensity	-0.214 (0.125)	-0.033 (0.688)	-0.065 (0.534)
New CEO in past 3 years	-0.074 (0.346)	**-0.139†** **(0.056)**	0.050 (0.5356)
Focal Firm Size - Number of Employees (log)	**0.126**** **(0.004)**	**0.104**** **(0.008)**	**0.106*** **(0.016)**
Firm Effects	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes
R-Squared	0.186	0.1636	0.1439
N	1996	1996	1996

Table 4: Acquisition Choice at the Transaction and Firm-Year Levels

Model	I	II	III	IV	V
	Transaction Level 2nd Stage Probit			Firm-Level QML Poisson	
	Core Acquisition	Non-Core Acquisition	Non-Core Acquisition	Core Acquisition	Non-Core Acquisition
Functional Non-Core Alliance Focus			**0.299**** **(0.008)**		
Tech Non-Core Alliance Focus			**0.720***** **(0.000)**		
Core Functional Alliance Portfolio	**0.028***** **(0.001)**	**-0.034***** **(0.000)**	**-0.030***** **(0.000)**	**0.023†** **(0.077)**	-0.013 (0.157)
Non-Core Functional Alliance Portfolio	**-0.006†** **(0.056)**	**0.006*** **(0.046)**	**0.004*** **(0.045)**	**-0.010*** **(0.041)**	**0.002†** **(0.068)**
Core Tech Alliance Portfolio	**-0.008†** **(0.068)**	**0.014*** **(0.014)**	0.008† (0.054)	**-0.024**** **(0.008)**	**0.023*** **(0.011)**
Non-Core Tech Alliance Portfolio	0.001 (0.385)	-0.001 (0.400)	-0.001 (0.188)	0.006 (0.131)	**-0.003**** **(0.005)**
Firm Effects	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes	Yes
Selection Adjustment	Yes	Yes	Yes	No	No
All Controls	Yes	Yes	Yes	Yes	Yes
R-Squared/ Log Likelihood	0.2041	0.2031	0.2205	-1381.62	-2115.01
N	3676	3676	3676	1753	1937

4.2 ACQUISITION CHOICE

4.2.1. Acquisition Choice Results

Table 3, Models I-III show the three versions of the first stage model, (likelihood of any acquisitions, non-core acquisitions only, core acquisitions only), including instruments[26] and all applicable controls. Some results here may be worth highlighting when it comes to the first stage, and the firm's choice to engage in any acquisitions at all. Financial constraints lower the likelihood of any acquisition (p = 0.000), while the size of non-core technological portfolios increase it for any acquisition and for non-core specifically (p = 0.010 and 0.008 respectively). Serial acquirers and large firms are more likely to continue acquiring in all spaces, while highly diversified firms are less likely to make core acquisitions and firms with new CEOs are less likely to make non-core acquisitions (p = 0.012 and 0.056 respectively).

Table 4 contains five total models. There are three models at the transaction level, all second stage probit models. Models I and II are almost mirror copies that estimate the likelihood of a transaction being either a core or a non-core technology acquisition, where only IMRs are different. Model III introduces measures of focus of acquirer's non-core technological and functional alliances in a non-core area where the transaction occurs. Table 4 contains two panel QML Poisson models (IV and V) with firm fixed effects, estimating count of core or non-core technology acquisitions at the firm-year level, but not adjusted for selection, providing an alternative specification for models in Table 3b, and incorporating observations where firms engage in no transactions at all. This makes

[26] Instruments are individually significant, and excluding any single instrument does not significantly alter the results.

acquisition choice independent as opposed to interdependent at the transaction level in the same table. All second stage probit or OLS models include the appropriate selection adjustment through IMR. All models contain all applicable controls as described in Table 2 (Controls not shown due to space limitation, available upon request).

When it comes to Hypotheses 1a and 1b, and the role of the firm's **functional** alliances, first, I find support for the role of cross-functional complementarity as the higher number of core functional alliances corresponds with the focal firm's likelihood to engage in core technology acquisitions, with the coefficient positive and significant in Models I and IV (p = 0.001 & 0.077 respectively). Similarly, there is evidence for the second part of H1a and the role of cross-functional complementarity with respect to non-core functional alliances, as the coefficient for the number of non-core functional alliances is positive and significant in Models II and III (p = 0.046 & 0.045 respectively), as well as Model V (p = 0.068). Notably, when it comes to the likelihood of acquisitions in non-core areas with no alliance focus, the effect is negative and significant, which may offer additional support for the overall logic and especially the role of focus as outlined in Hypothesis 1a. Firms may be less likely to acquire in non-core areas where they do not have access to non-core functional capabilities through alliances. When it comes to Hypothesis 1b and the role of functional alliances as disincentives to technology acquisitions in other areas, I find that the number of non-core functional alliances indeed has a significant and negative association with the likelihood and number of core acquisitions (Models I and IV, p = 0.056 and 0.041 respectively), but although the number of core functional alliances has a negative effect on likelihood of non-core acquisitions in models II and III, it is only negative but not significant ($p = 0.157$) in Model V. Overall, I interpret this as support for Hypothesis 1b.

When it comes to the substitutive role of the firm's **technological** alliances and decrease in the likelihood of core or non-core technology acquisitions, I find considerable evidence in support of Hypothesis 2a, but weaker evidence in support of Hypothesis 2b. Model I provides support for H2a, which asserts that core technological alliances are substitutes for core technology acquisitions, with a significant and negative coefficient ($p = 0.068$). Model IV provides additional support, with the coefficient again negative and significant ($p = 0.008$). However, Models II and III provide no support for H2b, which proposed that non-core technological alliances are substitutes for non-core technology acquisitions broadly, with only a negative, but insignificant coefficient. Model V provides additional support for H2b, with the coefficient again negative and significant ($p = 0.005$). Overall, the evidence supports the argument that the technological alliances may be substitutes for technology acquisitions at least in core settings, but the results with respect to the role of non-core technological alliances need to be investigated further. This is not entirely surprising, because as discussed previously, unlike the acquirer's core business, non-core segments are many and much more complex from the perspective of parsing out the role of various modes of external corporate development, so looking at the role of alliance focus in non-core areas should be more informative.

When it comes to the influence of non-core alliance focus on likelihood of indirectly related non-core acquisitions, as described in Hypotheses 1a and 2c, I find evidence in support of the positive effect of alliance focus in a non-core areas on acquisition likelihood in those areas. As Model III shows, the higher number of both technological and functional alliances in those non-core areas of focus indeed increases the likelihood of the focal firm engaging in acquisitions in those same areas, with strongly significant, positive coefficients (p = 0.000 and 0.008 respectively). This supports H1a and H2c. However, more analysis is necessary to understand the selection process with regard to this focus (i.e. interactions with other components of the alliance portfolio). Interestingly, although these effects are strong and significant across the entire sample, they are even stronger for single-business firms and casual (non-serial) acquirers (analysis not shown, available upon request).

The effects of the acquirer's alliances are economically significant. When it comes to core functional alliances, a relatively conservative move of increasing the number of these alliances from the mean by one standard deviation increases the likelihood of the firm engaging in a core technology acquisition by 18.25%, and decreases the likelihood of the firm engaging in a non-core technology acquisition by 7.78%. Doing the same for non-core functional alliances increases the likelihood of a non-core technology acquisition by 6.99%, and lowers the likelihood of a core technology acquisition by 13.29%. Additionally, a non-core technology acquisition is 11.6% more likely to be in a specific market where the focal firm has focused its non-core functional alliances. When it comes to core technological alliances, increasing the number of these from the mean by one standard deviation decreases the likelihood of the focal firm to make a core technology acquisition by 5.47%. Moreover, firms are 28.6% more likely to engage in non-core technology acquisitions of firms in specific markets where the focal firm has focused its non-core technological alliances. These economic effects were estimated using the summary statistics for all of the firms in the sample, and are significantly higher for the firms[27] that tend to be more active in using alliances and acquisitions.

Figure 7A: Summary of Findings - Effects of Functional Alliances on Capability Deployment through Technology Acquisition Choice

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="3">Technology Acquisitions in:</td></tr>
<tr><td>Core Market</td><td>Non-Core Unrelated Market</td><td>Non-Core Indirectly Related Market</td></tr>
<tr><td rowspan="2">Functional Alliances in:</td><td>Core Market</td><td><u>SUPPORTED:</u>
(p = 0.001 & 0.077)
Combining functional and technological capabilities in same business segment, whether core or non-core, increases opportunities for value creation and capture. (Hypothesis 1a).</td><td colspan="2"><u>PARTIALLY SUPPORTED</u>
(p = 0.000 & 0.157)
Capabilities accessible in some business segments disincentivize firms from investing in acquiring technological capabilities elsewhere (Hypothesis 1b).</td></tr>
<tr><td>Non-Core Market</td><td><u>SUPPORTED</u>
(p = 0.056 & 0.041)
Capabilities accessible in some business segments disincentivize firms from investing in acquiring technological capabilities elsewhere (Hypothesis 1b).</td><td colspan="2"><u>SUPPORTED</u>
(p = 0.046 & 0.045 & 0.008)
Combining functional and technological capabilities in same business segment, whether core or non-core, increases opportunities for value creation and capture. (Hypothesis 1a).</td></tr>
</table>

[27] These effects roughly double for the firms when estimated within the transaction level pooled data set, where they are biased by the actions of active acquirers.

Figure 7B: Summary of Findings - Effects of Technological Alliances on Capability Development through Technology Acquisition Choice

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="3">Technology Acquisitions in:</td></tr>
<tr><td>Core Market</td><td>Non-Core Unrelated Market</td><td>Non-Core Indirectly Related Market</td></tr>
<tr><td rowspan="2">Technological Alliances in:</td><td>Core Market</td><td><u>SUPPORTED:</u>
(p = 0.068 & 0.008)
Technological capabilities acquired through alliances or acquisitions may be substitutable, reducing this to a mode choice. (Hypothesis 2a)</td><td>Effects Not Theorized</td><td>Effects Not Theorized</td></tr>
<tr><td>Non-Core Market</td><td>Effects Not Theorized</td><td><u>PARTIALLY SUPPORTED:</u>
(p = 0.4, 0.18, 0.005)
Technological capabilities acquired through alliances or acquisitions may be substitutable when it comes to broad non-core exploration (Hypothesis 2b).</td><td><u>SUPPORTED:</u>
(p=0.000)
Combining tech capabilities from alliances and acquisitions in same non-core businesses may be complementary and increase likelihood of value creation and capture. (Hypothesis 2c)</td></tr>
</table>

4.2.2. Summary of Empirical Findings: Acquisition Choice

Figures 7a and 7b illustrate the empirical findings with respect to acquisition choice. First, I find support for my hypothesis that functional alliances may be complementary to technology acquisitions in same business segments (Hypothesis 1a, Figure 7a), and that they may also serve as disincentives to technology acquisitions in other business segments (Hypothesis 1b, Figure 7a), although Hypothesis 1b is only partially supported. Second, I also find evidence in support of my theories with respect to how technological alliances may generally substitute for technology acquisitions in core or non-core segments (Hypotheses 2a and 2b, Figure 7b), but may also be complementary to technology acquisitions within specific strategically important non-core business segments (Hypothesis 2c, Figure 2b), although support for Hypothesis 2b is partial. Third, my analysis shows that some of the non-core transactions may not be unrelated, as literature generally suggests, but instead in fact be indirectly related non-core technology acquisitions complementary to the acquirer through its alliance portfolio (Hypotheses 1a (non-core only) and 2c, Figures 7a and 7b). Next, I consider the more nuanced analysis of acquisition choice in the context of alliance portfolios for acquisition performance.

4.3 ACQUISITION PERFORMANCE

4.3.1 Do Firms Make "Right" Acquisition Choices?

Before analyzing the performance outcomes of firms' acquisition choices, I consider if the patterns of firm behavior match those theorized in this work. Here we can revisit the acquisition frequencies listed in Figure 6 that was presented earlier, which sheds some light on whether firms actually make acquisition choices similar to those proposed earlier in this study.

First, referring back to Figure 3 shown earlier, the acquisitions that are theorized to be less likely and to have negative performance implications due to substitutability and redundancy, that is core and unrelated non-core acquisitions when the focal firm has many core or non-core technological alliances are indeed the two most rare acquisition types, at 3.43% and 3.59% of all acquisitions in my data respectively. This offers some additional, albeit not conclusive support for my theory. However, 18.05% and 15.82% of all acquisitions are core and unrelated non-core acquisitions combined with many functional and technological core and non-core alliances respectively. The performance of these acquisitions is more difficult to interpret as they are subject to both negative and positive effects per my theorizing. I do not specifically elaborate the effects of these acquisitions, but by including and controlling for these in my model, I can focus on the variance for the relevant non-mixed cases only. Moreover, when it comes to indirectly related non-core acquisitions, 8.93% of these are in areas where firms focus their non-core technological alliances, 14.3% are in the areas where firms focus their non-core functional alliances, and 8.94% of these are where firms focus both functional and technological alliances. While these frequencies are purely descriptive and should not be taken as solid evidence, they provide some indication that firms may act in accordance with theoretical logic elaborated earlier in this study.

Table 5: Short Term Financial Acquisition Performance (CAR) – Transaction-Level Matching Models

Acquisition Performance - Cumulative Abnormal Returns - Propensity Score Matching Models			
Treatment:	Among All Acq.	Among Core Acq.	Among Non-Core Acq.
Core Acquisition*Core Tech Alliances	-0.002 (0.662)	-0.002 (0.745)	
Core Acquisition*Core Funct. Alliances	~~**-0.011**~~ ~~**(0.023)**~~	~~**-0.005**~~ ~~**(0.067)**~~	
Core Acquisition*Few Core Alliances	0.005 (0.167)	0.008 (0.147)	
Non-Core Acquisition Indirectly Related through Non-Core Tech Alliances	**0.007*** **(0.014)**		**0.010**** **(0.002)**
Non-Core Acquisition Indirectly Related through Non-Core Funct. Alliances	~~**0.005**~~ ~~**(0.049)**~~		0.001 (0.706)
Unrelated Non-Core Acquisition * Non-Core Tech Alliances	~~**-0.012**~~ ~~**(0.060)**~~		-0.006 (0.325)
Unrelated Non-Core Acquisition * Non-Core Funct. Alliances	**-0.002*** **(0.031)**		-0.000 (0.999)
Unrelated Non-Core Acquisition * Few Non-Core Alliances	0.003 (0.508)		0.009 (0.223)
Observations matched on all transaction and firm characteristics	Yes	Yes	Yes
N	3886	1313	2573

<u>**Each cell represents a different matching model.**</u> Propensity score matching models using all controls, measuring average treated effect on the treated, comparing treated acquisitions with five nearest untreated neighbor matches. P-values are in parentheses.

Table 6: Long Term Financial Acquisition Performance (BHAR) – Transaction-Level Matching Models

	Acquisition Performance - Buy and Hold Abnormal Returns - Matching Models		
Treatment:	Among All Acq.	Among Core Acq.	Among Non-Core Acq.
Core Acquisition*Core Tech Alliances	0.004 (0.954)	0.077 (0.238)	
Core Acquisition*Core Funct. Alliances	**-0.164***** **(0.000)**	~~**-0.188*****~~ ~~**(0.000)**~~	
Core Acquisition*Few Core Alliances	-0.021 (0.705)	~~**0.098†**~~ ~~**(0.060)**~~	
Non-Core Acquisition Indirectly Related through Non-Core Tech Alliances	**0.137**** **(0.006)**		**0.129*** **(0.023)**
Non-Core Acquisition Indirectly Related through Non-Core Funct. Alliances	-0.014 (0.730)		0.062 (0.176)
Unrelated Non-Core Acquisition * Non-Core Tech Alliances	-0.089 (0.257)		-0.086 (0.336)
Unrelated Non-Core Acquisition * Non-Core Funct. Alliances	-0.052 (0.156)		~~**-0.073**~~ ~~**(0.065)**~~
Unrelated Non-Core Acquisition * Few Non-Core Alliances	~~**-0.120**~~ ~~**(0.039)**~~		-0.078 (0.302)
Observations matched on all transaction and firm characteristics	Yes	Yes	Yes
N	3329	1128	2201

<u>Each cell represents a different matching model.</u> Propensity score matching models using all controls, measuring average treated effect on the treated, comparing treated acquisitions with five nearest untreated neighbor matches. P-values are in parentheses.

Table 7: Short Term Financial Acquisition Performance (CAR) – Transaction-Level 2nd Stage Regression Models

Model	I	II	III
	Acquisition Performance - CAR		
Treatment:	Among All Acq.	Among Core Acq.	Among Non-Core Acq.
Core Acquisition*Core Tech Alliances	-0.001 (0.842)	-0.010 (0.210)	
Core Acquisition*Core Funct. Alliances	-0.008 (0.148)	-0.009 (0.239)	
Core Acquisition*Many Core Alliances	-0.001 (0.613)	-0.005 (0.523)	
Core Acquisition*Few Core Alliances	0.002 (0.565)		
Non-Core Acquisition Indirectly Related through Non-Core Tech Alliances	**0.008**** **(0.006)**		**0.009*** **(0.011)**
Non-Core Acquisition Indirectly Related through Non-Core Funct. Alliances	0.001 (0.954)		0.001 (0.780)
Unrelated Non-Core Acquisition * Non-Core Tech Alliances	-0.010 (0.175)		-0.012 (0.119)
Unrelated Non-Core Acquisition * Non-Core Funct. Alliances	-0.003 (0.485)		-0.002 (0.601)
Unrelated Non-Core Acquisition * Many Non-Core Alliances	0.001 (0.751)		0.001 (0.787)
Core Tech Alliance Portfolio	-0.001 (0.258)	0.001 (0.112)	0.001 (0.447)
Core Functional Alliance Portfolio	0.001 (0.303)	**0.001*** **(0.037)**	-0.001 (0.213)
Non-Core Tech Alliance Portfolio	-0.001 (0.178)	-0.001 (0.633)	-0.001 (0.132)
Non-Core Functional Alliance Portfolio	0.000 (0.481)	-0.001 (0.263)	**0.001†** **(0.055)**
All other variables, controls, firm, industry and year effects included	Yes	Yes	Yes
Selection Adjustment	Any Acq. IMR	Core Acq. IMR	N/Core Acq. IMR
R-Squared	0.0584	0.0678	0.0545
Prob > F	0	0	0
N	3542	1176	2366

Table 8: Long Term Financial Acquisition Performance (BHAR) – Transaction-Level Regression Models

Model	I	II	III
	Acquisition Performance - BHAR		
Treatment:	Among All Acq.	Among Core Acq.	Among Non-Core Acq.
Core Acquisition*Core Tech Alliances	0.257 (0.821)	-0.067 (0.683)	
Core Acquisition*Core Funct. Alliances	**-0.166†** **(0.079)**	**-0.269*** **(0.023)**	
Core Acquisition*Many Core Alliances	0.010 (0.889)	-0.171 (0.211)	
Core Acquisition*Few Core Alliances	0.009 (0.902)		
Non-Core Acquisition Indirectly Related through Non-Core Tech Alliances	0.083 (0.291)		**0.168*** **(0.012)**
Non-Core Acquisition Indirectly Related through Non-Core Funct. Alliances	0.031 (0.744)		0.090 (0.496)
Unrelated Non-Core Acquisition * Non-Core Tech Alliances	-0.090 (0.376)		-0.122 (0.266)
Unrelated Non-Core Acquisition * Non-Core Funct. Alliances	0.017 (0.872)		0.090 (0.446)
Unrelated Non-Core Acquisition * Many Non-Core Alliances	0.0139 (0.561		0.099 (0.228)
Core Tech Alliance Portfolio	0.016 (0.105)	**0.033*** **(0.043)**	0.004 (0.458)
Core Functional Alliance Portfolio	-0.017† (0.059)	**-0.036*** **(0.035)**	-0.005 (0.444)
Non-Core Tech Alliance Portfolio	-0.001 (0.355)	-0.005 (0.250)	-0.001 (0.446)
Non-Core Functional Alliance Portfolio	0.001 (0.319)	0.008 (0.108)	0.002 (0.260)
All other variables, controls, firm, industry and year effects included	Yes	Yes	Yes
Selection Adjustment	Any Acq. IMR	Core Acq. IMR	N/Core Acq. IMR
R-Squared	0.1485	0.2187	0.1441
Prob > F	0	0	0
N	3023	1001	2022

Table 9: Accounting Acquisition Performance (Likelihood of Goodwill Impairment, Return on Assets) – Firm/Year-Level Regression Models

Model:	**I**	**II**	**III**
	L/Hood of GW Impair't (5yr)	**ROA (t-2,t+2) Ind. Avg. Adj**	**ROA (t-3,t+3) Ind. Avg. Adj**
Number of Core Acquisitions	**0.242** (0.001)**	**-0.011* (0.031)**	-0.006 (0.120)
Number of Non-Core Acquisitions (non-focus)	**0.291* (0.019)**	**-0.026* (0.020)**	**-0.018* (0.043)**
Core Tech Alliance Portfolio	-0.040 (0.121)	-0.001 (0.795)	0.000 (0.997)
Non-Core Tech Alliance Portfolio	**-0.022† (0.051)**	**0.001** (0.001)**	**0.001*** (0.000)**
Core Functional Alliance Portfolio	**0.080† (0.050)**	-0.001 (0.944)	0.001 (0.947)
Non-Core Functional Alliance Portfolio	**-0.062*** (0.000)**	**-0.001* (0.039)**	**-0.001* (0.018)**
Core Acq. * Core Tech Alliance Portfolio	-0.001 (0.828)	**0.001† (0.097)**	0.001 (0.177)
Core Acquisition * Core Funct. Alliance Portfolio	-0.007 (0.377)	-0.001 (0.707)	-0.001 (0.570)
Non-Core Acq. (N/Focus) * Non-Core Tech Alliance Portfolio	0.000 (0.997)	**0.001* (0.021)**	**0.001† (0.084)**
Non-Core Acq. (N/Focus) * Non-Core Funct Alliance Portfolio	**0.032* (0.037)**	**-0.002† (0.052)**	**-0.001† (0.095)**
Number of N/C Acq. in areas with Tech All. Focus	0.097 (0.153)	**-0.006† (0.069)**	-0.004 (0.136)
Number of N/C Acq. in areas with Funct Alliance Focus	0.002 (0.975)	**0.008* (0.030)**	**0.007* (0.055)**
Model Specification	**xtlogit**	**xtreg**	**xtreg**
Firm Effects	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes
Selection Adjustment	No	No	No
All Appl. Controls	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000
N	1790	1885	1825

4.3.2 Short-Term and Long-Term Financial Performance

Tables 5 and 6 show the results of sixteen different propensity-score matching models, where each coefficient is indicative of the difference in outcome between the treatment group and the matched control group within a distinct specification. For example, the top coefficient on the left in Table 5 is where the treatment is a core acquisition by an acquirer with a high number of core technological alliances in a sample of all acquisitions. Matching results are first obtained with the propensity score matching (PSM) model, then subjected to overlap and support tests, as well as tested in an additional treatment effects model specified as inverse probability weighting regression adjustment. Strikeout text indicates results that failed some additional robustness checks in matching models. Tables 7 and 8 show the results of three 2nd stage regressions each estimating the effects of all of the independent variables and their interactions simultaneously, within a sample of all, non-core only, and core acquisitions only. Tables 5 and 7 show at the performance outcomes as short-term cumulative abnormal returns (5-day CAR), while Tables 6 and 8 show the performance outcomes as long-term buy and hold returns (24 month BHAR).

When it comes to short-term financial performance shown in Tables 5 and 7, there are several results worth highlighting. First, while in CAR matching models (Table 5) for firms with a larger portfolio of core functional alliances, core technology acquisitions seem to underperform compared to both other core acquisitions (p=0.067), as well as all other acquisitions (p = 0.0023), these results are not robust to all additional matching tests, and although the coefficients are negative in respective regression models, these effects are not statistically significant. However, these same effects are more prominent

(p = 0.000 for both) in long-term transaction performance (BHAR) models (Table 6), although BHAR matching tests are borderline inconclusive on robustness of these effects in matching models. These effects are also duplicated in BHAR regression models compared to all and core only acquisitions (Table 8, Models I and II; p = 0.079 and 0.023 respectively). I interpret this as inconclusive evidence to the prediction in **Hypothesis 1a** that combinations of core technology acquisitions and core functional alliances may have positive implications related to how value is created and captured between partners.

Second, in line with **Hypothesis 2c**, indirectly related non-core acquisitions in markets where firms focus their technological alliances outperform all other acquisitions (p = 0.014) and all other non-core acquisitions (p = 0.002) when it comes to CAR models shown in Table 5, and these effects are similarly present in long-term BHAR models (p = 0.006 and 0.023 respectively) shown in Table 6. Interestingly, these effects are stronger for more experienced (serial) acquirers, but not present in a subsample of inexperienced, casual acquirers, and while CAR is larger for single-business firms engaging in these transactions, it is not statistically significant (analysis not shown, available upon request). Overall, this set of results is similarly significant and robust in all specifications and robustness tests, including IPWRA models. On the other hand, while indirectly related non-core acquisitions in markets where firms focus their functional alliances seem to outperform within the sample of all acquisitions (Table 5; p = 0.049), but not all non-core acquisitions, these results do not stand up to further robustness testing, although there is also limited support for these in BHAR regressions. In addition, there is weaker evidence (in the matching models only) in line with **Hypothesis 2b** that unrelated non-core technology acquisitions may underperform when compared to a sample of all other acquisitions in the presence of a high number of non-core technological alliances (Table 5; $p = 0.060$, but not supported by all additional tests) and, following **Hypothesis 1a**, in the presence of a high number of non-core functional alliances ($p = 0.031$, supported by additional robustness testing).

It is worth pointing out that the most robust of these performance effects are also highly economically significant. For example, indirectly related non-core acquisitions outperform all other acquisitions in the short-term by 0.7%, and in the long-term, by 13.7%, which even for a reasonably small firm (within this sample) with a $5 billion market cap would respectively translate to $35 million and $685 million in added shareholder value, and this becomes even more significant considering that many of the firms in my sample engage in multiple acquisitions every year.

4.3.3 Long-Term Accounting Performance

An alternative way to assess acquisition performance is to look at performance at the firm level, following a focal firm's acquisition activity that year, and given the acquirer's alliance portfolio, and its choice to engage in acquisitions. It is important to point out that firm-level performance given a <u>number</u> of acquisitions and other strategic decisions should be considered from a different perspective than the performance at the transaction level. Table 9 contains three models that show firm-level performance outcomes that can be compared to transaction level acquisition performance outcomes discussed above.

Model I is a panel logistic regression that shows the likelihood of a firm having a goodwill impairment (which amounts to negative performance) in the five years following the focal year. Both a higher number of core acquisitions and unrelated non-core acquisitions increase the likelihood of goodwill impairment, a signal of poor long-term acquisition performance specifically, while the number of indirectly related acquisitions, whether in areas of technological or functional non-core alliance focus do not increase this likelihood. While this does not confirm the positive performance effects of indirectly related acquisitions as discussed in **Hypothesis 2c** specifically, such acquisitions may be less risky than other types of acquisitions. Interestingly, unrelated non-core acquisitions lead to a higher chance of goodwill impairment when the focal firm has many non-core functional alliances ($p = 0.030$), even though a higher number of such alliances in itself decreases the chances of goodwill impairment overall. These results are also largely robust to conditioning the dependent variable on whether the firm had a goodwill impairment in the five years prior to the focal year.

Models II and III use return on equity (ROA) as a measure of long-term acquisition performance, comparing an acquirer's average industry-adjusted ROA two and three years before and two and three years after an acquisition respectively. Several effects are worth highlighting here as well. First, in general, the higher the number of acquisitions, whether core or non-core, the lower the ROA, in line with negative performance effect in Model I. However, contrary to some of my initial predictions (**Hypotheses 2a, 2b**), performance seems to improve for core acquisitions with a higher number of core technological alliances ($p = 0.025$) and for unrelated non-core acquisitions with a higher number of overall non-core technological alliances ($p = 0.012$). As predicted in **Hypothesis 2c,** performance also improves with a higher number of indirectly related non-core acquisitions in an area of functional alliance focus ($p = 0.020$), offering further support for the positive effects of indirectly related non-core acquisitions.

Contrary to **Hypotheses 2b and 1a**, performance is lower for indirectly related non-core acquisitions in an area of technological focus (p = 0.005), and for unrelated non-core acquisitions while having a higher number of functional alliances (p = 0.094).

Table 10: Innovative Acquisition Performance (Number of Patent Applications) – Firm/Year-Level Regression Models

Model:	**I**	**II**	**III**	**IV**
	New Pat. Apps t+1	**New Pat. Apps t+2**	**New Pat. Apps t+3**	**New Pat. Apps t+4**
Number of Core Acquisitions	**0.042*** **(0.050)**	0.031 (0.244)	0.012 (0.668)	-0.005 (0.866)
Number of Non-Core Acquisitions (non-focus)	**0.049***** **(0.000)**	**0.049***** **(0.001)**	-0.007 (0.616)	**-0.023†** **(0.071)**
Core Tech Alliance Portfolio	0.001 (0.854)	0.006 (0.305)	0.009 (0.174)	**0.011†** **(0.061)**
Non-Core Tech Alliance Portfolio	**0.003†** **(0.058)**	**0.003†** **(0.068)**	0.003 (0.136)	**0.004†** **(0.066)**
Core Functional Alliance Portfolio	**-0.012†** **(0.064)**	-0.012 (0.106)	-0.009 (0.280)	-0.011 (0.207)
Non-Core Functional Alliance Portfolio	**0.007***** **(0.000)**	**0.005***** **(0.000)**	**0.006**** **(0.003)**	**0.005*** **(0.022)**
Core Acq. * Core Tech Alliance Portfolio	**-0.002*** **(0.030)**	**-0.002*** **(0.014)**	-0.001 (0.357)	-0.001 (0.138)
Core Acquisition * Core Funct. Alliance Portfolio	**0.002†** **(0.077)**	**0.002*** **(0.039)**	0.002 (0.183)	**0.003*** **(0.042)**
Non-Core Acq. (N/Focus) * Non-Core Tech Alliance Portfolio	**-0.001**** **(0.005)**	-0.001 (0.540)	0.000 (0.833)	0.000 (0.294)
Non-Core Acq. (N/Focus) * Non-Core Funct Alliance Portfolio	**0.007***** **(0.000)**	**0.005***** **(0.000)**	**0.002†** **(0.080)**	**0.005*** **(0.022)**
Number of N/C Acq. in areas with Tech All. Focus	0.004 (0.621)	0.002 (0.836)	**-0.020*** **(0.043)**	-0.008 (0.419)
Number of N/C Acq. in areas with Funct Alliance Focus	0.000 (0.998)	-0.003 (0.749)	0.009 (0.370)	-0.005 (0.576)
Model Specification	**xtpqml**	**xtpqml**	**xtpqml**	**xtpqml**
Firm Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Selection Adjustment	No	No	No	No
All Appl. Controls	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000
N	1836	1781	1707	1569

Table 11: Innovative Acquisition Performance (Number of Citations to New Patents) – Firm/Year-Level Regression Models

Model:	**I**	**II**	**III**	**IV**
	New Pat. Citations t+1	**New Pat. Citations t+2**	**New Pat. Citations t+3**	**New Pat. Citations t+4**
Number of Core Acquisitions	0.042 (0.130)	-0.021 (0.406)	-0.016 (0.621)	-0.025 (0.459)
Number of Non-Core Acquisitions (non-focus)	**0.064***** **(0.000)**	**0.087***** **(0.000)**	**0.038†** **(0.078)**	**0.083**** **(0.005)**
Core Tech Alliance Portfolio	0.005 (0.679)	0.012 (0.139)	**0.017*** **(0.042)**	**0.023**** **(0.005)**
Non-Core Tech Alliance Portfolio	0.001 (0.764)	-0.000 (0.930)	0.000 (0.923)	0.002 (0.649)
Core Functional Alliance Portfolio	-0.007 (0.566)	-0.016 (0.166)	-0.012 (0.232)	**-0.018†** **(0.081)**
Non-Core Functional Alliance Portfolio	**0.007**** **(0.003)**	**0.009***** **(0.000)**	**0.008*** **(0.012)**	**0.006†** **(0.073)**
Core Acq. * Core Tech Alliance Portfolio	-0.001 (0.231)	-0.001 (0.383)	-0.001 (0.714)	-0.001 (0.490)
Core Acquisition * Core Funct. Alliance Portfolio	0.001 (0.425)	0.002 (0.186)	0.001 (0.425)	0.003 (0.105)
Non-Core Acq. (N/Focus) * Non-Core Tech Alliance Portfolio	**-0.001*** **(0.040)**	**-0.001*** **(0.033)**	0.000 (0.450)	**-0.001†** **(0.095)**
Non-Core Acq. (N/Focus) * Non-Core Funct Alliance Portfolio	**0.007***** **(0.000)**	**0.010***** **(0.000)**	**0.008*** **(0.012)**	-0.002 (0.250)
Number of N/C Acq. in areas with Tech All. Focus	0.004 (0.686)	-0.007 (0.554)	-0.019 (0.155)	**-0.031*** **(0.034)**
Number of N/C Acq. in areas with Funct Alliance Focus	0.005 (0.684)	0.014 (0.133)	0.011 (0.479)	0.011 (0.338)
Model Specification	**xtpqml**	**xtpqml**	**xtpqml**	**xtpqml**
Firm Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Selection Adjustment	No	No	No	No
All Appl. Controls	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000
N	1836	1781	1707	1569

Table 12: Innovative Acquisition Performance (Number of Breakthrough Patents, 95% level) – Firm/Year-Level Regression Models

Model:	**I**	**II**	**III**	**IV**
	Breakthrough Patents t+1	**Breakthrough Patents t+2**	**Breakthrough Patents t+3**	**Breakthrough Patents t+4**
Number of Core Acquisitions	-0.009 (0.752)	**-0.050† (0.058)**	-0.038 (0.264)	-0.052 (0.112)
Number of Non-Core Acquisitions (non-focus)	**0.050*** (0.000)**	**0.080*** (0.000)**	-0.019 (0.250)	**-0.044† (0.094)**
Core Tech Alliance Portfolio	0.001 (0.944)	**0.018† (0.088)**	**0.023* (0.025)**	**0.031** (0.001)**
Non-Core Tech Alliance Portfolio	**-0.009† (0.081)**	-0.007 (0.135)	-0.005 (0.251)	-0.002 (0.591)
Core Functional Alliance Portfolio	-0.003 (0.785)	-0.020 (0.130)	-0.017 (0.172)	**-0.028* (0.019)**
Non-Core Functional Alliance Portfolio	**0.010*** (0.001)**	**0.012*** (0.001)**	**0.011** (0.001)**	**0.009** (0.004)**
Core Acq. * Core Tech Alliance Portfolio	0.001 (0.609)	0.001 (0.661)	0.000 (0.388)	0.000 (0.931)
Core Acquisition * Core Funct. Alliance Portfolio	-0.000 (0.399)	0.001 (0.544)	0.000 (0.989)	0.002 (0.135)
Non-Core Acq. (N/Focus) * Non-Core Tech Alliance Portfolio	-0.001 (0.481)	-0.001 (0.207)	0.000 (0.331)	0.001 (0.472)
Non-Core Acq. (N/Focus) * Non-Core Funct Alliance Portfolio	**0.006*** (0.000)**	**0.011*** (0.000)**	**0.004* (0.019)**	-0.002 (0.306)
Number of N/C Acq. in areas with Tech All. Focus	0.012 (0.337)	0.001 (0.944)	-0.009 (0.440)	-0.019 (0.226)
Number of N/C Acq. in areas with Funct Alliance Focus	0.005 (0.704)	0.003 (0.762)	**0.020* (0.012)**	0.022 (0.132)
Model Specification	**xtpqml**	**xtpqml**	**xtpqml**	**xtpqml**
Firm Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Selection Adjustment	No	No	No	No
All Appl. Controls	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000
N	1629	1585	1533	1402

4.3.4 Long-Term Innovative Performance

Next, I assess the effects of acquisitions when it comes to firms' innovative performance. Tables 10-12 offer three distinct ways to analyze innovative activity of firms, including total patent output, external evaluation of these patents as a number of outside citations, and the number of highly important breakthrough patents.

Some of the most robust findings from the three different specifications are with regard to the innovative effects of unrelated non-core acquisitions from **Hypothesis 1a**, which raise the number of patent applications in the two years following these acquisitions (Table 10, Models I and II; $p = 0.000$ and 0.001 respectively), increase the number of citations to patents in the four years following the acquisition (see Table 11, Models I - IV for p-values), and increase the number of breakthrough patents in the two years following acquisition activity (Table 12, Models I and II; $p = 0.000$ for both) with the higher number of functional non-core alliances. This interaction of unrelated non-core acquisitions and non-core functional alliances is positive and significant across all three models in the first three years following the acquisition (see Tables 10-12 for p-values).

At the same time, when combined with a higher number of technological non-core alliances, the number of new patents decreases in the year following more non-core unrelated acquisitions (Table 10, Model I; $p = 0.005$), and the number of citations decreases to new patents in the two years following these acquisitions (Table 11, Models I and II; $p = 0.040$ and 0.033 respectively). This provides support for my theorizing in **Hypothesis 1a** the role of combining non-core functional alliances with non-core technological acquisitions in improving acquisition performance, and, from **Hypothesis 2b**, the negative effect of combining non-core technological alliances with unrelated non-core technological acquisitions. Interestingly, offering some additional support to **Hypothesis 2a**, I also find that the high number of core technology acquisitions combined with the high number of core technological alliances seems to decrease the quantity, that is the number of new patents in the two years following the focal year (Table 10, Models I and II; $p = 0.030$ and 0.014 respectively), but has no significant effect on their quality, that is number of citations or number of breakthrough patents. I interpret this as limited support for my theorizing that too many core acquisitions combined with too many core technological alliances may lead to resource redundancy and negative performance.

Figure 8A: Proposed Performance Effects of Functional Alliances on Technology Acquisitions

		Technology Acquisitions in:		
		Core Market	**Non-Core Unrelated Market**	**Non-Core Indirectly Related Market**
Functional Alliances in:	**Core Market**	FIN. PERFORMANCE: **INCONCLUSIVE*** (Predicted: Positive effects due to value creation opportunities resulting from complementarity in core markets) INNOV. PERFORMANCE: **PARTIAL SUPPORT for Patent Output (*p= 0.077, 0.039, 0.042)*** (Predicted: Positive effects due to recombination opportunities and knowledge spillovers, less chance of knowledge leakage due to functional nature of alliances)	Effects Not Theorized	Effects Not Theorized
	Non-Core Market	Effects Not Theorized	FIN. PERFORMANCE: **CONTRARY EVIDENCE (*p* = 0.031, 0.037, 0.052*)*** (Predicted: Positive effects due to value creation opportunities resulting from potential complementarity in other markets) INNOV. PERFORMANCE: **STRONG SUPPORT for Patent Output, Citations, B/Through*** (Predicted: Positive effects due to recombination opportunities and knowledge spillovers, less chance of knowledge leakage due to functional nature of alliances)	FIN. PERFORMANCE: **PARTIAL SUPPORT (*p* = 0.049, 0.17, 0.030*)*** (Predicted: Positive effects due to value creation opportunities resulting from complementarity in same markets) INNOV. PERFORMANCE: **WEAK SUPPORT for B/Through Pat.*** (Predicted: Positive effects due to recombination opportunities and knowledge spillovers, less chance of knowledge leakage due to functional nature of alliances)

* Please see appropriate performance analysis tables for *p*-values and more details.

Figure 8B: Proposed Performance Effects of Technological Alliances on Technology Acquisitions

		Technology Acquisitions in:		
		Core Market	**Non-Core Unrelated Market**	**Non-Core Indirectly Related Market**
Technological Alliances in:	**Core Market**	FIN. PERFORMANCE: **NO EVIDENCE*** (Predicted: Negative effects due to higher chances of redundancy and substitutability) INNOV. PERFORMANCE: **PARTIAL SUPPORT for Patent Output (p= 0.030, 0.014)** (Predicted: Negative effects due to higher chances of redundancy and substitutability)	Effects Not Theorized	Effects Not Theorized
	Non-Core Market	Effects Not Theorized	FIN. PERFORMANCE: **MIXED SUPPORT (p = 0.060, 0.176), *L/T Mixed*** (Predicted: Negative effects due to diverse redundancy, lack of knowledge and high resource demands) INNOV. PERFORMANCE: **SUPPORTED for Patent Output, Citations, (p= 0.005, 0.040, 0.033, 0.095)** (Predicted: Negative effects due to lack of knowledge and high resource demands, lack of focus)	FIN.PERFORMANCE: **SUPPORTED (p= 0.014, 0.002, 0.000), L/T mixed** (Predicted: Positive effects due to increased potential for value creation and value capture opportunities) INNOV. PERFORMANCE: **WEAK CONTRARY EVIDENCE*** for Pat. Output (Predicted: Positive effects due to more recombination opportunities, higher likelihood of radical innovation, and increased value creation and value capture opportunities)

* Please see appropriate performance analysis tables for *p*-values and more details.

4.3.5 Summary of Empirical Findings: Reconciling Acquisition Performance and Acquisition Choice

Figures 8a and 8b summarize the main findings of my empirical analysis with respect to acquisition performance. There are two aspects of the performance analysis that are worth mentioning before moving to the specific results. First, it is worth noting that while I focus on finding empirical evidence in support of or contrary to my predictions, absence of empirical evidence does not automatically equate to absence of a performance effect, as technically, with proper accounting for selection, no result may still be the expected positive performance, again, given the complex self-selection of firms in this context. Second, due to the complexity of the composition of the alliance portfolios and firms' combined strategic choices and all of the resulting interactions, effects can only be interpreted very conservatively, with a focus on the presence and direction, rather than the exact effect size, which would require expansive additional empirical analysis and testing.

Role of Functional Alliances

These results are summarized in the Figure 8a above. First, I find some support with respect to performance effects of functional alliances and their potential complementarity to technology acquisitions in the same business segments, following the logic of acquisition choice from **Hypothesis 1a**. In general, positive effects of these on innovative performance are supported in core and unrelated non-core markets, but I find only weak support for the positive effects of non-core functional alliances on innovative performance in indirectly related non-core markets, which is puzzling because a significant fraction of acquisitions fall in this area (14.3%). The effects of the functional alliances on financial performance are more difficult to interpret, as I find inconclusive results with respect to the effect of the core functional alliances on financial performance of core technology acquisitions where I expected negative effects, opposite results with respect to non-core functional alliances' effect on financial performance of unrelated non-core technology acquisitions where I expected positive effects, and, as already mentioned, partial support for their effect on financial performance of indirectly related non-core acquisitions.

While **Hypothesis 1a** was generally well-supported in my empirical analysis of acquisition choice, it is worth pointing out a few patterns in an attempt to reconcile choice and performance. First, firms rarely engage in core technology acquisitions given a high number of core functional alliances, which amounts to only 4.66% of all acquisition configurations in my sample. Given inconclusive or weak evidence in support of performance when it comes to this transaction type, it may be the case that when firms choose to engage in this type of acquisitions, it may be due to an idiosyncratic and rare combination of resources that is optimal in certain circumstances or for certain firms. Moreover, it is worth pointing out, as previously alluded to in my theory, that firms should have their own core functional capabilities by the virtue of it being their core business, so again, further theorizing and investigation may be required into when or why firms may need partners' core functional capabilities. In the case where a firm may have to rely on partners' core functional capabilities to extract value from core technological acquisitions instead, it may also be possible that the focal firm may fail to capture created value or a proportional fraction of that value, and so then the firm may realize negative financial performance from these acquisitions when it fails to capture necessary value (Yang *et al*., 2015; Zanarone *et al*., 2016).

Second, while the financial performance of unrelated non-core acquisitions seems to suffer in presence of non-core functional alliances, the innovative performance effects of these types of transactions seem to be strong and robust enough across the different approach to innovative performance to justify the performance tradeoff, as I discussed earlier in my theory section on reconciling performance and choice**.** *Functional collaborations combined with technology acquisitions seem to be an important source of innovation for the focal firm.* Third and final, it is intriguing that while firms seem to choose to engage in indirectly related acquisitions in areas where they focus their functional alliances (as my analysis of choice indicated), I find only weak or partial support for positive effects of such transactions on either financial or innovative performance. This also may require further inquiry in the future.

Role of Technological Alliances

These results are summarized in Figure 8b above. Following the logic of **Hypotheses 2a** and **2b**, I find mixed support for my theorizing with respect to how technological alliances may generally substitute for technology acquisitions in core or non-core markets, leading to negative performance if firms choose to engage in such transaction configurations. Given that these specific acquisition configurations are two of the most infrequent combinations (3.43% and 3.59%), it may be the case that firms generally avoid engaging in these types of acquisitions unless there is a very specific reason where such an acquisition may be required, which may explain mixed results in my empirical analysis. Moreover, in my empirical analysis with respect to acquisition choice, I found strong support for these types of acquisition choice only in the panel analysis, and weaker support or no support at the transaction level for core or unrelated core acquisitions respectively.

When it comes to financial performance of such acquisitions, I find no support for negative performance implications of core technology acquisitions given core technological alliances, and partial support for negative performance implications of unrelated non-core technology acquisitions given non-core technological alliances. However, when it comes to innovative performance, I do find partial support for negative performance effects of core acquisitions given a higher number of core technological alliances, and better support when it comes to the negative innovative performance effect of unrelated non-core technology acquisitions given a higher number of non-core technological alliances. Overall, given the infrequency of choice to engage in this type of a transaction, the case here may be that firms understand potential redundancy and substitutability of such acquisitions, and mostly choose to engage in them when there is a specific idiosyncratic need for a technological substitute.

I also find support for my assertion in **Hypothesis 2c** that indirectly related non-core technology acquisitions in strategically important non-core markets are more likely to be complementary to the acquirer through its technological alliance portfolio, and are more likely to lead to positive financial performance outcomes than truly unrelated non-core acquisitions, but I do not find evidence in support for its innovative performance effects. It may be that by internalizing technological capabilities through acquisition, a firm does not need to engage in additional patenting activity. This does pose a question about whether these types of transactions may be useful to capture, rather than create value when recombined with partners' technological capabilities in these strategically important non-core markets.

Summary of Results

Although I find evidence in support of my general logic with respect to the influence of the acquirer's alliances both on its acquisition choice and on its acquisition performance, especially the performance analysis may raise more questions than it gives answers. In itself, significant differences when various types of performance outcomes at different analysis levels are compared are no surprise to strategy scholars especially given the tradeoffs that firms face when they consider different aspects of performance (Cording *et al*., 2010). However, some patterns uncovered in this analysis may provide an avenue for future investigation and theoretical reconsideration by pointing to some potentially interesting research questions. For example: are some configurations of alliances and acquisitions more universal and useful when it comes to acquisition performance, while others fit specific cases of firm needs or are only beneficial for certain types of firms or some idiosyncratic resource configurations? Is redundancy of technological resources available through both alliances and acquisitions sometimes a positive factor when it comes to innovative activity in the core business of the firm, and negative factor when it comes to financial performance? And if so, can firms focus on one or the other aspect of firm performance sequentially? When it comes to performance improvement, why do functional alliances seem to produce more value when it comes to innovative performance, while technological alliances seem to lead to better financial performance, and as an example of potential theoretical mechanism, does it have to do with the distinction between value creation and value capture?

However, three things are clear as result of this analysis. First, firms' alliances should be considered interdependently with their acquisitions in order to better understand both the choices firms make when it comes to their corporate development strategies, as well as the performance outcomes of these choices. Second, there may be distinctions between how firms' alliances influence their acquisition choice, and how these interdependent systems of strategic choices then influence these firms' acquisition performance, but in general, more rational acquisition choices, as described in my theory, seem to be rewarded with better performance outcomes. Third, in order to better understand these same strategic choices and performance outcomes, it may be critical to update our understanding of the distinction between alliance types and their complementarity or substitutability vis-à-vis firms' own or internalized capabilities, as well as to refine our conceptualization of relatedness to include not only the relatedness between the firms' own internal resources and those of its acquisition target(s), but also the relatedness of external resources firms can access through their alliance portfolio, as these external resources may be interdependent with the rest of a firm's corporate development portfolio and its portfolio of deployed and available strategic actions.

4.4 ADDITIONAL ROBUSTNESS CHECKS

I conduct many robustness checks in my analysis. For my first stage selection models, I conduct multiple robustness checks with alternative instruments or combinations of instruments, and test multiple IMRs in my second stage models, with no significant effect on the final results. Relatedness is complex in this setting, so I attempted to operationalize it using SIC and VEIC classifications at different levels, while controlling for patent portfolio cosimilarity, and the results were largely similar. I have also tried several alternative model specifications, and generally, the most significant results are robust. Given that some of my models are fixed effects logistic models, I test for incidental parameters problem, and find no evidence to indicate that it is a major concern. Similarly, VIF testing alleviates any collinearity concerns and mean VIF is well below the generally recommended thresholds of 10 to 20 (Greene, 2012). Panel fixed-effects models are most challenging in this setting, as there may be little quantitative change year to year in portfolios where the portfolio composition is aggregated as a moving five year window, which is something to consider in future revisions. These panel models cannot be currently adjusted for selection. I also estimate acquisition choice using a similarly selection-adjusted probit specification within pooled firm-year (as opposed to transaction-level in Table 4) data, which allows acquisition choice to be independent between core and non-core settings since it is not tested at the transaction level, again controlling for industry, year, and firm effects in addition to other controls, and see largely similar results to both transaction-level and panel models (not shown, available upon request).

As already mentioned in the results, I perform multiple robustness checks on my matching models, and reject some of the results. First, I use overlap density and means analysis to ensure comparability of treatment and control groups, and reject matching results where these indicate a potential issue. Second, I use alternative treatment effects model specifications, including coarsened exact matching and inverse probability weighted regression adjustment (IPWRA), to retest my matching results results. IPWRA would overall be a preferable solution for treatment effects testing in my analysis, as it provides a more econometrically sophisticated way to estimate treatment selection and outcome simultaneously (Abadie and Imbens, 2011; Imbens and Wooldridge, 2009). However, due to certain data and sample limitations, I am only able to run suitable IPWRA models for some of my matching models, which fortunately include most of the models with significant results from the propensity score matching. I use the IPWRA models to find further support for some of my stronger results, and to reject weaker ones.

Industry dynamics are also a concern. My sample incorporates boom and bust years for various high-tech industries, which may influence both choice and performance outcomes at the firm level, even though all of my models include year and industry effects. I tested my models by excluding years surrounding unstable times, and my results were generally the same. I also tested my models by excluding some of the more idiosyncratic industries that may be biasing the outcomes: software, as well as biotechnology and pharmaceuticals, and my results were again largely the same.

Finally, this dissertation has benefited from multiple seminars and reviews, as mentioned in the acknowledgments, and some of the suggested additional controls to account for potential additional factors or alternative explanations have been implemented in my analysis based on these conversations. For example, in this final version, in addition to my original empirical analysis, I test multiple inverse Mills' ratios, use additional controls for financial constraints, divestiture experience, target industry M&A dynamics, and competing offers; and implement additional treatment effects tests and specifications.

5. DISCUSSION AND CONCLUSION

5.1 DISCUSSION AND IMPLICATIONS

The key message of this work is that not only should strategy scholars think of transaction modes as interdependent, but also that firms' strategic choices with respect to one transaction mode portfolio may be interdependent with its strategic choices and their respective performance outcomes with respect to another transaction mode portfolio. More specifically, this study offers important insights into the relationship between a firm's alliances and its acquisition choice and performance. Firms use both alliances and acquisitions interdependently, and often in pursuit of the same strategic goals, and configurations of firms' alliance portfolios influence both their acquisition strategies and their respective performance outcomes.

I show that a firm's alliances may not only be substitutes for, but also may be complementary to technology acquisitions, and that there is much to be gained by thinking more carefully about the interdependence of these external transaction modes. I find evidence that not only can functional alliances be complementary to technology acquisitions in specific markets where these acquisitions occur, they may also be disincentives to technology acquisitions in other markets where the focal firm does not have access to these functional alliances. I also show that although technological alliances may indeed generally be substitutes to technology acquisitions, they may be complementary to technology acquisitions in strategically important non-core markets where the focal firm accumulates technological capabilities through alliances. Moreover, I find some evidence that both functional and technological alliances play a complex role in performance outcomes of technology acquisitions, where rational acquisition choices in the context of the firm's alliance portfolio lead to better acquisition performance.

By offering these insights, I contribute to research in corporate strategy and technology and innovation management literatures. This study extends our understanding of how firms choose their acquisition targets by incorporating the role of the resources and capabilities accessible through these firms' alliance portfolios. It is not only the firms' internal technological and functional resources and capabilities that may influence the way these firms manage their boundaries as they engage in technology acquisitions (Ahuja and Katila, 2001; Makri *et al*., 2010), it is also the resources and capabilities that these firms can access through their alliance portfolios, and the effects of these portfolios are complex and multifaceted. I corroborate and extend other theorists' assertion that we need to understand the firm's whole governance mode portfolio and the transactions it represents as these may be interdependent, and not just potentially substitutable or somewhat related through indirect spillovers, but also potentially complementary (Argyres and Zenger, 2012; Capron, 2015; Kaul, 2013). Here I also contribute to improving our understanding of acquisition performance, as the evidence suggests that performance of technology acquisitions may depend on composition and size of firms' alliance portfolios and resources and capabilities these portfolios may contain, as well how the alliance partners' capabilities relate to those being acquired. Strategy scholars have to consider these factors when we set out to understand how firms may benefit from sourcing capabilities externally.

Moreover, this analysis highlights the complex system of tradeoffs that firms face when engaging in acquisitions, especially when it comes to not only the distinct and different performance implications of technology acquisitions, but also to the distinction between the acquisition choice and intent, as well as multifaceted nature of acquisition performance as distinct levels of analysis. For example, same strategic actions can lead to improved performance in one area, and decreased performance in another.

When it comes to both acquisition choice and performance, I show that our current understanding of acquisition relatedness and complementarity, generally focused on discrete transactions, is also in serious need of reassessment with regard to the acquirer's entire corporate development portfolio, including its alliances (Capron, 2015; Kapoor, 2013; Kapoor and Adner, 2012; Langlois, 1992; 2002; Moeen and Agarwal, 2017; Teece, 1986; 2006). This work also suggests a way to address some of the existing confusion and mixed results over when and why firms engage in seemingly unrelated acquisitions, and when these may improve or reduce performance (Harrison *et al*., 1991; King *et al*., 2004; Park, 2003; Seth, 1990). I show that sometimes these non-core, seemingly unrelated acquisitions may in fact be considered at least indirectly related *vis-à-vis* acquirer's alliance portfolio, and that relatedness may in some cases lead to better or worse performance outcomes for the acquirer.

Moreover, I contribute to literature on technology sourcing and innovation and ecosystems (Adner and Kapoor, 2010; Dittrich, Duysters, and de Man, 2007; Langlois, 1992; 2002; Mata and Woerter, 2013; Wassmer and Dussauge, 2012). I show how firms in knowledge-intensive settings, where they are embedded in complex and dynamic technological and business ecosystems with high inter-organizational and technological interdependence, can access, manage, and recombine complementary external resources and capabilities over market space and through time through both alliances and acquisitions concurrently and sequentially, as industries, firms, and capabilities evolve.

This study also speaks to work on dynamic capabilities, strategic renewal, and corporate venturing (Agarwal and Helfat, 2009; Helfat and Peteraf, 2009; Narayanan, Yang, and Zahra, 2009; Teece, 2007). First, acquirer's dynamic capabilities may represent an important set of factors which influence how firms may best source and recombine complementary resources and capabilities from alliances and acquisitions, and so may be considered in future research. Second, sourcing novel and complementary capabilities externally through both alliances and acquisitions may represent a key, perhaps even sometimes a required path to strategic corporate renewal. Third, in a similar spirit as the prior point, accessing and recombining capabilities through both alliances and acquisitions may also prove important for corporate venturing initiatives, as firms can combine internally developed capabilities with key resources and capabilities sourced externally to drive new business ventures.

5.2 LIMITATIONS

As any early work, this study has many limitations. This is an exploratory analysis, and the results should not be interpreted as intended to infer causality, but rather as a large scale correlational study that offers insights into underlying theoretical relationships and mechanisms. At this point the evidence suggests that there may be an association and interdependence worth considering between firms' alliance portfolios and these firms' technology acquisitions, both when it comes to choice and performance. Endogeneity is a feature of this complex setting where firms make strategic decisions and engage in transaction modes concurrently, so much work remains to be done when it comes to not only model specification, identification, validation, and additional robustness checks, but also deeper theorizing on interdependence of strategic assets and actions.

This study also focuses primarily on large incumbent firms in high-tech industries, so its generalizability should be assessed accordingly. Nonetheless, established technology firms play an ever increasingly important role in the global economy, and their activities influence billions of people around the globe, as well as thousands of other firms ranging from suppliers and partners to acquisition targets or competitors. Additionally, incumbent firms in this sample are still heterogeneous in their characteristics and strategies, and more work is needed to understand how these differences distill down to potential factors that could be incorporated in this analysis.

This work is also limited as it includes few factors with respect to competitive landscapes and dynamics in which focal firms operate. While it adds a critical layer of external relations and externally accessible capabilities, it would benefit from incorporating the strategic actions of competitors, regulators, and market dynamics beyond a few factors used as controls in the empirical analysis. Moreover, as industry dynamics vary over time and market space, more work needs to be done to more precisely identify effects of alliances on acquisitions. Additionally, firms' internal corporate development and associated strategic actions may require a more in-depth future analysis in this context. Although I assume that all firms engage in internal development, firms may still pursue heterogeneous strategies here that are interdependent with their external corporate development actions. Finally, analysis of acquisition performance has proven challenging for many of the reasons listed above, and so more work needs to be done in order to understand how various factors affecting performance operate and interact in this setting.

5.3 FUTURE RESEARCH DIRECTIONS

This study also suggests many directions for further inquiry. First, in line with limitations listed above, future research efforts may focus on conducting additional empirical analyses to be able to get closer to making causal statements in this context, which may be achieved with finding better instruments, testing more samples from various industries, and finding ways to conduct better quasi-experiments with appropriate counterfactuals. Deeper analysis is also necessary to understand the dynamics and interactions of building capability breadth and focus in non-core areas, as is manifested in the inconclusive results for Hypothesis 2b and developing a better understanding of when focus and depth or breadth are preferable for optimal performance outcomes. For example, under some conditions, alliances and acquisitions in non-core areas where the firm is not focusing its attention may be valuable for experimentation and sourcing novel capabilities for recombination, while under different conditions, these may be a distraction. Similarly, some of the more rare transactional configurations provide an interesting area to explore with respect to further understanding firms' rare and heterogeneous strategies in this context.

Following up, the related question of how firms interdependently structure their alliance and acquisition activity, and whether there are some distinct configuration preferences among firms, as well as performance outcomes of these choices, may provide a fertile ground for future research. In addition, more theorizing and empirical inquiry is needed to understand more complex portfolio structures, for example where there is overlap in functional and technological alliances in the same area. Moreover, limited analysis in this study hints that a more elaborate investigation is needed to understand how various heterogeneous acquirers, for example more or less experienced, or more or less diversified firms may make distinctly different choices, configure different corporate development portfolio structures, and realize heterogeneous performance consequences in the context of their interdependent external corporate development activity.

In addition to alliances, focal firms' portfolios of minority investments and corporate venture capital investments may also play an important role in their acquisition choice and performance (Benson and Ziedonis, 2009; 2010; Dushnitsky and Lavie, 2010), and these should also be considered in future studies. Additionally, differences between transaction-level and firm-level performance in my analysis point to the need to look at not only a single transaction, but also at interdependent patterns and whole programs of corporate development activity, as anecdotal evidence demonstrates that firms often engage in multiple acquisitions in pursuit of same strategic goals, and some of these acquisitions may be used to accomplish different aspects of these goals. Finally, a deeper investigation of the strategic decision-making making processes behind how firms engage in both alliance and acquisition strategic moves, and understanding how to distinguish various strategic motives that may be at play there may also provide fresh insights into this phenomena.

5.4 CONCLUDING REMARKS

Firms' distinct transaction mode portfolios are interdependent. In this context, I examine the relationship between a firm's alliances and its acquisition choice and performance. This study thus provides important insights to corporate strategy and technology and innovation management literatures by emphasizing the importance of considering interdependence of alliances and acquisitions and by showing that in some cases, these may indeed be substitutes, while in others they may actually be complementary to each other.

More specifically, I show that alliances may not only substitute for, but may also be complementary to technology acquisitions. I show how functional alliances may be complementary to technology acquisitions in same markets, but disincentives in others. I also find evidence that although technological alliances may be substitutes for technology acquisitions, they may actually be complementary to technology acquisitions in those strategically important non-core markets where acquirers accumulate capabilities through partnerships. Moreover, I show that both functional and technological alliances play a complex role in performance outcomes of technology acquisitions as performance and choice are interdependent in the context of the acquirer's alliances, and although acquisition performance generally seems to follow my choice theory, this merits further investigation. Additionally, I address the long-standing puzzle of unrelated acquisitions, showing that some of the seemingly unrelated acquisitions in non-core settings may in fact be at least indirectly related and complementary to the acquirer through its alliance portfolio.

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Appendix I: EMC Corporation's Notable Alliances and Acquisitions 1996-2016

YEARS	MODE	ENTERPRISE STORAGE HARDWARE (CORE BUS.)	MARKETING & RESALE (PURE FUNCTIONAL)	SERVICES	STORAGE MGMT & HARDWARE	CONTENT & eDOCS	SECURITY+	VIRTUALIZATION	CLOUD	COMPUTATIONAL
1996-2000	**ALLIANCE**	**IBM**	Siemens, Lucent, Comparex, NEC, Fujitsu	Baan, HP	Hewlett-Packard, BMC Software, PeopleSoft, Sequent, Baan, Forsythe, AppGenesys, Microsoft					
	ACQUISITION	**Data General, CrosStor**		VS Corp	Softworks, Avalon					
2001-2005	**ALLIANCE**	**Sun Microsystems**	Dell, Netview, MTI Tech, Brocade, Cerner, Langchao, Samsung, Siemens	Tata, Accenture, BearingPoint	Dell, Datacraft, AMC Corp, BMC Software, Nexsan, Hummingbird	Document Sciences, Thunderhead, Adobe Systems	Mobius Management, Surety LLC			
	ACQUISITION	**FilePool, Allocity**		Internosis	Luminate, Prisa Networks, Legato Networker, Dantz/Retrospect, Smarts Astrum	Documentum, Ask Once, Acartus, Captiva		Vmware, Rainfinity, Acxiom		
2006-2010	**ALLIANCE**	**IBM, NEC**	Stratus Technologies, Unisys, Digital China, SAP	Epicor, Verint, Digital China	NetQoS, HP Inc, NEC	Microsoft, NEC Corp, Arcot Systems, Oracle	McAfee, Neoscale, Verint	Wyse Technology, Oracle, Juniper Networks	Sonda	
	ACQUISITION	**Avamar, Iomega, Data Domain, Isilon Systems, Bus-Tech, Indigo Stone**		Interlink, Geniant, Business Edge, Conchange	Kashya, nLayers, Voyence, Infra Corp, WysDM, Configuresoft, Fastscale	Pro Activity, X-Hive, Document Sciences, Kazeon	RSA Security, Authentica, Network Intelligence, Valyd, Verid, Tablus, Archer Technologies	Akimbi, YottaYotta	Mozy, Pi Corp, Source Labs	Greenplum
2011-2016	**ALLIANCE**	**Cisco**	Mansoft Quatar, Terremark, T-Systems, Attunity, Lenovo, GE, Trend Micro, EY	Los Alamos Medical, Attunity, Knotice, LexisNexis, Brocade, EY, Edscha	Cisco	Adobe Systems	Zscaler, Fortinet	Cisco	Harris, VCA, Cap Gemini, BMC Software, Zend, GE, Afore, Brocade	Atos, Knotice, Afore, Capgemini
	ACQUISITION	**XtremeIO, Likewise, ScaleIO**		Asankya, Adaptivity	Watch4Net, iWave, Twinstrata, Renasar, ScaleIO	Syncplicity	Netwitness, Silicium Security, Silver Tail Systems, Aveksa	Syncplicity	Virtustream, Cloudlink Tech, Cloudscaling	ZettaPoint, Pivotal Labs, MoreVRP

Appendix II: Select Matching Test and Data

Figure 1: Overlap Density Graph Treatment is Core Acquisition on Core Functional Alliances

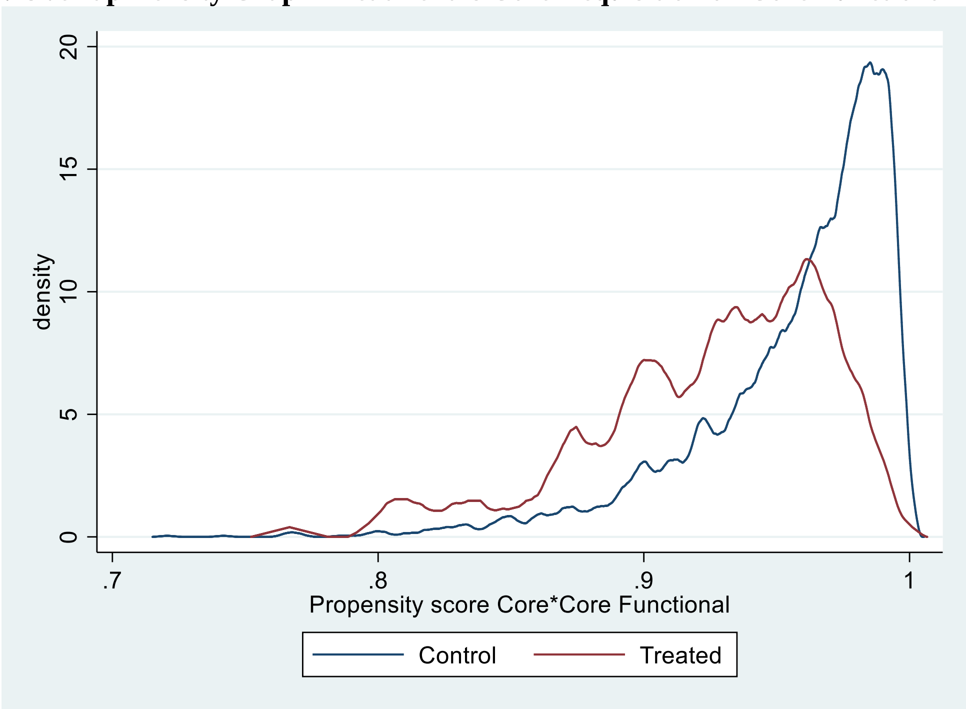

Figure 2: Overlap Density Graph Treatment is Indirectly Related N/Core Acquisition (Tech)

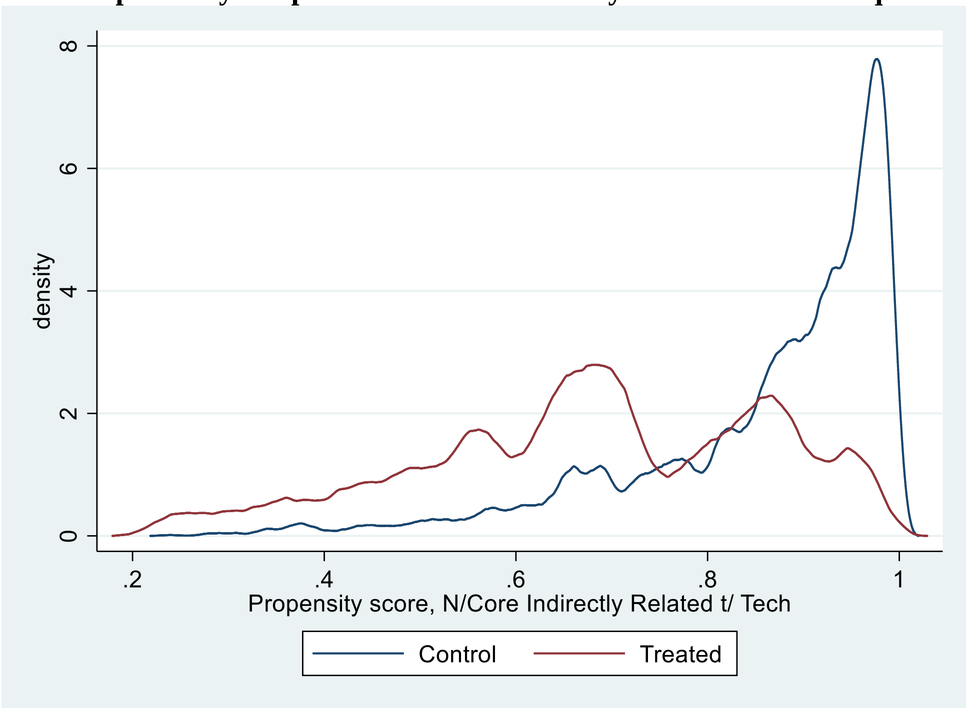

Figure 3: Overlap Density Graph Treatment is Indirectly Related N/Core Acquisition (Functional)

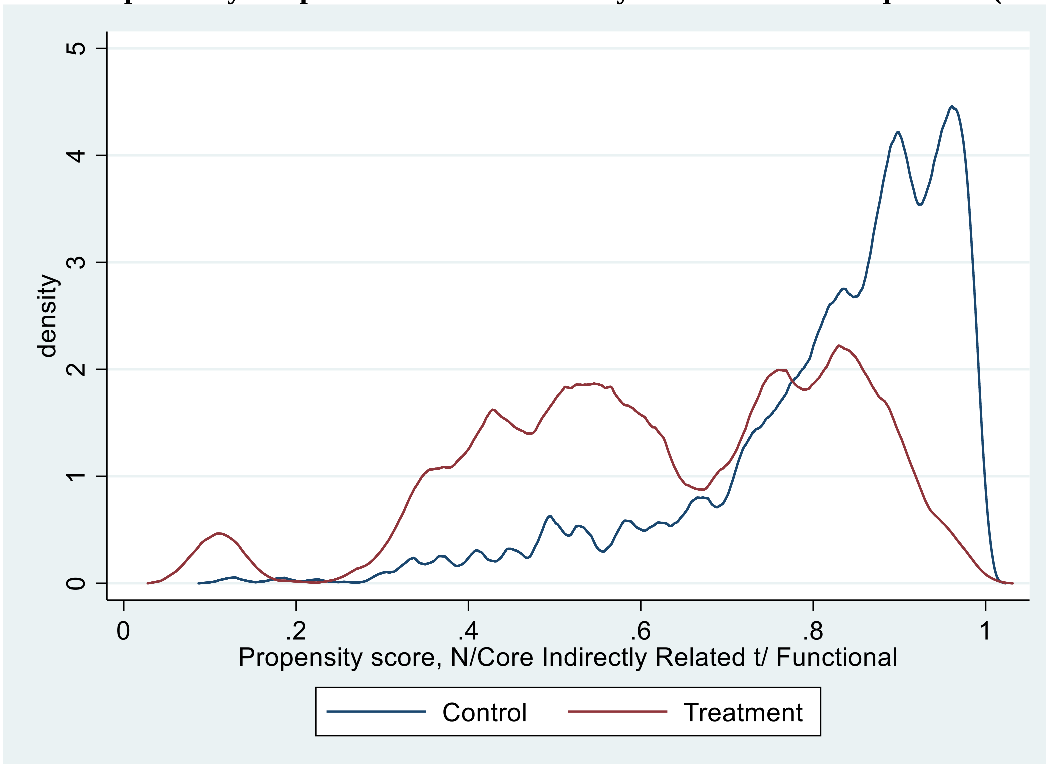

Figure 4: Overlap Density Graph Treatment is Unrelated N/Core Acquisition on Functional Alliances

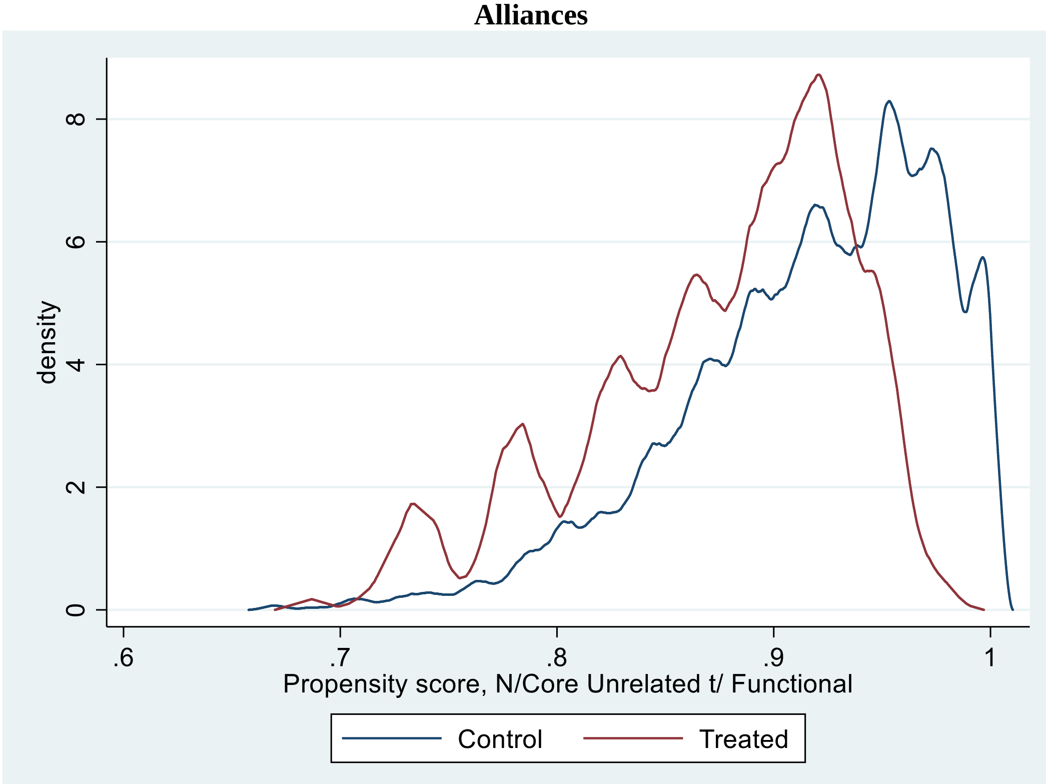

Figure 5: Overlap Density Graph Treatment is Indirectly Related N/Core Acquisition (Tech)

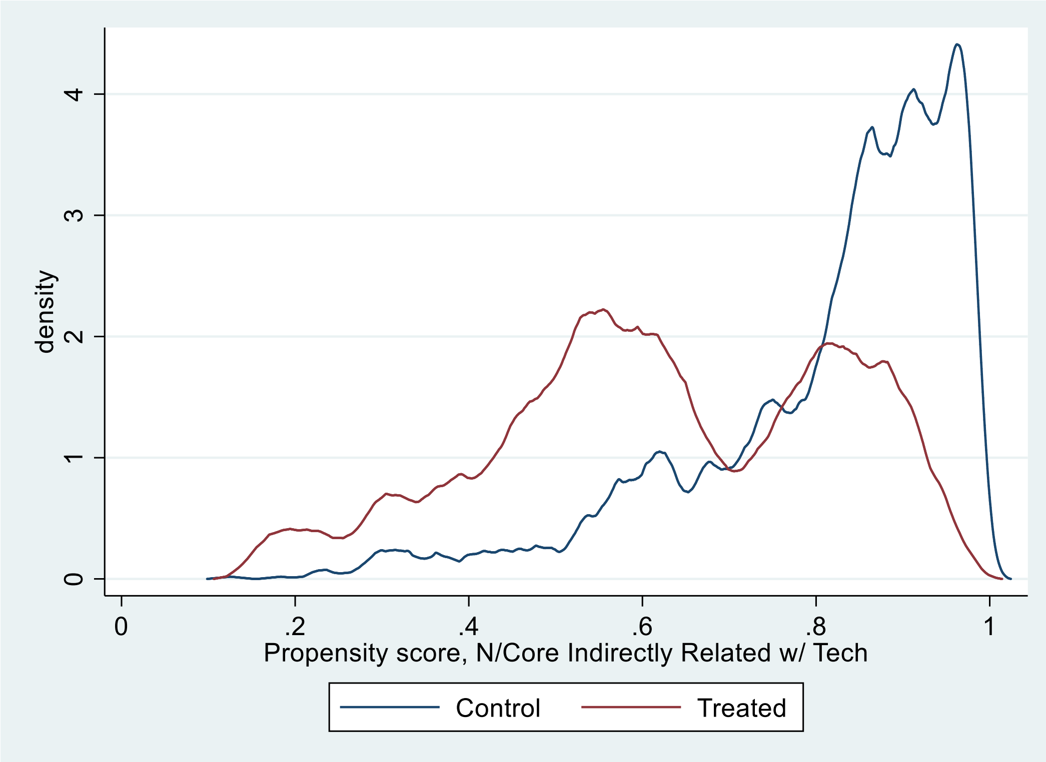

Figure 6: Overlap Density Graph Treatment is Core Acquisition on Core Functional Alliances

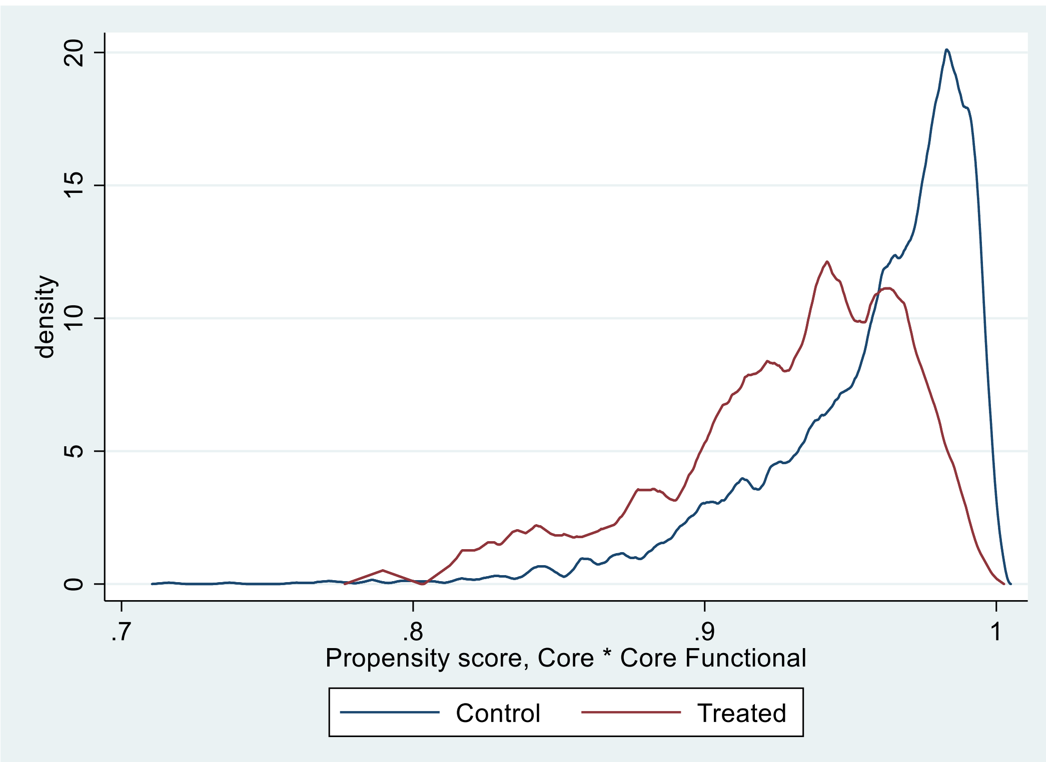

Figure 7: Overlap Density Graph Treatment is Indirectly Related N/Core Acquisition (Tech)

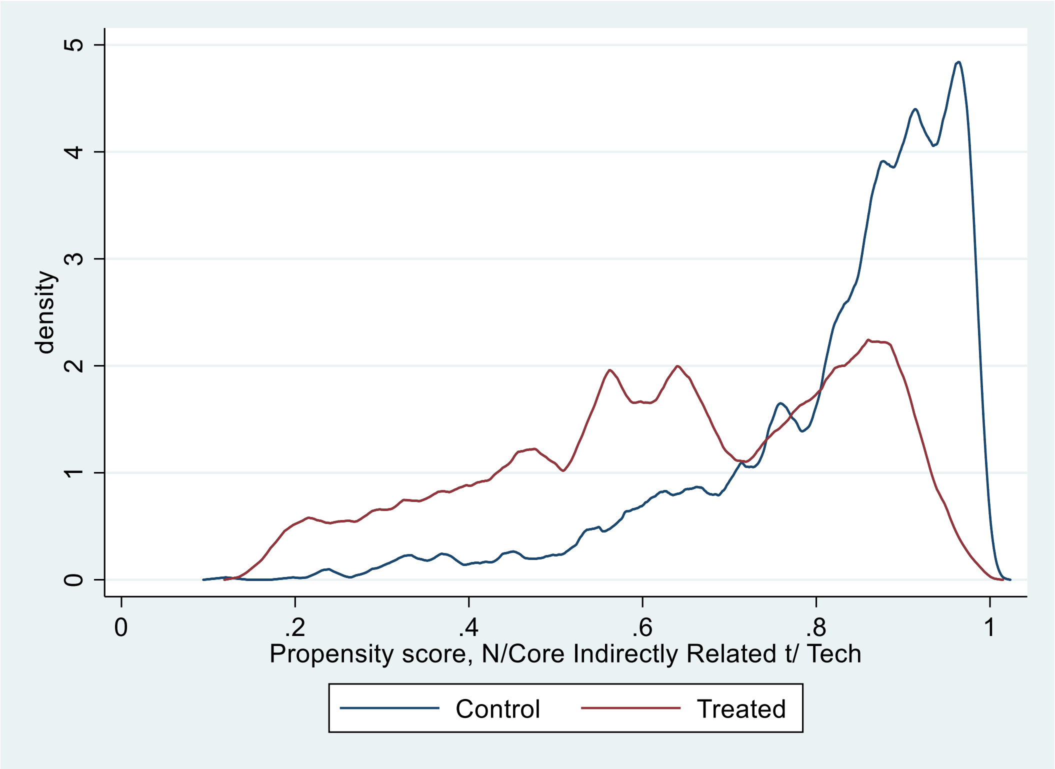

Table 1: Examples of Treatment and Control Group Means

	Treat. = Core Acq*Core All			Treat. = Indir. Rel. N/C Tech Acq			Treat. = Unrel N/C Acq*N/C Tech All		
	Means			Means			Means		
	Treated	Control	p-value >	Treated	Control	p-value >	Treated	Control	p-value >
Foreign Target	0.324	0.314	0.854	0.308	0.323	0.571	0.269	0.237	0.573
Public Target	0.139	0.160	0.588	0.138	0.131	0.688	0.185	0.187	0.974
Large Target	0.092	0.114	0.504	0.062	0.069	0.594	0.059	0.059	1.000
Cash Consideration	0.277	0.259	0.699	0.218	0.222	0.863	0.294	0.284	0.864
Target a Public Parent Divestiture	0.358	0.379	0.689	0.311	0.335	0.361	0.328	0.353	0.683
Core Tech Alliance Portfolio	0.000	0.000	.	10.595	9.165	0.179	2.101	1.946	0.752
Core Functional Alliance Portfolio	1.971	2.108	0.474	8.072	6.769	0.104	1.487	1.298	0.616
Non-Core Tech Alliance Portfolio	4.434	5.095	0.323	59.344	52.263	0.061	6.092	6.303	0.837
Non-Core Functional Alliance Portfolio	5.936	7.754	0.057	61.992	57.572	0.264	1.151	1.187	0.864
Target Patent Portfolio Size	4.809	5.941	0.768	4.087	5.427	0.592	2.992	2.459	0.754
Prior Alliance w/ Target	0.029	0.036	0.716	0.056	0.061	0.674	0.050	0.057	0.819
Sector Acquisition Activity	146.040	154.050	0.602	241.220	211.790	0.002	159.300	158.930	0.985
Focal Firm Acquisition Experience	13.936	14.903	0.495	29.743	30.052	0.788	10.067	10.978	0.539
Focal Firm Divestiture Experience	2.306	2.069	0.571	10.505	10.705	0.786	1.698	1.741	0.925
Focal Firm Patent Portfolio Size - 5 yr (log)	4.067	4.209	0.579	5.898	6.124	0.042	4.299	4.372	0.788
Focal Firm Diversification	0.189	0.185	0.854	0.306	0.330	0.136	0.099	0.107	0.782
Focal Firm R&D Intensity	0.113	0.123	0.368	0.105	0.103	0.634	0.150	0.146	0.759
Focal Firm Financial Constraint	0.268	0.272	0.860	0.211	0.203	0.315	0.181	0.184	0.828
Focal Firm Size - Number of Employees (log)	2.483	2.465	0.896	3.938	4.036	0.137	2.123	2.080	0.765
New CEO in past 3 years	0.341	0.353	0.822	0.355	0.326	0.272	0.361	0.363	0.979
Year	2005.600	2005.400	0.693	2002.100	2002.200	0.936	2003.200	2003.200	0.958
Industry	48.751	50.548	0.360	47.510	45.866	0.098	45.000	44.081	0.674

Appendix III: List of all Firms in the Data

Company Name	Ticker Symbol	First Year in Data	Last Year in Data	Years in Data
3COM CORP	COMS	1990	2008	18
ABBOTT LABORATORIES	ABT	1990	2014	24
ACT MANUFACTURING INC	AMNUQ	1994	2000	6
ACTERNA CORP	3ACTRQ	1990	2002	12
ADC TELECOMMUNICATIONS INC	ADCT	1990	2010	20
ADOBE SYSTEMS INC	ADBE	1990	2014	24
ADVANCED MICRO DEVICES	AMD	1990	2014	24
AFFILIATED COMPUTER SERVICES	ACS	1994	2009	15
AGERE SYSTEMS INC	AGR.3	1999	2006	7
AGILENT TECHNOLOGIES INC	A	1998	2014	16
AGILYSYS INC	AGYS	1990	2014	24
ALERE INC	ALR	2001	2014	13
ALLERGAN INC	AGN.2	1990	2014	24
ALPHABET INC	GOOGL	2002	2014	12
ALTERA CORP	ALTR	1990	2014	24
AMDAHL CORP	AMH.1	1990	1996	6
AMERICAN MANAGEMENT SYSTEMS	AMSY	1990	2003	13
AMGEN INC	AMGN	1990	2014	24
AMKOR TECHNOLOGY INC	AMKR	1997	2014	17
ANALOG DEVICES	ADI	1990	2014	24
ANTEON INTERNATIONAL CORP	ANT.2	1997	2005	8
APPLE INC	AAPL	1990	2014	24
APPLERA CORP-CONSOLIDATED	ABI.CM	1998	2008	10
ARMOR HOLDINGS INC	AH.Z	1990	2006	16
ASCEND COMMUNICATIONS INC	ASND.1	1993	1998	5
AST RESEARCH INC	ASTA	1990	1996	6
ATMEL CORP	ATML	1991	2014	23
AUTODESK INC	ADSK	1990	2014	24
AUTOMATIC DATA PROCESSING	ADP	1990	2014	24
AVAYA INC	5933B	1999	2014	15
BARD (C.R.) INC	BCR	1990	2014	24
BARR PHARMACEUTICALS INC	BRL	1990	2007	17
BAXTER INTERNATIONAL INC	BAX	1990	2014	24
BAY NETWORKS INC	BAY.3	1991	1998	7
BDM INTERNATIONAL INC	BDMI	1990	1996	6
BECKMAN COULTER INC	BEC	1990	2010	20
BECTON DICKINSON & CO	BDX	1990	2014	24
BENCHMARK ELECTRONICS INC	BHE	1990	2014	24
BIO-RAD LABORATORIES INC	BIO	1990	2014	24
BIOGEN INC	BIIB	1990	2014	24
BIOMET INC	5938B	1990	2013	23
BMC SOFTWARE INC	BMC	1990	2012	22
BOEING CO	BA	1990	2014	24
BOSTON SCIENTIFIC CORP	BSX	1991	2014	23
BRISTOL-MYERS SQUIBB CO	BMY	1990	2014	24

Company Name	Ticker Symbol	First Year in Data	Last Year in Data	Years in Data
BROADCOM CORP	BRCM	1996	2014	18
BROCADE COMMUNICATIONS SYS	BRCD	1997	2014	17
CA INC	CA	1990	2014	24
CACI INTL INC -CL A	CACI	1990	2014	24
CADENCE DESIGN SYSTEMS INC	CDNS	1990	2014	24
CATALENT PHARMA SOLUTIONS	5051B	2008	2013	5
CELGENE CORP	CELG	1990	2014	24
CERNER CORP	CERN	1990	2014	24
CHIRON CORP	CHIR	1990	2005	15
CIENA CORP	CIEN	1996	2014	18
CIRRUS LOGIC INC	CRUS	1990	2014	24
CISCO SYSTEMS INC	CSCO	1990	2014	24
CITRIX SYSTEMS INC	CTXS	1994	2014	20
COGNIZANT TECH SOLUTIONS	CTSH	1996	2014	18
COMMSCOPE HOLDING CO INC	COMM	2008	2014	6
COMPAQ COMPUTER CORP	CPQ.2	1990	2001	11
COMPUTER SCIENCES CORP	CSC	1990	2014	24
COMPUWARE CORP	CPWR	1991	2013	22
COMVERSE TECHNOLOGY INC	CMVT	1990	2011	21
CONEXANT SYSTEMS INC	CNXT.1	1996	2010	14
CORNING INC	GLW	1990	2014	24
CYPRESS SEMICONDUCTOR CORP	CY	1990	2014	24
DADE BEHRING HOLDINGS INC	DADE	1997	2006	9
DANAHER CORP	DHR	1990	2014	24
DATA GENERAL CORP	DGN.	1990	1998	8
DELL INC	DELL	1990	2012	22
DIEBOLD INC	DBD	1990	2014	24
DIGITAL EQUIPMENT	DEC.1	1990	1997	7
DRS TECHNOLOGIES INC	DRS	1990	2007	17
DSC COMMUNICATIONS CORP	DIGI.1	1990	1997	7
DST SYSTEMS INC	DST	1990	2014	24
EARTHLINK HOLDINGS CORP	ELNK	1995	2014	19
EASTMAN KODAK CO	KODK	1990	2014	24
EBAY INC	EBAY	1996	2014	18
ELECTRONIC ARTS INC	EA	1990	2014	24
ELECTRONIC DATA SYSTEMS CORP	EDS.	1990	2007	17
EMC CORP/MA	EMC	1990	2014	24
EMERSON ELECTRIC CO	EMR	1990	2014	24
ENTERASYS NETWORKS INC	ETS	1990	2004	14
FACEBOOK INC	FB	2007	2014	7
FAIRCHILD SEMICONDUCTOR INTL	FCS	1995	2014	19
FIRST DATA CORP	FDC	1991	2014	23
FIRST SOLAR INC	FSLR	2005	2014	9
FOREST LABORATORIES -CL A	FRX	1990	2013	23
FREESCALE SEMICONDUCTOR LTD	FSL	2005	2014	9

Company Name	Ticker Symbol	First Year in Data	Last Year in Data	Years in Data
GALILEO INTERNATIONAL INC	GLC.3	1992	2000	8
GATEWAY INC	GTW	1992	2006	14
GENERAL DYNAMICS CORP	GD	1990	2014	24
GENERAL INSTRUMENT CORP	GIC.3	1990	1998	8
GENUITY INC	GENUQ	1995	2001	6
GENZYME CORP	GENZ	1996	2010	14
GILEAD SCIENCES INC	GILD	1990	2014	24
GOODRICH CORP	GR	1990	2011	21
GUIDANT CORP	GDT	1993	2005	12
GULFSTREAM AEROSPACE	GAC.3	1991	1998	7
HARRIS CORP	HRS	1990	2014	24
HEWLETT-PACKARD CO	HPQ	1990	2014	24
HOLOGIC INC	HOLX	1990	2014	24
HOSPIRA INC	HSP	2002	2014	12
IAC/INTERACTIVECORP	IACI	1992	2014	22
IMATION CORP	IMN	1995	2014	19
INTEL CORP	INTC	1990	2014	24
INTERGRAPH CORP	INGR.	1990	2005	15
INTL BUSINESS MACHINES CORP	IBM	1990	2014	24
INTUIT INC	INTU	1992	2014	22
INVACARE CORP	IVC	1990	2014	24
IOMEGA CORP	IOM	1990	2007	17
ITRON INC	ITRI	1992	2014	22
IVAX CORP	IVX.2	1990	2004	14
JABIL CIRCUIT INC	JBL	1992	2014	22
JDS UNIPHASE CANADA LTD	JDUCF	1997	2014	17
JOHNSON & JOHNSON	JNJ	1990	2014	24
JUNIPER NETWORKS INC	JNPR	1997	2014	17
KING PHARMACEUTICALS INC	KG	1996	2009	13
KLA-TENCOR CORP	KLAC	1990	2014	24
L-3 COMMUNICATIONS HLDGS INC	LLL	1996	2014	18
LEXMARK INTL INC -CL A	LXK	1994	2014	20
LILLY (ELI) & CO	LLY	1990	2014	24
LOCKHEED MARTIN CORP	LMT	1990	2014	24
LORAL CORP	LOR.2	1990	1994	4
LSI CORP	LSI	1990	2013	23
LUCENT TECHNOLOGIES INC	LU	1995	2006	11
MALLINCKRODT INC	MKG	1990	2000	10
MAXIM INTEGRATED PRODUCTS	MXIM	1990	2014	24
MAXTOR CORP	MXO	1990	2005	15
MCAFEE INC	MFE	1991	2010	19
MCDONNELL DOUGLAS CORP	MD.1	1990	1996	6
MEDTRONIC PLC	MDT	1990	2014	24
MERCK & CO	MRK	1990	2014	24
METTLER-TOLEDO INTL INC	MTD	1996	2014	18

Company Name	Ticker Symbol	First Year in Data	Last Year in Data	Years in Data
MICRON TECHNOLOGY INC	MU	1990	2014	24
MICROSOFT CORP	MSFT	1990	2014	24
MILLIPORE CORP	MIL.	1990	2009	19
MODUSLINK GLOBAL SOLUTIONS	MLNK	1993	2014	21
MOTOROLA SOLUTIONS INC	MSI	1990	2014	24
MYLAN NV	MYL	1990	2014	24
NATIONAL SEMICONDUCTOR CORP	NSM.2	1990	2010	20
NBTY INC	0170A	1990	2014	24
NCR CORP	NCR	1990	2014	24
NETAPP INC	NTAP	1994	2014	20
NORTHROP GRUMMAN CORP	NOC	1990	2014	24
NOVELL INC	NOVL	1990	2010	20
NVIDIA CORP	NVDA	1996	2014	18
ON SEMICONDUCTOR CORP	ON	1999	2014	15
ORACLE CORP	ORCL	1990	2014	24
PALM INC	PALM	1997	2008	11
PEOPLESOFT INC	PSFT.	1991	2003	12
PERKINELMER INC	PKI	1990	2014	24
PEROT SYSTEMS CORP	PER.1	1996	2008	12
PERRIGO CO PLC	PRGO	1991	2014	23
PFIZER INC	PFE	1990	2014	24
PHARMACIA CORP	PHA.1	1990	2002	12
PITNEY BOWES INC	PBI	1990	2014	24
PITTWAY CORP/DE -CL A	PRY.A.	1990	1998	8
PLEXUS CORP	PLXS	1990	2014	24
PRIMARY PDC INC	PRDCQ	1990	2000	10
QUALCOMM INC	QCOM	1991	2014	23
QUANTUM CORP	QTM	1990	2014	24
RAYTHEON CO	RTN	1990	2014	24
READ-RITE CORP	RDRTQ	1990	2002	12
REYNOLDS & REYNOLDS -CL A	REY	1990	2005	15
ROCKWELL COLLINS INC	COL	1999	2014	15
ROPER TECHNOLOGIES INC	ROP	1991	2014	23
SALESFORCE.COM INC	CRM	2002	2014	12
SANDISK CORP	SNDK	1994	2014	20
SANMINA CORP	SANM	1992	2014	22
SCHERING-PLOUGH	SGP	1990	2008	18
SCIENCE APPLICATIONS INTL CP	SAIC	2008	2014	6
SCIENTIFIC-ATLANTA INC	SFA.1	1990	2005	15
SEAGATE TECHNOLOGY PLC	STX	2001	2014	13
SEAGATE TECHNOLOGY-OLD	SEG.2	1990	2000	10
SEQUA CORP -CL A	SQA.A	1990	2006	16
SHARED MEDICAL SYSTEMS CORP	SMS.2	1990	1999	9
SIEBEL SYSTEMS INC	SEBL	1995	2004	9
SILICON GRAPHICS INC	SGICQ	1990	2008	18

Company Name	Ticker Symbol	First Year in Data	Last Year in Data	Years in Data
SOLECTRON CORP	SLR	1990	2006	16
SPANSION INC	CODE	2003	2014	11
SRA INTERNATIONAL INC	SRX	2000	2010	10
ST JUDE MEDICAL INC	STJ	1990	2014	24
STORAGE TECHNOLOGY CP	STK.1	1990	2004	14
STRYKER CORP	SYK	1990	2014	24
SUN MICROSYSTEMS INC	JAVA	1990	2009	19
SUNEDISON INC	SUNE	1994	2014	20
SUNGARD DATA SYSTEMS INC	0139A	1990	2014	24
SUNPOWER CORP	SPWR	2003	2014	11
SYBASE INC	SY.3	1990	2009	19
SYMANTEC CORP	SYMC	1990	2014	24
SYMBOL TECHNOLOGIES	SBL.2	1990	2005	15
TANDEM COMPUTERS INC	TDM.	1990	1996	6
TEKTRONIX INC	TEK.1	1990	2006	16
TELEDYNE TECHNOLOGIES INC	TDY	1998	2014	16
TELEFLEX INC	TFX	1990	2014	24
TELLABS INC	TLAB	1990	2012	22
TERADATA CORP	TDC	2005	2014	9
TERADYNE INC	TER	1990	2014	24
TEXAS INSTRUMENTS INC	TXN	1990	2014	24
TEXTRON INC	TXT	1990	2014	24
THERMO FISHER SCIENTIFIC INC	TMO	1990	2014	24
TITAN CORP	TTN	1990	2004	14
U S ROBOTICS CORP	USRX	1990	1996	6
U S SURGICAL CORP	USS.2	1990	1997	7
UNISYS CORP	UIS	1990	2014	24
UNITED TECHNOLOGIES CORP	UTX	1990	2014	24
VARIAN INC	VARI	1997	2009	12
VARIAN MEDICAL SYSTEMS INC	VAR	1990	2014	24
VERISIGN INC	VRSN	1995	2014	19
VERITAS SOFTWARE CORP	VRTS.1	1992	2004	12
VIASYSTEMS GROUP INC	VIAS	1998	2014	16
VOUGHT AIRCRAFT HOLDNGS-REDH	VTC	2006	2007	1
WANG LABS INC	WANG	1990	1998	8
WARNER-LAMBERT CO	WLA	1990	1999	9
WESTERN DIGITAL CORP	WDC	1990	2014	24
WYETH	WYE	1990	2008	18
XEROX CORP	XRX	1990	2014	24
XILINX INC	XLNX	1990	2014	24
YAHOO INC	YHOO	1995	2014	19
ZIMMER BIOMET HOLDINGS INC	ZBH	1999	2014	15