Value Creation, Appropriation, And Product Design Strategies In Technology Ecosystems: Three Essays On The Role Of Complementary Technologies

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Advisors: J. Myles Shaver, Puay Khoon Toh

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Dedication

To Janell, Carson, Joe, Eddie Jo, and Stella

Abstract

Firms are often embedded in a technology ecosystem comprised of complementary technologies that span multiple product markets. In this dissertation, I examine how complementarity between the firm's technologies influences its strategies to create and appropriate value in the ecosystem. I investigate this overarching question in two contexts: firm's participation in compatibility standards and how it designs products for a new market.

In Chapter 2 and 3, I explore how complementarity within the firm's technology portfolio affects how and where it creates and appropriates value from intellectual property disclosures to major compatibility standards. In Chapter 2, I theorize as to how a portfolio of complementary technologies allows the firm to create value from its technological position in an industry standard. I empirically test my prediction using data on major compatibility standards in the information and communications technology industry. I find that firms generate positive returns from disclosure only when they own complementary technologies. In Chapter 3, I extend this argument to study value appropriation. I find that firms focus their appropriation strategy around their complementary technologies.

Chapter 4 examines how product complementarities influence product strategy in a new market. I propose that firms with complementary products will enter markets with products that exhibit lower technical performance than firms without complementary products. I also argue that firms choose features that function with their complementary products and will tradeoff non-complementary features when necessary. Examining entry into the nascent smartphone market using a rich set of data on smartphone product technology and features, I find strong support for these conclusions. I identify complementarities within the firm's product portfolio as an important driver of firm's product strategy.

Through this dissertation, I demonstrate the benefit of a more systemic view of the firm's portfolio, one that appreciates the relationships between the firm's various technologies and products, and how these relationships influence the firm's technology strategy.

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CHAPTER 1

Introduction

How firms create and capture value from innovation has long been a central topic in strategic management (Schumpeter, 1934; Penrose, 1959; Nelson and Winter, 1982; Teece, 1986). Complementarities across different resources within the firm play an important role in value creation and appropriation strategies, and have been the focus of several streams of research.[1]

Research on technological search and invention investigates the role that different knowledge inputs play in increasing the combinatorial possibilities that can lead to a value creating innovation (Arora and Gambardella, 1990; Ahuja and Katila, 2001; Ahuja and Lampert, 2001; Cassiman and Veugelers, 2006; Hess and Rothaermel, 2011). Work in this stream tends to focus on evaluating whether knowledge acquisition strategies, such as mergers, alliances, human capital mobility, or licensing, can give rise to complementarities. The emphasis is on determining under what conditions certain knowledge elements function well together. For instance, external knowledge acquisition can complement internal research efforts when firms focus on basic research (Cassiman and Veugelers, 2006) or when external and internal knowledge are moderately related (Ahuja and Katila, 2001).

Past literature also demonstrates that complementarities perform a vital role in appropriating returns from innovation. Complementary assets[2] provide an advantage in

[1] It is worth noting the importance complementarity plays in demand theory (Allen 1934, Hicks and Allen, 1934a; 1934b). See Samuelson (1974) for a good overview.
[2] For example, distribution and product service capabilities.

market competition and thus support the firm's ability to profit from an innovation (Teece, 1986; Rothaermel, 2001). Complementary assets also buffer the firm from technological change (Tripsas, 1997; Rothaermel and Hill, 2005) because many downstream assets retain their value under various technology regimes.

Complementary assets also influence a firm's incentive to innovate and the direction of this innovation (Levin *et al.*, 1987 Cohen *et al.*, 2000; Arora and Ceccagnoli, 2006; Ceccagnoli, Graph, Higgins, and Lee, 2010; Hess and Rothaermel, 2011; Wu, Wan, and Levinthal, 2013). Resources that enhance the ability to profit from innovation, in turn, spur the firm to increase its innovative effort. Firms tend to align their innovation strategies with their complementary assets.[3] Complementary assets can even influence the firm's technology trajectory (Wu *et al.*, 2013).

This literature demonstrates the importance of complementarities in influencing firms' technology strategy and innovative performance. However, the focus is often on creating or supporting a single innovation. For example, the literature on complementary downstream assets typically assumes that the firm has an innovation and then examines the role of complementary assets in appropriating value from this innovation. Likewise, research on technology search investigates how different knowledge elements combine to create a single innovation.

From extant literature, it is less clear how firms strategize around a set of technologies or products, or how complementarities between technologies or products

[3] For example, pharmaceutical firms enter into research and development (R&D) alliances with new entrants when they can exploit knowledge through complementary assets (Rothaermel, 2001). These same firms avoid licensing technology that does not fit with their complementary assets (Ceccagnoli *et al.*, 2010).

influence strategy. This limits our ability to apply the theory of complementarities to sufficiently answer more complex questions. For example, why did Google enter the mobile phone operating system market and do so by providing the operating system for free? Understanding the focal technology (e.g., the operating system) only partially reveals how it was used in Google's value creation and capture strategy. Why did Merrill Lynch, a firm with vast financial and technological resources enter the online brokerage market well behind the technological frontier? Focusing on only the new product (e.g. online trading) obscures how Merrill Lynch could still provide value to clients in other ways (e.g. investment research). Why would firms be willing to spend millions of dollars to develop technology that runs mobile browsing standards just to freely license the IP to anyone adopting the standard? Focusing on the disclosed IP alone does not reveal its role in the broader role in the firm's value creation and capture strategy.

To approach such questions with sufficient rigor, I take a more systemic perspective of the firm's portfolio of technologies. To do this I utilize the concept of a technology ecosystem (also known as an innovation ecosystem or product ecosystem) (Adner and Kapoor, 2010). Technology ecosystems consist of multiple interrelated technologies, and the structure of and interaction between them influence the value proposition of the ecosystem.[4] The concept is similar to business ecosystems, where to understand how value can materialize, one needs to understand the alignment structure of various parties that

[4] Prior literature demonstrates the importance of analyzing the structure of and interaction for understanding firms' technology strategy (Henderson and Clark, 1990; Baldwin, 2000; Ethiraj, 2007). For example, Ethiraj (2007) finds that slower technological advancement of one component in the system can reduce the value of technological advancement of other interacting technological components, which changes the R&D incentives for firms that own the more advanced components.

comprise the ecosystem (Adner, 2017). However, unlike business ecosystem research that tends to emphasize cross-firm relationships, I focus on cross-technology or cross-product relationships. These products and technologies do not necessarily need to be owned by different firms. I focus on the case when the firm itself owns the different technologies or products.

In this dissertation, I focus on the complementarity between technologies and how the position of one in the ecosystem can affect the value of the other. Two technologies are complementary when they are compatible (i.e. co-function together) and when both are functioning, can create more value together than they do alone (Milgrom and Roberts, 1990; 1995; Toh and Miller, 2017). The extent to which the co-created value is of significance to the firm will depend on the technologies' positons in the ecosystem. I utilize this concept to help understand how a firm's incentives, and thus its technology strategies, will differ based on whether it can benefit from complementarities.

To better understand this concept, take for example two compatible technologies: technology A and technology B. If A takes an important position in the ecosystem, such as inside a major industry standard, then not only does the value of A rise, the value of B may as well. A firm that owns both A and B can benefit from this complementary value. Focusing only on A provides an incomplete picture of the value created from its position in the ecosystem because it ignores the complementarity it has with B.

Take the following simple example from Qualcomm. Qualcomm developed the baseband processing technology[5] used in CDMA-based wireless networks. Revenue is generated as base station producers license the technology from Qualcomm. However, the benefit to Qualcomm does not stop there. Qualcomm strategically designed its Radio Frequency component of its chipsets, which power mobile phones, to optimally interoperate with the baseband processing technology.[6] Doing so, Qualcomm could offer users superior reception and power management capabilities, which led to Qualcomm's dominance in the CDMA-based chipset market.

To help link the concept of complementary to the demand side of the equation, I draw on the concept of network externalities that are commonly used in the literature on platforms. A portfolio of complementary technologies can create positive network externalities that the firm can capture—as demand for one technology increases, the demand for others will likely increase as well. Therefore, a strategy implemented on one can impact the value of the other. Firms with portfolios subject to such effects will have different incentives and will likely employ different strategies than firms that do not.

Structure of the Dissertation

The objective of my dissertation is to examine how complementarities within the firm's portfolio of technologies and products influence its technology strategy. Through

[5] In a wireless network, a baseband unit will process the transmission and reception of voice signals sent to handsets and received by the mobile unit. Baseband refers to the frequency range of transmission signal prior to modulation.

[6] For example, see Qualcomm press release, February 8, 1999 https://www.qualcomm.com/news/releases/1999/02/08/qualcomm-introduces-next-generation-cdma-rf-and-analog-chipsets [Last accessed April 30, 2017].

three essays (Chapters 2-4), I highlight the influential role that complementarities play in several important settings. My arguments and findings demonstrate the value of adopting a systemic perspective on the firm's technology portfolio. I discuss each briefly below.

In Chapter 2 (coauthored with Puay Khoon Toh), we investigate if and how firms create value from supplying technology and intellectual property (IP) to compatibility standards. Compatibility standards define how component technologies in a system function together, and lie at the core of technology ecosystems in industries where interoperability between products and services is needed to create value for consumers. Prior research assumes that firms generate most of their reward from supplying IP to the standard through licensing this essential technology to adopters of the standard (Bekkers, Bongard, and Nuvolari, 2011; Pohlmann, Neuhausler, and Blind, 2015). Yet, there are reasons to believe that licensing standard essential technology may not fully compensate the firm for the costs of its disclosure (Updegrove, 2007).

We argue that a firm generates more value from disclosing technology to a standard when it owns non-disclosed complementary technologies. These non-disclosed technologies, by virtue of being complementary to the disclosed, standard essential technology, become compatible to and complementary with the standard. We propose that as the disclosed technologies take a prominent place in the ecosystem (i.e. inside the standard), the value of their complementary technologies rise, which increases the firm's return from disclosure.

To test how the firm benefits from disclosure, we conduct a stock market event study using data on disclosures to major compatibility standards in the information and communications technology (ICT) industry between 1988 and 2010. To test how value changes at the technology level, we trace how patent citations increase once a technology becomes complementary to technologies in the standard.

We find that on average, firms generate negative cumulative abnormal returns from disclosing technology alone. Returns are positive only when the firm owns complementary technologies. Results at the patent level demonstrate that the complementary patents experience a significant increase in citations once the firm discloses the other, standard essential patents.

In Chapter 3, I study how firms appropriate returns in cooperative settings. In many contexts, such as compatibility standards, firms need to reveal IP to others to create value, but doing so reduces the firm's ability to appropriate returns (Arrow, 1962; Henkel, Scholeberl, and Alexy, 2014). Disclosing IP reduces appropriability because the firm relinquishes secrecy and often, its ability to enforce legal rights on others. So how do firms capture value in such a setting?

To answer this question, I trace firms' patent litigation suits in the context of compatibility standards. I predict that firms will focus their appropriation efforts on technology complementary to standard essential technology. Therefore, I expect to observe higher litigation rates among complementary patents than in a sample of similar, but non-complementary patents.

I test my argument using data on patent litigation and ICT standards between 1988 and 2010. Relative to similar patents in the firm's portfolio, complementary patents have similar litigation rates prior to the standard, but experience a significantly higher rate of litigation post-standard. Comparing the patent's own litigation history, complementary patents experience an increase in the number of lawsuits and the likelihood of future litigation after the firm discloses to the standard.

In Chapter 4, I examine the role that product complementarities play in the firms' product design strategy at they enter a new market. While market entry has long been a central topic in strategic management, literature typically focuses on the antecedents of entry, predicting if and when a firm enters. We know much less about product strategies firms use upon entry, even though they play a vital role in post-entry success (Brown and Eisenhardt, 1995; Krishnan and Ulrich, 2001). Evidence also suggests that firms can differ quite widely on their post-entry design strategy in nascent markets, even when they have similar capabilities or access to technology (Benner and Tripsas, 2012). For example, there are puzzling cases where firms with strong technological resources enter a new high-technology market with seemingly inferior technology.

To explore this issue, I study firms' product strategy in the nascent stage of a new product market. I begin with the observation that in many high-technology industries, new product markets form in the context of a larger innovation ecosystem consisting of multiple, potentially complementary product markets. Firms often operate in many of these product markets, and in some instances, offer existing products that are complementary to the new market. I consider how complementarities in the firm's product portfolio influence its product strategy as it enters a new market. I propose that firms with complementary products will be more likely to enter, but will enter with products that exhibit lower technical performance than firms without complementary products. I also argue that firms choose features that function with their complementary products and tradeoff features that do not function with them.

I test my predictions using detailed product information from the nascent stage of the global smartphone market. Firms with complementary products are more likely to enter the smartphone market, and enter with smartphones that exhibit significantly lower technical performance as compared to firms without complementary products. Complementarity influences feature choice, with firms more likely to include product features that correspond to their complementary products and more likely to exclude features that do not function with their complementary products. I also find that complementary products positively influence market share.

At the heart of this dissertation is the notation of a firm embedded in an ecosystem of complementary technologies and products, some of which the it owns. How the firm operates in this ecosystem, including how it collaborates with other firms, how it designs products, and how it executes other strategic actions, will all be influenced by the complementarities in its own portfolio. Through these three essays, I advance our knowledge of the role of complementarities in technology strategy.

CHAPTER 2

Complementary Technologies and Firm Value in Disclosure During Standard Setting

(With Puay Khoon Toh)

Abstract *Compatibility standards play an important role in many product markets by allowing technologies supplied by many independent parties to work together. Despite being a significant source of value creation in technology ecosystems, the extent to which individual firms capture value from their contribution to standards remains unclear. We assess how firms' benefit from technology disclosures to major standards using a stock market event study. We predict and find that firms that own technologies that are complementary to their disclosed technologies gain more from disclosure than firms that do not own complementary technologies. Patents that become complementary to the standard also increase in value. The findings stress the importance of taking a systemic view of the firm's technology portfolio.*

INTRODUCTION

Standard setting facilitates development of different firms' technologies that need to be interoperable within an industry (Leiponen, 2008; Lerner and Tirole, 2015). Often, a technological system, such as the mobile communication network, consists of multiple complementary technologies, i.e. ones whose values are superadditive in combination (Milgrom and Roberts, 1995) and whose operations rely on the functioning of each other (Toh and Miller, 2017). When these technologies are distributed across firms without clear presence of a 'platform leader' (Bresnahan and Greenstein, 1999), coordination becomes crucial in their development, without which the system risks 'forking' and suffers incompatibility problems (Rosenkopf and Tushman, 1998). Compatibility standard setting enables such coordination by spelling out the technical specifications through which the complementary technologies will connect.

Standards are commonly set *de jure* via voluntary standard setting organizations (SSOs). Research has shown that when firms disclose their intellectual properties (IP) to SSOs so to establish the underlying technologies as part of an industry standard, they promote 'openness' of their technologies and mitigate subsequent hold-up problems within the system (Weiss and Sirbu, 1990; Besen and Farrell, 1991). Coordination occurs more efficiently than in *de facto* standard setting (Farrell and Saloner, 1988). Recent empirical work also demonstrates that patents disclosed to SSOs subsequently become more valuable, as indicated by citations received and litigation rates. The higher values did not merely arise from a selection effect—more valuable patents are more likely to be disclosed—but also from a marginal effect—the disclosures *per se* added to the patents' values (Rysman and Simcoe, 2008; Bekkers *et* al, 2017).

Despite these demonstrations, there has been little evidence or understanding of whether and how the value created during disclosure accrues to the disclosing firm (see Pohlmann, Neuhausler, and Blind, 2015), even as the system benefits from improved coordination and the disclosed patents themselves gain intrinsic value. There are reasons to doubt that licensing of standard essential patents (SEPs) would fully compensate for the costs borne by the disclosing firm. For one, the firm can spend millions of dollars and thousands of labor hours on standard-setting activities (Chiao *et al*, 2007; Bar and Leiponen, 2014). Given SSOs' typical mandates to provide open access to all users, the disclosing firm is usually obligated to license out its disclosed SEPs to any user at a 'fair, reasonable, and non-discriminatory' (FRAND) rate, which is likely lower than the monopoly price (Lemley and Shapiro, 2013). When patent pools are used, licensing fees are further split among multiple patent owners. SSOs are increasingly advocating royalty-free licensing (Bekkers *et al*, 2012). The disclosing firm further bears the cost of potential undue expropriation of the disclosed technology, and conflicts, delays, and strategic gaming by rivals as the firm attempts to gather consensus around the SEPs (Updegrove, 2007; Farrell and Simcoe, 2012). Yet, with these hurdles in generating returns from the disclosed technology, firm participation in SSOs is still on the rise. This calls into question whether out-licensing of disclosed SEPs is indeed the main way through which the disclosing firm captures value, if the firm does at all.

In this paper, we study whether and how a firm's disclosure to SSOs during standard setting adds to firm value. We examine disclosures made by firms to 13 SSOs during standard setting within the information and communication technology (ICT) industry 1988-2010. We start with a key observation: contrary to the common depiction of 'complementary technologies within the system requiring coordination being owned by different firms,' in our sample, more than two-thirds of disclosing firms own multiple of these complementary technologies themselves, not all of which are disclosed to SSOs. This forms the basis of our main assertion: as the firm discloses to SSOs, increase in its value occurs mainly through its other complementary technologies that remain non-disclosed, rather than through its disclosed technology.

In firm-level analyses, we use Tobin's Q as a measure of firm value, and examine its relationship with the firm's non-disclosed complementary technologies over disclosure events using panel fixed effect models. We then explore the effect of complementary technologies on the returns to disclosure more rigorously using a stock market event study. As the development of complementary technologies are endogenous firm choices, there may be selection issues that bias our estimated effect that are not adequately addressed in the regression models. We further use inverse propensity-weighted regression adjustment (IPWRA) models (Wooldridge, 2007; Elfenbein, Hamilton, and Zenger, 2010), which account for the firm's propensity to have complementary technologies, and compare treatment effects on a set of treated observations relative to the same set of observations themselves as if they have not been treated. We then explore two potential explanations of how the firm's non-disclosed complementary technologies increase firm value during disclosure—increased compatibility and competitiveness of these complementary technologies.

Our main firm-level findings are as follows: a firm's disclosure does not seem to increase its firm value in general; in fact, we find weak evidence suggesting that such effect of disclosure is negative. However, we find that disclosing firms with non-disclosed complementary technologies experience an increase in Tobin's Q post disclosure. Evidence from our event study strongly indicates that non-disclosed complementary technologies significantly increase firm value. A one-standard-deviation increase in complementary technologies increases the cumulative abnormal returns over a three-day window by 0.48% on average, translating into approximately $328 million increase in market value over three days. Evidence also aligns with our explanations of this main effect—that disclosure increases compatibility and competitiveness of the non-disclosed complementary technologies. We find that the main effect of complementary technologies is weaker when these technologies are also compatible to other firms' potential substitutes for the firm's disclosed technology (and hence increased compatibility is less valued), and is stronger when the disclosing firm active in downstream markets faces more competition downstream (and hence increased competitiveness is more valued).

We further conduct patent-level analyses which allow us to more closely trace changes in value of non-disclosed complementary technologies during disclosure, using subsequent citation received as an indication of value (Rysman and Simcoe, 2008). Fixed-effect Poisson models are used to examine changes in citations received by a non-disclosed patent when its complementary counterpart was disclosed. An observed increase in citation over the disclosure event could stem from other non-observed disclosure-related factors, instead of from the non-disclosed patent being complementary to the firm's disclosed SEP, which would bias estimates even in fixed effect models. To address this potential issue, we conduct patent matching with difference-in-difference analyses. For each non-disclosed patent that became complementary to a disclosed SEP over a disclosure event, we match it to one (or more) almost identical non-disclosed patent(s) from the same firm, technology class and application year, and similar in various attributes, but that did not become complementary to any disclosed SEPs. We then compare the relative changes in citations received over the disclosure event between the treatment and control. By creating counterfactuals for complementary technologies using the firm's similar, non-complementary patents, we can suppress potential effect of firm-level unobservables that may select the firm into disclosure.

The main patent-level findings are as follows: a non-disclosed patent experiences an average of 13.3% increase in citations received after its complementary patent belonging to the same firm is disclosed as a SEP during standard setting. This effect is magnified in the post dot-com era (2003-2010), at 32% increase in received citations, which is substantially larger than even the increases experienced by the disclosed SEPs themselves post disclosure event (16.2%). Hence, disclosures to SSOs appear to enhance firm value though the firm's non-disclosed complementary technologies. Additionally, we find that the firm itself is more likely to build on (self-cite) these non-disclosed complementary technologies after the disclosure event, relative to the firm's own disclosed SEPs or to similar non-disclosed and non-complementary patents in its portfolio.

These findings have clear managerial implications. As the firm strategizes on the extent to which it should participate in organized standard setting within the industry, by disclosing its IP to SSOs, the tradeoff it faces goes beyond ‘enhancing coordination in an open system and increasing efficiencies of technological development’ versus ‘risking the loss of control over and its ability to appropriate returns to the technologies it puts forth during disclosure’ (Gawer and Henderson, 2007). Gains in value of other complementary technologies in the firm’s portfolio, that are not part of disclosures and hence remain uncompromised, should be factored into consideration as well. While the focus in past literature in standard setting has largely been on the appropriation conditions surrounding the disclosed technology, in terms of IP enforceability, changes in value, terms of licensing, etc., our findings provide an alternative view of how firms profit from disclosures—via its complementary technologies rather than the SEPs themselves. This suggests that managers instead focus on appropriation conditions surrounding the complementary technologies.

Our findings may have implications for policy makers as well. In supervising standard setting activities, the objective of institutions such as the U.S. Department of Justice and Federal Trade Commission (FTC) is usually to ensure that firms are not manipulating these activities to gain market power in fraudulent manners or locking in users at monopolistic prices. Cases in point are FTC’s lawsuits against Dell in 1996 and more recently against Rambus in 2005.[7] There have also been efforts to insert protective

[7] In the case of FTC against Dell, Dell was accused of knowingly not disclose IP that are central to the standard being set by the Video Electronics Standards Association. Only after the standard was set did Dell then asserted its IP to demanded royalty payments. It was subsequently ruled that Dell had violated antitrust laws. Dell was then subjected to FTC oversight in subsequent standard-setting activities for ten years, and was made to grant royalty-free licenses to all users. In the Rambus case, FTC alleged that Rambus had failed to disclose relevant IP and illegally manipulated the standard setting process to acquire and exert monopoly power.

mechanisms in the standard setting process, such as the 'defensive suspension' terms[8] in licensing contracts, to prevent disclosing firms from subsequently reneging on licensing at FRAND rates once lock-ins occur (Updegrove, 2007; Sidak, 2015). Our findings suggest a different potential problem: even if a firm's assertion of market power over its disclosed SEP is curtailed, it may still be able to create socially undesirable lock-ins via its complementary technologies that are not disclosed and hence not subjected to oversight. By retaining control over licensing and use of these complementary technologies, the firm may create distortions from socially optimal equilibrium prices and usage as it maximizes profits.[9] We clearly do not offer evidence of such distortions in this paper, but simply raise a possibility that may be worth examining.

RELATED LITURATURE

In this section, we provide a brief review of standards literature. Here, we refer to compatibility standards, as opposed to minimum quality, safety, or reference standards. Compatibility standards define interoperability between various components in a technological system.[10]

[8] The 'defensive suspension' term in contracts allows a party to revoke its cross-licensing agreement with another party if the latter subsequently attempts to assert licensing under non-FRAND rates.

[9] Qualcomm is accused of employing a similar strategy in which it combines its SEPs and complementary technologies in noncompetitive ways. A $975 million antitrust fine was levied against Qualcomm in China in 2015 and $835 million fine in South Korea in 2016.

[10] For example, a mobile phone communications network will consist of the radio transmission protocol that defines how information signals are modulated and communication channels are shared (multiplexing), a base station system for transmitting signals, a network switching system to control 'traffic', receiver and transmitter technology to allow a phone to send and receive signals, and operation support system for testing and maintenance of the communication network, all of which need to be function together to create any value for users. Because many of the components are independently supplied, the coordination through standards setting is necessary to assure interoperability.

Standards play an important role in the evolution of markets by functioning as a mechanism of selection and diffusion of innovation (Antonelli, 1994). Standards can be "selected" through market competition,[11] or as we focus on in this paper, through consensus within SSOs (Farrell and Saloner, 1988). Standards increase the diffusion of standard-based products by reducing user transaction costs and purchase risk, and allowing users to benefit from direct network effects (Demsetz, 1993; Antonelli, 1994). Standards also impact the supply side. Access to technological specifications and IP behind a standard can reduce the barrier of entry into standards-based product markets by reducing tacit knowledge and decreasing design and production costs (Anotelli, 1994). Alternatively, standards can be a source of market power by creating a barrier to entry when access to essential IP is restricted. The outcome of the standardization process can create winners and losers. The process of selecting between alternative technology paths, the standard can render some knowledge, technologies, and physical resources valuable, and others obsolete.

The importance of the selection process to market evolution is why much of the literature on standards focuses on the standard setting process (Farrell and Saloner, 1985; Farrell, 1996; Chiao, Lerner, and Tirole, 2007; Dokko, Nigam, Rosenkopf, 2012; Farrell and Simcoe, 2012; Simcoe, 2012; Lerner and Tirole, 2015; Lerner, Tabakovic, Tirole, 2016). Several issues emerge from this stream. First, is the difficulty in pricing standard essential technology (Lerner and Tirole, 2015). Theoretically, licensing rates for standard essential technology can surpass the price they would fetch in market competition because

[11] For example, VHS standard prevailed over its rival, Betamax.

the ex-ante price of a candidate technology is partially the function of competing technological options. Yet, pricing is not considered in the selection process because discussing licensing rates ex ante creates antitrust concerns (Lerner and Tirole, 2015). Instead, price negotiations often begin post-selection, when the technology has a monopoly position in the standard. This has led to the development of frameworks to analyze price commitments within the standard setting process (e.g. Lerner and Tirole, 2015). The legal literature also identifies the importance of price commitments, and extant research reviews litigation stemming from the issue (Lemely, 2002; Skitol, 2005; Lemley 2007; Sidak, 2015). To deter malignant strategies,[12] many SSOs have adopted strict IP disclosure and licensing rules (Bekkers *et al.*, 2015), policy that the Antitrust Division of the U.S. Department of Justice encouraged (Sidak, 2015). Such policies may unfairly favor licensees over SEPs owners (Sidak, 2015).

Second, the process of achieving consensus can be difficult because firms have vested interests in the outcome of the standard (Farrell and Simcoe, 2012). Therefore, several papers study rule making and barging in standards (Farrell and Saloner, 1988; Shapiro and Varian, 1998; Chiao, Lerner, and Tirole, 2007; Farrell and Simcoe, 2012; Simcoe, 2012). This stream commonly views the standards setting process as a war of attrition that leads to slow selection process (Farrell and Saloner, 1988; Farrell and Simcoe, 2012). For example, Simcoe (2012) finds that vested interests created coordination issues

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[12] IP policies deter a firm from employing a 'submarine strategy' by which the firm waits until its IP becomes essential to the standard before disclosing its stakes and licensing rates. Cases such as Rambus vs. Infineon Tech highlight the problem faced when an SSO does not have a sufficient IP policy (see Rambus, Inc. v. Infineon Techs. AG, 164 F. Supp. 2d 743 (E.D. Va. 2001), or Lemely (2002) for an analysis). These polices also help ensure that all adopters will have equal access to technology that is essential to run the standard.

that delayed the adoption of several important internet standards. This stream highlights firm's rent seeking behavior within the standard setting process, and by doing so, suggests that valuable stakes are involved.

Another stream investigates the properties of patents deemed essential for a standard (Rysman and Simcoe, 2008; Simcoe, Graham, Feldman, 2009; Bekkers, Bongard, and Nuvolari, 2011). Rysman and Simcoe (2008) study four SSOs that sponsor technology standards and find that firms disclose valuable technology during the standard setting process. Results suggest that consensus standardization selects technology that creates value for consumers and adopters. Bekkers *et al.* (2011), however, find that participation by IP owners in the standard setting process increases the odds of their technology becoming essential more than technological merit alone. Their results point to strategic behavior on the part of firms. Simcoe *et al.* (2009) find that technology increases in value after it becomes essential to the standard. Overall, this stream demonstrates that standards select valuable technology, and that post-adoption, this now essential technology becomes even more valuable.

Several recent papers examine the impact of standards on firm performance. Aggarwal, Dai, and Walden (2011) examine how the number of participants in a standard setting initiative impacts firm performance, by tracing the announcement of standard setting initiatives on firm stock market performance. They find that as the number of participants increase, a participant's idiosyncratic risk tends to increase while its near-term stock returns decrease, suggesting that the market anticipates that the outcome of the standard setting process will create winners and losers among the participants. Pohlmann *et al.* (2015) research the relationship between a firm's return on assets and the ownership of SEPs, and find that they are positively correlated. Interestingly, they also find that the impact of SEPs on firm performance rapidly declines as the number of SEPs increases, which they attribute to FRAND licensing restrictions and poorly positioned patent portfolios. Both papers point to the possibility that value creation in standards cannot be fully deciphered by looking at only participation in the standard setting process or ownership of SEPs.

DISCLOSURES DURING STANDARD SETTING

In this section, we discuss key features of the standard setting process in SSOs.[13] For a given standard, a typical process would start with an open call for all members to mention their IP or awareness of existing IP that are relevant to the standard. Committees and workgroups, staffed by representatives from participating firms, are then formed to develop technical specifications for the standard (Leiponen, 2008). Participation in committees is voluntary, though members who are active in related technologies would tend to be on these committees.[14] These representatives from member firms would try to influence the direction of development in favor of their firms' technologies and work to reject developments that would be detrimental to them. Once the exact specifications are

[13] We appreciate helpful insights on the standard setting process from an expert industry practitioner who represented Motorola and Nokia in standard setting activities on multiple occasions over the past decade. He has experience on standard setting in the following: Location Interoperability Forum (LIF) for location technologies, Open Mobile Alliance (OMA), browsing technologies (XHTML, HTML4), and W3C internet standards. He has also chaired device capabilities working groups during standard setting.

[14] Note that most SSOs charge a nominal membership fee (Updegrove, 2007). As SSOs strive to create widely adopted standards, firms can still license technology even if they are not members of the SSO or fail to participate in the standard setting process.

determined, members with SEPs would then officially make disclosures to the SSO via declaration letters, and in doing so formally establish the standard. It is common for uncertainty over exact specifications to remain till the end of the process, as firms have incentives to delay disclosing technologies details even within workgroups.[15] Not all IP mentioned during the initial call would be included in the standard, depending on how the standard evolves in the negotiated process. While most disclosed SEPs belong to participating members in the workgroups, members who did not participate in the technical committees can also disclose.[16]

Firms typically state their relevant technologies in a declaration letter or email to the SSO. A declaration letter is meant to disclose 'technically essential' components which are needed by any firm to implement the standard (Bekkers *et al*, 2012).[17] Letters can take two forms: specific disclosures that list patents and IP claims over essential technology and blanket disclosures that indicate ownership IP but do not list specific patent or patent applications.[18]

Disclosures to SSOs can be costly. First, firms typically spend millions of R&D dollars on standard related projects. Therefore, the baseline cost of generating relevant IP

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[15] In early stages, there is often uncertainty about how the standard would shape up and hence how valuable each technological component will eventually be. Firms are concerned that early disclosure of details and commitment to license would allow rivals to conspire and trap them into unnecessarily disclosing too much of the valuable technologies (Chiao *et al.*, 2007; Updegrove, 2007).

[16] It is also possible for a participant to disclose another participant's technology, though based on our analysis of disclosures, this is very rare.

[17] 'Commercially essential' IP, such as ones protecting methods of implementation that enable substantial quality improvements or cost reductions, are not required to be disclosed during this process.

[18] Firms may use blanket disclosures when they own large patent portfolios and would incur high search costs to determine the exact relevant patents or claims (Updegrove 2007). However, some scholars debate whether search costs play a role. Bekkers and Martinelli (2013) suggest that blanket disclosures may signal that the firm has lower quality patents, though they do not provide evidence that firms making blanket disclosures lack standard essential IP.

is nontrivial. Second, IP may also have uses outside the standard, but disclosure can facilitate efforts to circumvent the patent in outside uses, which can reduce the firm's ability to fully appropriate returns from the IP (Chiao *et al.*, 2007). Third, SSO IP policies typically dictate that disclosing firms must make SEPs available to license on a non-discriminatory basis (Bekkers, *et al.*, 2012).[19] While facilitating the widespread adoption of the standard, the requirement reduces the firm's ability of to benefit from exclusive use of the technology. Moreover, it eliminants the firm's ability to block or slow rivals' development along a lucrative technological trajectory or deter them from a technological space altogether (Clarkson & Toh, 2010). Fourth, by disclosing IP, the firm reveals valuable information about their patent portfolio and future technology strategies to rivals (Chiao *et al.*, 2007). Moreover, during the standard setting process, knowledge beyond what is typically specified in the essential patent document can spillover to rivals (Rosenkopf *et al*, 2001). Such spillovers can further inform rivals of the focal firms' technology strategy and facilitate imitation.[20]

Returns from licensing essential IP may not fully compensate for the aforementioned costs. Most SSOs' IP policies commit firms to FRAND licensing terms. While SSOs' IP policies rarely define what counts as 'fair and reasonable,' some SSOs do place a ceiling on licensing rates. Even when rates are not capped, outcomes often represent a 'middle-ground' from negotiations that may not favor the disclosing firm (Updegrove,

[19] If the firm fails to disclose certain patents or IP, it may still be obligated to abide by the SSO IP policy and license patents on a FRAND basis if it has participated in a standard setting committee for a certain amount of time (e.g. more than 60 days).

[20] From a conversation with an industry participant, we found that firms are aware of such spillovers and try to mitigate them by using managers with standards setting experience.

2007; Sidak, 2015). Some standards have patent pools, which represent an alternative to party-to-party negotiations. Patent pools allow a licensee to access all patents in the pool for one fee. Patent owners typically split revenue based on their proportion of patents in the pool. Firms with more important IP may receive less revenue than they otherwise would have under party-to-party negotiations. Moreover, royalty-free licensing is increasingly being used in many important standards (e.g. mobile browsing). Therefore, knowing the extent of the firm's SEPs is only a first step in understanding how it creates value from its standard-setting activities.

COMPLEMENTARY TECHNOLOIGES AND VALUE CREATION

In this section, we discuss complementary technologies and how they affect value created from firm's disclosures to SSOs. Two technologies are 'complementary' when they are compatible (i.e. co-function together) and when both are functioning, can create more value together than they do alone (Milgrom and Roberts, 1990; 1995; Toh and Miller, 2017). Complementary technologies are often used jointly, as they can represent separate parts of a technological solution. For example, to solve the problem of sending data over a wireless network channel, Qualcomm developed a technology for 'high rate packet data transmission' (see patent US 6173007). The technology efficiently packeted data to better utilize the communication channel, and became an essential technology in the UMTS standard. However, the technology by itself did not allow for fair allocation of data speed to all users of the network. To solve the problem, Qualcomm created a complementary technology for generating optimal data packet lengths (patent: US 6064678) to complement the data transmission technology. The technology was programmed into base station software which then ensures that all users get their fair share of data throughput, and therefore optimized the performance of the data transmission technology.

It is common for a firm to own and develop multiple complementary technologies within a technology ecosystem (Baldwin and Woodward, 2009; Toh and Miller, 2017). How the firm strategizes around these technologies to create value will depend on the location of the technologies in the system. In the standard setting context, a firm can leverage a technology's position inside the standard to increase the value of nondisclosed technologies that are complementary. To illustrate the basic value creating strategy that underlies this argument, take the following example. Nokia included its innovation for encoding radio signals into the GSM communications standard, but is forced to license this technology to rivals. However, Nokia also developed a technology that works with its radio signal method to enhance the signal clarity in its mobile phones. Nokia embeds this proprietary technology into its phones, which allows users to experience better voice clarity when making calls, and therefore, differentiates Nokia's phones from competitors. If a rival had placed a substitute technology in the standard, the value of Nokia's signal clarity technology could be zero if Nokia's technology was incompatible with the substitute.

This example illustrates how the firm can utilize disclosed, standard essential technology to enhance the value of its undisclosed, complementary technologies. Several interrelated mechanisms drive the relationship. First is the increase in the compatibility between the firm's technologies and the standard. Because a standard often defines the core technology platform in the industry, the value of technologies within the same domain will depend on whether they function in conjunction with this platform (Baldwin and Woodward, 2009). When one technology becomes part of the industry standard, its complementary technologies become interoperable with the standard, which increases their value creating potential. The firm's complementary technologies are also more likely to be interoperable with other complementary components in the system. Therefore, the firm with complementary technologies can more fully benefit from the coordination standards provide.

Second, the firm increases its competitiveness by owning a portfolio of complementary technologies. At the individual technology level, compatibility with standard enhances potential users' willingness-to-pay for complementary technologies,[21] which can have a positive effect on the firm's competitiveness in several ways. For a firm that focuses on licensing technologies, the more technologies it has that are interoperable with the standard, the more likely it is to attract potential licensees. The larger the firm's portfolio of complementary technologies, potentially the greater bargaining power it will have over licensees. A firm that produces products that function on the standard can embed its complementary technologies into the products to differentiate them. As noted in the prior example, Nokia increased consumers' willingness-to-pay for its phones by utilizing its complementary technology to enhance voice clarity. Qualcomm designed its chipsets to optimize battery life on wireless networks that used its CDMA technology, thus differentiating the chipsets from those of competitors (Mock, 2005).

[21] Because the firm may co-design both the disclosed and nondisclosed technologies together, the firm's own complementary technology may represent the best way to harness the functionality of its disclosed technology.

By making its technologies compatible with the standard, the firm mitigates the need to convert its technologies to be compatible with rivals' standards proposals, while potentially forcing rivals to do so (Eggers 2012). For example, Nokia did not have the same position in CDMA based wireless compunction standards as it did in TDMA based standards (as noted in the example at the beginning of the section). Nokia lacked complementary technologies needed to differentiate its CDMA mobile phones, and thus, exited the CDMA-based phone market to focus on the TDMA-based market.[22] To compete in the same way in the CDMA-based phone market as it did in the TDMA-based market, Nokia would need to develop a similar set of technologies or licensee such technologies from rivals like Qualcomm and Motorola.

Third, the firm is better positioned to gain from future development of the ecosystem surrounding the standard. New applications for the standard often develop in the surrounding technology ecosystem. The firm can adapt or further develop its complementary technologies to capitalize on new opportunities. For example, in the late 2000s, products in many industries began to utilize wireless communications networks. Qualcomm built upon its previously established complementary technologies to meet the needs of industries such as automotive, home appliance, and health care.[23]

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[22] See, "Nokia to exit CDMA after scrapping Sanyo JV plans", via http://www.itwire.com/it-industry-news/strategy/4724-nokia-to-exit-cdma-after-scrapping-sanyo-jv-plans. [Last accessed, March 2017.]
[23] See for example the Qualcomm Incorporated press release from May 14, 2015: https://www.qualcomm.com/news/releases/2015/05/14-0. [Last accessed, March 2017.]

From these mechanisms, we draw our core hypothesis: the more non-disclosed technologies the firm has that are complementary to its disclosed technology, the greater the gain in firm value upon disclosure to SSOs.

EMPRICAL ANALYSIS

Data

We conduct the empirical analysis in the information and communication technology (ICT) industry between 1988 and 2010. Standards are essential for many products within the ICT industry to function properly and many firms within the industry engage in standard-setting activities across multiple standards and SSOs. Example types of standards include: wireless telecommunication standards (e.g. GSM, GPRS, CDMA, WCDMA, LTE), local area networks (e.g. Wi-Fi), mobile browsing (e.g. xtml), and audio-video compression (e.g. MPEG-4).

We use multiple data sources in our analysis. Data on IP disclosures to standards comes from the Disclosed Standard Essential Patents (dSEP) database (Bekkers *et al*., 2012). The dSEP Database includes the date of disclosure, the entity disclosing, the name of the standard or technical committee, the name of the SSO, and any disclosed patents. Patent data is collected from the U.S. Patent and Trademark Office (USPTO). We obtain citations data by merging the National Bureau of Economic Research (NBER) (Hall *et al*., 2001) patent citation data from the Patent Network Dataverse (Lai *et al.*, 2013). We collect data on stock prices from the Center for Research in Security Prices (CRSP). Data on firm's financials and SIC codes come from Compustat and firms' 10Ks. We collect information on mergers, acquisitions, and stock buybacks from Thomson SDC. We conduct our analysis using multiple samples at both the firm and patent level, and will separately detail how we construct the dependent variable and sample prior to each analysis.

IP Disclosures & Complementary Technologies

To create the disclosure dataset, we use the dSEP database to identify 4,609 disclosures events to 13 different SSOs between 1988 and 2010. Each disclosure event consists of one or more letters or emails to a given SSO on a single date indicating that the entity believes it owns IP essential for the functionality of a proposed standard. These disclosures can either contain information on specific patents or patent applications, or make a blanket disclosure.

To link the disclosure data to stock price information, we manually match the disclosure letters to publicly traded firms listed in the CRSP database, which results in 2,882 disclosure events from 270 firms. Of these disclosure events, 1,012 (from 143 different firms) have at least one U.S. patent or patent application. We identify 3,820 granted U.S. patents, some of which were disclosed on more than one occasion. Table 2.1 provides a summary of IP disclosures by SSO and information on the types of standards the SSO's manages.

The main independent variable, *Complementary Technologies*, captures the number of technologies the firm owns that are complementary to the disclosed IP. To identify complementarity, we rely on the established idea that inventions that draw on combinations of technologies reflect the complementarities between them (Fleming, 2001; Toh and

Miller, 2017). To apply this principal, we identify all the U.S. patents that the firm discloses during a disclosure event. We then trace all unique undisclosed patents that the firm owns that are co-cited with at least one of its disclosed patents prior to or in the year of the disclosure. We only count co-cited patents from a different technology class than the disclosed patent because patents in the same class may refer to different components of the same technology or to prior versions of the same technological concept, rather than complementarity across separate and distinct technologies (Makri *et al*., 2010). At the patent level, *Complementary Technology* is a binary variable that takes the value of one if the patent meets the above criteria. In our event study, *Complementary Technologies* measures the total number of patents meeting the above criteria that have not been previously disclosed to a standard.[24]

We may underestimate complementarity because not all technologies are patented. However, focusing on the ICT industry, where patenting is important and patent propensity is likely similar across firms, helps mitigate this issue.

Descriptive Analysis of Disclosure on Firm Performance

We begin by investigating the broad relationship between IP disclosures and firm value. We draw a sample of firms in which standards in the ICT industry are likely relevant. We define this set as firms that patent in the 89 USPTO technology classes related to communications equipment as per the NBER concordance system. After matching with

[24] We exclude patents that are previously disclosed because licensing requirements associated with such disclosures could restrict the firm's ability to exercise IP rights over these patents.

Compustat and CRSP, we have an unbalanced panel of 412 firms with observations that span 1988-2010 period.

We measure firm performance using *Tobin's Q*, which is widely used in the economics, finance, and management literatures (Venkatraman and Ramanujam, 1986; Lang and Stulz, 1994). We calculate *Tobin's Q* as the sum firm's end of the year market value of equity and reported book value of total liabilities divided by the total book value of assets. To measure the effect of disclosure, we calculate the number of disclosure events the firm has in a year (*Disclosure Events*). The measure should proxy for the number of different standard setting activities the firm participated in during the year.

Panel A of Table 2.2 provides the descriptive statistics for the firm-year panel. *Tobin's Q* averages 2.14 in the sample with a standard deviation of 2.7 and a median of 1.54. Several small software and IP development firms have a *Tobin's Q* greater than 20 (for example, mobile internet IP firm Unwired Planet[25]).[26] Their inclusion does not significantly change the analysis. On average, firms have 0.4 *Disclosure Events* per year. Approximately 12 percent of the firm-year observations have at least one disclosure event.

We control for various firm, industry, and technology related factors. We control for *R&D* spending and the firm's patent stock over the past five-years (*Total Patents*) because highly research active firms are more likely to have technologies relevant to standards. We control for firm size using the natural log of total revenues (*ln(Revenues)*) and profitability using the firms *Operating Margin*.[27] To account for industry, technology,

[25] The firm was more commonly known as Openwave.
[26] Note that the max *Tobin's Q* is 76. However, the 99th percentile value is only 10.
[27] Calculated as operating income (e.g. earnings before interest and taxes) over revenue

and year trends, we include fixed effects for the firm's four digit SIC code, technology subclass for which the firm applies for patents in during the year, and year.

To assess the effect of the disclosure of standard essential technologies on firm performance, we regress *Tobin's Q* on *Disclosure Events* and controls (Model 1 of Table 2.3). We find negative but insignificant effect of *Disclosure Events*. To help suppress unobserved heterogeneity, such as the firm's propensity to participate in standard setting activities, we rerun the model with firm-level fixed effects. In Model 2 of Table 2.3, we find that *Disclosure Events* is negative (-0.065), with a p-value of 0.063. These results suggest that, contrary to expectations from prior literature, disclosure of standard essential technologies may have a slight negative affect on firm performance. Using the estimate in Model 2, an additional disclosure event reduces *Tobin's Q* by about 3 percent.[28]

Note that the negative correlation between disclosures and *Tobin's Q* is not out of line with our expectations. As discussed previously, firms give up exclusivity and uniqueness of their standard essential IP and may not always receive sufficient licensing revenue in return. We argue, however, that firms can benefit when they own non-disclosed complementary technologies. To assess this potential effect on performance, we split *Disclosure Events* into two variables: disclosure events in which the firm does not have any traceable complementary technologies (*Disclosures Events Without Comp. Tech.)* and disclosure events in which the firm has at least one traceable complementary technology (*Disclosures Events With Comp. Tech.)*.[29] *Disclosures Events Without Comp. Tech.* is

[28] Coefficient of -0.065 divided by mean Tobin's Q of 2.14.
[29] Disclosure events include blanket disclosures, which may cause us to underreport the number of events with complementary technologies.

negative but statistically insignificant (-0.054; p-value 0.203) in Model 3 and negative and significant in the firm fixed effect estimation in Model 4 (-0.105; p-value 0.019). We find a positive effect significant at the 10 percent level for *Disclosures Events With Complementary Technologies* in Model 3 (0.122; p-value 0.088) and a positive but insignificant effect Model 4 (0.059; p-value 0.470). The results point to interesting heterogeneity related to having complementary technologies.

A firm's IP and standard strategy may change over time. To allow the fixed effect models to better absorb potential cofounding firm level effects, we break the long panel into three shorter panels (Models 5-7). We find that *Disclosures Events Without Comp. Tech.* is consistently negative in all three models and statistically significant in the 2003-2010 period (Model 5), while the coefficient on *Disclosures Events With Comp. Tech.* is consistently positive in all three models and statistically significant at the 10 percent level in the 1996-2002 period (Model 6).

To check whether the amount of disclosed IP drives the above results, we estimate how the total number of IP disclosures (either blanket letters or patents) in a year effects *Tobin's Q*.[30] We find results similar to Model 1, with *IP Disclosed* negative and statistically insignificant (see Model 8). Splitting the count of *IP Disclosed* by whether we can trace at least one complementary patent to the disclosure, Model 9 shows that *IP Disclosed Without Comp. Tech.* is negative and insignificant (-0.001; p-value 0.325) while *IP Disclosed With Comp. Tech.* is positive and significant (0.0009; p-value 0.012). Using coefficient for *IP*

[30] To be clear, *IP Disclosed* measures the total number IP disclosures the firm makes in a year.

Disclosed With Comp. Tech from Model 9, a one standard deviation increase in the number of disclosures with complementary technologies increases Tobin's Q by 2.5 percent.

Conventional wisdom suggests that firms benefit financially from disclosing patents that become essential to a standard (Pohlmann *et al.*, 2015). The results in this section provide a description of the IP disclosure-performance relationship that is contrary to this view. The results suggest a weak negative correlation between IP disclosure and performance. By investigating the variance across disclosure, we find some evidence that the negative correlation stems from disclosures that lack associated complementary technologies, and that disclosures with complementary technologies may be positively related to performance. This provides an empirical motivation for a more focused analysis of how complementarity technologies affect the disclosure-performance relationship. In the next sections, we attempt to better identify the effect of complementarity by performing more nuanced tests at the event level and at the patent level.

Disclosure Event Study

To provide a more specific test of value creation at the firm level, we use an event study approach to trace how the firm's stock market value changes in response to its disclosure of standard essential IP. Equity market event studies are commonly used in economics, finance, and management research to assess the how events affect firm value (MacKinlay, 1997; McWilliams and Siegel, 1997). The approach assumes that capital markets receive information regarding the event and will efficiently incorporate this information into the firm's stock price. IP disclosures in the ICT industry are usually made public through online disclosure databases[31] and are often simultaneously highlighted in press releases by the firm. We assume that investors monitor firms' standard-setting activity (Aggarwal *et al.*, 2011), as equity analysts commonly mention firms' SEPs or recent developments in standards in their analyses (for example, see Sur, Peterson, and Chuang, 2015).[32]

To estimate the impact of the disclosure event, we calculate daily abnormal returns using the Capital Asset Pricing Model. We calibrate the CAPM on 250 trading days prior to the beginning of the event window, using the S&P 500 as the market index.[33] The main dependent variable, *CAR*, is the cumulative abnormal return in the t-1, t0, t+1 event window, where t0 is the day of the disclosure. We focus on the typical three-day window because its tends to capture most of the market's reaction to the event (MacKinlay, 1997). It also decreases the likelihood that the event window picks up the market reaction to other, confounding news. For robustness, we also provide estimates for several other window lengths.

We begin by analyzing *CAR* for the full sample of 2,732 disclosures from firms with available stock price data during the 1988-2010 period. In Panel A of Table 2.4, we test whether the average *CAR* equals zero using a *t*-test. Test 1 shows that the average three-

[31] For example, European Telecommunications Standards Institute (ETSI), which has overseen the standardization of telecommunication standards such as the GSM cellular standard, lists IP disclosures on its website as they are made (see https://ipr.etsi.org/).

[32] Prior work also supports the assumption that equity market participants monitor standard-setting activity. For example, Aggarwal *et al.*, (2011) show that the equity market reacts to announcements of a firm's participation in information technology standards. We also observe that firms position in standards or changes in SSO policies trigger updated stock reports and ratings. For example, the recent change the IEEE patent policy triggered updated research and outlooks on Broadcom and Marvell (Sur *et al.*, 2015).

[33] The CAPM regresses the firm's risk adjusted returns on the benchmark return. The risk-free rate is specified using the daily interest factor from that day's three-month Treasury Bill rate. As a robustness check, we calibrate the CAPM models using 500 daily trading days, all results are robust.

day *CAR* is negative and significantly different from zero (-0.30 percent; p-value 0.002). Tests 2-5 replicate the test for longer windows. As we increase the window length, average *CAR* continues to be negative but is only significantly different than zero in five-day window (Test 3).

In Panel B of Table 2.4, we replicate the *t*-tests on a sample of disclosures with traceable U.S. patents and no confounding events in the estimation window. To remove events, we do the following. First, we use data from Thomson SDC to exclude observations with any merger or acquisition related announcement[34] or stock repurchase in the event window. Next, we remove observations with other IP disclosures in the event window. Finally, using a LexisNexus search, we remove any observations in which another important announcement (e.g. earnings, earnings guidance, lawsuits) occurred in the window. This results in a sample consisting of 123 firms making 752 IP disclosures in 'clean' three-day windows. T-tests on this sample (Tests 6-10) show that the average *CAR* is positive across all windows, but not significantly different from zero.

To probe how complementary technologies influence the return from disclosure, we split the sample from Table 2.4 Panel B into two groups: observations with and observations without at least one complementary patent. For the three-day window (Test 1 of Table 2.5), we find a positive and significant *CAR* (0.53 percent; p-value 0.02) when the firm owns *Complementary Technologies* and a negative and significant *CAR* (-0.66 percent; p-value 0.01) when the firm has no *Complementary Technologies*. Testing the equality of means using Welch's *t*-test, we find that *CAR* is 1.19 percentage points greater

[34] This also includes announcements of a withdrawal from a merger.

when the firm has *Complementary Technologies* than when it does not, and that the difference in means is statistically significant (p-value 0.003). We find a broadly similar pattern in the other windows (Tests 2-5). Firms typically have a positive *CAR* when they own *Complementary Technologies* and a negative *CAR* when they do not. For all the windows, we find a statistically significant difference in the means of the two subsamples.

Event Study Regression Analysis

In this section, we use a regression analysis to more closely examination of how *Complementary Technologies* affect returns to disclosure. We use the sample of 752 disclosures with traceable patents and no confounding actions in the event window.

We begin by describing the variables used in the analysis. As discussed before, *Complementary Technologies* provides a count of the number of patents complementary to the firm's disclosed patents. To account for how much IP the firm disclosed to the SSO, we calculate *IP Disclosed* as the sum of the disclosed patents and blanket disclosures.

We propose that the firm can benefit from disclosing IP by creating compatibility between its portfolio technologies and the standard. However, when the firm's technologies are complementary to rivals' proposed solutions for the standard, the firm may reap the gains from compatibility regardless of whose IP becomes essential to the standard. To account for this, we first identify all patents from other firms over the prior three years that are in the same technology class as the focal firm's disclosed IP. To calculate *Compatibility With Rivals*, we count all of the focal firm's patents that are co-cited with the identified set of other firms' patents.[35] We exclude co-citations between patents in the same technology class so to not include patents covering the same technology.

We include various firm, technology, and environmental factors as controls. Firms with more patents may be more likely to have *Complementary Technologies* and could have more valuable disclosures, so we control for the firm's total patents in the five-years prior to disclosure (*Total Patents*). To control for the firm's size and overall profitability we include the natural log of revenues (*ln(Revenues)*) and *Operating Margin*[36] in the year prior to disclosure. Some types of standards may create more value than others. To account for this, we aggregate the standards in to three areas. Telecommunications standards that cover mobile phone networks, such as GSM, and local area networks, such as Wi-Fi. Information technology standards that cover internet standards and computer connectivity standards (e.g. firewire). The third bucket covers the 4 percent of the remaining disclosures, and is comprised of audio-visual standards and electrical standards. We also control for the industry and year of disclosure.

Panel B of Table 2.2 provides the descriptive statistics and correlations for the sample. On average, firms make 29 IP disclosures per event. Of the 752 disclosure events, 527 have *Complementary Technologies* greater than zero, with an average of 42 and a standard deviation of 119. Firms in the sample are highly research active, with an average of 2,714 patents applications over five years prior to disclosure.

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[35] For example, if the focal firm only discloses in technology class A during the disclosure event, then *Compatibility With Rivals* measures how many of its patents that are not from technology class A are co-cited with rivals' patents from technology class A.

[36] Operating income divided by revenues

Table 2.6 provides the baseline estimates of the return to disclosure. We begin by analyzing the return to disclosure using the constant and *IP Disclosed*. In the univariate model (Model 1), we find a positive and significant effect of *IP Disclosed*. We also find a positive and significant effect for *Complementary Technologies* in a univariate estimation (Model 2). Adding both variables in Model 3, *Complementary Technologies* remains positive and significant and while *IP Disclosed* becomes negative and insignificant. The constant, which proxies for the average return to disclosure, is positive but insignificant. The results in Model 3 suggests that it is not disclosures per se or the amount of IP disclosed that drive positive returns. Instead, positive returns stem from having a portfolio of technologies that become complementary to the standard. This result is consistent with the *t*-tests from Table 2.5.

Model 5 displays the fully specified model. We find a positive and significant effect of *Complementary Technologies* (0.004; p-value 0.032). Using this estimate, a one standard deviation increase in *Complementary Technologies* increases the three-day *CAR* by approximate 0.48 percent. To put the estimate into perspective, the average market value for firms in the sample without adjusting for inflation is $68.3 billion. Therefore, a 0.48 percent return equates to an increase in market value of $328 million over three days.

Notice that *Operating Margin* is surprisingly negative and significant. This is due to the presence of one outlier that had a very negative operating margin (-78 percent). Removing this observation and rerunning Model 5, *Operating Margin* becomes insignificant while the coefficient on *Complementary Technologies* remains similar (0.004; p-value 0.032).

Sensitivity Analysis

We conduct several sensitivity analyses. In Model 6 we include a SSO fixed effect and obtain similar results (Complementary Technologies coefficient of 0.004; p-value 0.027).[37] We also rerun Model 5 with different event widows and find similar results (see Models 7-9).

Event studies assume that *CAR* can accurately be estimated using some model of to adjust returns for market risk factors. However, the precisions in which the benchmark accounts for typical returns in the stock can vary. To account for this, we run the full model using weighted least squares (Model 10), using the precision of the estimated abnormal returns as weights[38] (Girotra, Terwiesch, and Ulrich, 2007). The estimates remain robust.

To check the sensitivity of our results to the chosen benchmark model (CAPM using S&P 500 as benchmark), we rerun the full model with abnormal returns calculated using a CAPM with the CRSP market weighted index as a benchmark. We also estimate abnormal returns using a Fama-French three factor model (MacKinlay, 1997). While not shown, results remain robust. We also check the sensitivity to the calibration window length. Instead of 250 day CAPM we use a 500 day CAPM and find similar results.

Selection into Complementary Technologies

Unobserved factors, such as differences in firms IP strategy or differences in their ability to create complementary technologies could affect both returns to disclosure and likelihood of having complementary technologies. To help suppress these concerns, we

[37] In fact, all results in Table 6 remain robust to the inclusion of SSO fixed effects.
[38] The weight is calculated as 1/(1- R-Square), where R-Square is from the CAPM model.

take advantage of within-firm variation across disclosures by rerunning the full model using firm fixed effects. In the firm-event panel there are approximately six disclosure events per firm. Amongst firms with *Complementary Technologies* in at least one disclosure, the average within-firm coefficient of variation for *Complementary Technologies* is 110 percent. Other variables also exhibit some within-firm variation.[39] Model 11 of Table 2.6 presents the fixed effect estimates for the entire sample. We find a positive and significant effect for *Complementary Technologies* (0.004; p-value 0.011).

Because firms' strategies and abilities likely change over time, a firm fixed effects can more effectively account for unobserved factors when the panel is shorter. We rerun the fixed effect model on the 2003-2010 sample. The sample begins after the dot-com bubble and telecommunication sector stock crash, and comprises about three quarters of our sample (Model 12). We find a positive and significant effect for *Complementary Technologies* (0.004; p-value 0.019).

We also attempt to suppress the potential selection effect stemming from differences in firms' ability to create complementary technologies by directly estimating this propensity. We do this using the inverse probability-weighted regression adjustment (IPWRA) model (Wooldridge, 2007, Elfenbein *et al.*, 2010). To conduct the IPWRA analysis, we separate the sample into treated and untreated groups, by first converting *Complementary Technologies* into a binary variable indicating whether the firm-disclosure observation has complementary technologies (value=1) or not (value=0). In the 1st stage, we estimate the propensity to have technologies complementary to the disclosure using a

[39] For example, the mean within-firm coefficient of variation is 58% for *IP Disclosures*, 122% for *Operating Margin*, 27% for revenues.

logit regression. The inverse of the predicted propensity is then used as a weight in two separate 2^{nd} stage models, one for the treated (firms with complementary technologies) and one for the untreated (no complementary technologies). Each 2^{nd} stage model uses a linear regression to estimate *CAR*. We estimate parameters of the treated (untreated) 2^{nd} stage model using only observations with complementary technologies (no complementary technologies).[40] These parameters essentially tell us how the control variables adjust returns for disclosure for the treated (untreated) firms. This estimation is robust to misspecification of one of the models in either 1^{st} or 2^{nd} stage (Wooldridge, 2007).[41]

To determine the effect of complementary technologies, we calculate the average treatment effect on the treated (ATET), which estimates the additional return from disclosure the firm receives from having complementary technologies as compared to if the same firm had not had complementary technologies. To calculate treatment effect on the treated, we enter each treated observation separately into the two 2^{nd} stage (treated and untreated) models, and predict two respective *CARs*. We then calculate the difference in

[40] The three equations comprise an exactly identified system of equations that can be handled by generalized method of moments. The exact specifications are as follows. Let the 1^{st} stage logit estimate of the propensity of the firm having complementary technologies be given by $p(z_i , c_i , \hat{\gamma}) = \left[\frac{g(z_i \hat{\gamma}')\,[\tau_i - G(z_i \hat{\gamma}')]}{G(z_i \hat{\gamma}')[1 - G(z_i \hat{\gamma}')]} \right] z_i$ where the z variables are the predictors of the treatment effect, c_i is a binary indicator of the treatment, $G(z)$ is the cumulative distribution function (cdf) for the logit, and $g(.)$ is probability distribution function given by the partial derivative of the cdf with respect to z. From the propensity score model, we derive the inverse probability weight, $w_i(c)$, which is equal to the inverse of $p(z_i , c_i , \hat{\gamma})$ in treated model and the inverse of 1-$p(z_i , c_i , \hat{\gamma})$ in the untreated model. The conditional outcomes for the linear treated and untreated models are estimated using the following equation: $u_c\{x_i, \hat{\beta}_i, w_i(c)\} = w_i(c) c_i [y_{i-} \left(x_i \hat{\beta}'\right)] x_i$. We do not report the propensity score, treated and untreated model output, as interpreting their coefficients do not directly shed light on our overall prediction.

[41] Consistent estimates of the treatment effect are based on two assumptions. First, conditional on observables, the conditional mean of disclosure for treated and untreated firms is independent of the treatment. Second, for similar values of the observables, there are firms that will have complement technologies and firms what will not. This second assumption is also referred to as the overlap or common domain assumption. Together, these two assumptions provide a weak condition for 'strong ignorability' (Rosenbaum and Rubin, 1983).

predicted *CARs* for the same observation, weighted by the inverse propensity score. This difference shows how much the treatment (complementary technologies) has changed the return to disclosure for that one observation (estimated via the treatment model parameters), compared to itself without treatment (estimated via the control model parameters). ATET is the average of this difference over all treated observations.

To estimate the 1st stage, covariates are chosen based on maximizing model fit and to control for potential confounding factors. Firms with broader patenting scope (*Scope*[42]), larger patent stock (*Total Patents* over the prior five years), and higher *R&D* should be more likely to have *Complementary Technologies*. Firms with greater *Capital Expenditure Intensity*[43] or *Property Plant & Equipment* may be advantaged in downstream competition, thus may be more likely to disclose without complementary technologies. We also include *IP Disclosed*, *ln(Revenues)*, *Operating Margin*, and fixed effects for the standards type, technology subcategory and year. We estimate 2nd stage models using the same control variables as Model 4 of Table 2.6.

We report the estimates of ATET in the Table 2.7. The 1st stage, while not shown, predicts the propensity to have *Complementary Technologies* reasonably well, with a Pseudo R-squared of 0.38. Model 1 of Table 2.7 shows a statistically and economically significant ATET (1.37 percent; p-value of 0.01) for the three-day window. We find similar results for the other windows (Models 2-4). Overall, as we attempt to suppress potential

[42] We calculate scope as 1-Herfindal index of firm's patents across different technology classes. Higher scope indicates the firm patents more broadly.
[43] Calculated as total capital expenditures divided by total revenues.

selection concerns, our estimated effect of *Complementary Technologies* on *CAR* remains robust.

Demonstrating the Compatibility and Competitiveness Mechanisms

In this section, we provide empirical support for two mechanisms that underlie our theoretical argument: compatibility and competitiveness. We begin by highlighting the effect of compatibility with the standard on returns to disclosure.

The firm can benefit from creating compatibility between its portfolio of technologies and the standard. To do so, the firm needs to have its technological proposal (which has non-disclosed complementary technologies) accepted by the standard. However, when the firm's complementary technology is compatible with rivals' substitute proposals, the compatibility based benefit from disclosure should decline. This is because the focal firm's technology will be compatible with the standard even if the firm does not disclose standard essential technology.

To test this mechanism, we interact *Complementary Technologies* with *Compatibility With Rivals. Compatibility With Rivals* measures how many of the firm's non-disclosed patents are compatible with rivals' patents in the same technology class as the firm's disclosed patents. High values of *Compatibility With Rivals* indicates that the focal firm patents would likely be compatible with rivals' alternative proposals for the standard. We expect that as *Compatibility With Rivals* increases, the likelihood the firm would have technology compatible with the standard increases, even if the firm did not disclose technology to the standard. Therefore, when *Compatibility With Rivals* is high, the firm would likely accrue the benefits of compatibility even without disclosure.

In Model 1 of Table 2.8, we find a positive and significant effect for *Complementary Technologies* (0.005; p-value 0.009) and a negative and significant effect of the interaction between *Complementary Technologies* and *Compatibility With Rivals* (-0.00001; p-value 0.021). Using the estimates of Model 1, a one standard deviation increase in *Complementary Technologies* increases *CAR* by 0.55 percent when *Compatibility With Rivals* is zero. The return declines to 0.38 percent when *Compatibility With Rivals* increases by one standard deviation. The return falls to zero when *Compatibility With Rivals* reaches the 95 percentile. At high levels of *Compatibility With Rivals*, the firm receives little compatibility based benefit from disclosure.[44]

Next, we explore how complementary technologies can affect the competitiveness of the firm. We argue that complementary technologies enhance the firm's ability to compete against rivals across the various product markets that the standard enables. Therefore, the saliency of this mechanism will depend on the level of competition the firm faces. As the market tends towards monopoly, the marginal benefit the dominant firm accrues from an additional complementary technology should be small because the firm already has a strong market position. In more competitive markets, the marginal benefit of an additional complement technology should be larger. Thus, to highlight our mechanism, we test how complementary technologies impact returns to disclosure under different levels of market competition.

[44] We rerun the analysis by calculating *Compatibility With Rivals* over five-years instead of three-years, results remain fully robust.

To proxy for a market's competitiveness, we utilize the sales concentration in the firm's four-digit SIC code. This empirical strategy maps well to firms that primarily compete in products markets downstream from the standard, but may not capture competition for upstream-focused, technology licensers. Hence, we focus our analysis on downstream firms for which sales concentration in the four-digit SIC industry is a valid proxy of competitive conditions. We classify a firm as 'downstream' if it primarily produces products that function on the standard (e.g. Nokia and Motorola) or if it must adopt a standard to service its customers (e.g. AT&T).[45] Alternatively, we classify a firm as 'upstream' if it primarily develops and licenses technologies (e.g. Interdigital and Intellectual Ventures LLC) or if it focuses on both licensing technologies and the development of components for downstream firms (e.g. Qualcomm and Broadcom).[46]

We begin the analysis by analyzing the full downstream sample (Model 2). We find that *Complementary Technologies* is positive but only significant at the 10% level (0.006; p-value 0.089). Differences in downstream market competition may account for the weaker significance level. To test whether this is the case and to highlight the competitive mechanism, we split the downstream sample into two subsamples based on competitive conditions in the market. To proxy for competitive conditions in the firm's downstream product market we use an established measure of market competition, the Herfindahl-

[45] For a wireless communications standard, firms that only offer technologies (Interdigital) and ones that offer technology and components like chipsets (Qualcomm) are upstream firms, while firms that primarily make standard based products such as base stations, routers, switch gear, and handsets (Alcatel, Ericsson, Nokia, and Motorola) are downstream firms.

[46] This includes most semiconductor firms that actively create technologies for standards but rarely product products that adopt the standard or must license standard essential technologies to function.

Hirschman Index (HHI)[47] of market share in the firm's four-digit SIC industry. We then create the two subsamples based on the U.S. Justice department's standard for a highly concentrated market (an HHI greater than or equal to 2,500).[48] The high (low) concentration subsample will proxy for a less (more) competitive downstream market.

We find a positive but insignificant effect for *Complementary Technologies* in the high HHI subsample (Model 3). The result indicates that *Complementary Technologies* benefit firms' competitive position less in highly concentrated markets. Put differently, a firm with a large market share already has a strong competitive position in the market and the marginal benefit of *Complementary Technologies* on its competitive position is minimal.

In a more competitive market (HHI < 2,500; Model 3), we find a positive and significant effect for *Complementary Technologies* (0.007; p-value 0.046). *Complementary Technologies* enhance a firm's position in a competitive market. The estimated effect is almost twice the size of the baseline estimate from Table 2.6-Model 5. In a competitive market, increasing *Complementary Technologies* by one standard deviation results in a 0.7 percentage point increase in *CAR*.

If *Complementary Technologies* enhance competitiveness (and thus, returns to disclosure), then we should observe a high marginal benefit for firms with small market shares in highly concentrated markets. To test this conjecture, we interact *Complementary Technologies* with the *ln(Revenues)* in the high concentration sample (i.e. HHI >= 2,500).

[47] The HHI is calculated as the sum of squared market shares for all firms in the market. The number ranges from 0 to 10,000 if the market shares are expressed as whole numbers.
[48] Please see the United States Department of Justice website: https://www.justice.gov/atr/herfindahl-hirschman-index. [Last accessed April 10, 2017].

Model 5 shows a positive and significant effect for *Complementary Technologies* (0.211; p-value 0.001) and a negative and significant effect for its interaction with *ln(Revenues)* (-0.019; p-value 0.001). To put the results in perspective, a one standard deviation increase in *Complementary Technologies* (about 75 patents using the high concentration sample) results in a *CAR* of 7 percent when the firm has revenue in the lower 5th percentile of the sample, holding all else constant. *CAR* declines to 3 percent when revenues increase to the 25th percentile, 0.45 percent at the 75th percentile, and -0.28 percent at the 95th percentile. The results suggest that in a concentrated market, the firm with a dominant market position will likely benefit from the standard regardless of whether they own complementary technologies, while the firm with a small market share will greatly enhance its competitive position through complementary technologies.

In Models 6-8 we rerun the previous analysis using a typical alternative to the HHI, the four-firm concentration ratio. We use 75 percent four-firm market share to denote high concentration and find robust results.

Before concluding, we conduct two robustness checks. We first test for whether we need to control for the firm's business model in our main analysis. To do so, we code the dummy, *Downstream Firm*, one if the firm meets our downstream criteria and zero if it meets the upstream criteria. Model 9 of Table 2.7 shows that *Downstream Firm* is negative but insignificant. Next, we check to see if our proposed effect holds in the upstream subsample. For upstream firms (Model 10), we find a positive and significant effect for *Complementary Technologies* (0.01; p-value 0.018). A one standard deviation increase in upstream firms' *Complementary Technologies* increases the three-day *CAR* by 1.01 percent.

In sum, results in Table 2.8 provide some empirical support for our assertion that *Complementary Technologies* enhance returns to disclosure through two of our proposed mechanisms: compatibility and competitiveness.

The Patent-Level Analysis of Value Creation

In this section, we analyze how technologies become more valuable once they become complementary to the standards. We propose that after the firm discloses technology to the standard, its complementary technologies will increase in value. Demonstrating our proposed effect at the patent level helps underscore how value is created at the firm level.

Analyzing value creation at the patent level also allows us to bypass some potential confounding issues at the firm level. In some instances, we may under report complementarity at the firm level if the firm has complementary technologies to its IP covered in blanket disclosures, because we cannot observe such IP from the disclosure letter alone. Our analysis at the patent level allows us to bypass this issue by precisely linking the disclosed technology to its complementary technologies. At the patent level, we can also suppress selection concerns related to unobservable firm-level factors that influence the decision to disclose technology to a standard, by comparing similar complementary and non-complementary technologies within the firm's own portfolio.

To investigate how becoming complementary to the standard creates value at the technology level, we analyze a patent's received citations (also known as forward citations). Received citations—citations a patent receives from other patent applications—is an established measure of economic and technological value in the strategy and economics literature (Harhoff *et al.*, 1999; Jaffe and Trajtenberg 2004; Allison *et al.*, 2004; Hall *et al.*, 2005) and has been used to understand the effect of standards on the value of disclosed IP (Rysman & Simcoe, 2008; Simcoe *et al.*, 2009).[49]

We begin by analyzing the effect of becoming 'complementary to the standard' for a sample of 9,824 complementary patents. We collect a seven-year panel for each patent. At time t0, the firm discloses the standard essential IP, which makes the complementary patent compatible with the standard. The sample ranges from three-years prior to three-years after the year of disclosure. We drop any patents that do not have all seven years of citation data. We only include the first time a patent is complementary to a disclosure. *Complementary Technology* takes the value of one once the patent becomes complementary to the standard and zero otherwise. *Age* measures the time in years between the application date and time *t*. Because the typical patent exhibits a humped shaped relationship between citations and age, we also control for *Age Squared* (Hall *et al*., 2002; Mehtra, Rysman, and Simcoe, 2010). Results are very similar if we use grant date instead of application date to calculate our age controls.

[49] Hall *et al.* (2005) find a firm's market value is more highly correlated with its citation weighted patent stock than its unweighted patent stock. Rysman & Simcoe (2008) use forward citations to measure the value of standard essential patents.

We estimate the effect of becoming complementary using a fixed effect Poisson model. Model 1 of Table 2.9 displays the results for the full sample. The coefficient on *Complementary Technology* is positive and significant (0.133; p-value 0.000). Patents experience a 13.3 percent jump in citations once they become complementary to the standard via the firm's IP disclosure. To see if this trend differs across time, we separate the sample into two groups. Model 2 shows the sample of patents between 1988 and 2002. Patents see an 8.6 percent yearly bump in citations once they become complementary to a standard. This effect increases in the years after the dot-com and telecommunications crash (Model 3). Patents in this period experience a 32 percent increase in citations once they become complementary to a standard.

Prior literature finds that SEPs increase I values post-standard (Rysman and Simcoe, 2008). To benchmark these results, we estimate the effect on citations from disclosure to a standard on a sample 1,683 disclosed patents. We use the same sampling strategy and control variables as before. From Model 4 of Table 2.9, we find that a patent receives a 14 percent yearly increase in citations once it is disclosed to a standard. The result is similar to the estimate for complementary technologies in Model 1 (13.3 percent). Comparing the complementary technologies verse SEPs in the different periods, we find complementary technologies experience a smaller post-standard increase in the 1988-2002 period (8.6 percent vs. 15.3 percent) and a larger post-standard bump in the 2003-2010 period (32 percent vs. 16.2 percent).

Firms that disclose to standards may raise the visibility of their entire technological portfolio. In the prior analysis, we use the patent own history as the counterfactual. With this analysis alone, we cannot tell if the increase in citations stems from being complementary to the standard or from some firm wide effect related to standards participation. To tease out this possibility, we compare patents that become complementary to the standard to a control group comprised of one or more of the firm's similar, but non-complementary patents.

To conduct the test, we proceed as follows. For each complementary patent, we assemble a set of potential control patents that are from the same firm, technology class, and application year. Then, we match complementary patents to one or more of these control patents using three variables: *Received Citations*$_{t\text{-}3 \text{ to } t\text{-}1}$, *Backward Citations* and *Breadth of Citations*. *Received Citations*$_{t\text{-}3 \text{ to } t\text{-}1}$ is calculated as the number of citations the patent received over the three years prior to the disclosure date (t0), and proxies for the value of the patent prior to the disclosure event. *Backward Citations* measures the number of citations made by each patent, which captures the depth of knowledge used (Lanjouw and Schankerman, 2004). *Breadth of Citations* measures the number of different technology classes cited by the patent, which serves as a proxy for the diversity of knowledge used in the invention (Toh and Miller, 2017). We match the treated patent (i.e. patent that is complementary) to a minimum of one 'nearest neighbor' untreated (non-complementary) patent within the set, based on the lowest Mahalnobis Distance on these three variables.[50] Upon creating these matches, we compute the bias-adjusted average treatment effect on the treated[51] (Abadie *et al.* 2004, Abadie and Imbens, 2011). ATET

[50] When there are multiple untreated patents within the set with the same distance, the matching algorithm takes the average across them.
[51] Nearest neighbor match using continuous covariates is nonparametric, which makes it flexible. However, it also converges at a rate less than $\sqrt{N}$, which makes it potentially inconsistent even in infinitely large

indicates how many more citations a patent with complementary technologies receives as compared to its counterfactual created from an almost identical non-complementary patent(s).

Table 2.10 Panel A provides the results of the within-firm matching. From Test 1, we find that becoming complementary to the standard increases the number of citations received in t0 to t+3 window by 1.59 (p-value 0.000). ATET increases as we increase the window length (2.5 in Test 2 and 3.41 in Test 3).

We also rerun the within-firm analysis with the percent change in citations as the dependent variable. Test 1 in Panel B show that results for the percent change in citations t0 to t+3 over t-1 to t-4. Patents that become complementary to the standard have approximately 12 percentage point larger increase in citations than a counterfactual derived from the firm's similar, but non-complementary patents.[52] We find similar results for the other windows (see Tests 2-4 in Panel B). The results in Table 2.10 suggest that patents that become complementary to a standard become more important than similar patents from the same firm. These estimates are in line with the fixed effect analysis. Therefore, we are more confident that the prior results are driven primarily by the effect of complementarity not an unobserved factor that influences the firm's entire portfolio of patents.

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samples. To correct for this potential inconsistency, we use the adjustment that makes the estimate $\sqrt{N}-$ consistent and asymptotically normal. This basically combines our nearest neighbor matching and a regression adjustment to create the counterfactual (see Abadie and Imbens 2011, pages 3 and 4 for the exact formula).

[52] The result is approximate to a difference-in-difference analysis.

Complementary Technologies and the Firm's Technological Trajectory

We argue that having complementary technologies places the firm in a better position to gain from the future development of the ecosystem surrounding the standard. A firm may do so by building on the knowledge underlying its complementary technologies. This suggest that we should observe firms citing their complementary patents more than similar, but non-complementary patents.

To assess the empirical support for this mechanism, we begin by analyzing the probability that the firm will cite a complementary patent as compared to a similar, non-complementary patent. To conduct the analysis, we create a firm-patent-event sample, where for each disclosure event, we observe all the firms patent applications and granted patents at the time of the disclosure. Our dependent variable *Self-Cite*, takes the value of one if the firm cites a patent in the three years after disclosing to a standard and zero otherwise.[53] *Complementary Technology* takes the value of one if the patent is complementary to a patent disclosed to the standard and is zero otherwise.

We then run a logit model controlling for *Backward Citations*, *Breadth of Citations*, application year, technology class, and year. Model 1 of Table 2.11 displays the average partial effects (APE) from the logit model. Becoming complementary increases the probability of being cited by 16.5 percent (0.165 APE for *Complementary Technology*). If we add a control for *Received Citations*$_{t\text{-}3 \text{ to } t\text{-}1}$ (Model 2) or in addition, add firm fixed effects (Model 3), the APE for *Complementary Technology* remains positive and significant (9.5 percent, p-value 0.000).

[53] For a firm, we observe Self Cite in the three-year window for all the firm's patents.

As a robustness check, we employ a nearest-neighbor matching model as described in the previous section. We separate the sample into 'treated' patents (i.e. *Complementary Technology* equal to one) and 'untreated' patents (i.e. *Complementary Technology* equal to zero). Then for each treated patent, we match one or more untreated patents from a sample that comes from the same firm, application year, and technology class using a nearest neighbor' match based on the lowest Mahalnobis Distance on these three variable (*Backward Citations*, *Breadth of Citations* and *Received Citations*$_{t\text{-}3\ to\ t\text{-}1}$). While not shown, the resulting ATET is 7.73 percent (p-value of 0.000). The results suggest that firms are more likely to build on their complementary patents than on other, similar patents in their portfolio.

We conduct two additional robustness checks. In Model 4, we estimate how *Complementary Technology* affects the number of self-citations a patent receives in the three years after the firm discloses to a standard. Using the same sample and control set as Model 3, our firm-fixed effect Poisson estimates show that complementary patents receive about 75 percent more citations than similar non-complementary patents (coefficient on *Complementary Technology* 0.746, p-value 0.000).

The prior results could be biased if we cannot control for unobserved factors at the technology level that can make a patent more central to the firm's technology strategy. To help suppress these concerns, we estimate a seven-year panel of self-citations using a sample of patents that become complementary to the standard. This is the same strategy used in Table 2.9, except we use the yearly number of self-citations as the dependent variable. From Model 5, we find that when a patent becomes complementary to a standard, the number of yearly self-citations increases by 18.4 percent (p-value of 0.000).[54]

We also compare the likelihood of self-cites between the firm's SEPs and complementary technologies. To do this, we rerun the analysis in Model 1 but use SEPs as the control group for complementary technologies. In Model 6, we analyze the probability the firm will self-cite a patent in the three-years following disclosure. We find that the firm has a 5.2 pp greater propensity to cite complementary technologies than SEPs (p-value 0.000). Controlling for technology class, the effect remains positive and significant (4.1 pp; p-value 0.000). Rerunning the analysis using citation counts provides similar conclusions.

Our results in this section suggest that complementary technologies become central to a firm's post-standard technological trajectory. However, we interpret this analysis with caution, as the firm, by building on the standard essential technology, may also cite the complementary technology. Hence we cannot be certain that effect found in the previous analysis is not spurious.[55] To probe this effect, we calculate the proportion of the firm's patents that cite complementary patents after the disclosure event that also cite one or more of the firm's own disclosed SEPs. We find that only 10.6 percent do so. The evidence suggests that the self-citation analysis indicate that firms are strategically building on their complementary technologies, not just the SEPs.

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[54] Note that the sample in Model 5 (4,880 patents) is smaller than the sample used in Model 1 of Table 2.9 (9,824). This is because all outcomes (self-citations) for discrepancy (4,944 patents) are zero. The low self-citation count can be explained partially by the fact that the 4,944 excluded patents are significantly older than the 4,880 included patents at the time of disclosure (8.8 years vs. 6.8 years).

[55] Firms may build on their platform of SEP technologies and just happen to cite the complementary technology.

Discussion Regarding Firms' Selection into Disclosure

As disclosures are endogenous firm choices, there may be selection issues in our firm-level estimations that are not adequately addressed through fixed effects models and event windows. Hence, we interpret our firm-level estimates with caution because we do not account for selection into disclosure. Arguably any observable factor that would influence the firm's decision to disclosure would also correlate with the returns to disclosure, making it difficult to find a suitable instrument to identify the selection threshold.

Nevertheless, selection bias may not undermine our analysis. In our sample, firms that disclose without complementary technologies tend to be the same firms that disclose with complementary technologies. Hence, we do not compare firms of different 'types,' rather, we compare different instances of disclosure. If selection of technology proposals by the committee members is not correlated with the proposal owner's complementary technologies, then disclosures without complementary technologies could potentially be a suitable control for disclosures with complementary technologies.

A concern is the possibility that firms disclosing without complementary technologies exhibit lower returns to disclosure than the true counterfactual for disclosures with complementary technologies. Returns could be lower if the disclosed technology with complementary technologies is less valuable than disclosed technology without complementary technologies, because both would likely receive similar licensing rates but the former would have a lower opportunity cost. We do not find evidence that this is so. To assess pre-disclosure value of disclosed technologies, we regress the count of citations in the three-years prior to disclosure on a binary indicator that the disclosed technology has complementary technologies, and control for age, standards area, SSO, and firm fixed effects.[56] We find no significant difference between disclosures with and without complementarities (indicator variable APE 1.8, p-value 0.746).

Our estimates may be inconsistent if technology without complementary technologies are disclosed to less important standards or to less important parts of a standard. If this is so, then these SEPs will likely garner fewer citations post-disclosure relative to SEPs with complementary technologies. Using citation received in the three years after disclosure as the dependent variable and controlling for the same set of variables as in the previous regression, we find that the indicator for disclosure with complementary technologies has an APE of -5.49, but is insignificant (p-value 0.495). Hence, we find no significant difference in the post-disclosure increase in value between disclosure with and without complementary technologies.

Finally, our within-firm patent matching would suppress firm-level unobservables that might select firms into disclosure. The within-firm matching analysis strongly suggests that complementary technologies increase in value once their corresponding SEPs are disclosed.

CONCLUSION

This research examines whether and how a firm's disclosure to SSOs during standard setting adds to firm value. We propose that as the firm discloses to SSOs, value

[56] We use a negative binomial model.

accrues primarily through the firm's non-disclosed complementary technologies rather than through its disclosed technologies. Our empirical results support this hypothesis. Firms experience negative returns from disclosure without accompanying complementary technologies. Complementary technologies significantly enhance the effect of disclosure on firm value. The positive effect is enhanced when increased competitiveness is more valued and weakened when increased compatibility is less valued. We also find complementary technologies themselves increase in value after their complementary SEPs are disclosed.

Our results raise an interesting issue as to why a firm would disclose without complementary technologies. Indeed, our firm-level results show that cumulative abnormal returns over a three-day window are negative (-0.66 percent). There may be several explanations. One, firms may rationally choose to disclose because they would be worse off otherwise. Unfortunately, our data do not allow us to accurately estimate the counterfactual for such firms. Two, firms may have initially suggested a larger proposal for the standard, one in which the firm had complementary technologies; however, the committee only included a subsection of the proposal, the part without complementary technologies. Three, firms may overestimate the potential licensing revenue from SEPs or underestimate the costs of disclosure.

At the heart of our argument is the notation that strategic actions conducted on one technology can impact the value of complementary technologies. In context of compatibility standards, by disclosing technology and establishing it as part of a standard, the firm not only enables coordination across various technologies within the standard, but also can increase the compatibility and competitiveness of firm's other technologies. Complementarities within the firm's portfolio provide the firm a source of competitive advantage which can potentially explain why firms differ in how they benefit from their standard settings activates. This finding is of interest to both managers and policy makers.

We also contribute to the literature on complementary technologies. Prior work on complementary technologies focuses on primarily on the how they are recombined to create new innovations. We provide a different lens to view value-creation of complementary technologies, beyond that of recombination. Even without combining them, the presence of complementary technologies within the firm's portfolio alone can alter its strategic calculations and present additional strategies through which the firm creates value.

Table 2.1. SSOs and patent disclosures

Standard Setting Organization (SSO)	Description of standard setting activity relevant to sample	Number of U.S. patent disclosures (1988-2010)
American National Standards Institute (ANSI)	DSL & cellular telephony protocol (TDMA)	296
Alliance for Telecommunications Industry Standards (ATIS)	Telecommunications networks	281
Broadband Forum (BBF)	Broadband standards (e.g. DSL)	35
European Committee for Electrotechnical Standardization (CENELEC)	Fiber optics, cable tv, electrical engineering of computers networks, electrical systems in commercial buildings	3
European Telecommunications Standards Institute (ETSI)	Telecommunications standards, such as GSM and WCDMA	4,059
International electrotechnical Commission (IEC)	Power generation and transmission, electronics, and magnetics used in telecom, fiber optics, batteries, and medical fields	63
International Organization for Standards (ISO)	Coordinates with all of the SSOs on telecommunications standards	135
International Telecommunications Union (ITU)	Broadband, wireless technologies, navigation, radio astronomy, VoIP, satellites	774
Internet Engineering Task Force (IETF)	Internet protocol	1,292
ISO/IEC JTC1	ISO's joint standards with IEC for information and communication technologies: IC cards (smart cards), automatic identification and data capture (AIDC) technologies, information security, biometrics, cloud computing, multimedia (MPEG), database query and programming languages	777
Open Mobile Alliance for mobile phone standards (OMA)	Mobile phone service standards	283
The Institute for Electrical and Electronic Engineering (IEEE)	Ethernet, Lan/Man, Wi-Fi	994
The Telecommunications Industry Association (TIA)	Cellular towers, satellites, voice of internet protocol, communications equipment	298

Table 2.2. Descriptive statistics

Panel A: Firm-Year Panel Data Descriptives					**Correlations**						
Variable	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	
(1) Tobin's Q	2.14	2.70	0.21	76.24	1						
(2) Disclosure Events	0.40	2.32	0.00	62.00	0.007	1					
(3) Total Patents (5-years)	121.83	432.71	0.00	4,075.00	-0.057	0.085	1				
(4) ln(Revenues)	6.70	2.22	-3.54	12.11	-0.115	0.242	0.434	1			
(5) Operating Margin	-0.04	2.95	-176.06	0.60	-0.06	0.009	0.015	0.153	1		
(6) R&D	361.83	1,002.23	0	10,991.00	-0.004	0.486	0.448	0.539	0.02	1	
Obs: 5,767											
Panel B: Event Study Data Descriptives					**Correlations**						
	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) CAR (t-1 to t+1)	0.17	4.94	-19.37	41.65	1						
(2) Complementary Technologies	29.73	101.66	0.00	2,004.00	0.059	1					
(3) IP Disclosed	29.38	181.97	1.00	3,034.00	0.029	0.644	1				
(4) Compatibility With Rivals	99.53	276.62	0.00	3,167.00	0.004	0.219	0.051	1			
(5) Total Patents (5-years)	2,713.71	3,587.77	0.00	20,422.00	0.002	0.14	-0.053	0.216	1		
(6) ln(Revenues)	9.52	1.90	-3.54	12.11	0.000	0.082	-0.066	0.124	0.433	1	
(7) Operating Margin	0.00	2.86	-78.03	0.51	0.145	0.015	0.01	0.014	0.032	0.273	1
Obs: 752											

Table 2.3. Analysis of disclosure events on Tobin's Q

Dependent Variable: Tobin's Q	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**
	Full Sample	Full Sample	Full Sample	Full Sample	2003-2010	1996-2002	1988-1995	Full Sample	Full Sample
	Pooled OLS	Fixed Effect	Pooled OLS	Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect	Pooled OLS	Pooled OLS
Disclosure Events	-0.009	-0.065*							
	(0.722)	(0.063)							
Disclosure Events Without Comp. Tech.			-0.054	-0.105**	-0.028***	-0.112	-0.042		
			(0.203)	(0.019)	(0.004)	(0.261)	(0.650)		
Disclosure Events With Comp. Tech.			0.122*	0.059	0.008	0.694*	0.030		
			(0.088)	(0.470)	(0.740)	(0.081)	(0.809)		
IP Disclosed								-0.0003	
								(0.772)	
IP Disclosed Without Comp. Tech.									-0.002
									(0.325)
IP Discosed With Comp. Tech.									0.001**
									(0.0125)
Total Patents (5-years) (000s)	0.175	0.202	0.151	0.172	-0.016	1.710***	-2.650	0.179	0.180
	(0.189)	(0.509)	(0.243)	(0.573)	(0.910)	(0.00792)	(0.492)	(0.166)	(0.163)
R&D	-0.250**	-0.210	-0.249**	-0.207	-0.242	-0.717	0.349**	-0.250**	-0.250**
	(0.044)	(0.129)	(0.045)	(0.131)	(0.261)	(0.246)	(0.047)	(0.043)	(0.043)
ln(Revenues)	0.0340	0.107***	0.0339	0.107***	-0.792	0.043*	0.033***	0.034	0.034
	(0.326)	(0.000)	(0.327)	(0.000)	(0.262)	(0.074)	(0.001)	(0.326)	(0.322)
Operating Margin	0.0002	-0.0002	0.0001	-0.0002	-0.0002***	-0.0004	-0.0002	0.0001	0.0001
	(0.203)	(0.151)	(0.215)	(0.128)	(0.003)	(0.217)	(0.322)	(0.230)	(0.211)
Constant	2.219**		2.210**					2.218**	2.209**
	(0.026)		(0.026)					(0.025)	(0.025)
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry Fixed Effect	YES	NO	YES	NO	NO	NO	NO	YES	YES
Technology Subcategory Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,769	5,769	5,769	5,769	1,787	2,035	1,947	5,769	5,769
R-squared	0.239	0.086	0.240	0.087	0.198	0.125	0.067	0.239	0.240

Robust p-values that account for within firm clustering in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Total Patents in thousands.

Table 2.4. T-tests for cumulative abnormal returns

Panel A. All disclosure evemts			
Window	**Mean (Std. dev.)**	**p-value**	***N***
(1) t-1 to t+1	-0.30 (5.28)	0.00	2,732
(2) t-2 to t+2	-0.13 (5.10)	0.18	2,732
(3) t-2 to t+2	-0.29 (671)	0.02	2,732
(4) t-3 to t+3	-0.17 (7.85)	0.23	2,732
(5) t-2 to t+4	-0.22 (8.17)	0.16	2,732
Panel B. Disclosures with tracable U.S. patents and no confounding events			
	Mean (Std. dev.)	**p-value**	***N***
(6) t-1 to t+1	0.17 (4.93)	0.35	752
(7) t-2 to t+2	0.18 (4.72)	0.31	710
(8) t-2 to t+2	0.08 (5.99)	0.72	711
(9) t-3 to t+3	0.31 (7.45	0.28	668
(10) t-2 to t+4	0.34 (7.32)	0.23	672

Table 2.5. Comparing disclosures events with and without complementary technologies

Dependent Variable: Cumlative Abnormal Return (%)								
Window	**Mean (SD) | With Complementary Technology**	**p-value**	**N**	**Mean (SD) | No Complementary Technology**	**p-value**	**N**	**Difference In Means**	**p-value**
(1) t-1 to t+1	0.53 (5.28)	0.02	527	-0.66 (3.91)	0.01	225	1.19	0.00
(2) t-2 to t+2	0.38 (4.96)	0.08	503	-0.32 (4.07)	0.27	206	0.70	0.07
(3) t-2 to t+2	0.43 (6.06)	0.11	503	-0.76 (5.77)	0.06	208	1.18	0.01
(4) t-3 to t+3	0.73 (7.68)	0.04	475	-0.71 (6.74)	0.01	222	1.44	0.02
(5) t-2 to t+4	0.70 (7.49)	0.04	477	-0.53 (6.79)	0.27	195	1.26	0.04

Any observation that has a cofounding event in the window is excluded. Complementary Technologies includes only patents that have not been previously disclosed. I test the difference in means using Welch's *t*-test.

Table 2.6. Regression analysis of cumulative abnormal returns

Dependent Variable: CAR	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Window	t-1 to t+1	t-1 to t+1	t-1 to t+1	t-1 to t+1	t-1 to t+1	t-1 to t+1	t0 to t+2	t-2 to t+2	t-3 to t+3	t-1 to t+1	t-1 to t+1	t-1 to t+1
Method	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Weighted Least Squares	Firm Fixed Effect	Firm Fixed Effect
Sample	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full	2003-2010
Complementary Technologies		0.003***	0.003**	0.004**	0.004**	0.004**	0.003**	0.005**	0.007**	0.004**	0.004**	0.004**
		(0.004)	(0.027)	(0.017)	(0.032)	(0.027)	(0.046)	(0.017)	(0.021)	(0.017)	(0.011)	(0.019)
IP Disclosed	0.0008**		-0.0004	-0.0008	-0.0008	0.0004	-0.001	-0.002	-0.003	-0.0009	-0.0007	-0.0008
	(0.026)		(0.535)	(0.343)	(0.379)	(0.551)	(0.407)	(0.189)	(0.113)	(0.267)	(0.274)	(0.396)
Compatibility With Rivals					0.0005	-0.0008	0.0003	-0.0006	-0.0007	0.0004	-0.00002	-0.003
					(0.325)	(0.323)	(0.587)	(0.532)	(0.521)	(0.449)	(0.956)	(0.298)
Total Patents (5-years) (000s)				-0.025	-0.026	-0.041	-0.010	-0.018	-0.080	-0.034	-0.055	-0.040
				(0.713)	(0.695)	(0.568)	(0.860)	(0.839)	(0.415)	(0.587)	(0.577)	(0.826)
ln(Revenues)				0.171	0.154	0.198	0.125	0.228	0.0394	0.0851	1.338*	1.166
				(0.209)	(0.264)	(0.174)	(0.347)	(0.242)	(0.857)	(0.528)	(0.0894)	(0.251)
Operating Margin				-0.305***	-0.305***	-0.324***	-0.214***	-0.294***	-0.242***	-0.297***	-7.899	3.325
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.166)	(0.405)
Constant	0.147	0.0846	0.0825	-5.982**	-6.228**	-3.980	-2.811	-4.069	3.421	-5.965***		
	(0.360)	(0.618)	(0.627)	(0.014)	(0.0141)	(0.175)	(0.305)	(0.108)	(0.243)	(0.003)		
Year Fixed Effect	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry Fixed Effect	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	NO	NO
Standards Area Fixed Effect	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
SSO Fixed Effect	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO
Observations	752	752	752	752	752	752	751	711	669	752	752	560
Number of Firms	123	123	123	123	123	123	123	123	122	123	123	85
R-squared	0.00	0.00	0.00	0.07	0.07	0.08	0.07	0.06	0.07	0.06	0.06	0.04

Robust p-values that account for within firm clustering in parentheses. Total Patents in thousands.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7. Inverse probability weighted adjustment analysis of cumulative abnormal returns

Dependent Variable: Cumulative Abnormal Return				
Window	**Average Treatment Effect on Treated (%)**	**A&I Robust SE**	**p-value**	**Total *N***
(1) t-1 to t+1	1.37	0.53	0.01	726
(2) t0 to t+2	1.30	0.42	0.00	724
(3) t-2 to t+2	1.51	0.72	0.04	684
(4) t-3 to t+3	1.40	0.81	0.09	644

Test statistics use Abadie & Imbens' robust standard errors. Treatment is the presence of complementary technologies. Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

Table 2.8. Highlighting the effect of compatibility and competitiveness on the complementary technology-cumulative abnormal return relationship

Dependent Variable: CAR t-1 to t+1	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**
Test Type:	Compatibility mechanism		Competiveness mechanisms for downstream firms using HHI			Competiveness mechanisms for downstream firms using C4			Robustness check	Robustness check
Sample:	Full	Downstream firms	Downstream firms: Highly concentrated market (HHI >= 2,500)	Downstream firms: Less concentrated market (HHI < 2,500)	Downstream firms: Highly concentrated market (HHI >= 2,500)	Downstream firms: Highly concentrated market (C4 >= 75%)	Downstream firms: Less concentrated market (C4 < 75%)	Downstream firms: Highly concentrated market (C4 >= 75%)	Full	Upstream firms
Complementary Technologies	0.005***	0.006*	0.002	0.007**	0.211***	0.010	0.007**	0.107**	0.004**	0.010**
	(0.009)	(0.089)	(0.708)	(0.046)	(0.001)	(0.290)	(0.032)	(0.044)	(0.028)	(0.018)
Compatibility With Rivals	0.001*	0.002	0.002***	-0.001	0.002***	0.0001	-0.003*	-0.004*	0.001	-0.01**
	(0.072)	(0.702)	(0.002)	(0.189)	(0.007)	(0.824)	(0.083)	(0.067)	(0.360)	(0.018)
Comp. Tech.* Compatibility With Rivals	-0.00001**									
	(0.025)									
IP Disclosed	-0.001	-0.0003	0.044	-0.003	0.034	0.025	-0.003	-0.009*	-0.001	-0.0003
	(0.385)	(0.292)	(0.187)	(0.166)	(0.251)	(0.339)	(0.150)	(0.0594)	(0.323)	(0.632)
Total Patents (5-years) (000s)	-0.020	-0.068	-0.082	-0.006	-0.008	-0.258	-0.143	-0.095	-0.043	-0.24
	(0.763)	(0.360)	(0.479)	(0.515)	(0.946)	(0.116)	(0.183)	(0.314)	(0.531)	(0.471)
ln(Revenues)	0.133	0.291	-0.050	0.524**	0.0330	0.329	0.675**	0.708**	0.218	0.110
	(0.333)	(0.113)	(0.854)	(0.022)	(0.902)	(0.328)	(0.015)	(0.014)	(0.187)	(0.840)
Operating Margin	-0.302***	-0.323***	-0.204***	0.787	-0.245***	-0.322***	-3.453	-3.864	-0.315***	-0.318
	(0.000)	(0.000)	(0.000)	(0.838)	(0.000)	(0.000)	(0.395)	(0.345)	(0.000)	(0.810)
Downstream Firm									-0.632	
									(0.291)	
Comp. Tech. * ln(Revenues)					-0.019***			-0.009**		
					(0.001)			(0.0488)		
Constant	-6.574**	-7.256***	-6.679**	0.375	-7.427***	-1.686	-9.863***	-10.39***	-6.014**	-11.69***
	(0.013)	(0.004)	(0.017)	(0.856)	(0.008)	(0.623)	(0.000)	(0.000)	(0.018)	(0.003)
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Standards Area Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	752	643	249	381	249	280	350	350	752	109
R-squared	0.070	0.075	0.251	0.097	0.276	0.212	0.148	0.157	0.070	0.423

Robust p-values that account for within firm clustering in parentheses. Total Patents in thousands.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.9. Analysis of yearly citation counts using fixed effect Poisson models

DV: Yearly received citations	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Sample:	Full Sample	1988-2002	2003 to 2010	Full Sample	1988-2002	2003 to 2010
Complementary Technology	0.133***	0.086***	0.320***			
	(0.000)	(0.000)	(0.000)			
Standard Essential Patent				0.140***	0.153***	0.162***
				(0.000)	(0.000)	(0.001)
Age	0.007	0.028***	-0.191***	0.027	0.087***	-0.112***
	(0.396)	(0.000)	(0.000)	(0.170)	(0.002)	(0.000)
Age Squared	-0.009***	-0.006***	-0.008***	-0.009***	-0.0092***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	68,768	41,426	27,342	11,781	5,138	6,643
Number of patents	9,824	5,918	3,906	1,683	734	949

Patent-year panel from t-3 to t+3, with t0 denoting the disclosure date. Mean yearly received citations in sample: 3.61 and standard deviation of 5.8. P-values calculated from robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.10. Within-firm matching analysis of patent citations

Panel A. Dependent variable: Count of citations received				
Window	**Average Treament Effect on Treated (Count)**	**A&I Robust SE**	**p-val**	***N***
(1) t0 to t+3	1.59	0.13	0.000	69,812
(2) t0 to t+4	2.50	0.180	0.000	57,628
(3) t0 to t+5	3.41	0.23	0.000	47,500
(4) t+1 to t+5	2.76	0.20	0.000	47,500

Panel B. Dependent variable: Percent change In citations received				
Window	**Average Treament Effect on Treated (%)**	**A&I Robust SE**	**p-val**	***N***
(1) % Change: t-1: t-4 to t0:t+3	11.53	0.016	0.000	54,121
(2) % Change: t-1:t-5 to t0:t+4	9.83	0.018	0.000	39,179
(3) % Change: t-1: t-4 to t+1:t+4	11.45	0.019	0.000	44,693
(4) % Change: t-1: t-5 to t1:t+5	9.41	0.02	0.000	30,905

Exact Match: Within Firm, Disclosure Year, Application Year, and Technology Class. Nearest-Neighbor Matching: Citations received (t-3 to t-1), breadth of backward citations: number of backward citations. Test statistics use Abadie & Imbens' robust standard errors. Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

Table 2.11. Analysis of self-citations

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Sample:	Firm-Patent	Firm-Patent	Firm-Patent	Firm-patent	Patent-Year for t-3 to t+3	Firm-Patent: SEPs vs. complementary patents	Firm-Patent: SEPs vs. complementary patents
Dependent Variable:	Self-Citation (1/0) in t+1:t+3 window	Self-Citation (1/0) in t+1:t+3 window	Self-Citation (1/0) in t+1:t+3 window	Count of Self-Citation in t+1:t+3 window	Count of yearly self-citations	Self-Citation (1/0) in t+1:t+3 window	Self-Citation (1/0) in t+1:t+3 window
Method:	Logit	Logit	Logit	Conditional Fixed Effect (Firm Level) Poisson	Conditional Fixed Effect (Patent Level) Poisson	Logit	Logit
Information Shown:	Average Partial Effects	Average Partial Effects	Average Partial Effects	Coeffiecient	Coeffiecient	Average Partial Effects	Average Partial Effects
Complementary Technology	0.165***	0.094***	0.095***	0.746***	0.184***	0.052***	0.041***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Backward Citations	0.001***	0.001***	0.0003***	0.003***		0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Breadth of Citations	0.001	-0.0001	-0.002***	-0.0017		0.003**	-0.003**
	(0.153)	(0.887)	(0.000)	(0.469)		(0.031)	(0.026)
Received Citations t-3 to t-1		0.007***	0.007***	0.019***			
		(0.000)	(0.000)	(0.000)			
Age					-0.071**		
					(0.010)		
Age Squared					-0.011***		
					(0.000)		
Year Fixed Effect	YES	YES	YES	YES	NO	YES	YES
Application Year Fixed Effect	YES	YES	YES	YES	NO	YES	YES
Technology Class Fixed Effect	YES	YES	YES	YES	NO	NO	YES
Firm Fixed Effect	NO	NO	Yes	YES	NO	NO	NO
Observations	160,842	160,842	160,842	159,394	34,160	28,964	28,700
Pseudo R-Square	0.17	0.20	0.27			0.15	0.17

P-values are in parentheses. P-values from robust standard errors used in Poisson models.
*** p<0.01, ** p<0.05, * p<0.1

CHAPTER 3

The Effect Of Complementary Technologies On Value Appropriation In Cooperative Settings: Evidence From Patent Litigation Related To Compatibility Standards

Abstract

In many settings, firms must reveal intellectual property to other, potentially rival, firms so to enable coordination and value creation. Such disclosures come with a cost, as the firm will often lose exclusivity over its intellectual property, which can severely deteriorate its ability to appropriate value directly from the associated technology. In this essay, I examine how firms incorporate disclosures into their strategy. In the context of compatibility standards, I examine where the firm appropriates value after it discloses technology to the standard setting body. I argue that firms utilize their disclosures to increase the value of their portfolio of complementary technologies. Using patent litigation as a signal of appropriation efforts, I estimate the impact of complementarity on patent litigation rates. Findings suggest that after disclosure to a standard, firms' focus their litigation efforts around their complementary technologies.

INTRODUCTION

In technology ecosystems, firms often need to cooperate to create value (Rosenkopf and Tushman, 1998; Adner and Kapoor, 2010; Kapoor and Lee, 2013). For example, many rival firms collaborated to produce the LTE wireless communications network standard, the Apollo spacecraft, and the HTML5 markup language. In these settings, different firms create technological solutions to separate parts of a larger problem, and therefore, need to reveal intellectual property (IP) to other participants. By revealing IP, the firm risks its ability to appropriate returns from the innovation (Arrow, 1962); however, if no one cooperates, little value can be created (Mizik and Jacobson, 2003; Henkel, Scholeberl, and Alexy, 2014).

The ability to appropriate value from innovation plays a central role in a firm's success (Teece, 1986). To appropriate returns from innovation, firms typically need an isolating mechanism (Rumlet, 1984). Extant literature on appropriability highlights four such mechanisms: legal protection (i.e. patents), secrecy, lead time, and complementary assets (Levin *et al.*, 1987; Cohen *et al.* 2000; James, Leiblein, and Lu, 2013). The first two mechanisms, patents and secrecy, allow the firm to maintain exclusivity of its IP. Yet, in settings such as compatibility standards or open source software development, firms compromise both legal protection and secrecy to create value through cooperation. In collaborative standard setting, firms' both reveal their technology to others and relinquish their ability to control who uses their technology.[57] Downstream mechanisms do not

[57] In some cases, the IP deemed essential to the functionality of the standard can generate substantial licensing revenue for the IP owner because the standard becomes widely adopted. However, the costs of disclosure can also be substantial because knowledge about the technology, the firm's technological capabilities, and current development projects can spillover to rivals. Licensing revenue from standard

necessarily explain cooperation, as firms with complementary assets or lead time advantages stand to benefit from the establishment of any standard, whether they disclose IP or not.[58] So how do IP disclosures figure into the firm's upstream IP strategy? In other words, if the firm gives up some or all measures of appropriability of a disclosed technology, can the firm capture some of the value created through the disclosure in other parts of its IP portfolio, if so, where? The answer to this question can explain how and why firms differ in the way they benefit from revealing IP in cooperative settings.

To approach this question, I begin with the observation that disclosing often own other complementary technologies within the ecosystem. Technologies are complementary when the value of one is greater when used in conjunction with the other (Milgrom and Roberts, 1990; Toh and Miller, 2017). I then argue that by disclosing a technology so to be part of the standard, the firm increases the value of the non-disclosed complementary technologies. Therefore, the strategic concern of these firms may not be limited to the disclosed technology; rather, appropriating returns from its non-disclosed complementary technologies could be just as critical, if not more so.[59]

In an ideal test of my theory, I would observe how the firm's appropriation strategy, such as licensing efforts or product design, change once it discloses IP. While I cannot consistently observe such appropriation efforts across all firms, I can observe a closely related factor—the assertion of IP rights via litigation. Therefore, to address the question

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essential patents will often not fully compensate the firm for the costs of its IP disclosure (Updegrove, 2007). Of course, when essential technology is provided royalty free, then the firm will not 'capture' value simply by disclosing technology.

[58] To elaborate, a firm would not need to participate in the standard setting process unless without participation, the standard would negatively affect the firm downstream assets.

[59] For example, JP Morgan equity analysts reported that Nokia had much to gain by asserting its non-SEPs related to communication networks (Deshpande *et al*, 2013).

posed, I investigate IP lawsuits in the context of compatibility standards. Specifically, I examine where the firm uses legal disputes to assert IP rights after disclosing technology to a compatibility standard. I hypothesize that after the formation of the standard, litigation rates will be higher for technology complementary to the standard, as compared to similar non-complementary technologies. Moreover, the litigation rate will increase for complementary technologies post-disclosure of their complementary SEP.

I test my argument using data on patent litigations and ICT standards between 1988 and 2010. Legal disputes over IP are common in the ICT industry, and should correlate with other value appropriation activities such as licensing. To estimate the effect of complementarity on the incidence of litigation, I use information on similar, non-complementary patents in the firm's portfolio to create counterfactuals. I also examine how the litigation rate changes for complementary patents using both patent-level fixed effect regressions and difference-in-difference matching estimators. Results show that, prior to the disclosure event, complementary patents do not have a significantly different litigation rate than their counterfactual computed using similar patents in the firm's portfolio. Once they become complementary to the standard, the likelihood of future litigation for complementary patents is approximately 2.8 percentage points higher than for their counterfactual. Using a patents own litigation history, I find that the likelihood of litigation in a five-year window post-becoming complementary jumps 54 percent over the prior five years. Empirical evidence strongly support my predictions.

I also decompose the effect of complementarity on litigation rates into two underlying factors: the firm's incentive to protect the IP and the increased incidence of infringement due to the greater demand for technologies related to the standard. Allowing for the endogeneity of demand and future litigation rates in a simultaneous equation model, I find evidence for both the incentive and demand effects are significant. Rough calculations suggest that firm incentives account for 50 to 85 percent of the effect, evidence which supports the notion that the higher post-disclosure litigation rate on complementary technologies is partially a function of firms' strategies.

My arguments differ from and expand on prior literature on appropriation in several ways. First, extant work on the standard setting context suggests that firms with downstream resources will cooperate on standards and seek rents in downstream product markets (Simcoe *et al.*, 2009). This, however, does not explain why the firm would provide technology to the standard rather than free ride on the efforts of others.[60] Instead, I argue that the firm's technology disclosure to the standard directly impacts the value of the firm's complementary technology—technology that the firm can use to appropriate value by embedding them into products or by licensing them to implementers of the standard. Even in the absence of compensating licensing revenue and in the presence of high disclosure costs, the firm may still be willing to reveal technology to others if doing so enables it to capture value in other parts of its technology portfolio.

Second, profiting from innovation literature tends to emphasize the importance of complementary downstream assets for appropriating value from innovations (Teece, 1986; Pisano, 2006; Arora and Coeccagnoli, 2006). I expand on this literature by arguing that

[60] The firm may lower the cost of licensing technology from others if it to owns technology essential to the standard. Yet, the emergence of IP policies in SSOs and the increased use of patent pools to regulate and ease licensing reduce the explanatory power of the cross-licensing argument.

complementarities in the firm’s upstream technology portfolio also play an important role in the firm’s appropriation strategy and ultimately firm success (Teece, 1996). However, unlike specialized supporting assets that play a supporting role in an innovation’s competitiveness, I suggest that complementary technologies provide additional channels for which the firm can capture value from the focal innovation. By accounting for upstream complementarities, I provide a more complete view of the role complementarity plays in appropriating returns.

I also contribute to the work on the economics of IP litigation. I demonstrate how the firm’s technological position in cooperatively set standards can change its incentives to protect IP. Accounting for how complementarities influence these incentives helps explain recent patterns in IP litigation. For example, the role of complementarity between technologies that underlie wireless communication standards and technologies embedded in smartphones can help explain the uptick in patent litigation in the ICT industry over the past decade. [61]

THEORY

IP Protection and Appropriation in Cooperative Settings

A hi-tech firm’s innovations tend to be embedded in a technology ecosystem consisting of multiple innovations from a variety of competing firms (Adner and Kapoor, 2010). Most innovations do not function independently, but instead depend on other

[61] Some of the increase in patent litigation in the ICT industry is related to the so-called smartphone wars (Kumar & Shasin, 2016). One area of dispute concerns wireless communication technologies embedded in smartphones.

interdependent innovations to create value (Adner, 2006). To manage these interdependences, firms often need to cooperate with others (Rosenkopf and Tushman, 1998). Cooperation can entail disclosing important IP to other, potentially rival, firms so interfaces between technologies can be created or to allow the technologies to be developed further. While revealing IP to others can be essential to value creation, it can dampen the firm's ability to appropriate value (Arrow, 1962). The extent of this concern, of course, will depend on the context. In simple bilateral cooperative arrangements, such as an R&D alliance, appropriation conditions can be (imperfectly) specified upfront. However, in many important contexts, firms must reveal IP to rivals or contribute IP to a project without much formal guarantee that they will be able to capture any of the value that their IP helps create (West, 2014). Example contexts in which multiparty cooperation is needed include open-technology systems, such Linux software, and compatibility standards, such as LTE wireless communications standard or HTML5 markup language. So how do firms capture value in these contexts?

A burgeoning literature on firm's incentive to cooperate in open source software systems or in technology standards provide some evidence (Allen, 1983; Harroff, Henkle, and von Hipple, 2003; Henkle, 2006; Pisano, 2006; Simcoe *et al.*, 2009). First, firms will cooperate with others in order to grow the potential market (Simcoe, 2005; West, 2014). Literature on compatibility standards suggests that firms cooperate on standards and compete on implementation' (Simcoe, 2005). However, these firms need to have resources or capabilities that provide an advantage in capturing value in the downstream market (Rumlet, 1984; Teece, 1986; Barney, 1991). Typically, this includes a lead time advantage, costs advantages, or some set of specialized downstream assets (James *et al.*, 2013). For instance, Seagate Technologies provided royalty free licensing to their technology that increased the data flow rate between the computer's systems board and disk storage drive (Ethiraj, 2007). By making technology widely available, Seagate could grow the market for more complex disk and storage drives for which it had strong design and production capabilities. In the context of compatibility standards, Simcoe *et al.* (2009) find that firms with downstream capabilities litigated standard essential patents less than more specialized upstream technology suppliers that had lesser ability to appropriation returns downstream. Overall, this stream of literature suggests that a downstream appropriation mechanism is needed to incent firms to reveal IP to others.

Second, literature suggests that some firms, particularly small entrepreneurial ventures, may benefit from revealing IP, not by directly creating profits from their IP, but rather by increasing their reputation or signaling their quality to others (Allen, 1983; Lerner and Tirole, 2002; Haroff *et al.*, 2003; Waguespack and Fleming, 2009; Henkel *et al.*, 2014). Henkel *et al.* (2014) find that firms reveal source code in Linux development because they believe it provides a signal that is beneficial in marketing. Waguespack and Fleming (2009) find small entrepreneurial ventures' participation in open standards positively correlates with likelihood of a near-term IPO or acquisition. Overall, cooperation can create indirect benefits that allow firms to acquire valuable reputation or access financial resources.

Third, firms disclose IP to others to increase diffusion of the innovation. The firm can benefit from widespread adoption of its innovation if it leads to a decrease in the cost of inputs, or the availability of or improvements in co-specialized equipment. Haroff *et al.*

(2003) detail how IBM revealed information about its process to manufacture semiconductors using copper based circuitry rather than aluminum circuitry so that suppliers of specialized semiconductor equipment would build new equipment that utilized the new technology. Without a large customer pool (i.e. IBM plus rival semiconductor firms), the suppliers would not have been willing to switch their designs to incorporate the new technology.

Finally, firms can receive payment for their contributions to multiparty technology systems. Payment often comes in the form of licensing revenue or royalties tied to the IP that becomes essential to the system. In Apache open source development, software engineers were compensated for their contributions. In many compatibility standards, firms receive "Fair, Reasonable, and Non-Discriminatory" (FRAND) licensing rates for IP essential for the standard to function properly (i.e., standard essential patents or SEPs) (Rysman & Simcoe, 2006). Much of the literature on standards either explicitly or implicitly assumes that the firm's objective is to place its technology into the standard for the purpose of licensing this technology to implementers. This literature places the locus of value appropriation 'inside' the standard.

To expand on this literature, I offer a different perspective on value capture in collaborative settings. I propose that firms leverage technology disclosures in standards so to create and appropriate value in their portfolio of non-disclosed, complementary technologies. This differs from the growing the market perspective in that I directly link the way the firm participates in the cooperative setting (e.g. disclosures to SSOs) to how the firm enhances and appropriates value (e.g. through technology complementary to the disclosed technology).[62] In contrast to the notation that licensing revenue from SEPs is the main source of value, I instead argue that firms may participate even when licensing revenue is zero.

Before laying out my argument, I briefly review the standard setting process and how I trace appropriation efforts.

Standard Setting & Intellectual Property Disclosure

Standards[63] play a central role in many technology markets by providing the blueprint for how different technologies function together. Most modern compatibility standards typically require technology from multiple parties and thus require coordination. Standard Setting Organizations (SSOs) coordinate the standard setting process and provide a forum for interested parties to achieve a consensus on the blueprint for the standard. During the standard setting process, firms voluntarily disclose patents essential on the standard to function (i.e., SEPs). While the disclosure process is voluntary, the firms that participate in the standard setting process typical must adhere to the SSO's IP disclosure policy. Such policies try to avoid "submarine" strategies in which a firm with IP essential to the standard waits for a standard to be finalized then asserts its IP rights at unreasonable rates (Farrell *et al.*, 2004). Therefore, IP policies detail when a firm must disclose its technology to other participants, which typically predates the final approval of the

[62] In the case of standards, the firm with strong downstream capabilities could benefit from a new standard whether or not it discloses to the standard.
[63] There are a variety of standards, including compatibility standards, minimum quality or safety standards, and reference standards. I focus on compatibility standards that define interoperability between various technological components. Any reference to 'standards' henceforth will refer to such standards.

standards. These policies may also detail licensing rates, which may range from free, as in many internet standards, to fair, reasonable, and nondiscriminatory (FRAND), like in many wireless communications standards.

Literature on standards assumes that licensing revenue from SEPs motivates IP disclosure, however, prior research also finds that the costs of disclosing can be substantial (Cargill, 2002; Farrell and Simcoe, 2012). Firms spend significant time and money on standard setting activities (Siegel, 2002; Updegrove, 2003; Chiao *et al.*, 2007; Farrell and Simcoe, 2012). Through the process of negotiating technological specifications, a firm can reveal strategic information about its knowledge base and future development path (Rosenkopf, Metiu, and George, 2001). So not only do firms relinquish exclusivity of disclosed technologies, they can compromise secrecy of their knowledge base (Toh and Miller, 2017). Thus, the returns to IP disclosure may not always compensate the firm for the costs incurred. While firms strive to capture value through licensing SEPs, firms may also have other incentives to disclose technology to the standard. To explore how the firm's SEPs can be leveraged in an alternative appropriation strategy, I theorize as to where firms will focus their IP protection efforts after disclosing to the standard.

Patent Litigation

Patent litigation signals the strategic behavior and appropriation concerns of the firm (Lerner, 1995; Lanjouw and Schankerman, 2001; Somaya, 2003; 2012). Patents provide the firm with the firm with the ability to *attempt* to exclude others from using its IP (Lemly and Shapiro, 2005). For a patent to function as an isolating mechanism that can help the firm appropriate value from its IP, the firm must be willing to enforce the patent in court (Rivette and Kline, 2000; Lanjouw and Schankerman, 2001; Somaya, 2003). Prior research demonstrates that patent litigation[64] signals that the stakes surrounding the IP are high. Median legal costs for a $1 million patent claim is $650,000; litigation costs range between $1 million and $5 million as claims grow above $1 million (Kersetter, 2012). Firms also accrues other costs. A firm's stock market value typically dips by 2% to 3% on average after filing a patent lawsuit (Bhagat, Brickley, and Coles, 1994; Lerner, 1995). Patent suits can be both time consuming and distracting for senior managers. Therefore, patent litigation strongly signals appropriability concerns (Lerner, 1995; Lanjouw and Schankerman, 2001). It should also be correlated with licensing, as the two go hand in hand (Auora, Fosfuri, and Gambardella; 2001; Galasso, Schankerman, and Serrano, 2013). Because of the difficulty in tracing how firms embed complementary technologies into products or the details behind their licensing behavior, I instead rely on patent litigation as evidence of the firm's appropriation strategy.

Prior literature finds a link between SEPs and litigation. Standards tend to be based on valuable IP (Rysman and Simoce, 2008), and there is a positive correlation between IP value, the likelihood of infringement, and the likelihood of litigation. Because standards form the backbone of many technology ecosystems, technology included in the standard becomes more valuable (Chiao *et al.*, 2007; Farrell *et al.*, 2007; Rysman and Simcoe, 2008). The increased stakes surrounding these technologies should increase the incentive

[64] Why should we see litigation in a valuable area? Would firms not put extra effort into bargaining of valuable technologies? Literature offers three core explanations: asymmetric stakes or reputational benefits (Lanjouw and Lerner, 1998; Agarwal, Ganco, and Ziedonis, 2009), asymmetric information (Nalebuff, 1987), and differences in expectations (Priest and Klein, 1984; Galasso, 2008).

to litigate (Besen and Levinson, 2012), which bears out in empirical research. Indeed, Simcoe *et al.* (2009) find that litigation rates for SEPs increase after disclosure relative to a random control sample of non-essential patents.

Appropriation of Value Through Complementary Technologies

Although firms can capture value by licensing SEPs, this is not the only strategy to appropriate value from standards. A firm can leverage its standard essential technologies to raise the value of its portfolio of complementary technologies.[65] As the value increases, the firm has greater incentive to protect them. Moreover, as the standard becomes central to the industry, more firms will move into this knowledge space, causing the incidence of infringement of complementary technologies to rise. I explain this logic in more detail below.

When the disclosed technology becomes essential to the standard, technologies complementary to the disclosed technology become compatible, and thus complementary with the standard. As firms adopt the standard, interoperability with the standard becomes valuable because the standard provides the blueprint for the ecosystem. In a wireless communication system for instance, handsets, base stations, multiplexers, testing equipment, and other network gear must function with the standard. A compatible

[65] My argument can be viewed as a more complex version of the razor blade-razor model, in which the firm gives one component at a subsidized price (i.e. the razor) in hopes of selling a complementary component (razor blades) at higher prices. This does have some precedent in intra-firm cooperation. For instance, Hewlett-Packard revealed software code that controlled the interface of its RISC-based hardware products with the hope that Linux users would create compatibility between Linux open source software and Hewlett-Packard's hardware (Lerner and Tirole, 2002). By doing so, Hewlett-Packard hoped to bring additional customers onto its platform by making its hardware (i.e. its razors) more attractive so that it could sign lucrative long-term IT services contracts with reoccurring revenue (i.e. its razor-blades).

technology will likely function with other parts of the ecosystem, thus its value will rise. If the firm had not disclosed essential technology, the associated complementary technology might not function with the standard, and therefore, may provide little value.

By developing knowledge underlying both the standard essential technology and the complementary technology, the firm is in a better position to understand the nuances of the interdependences between the standard and the complementary technology, and thus create more valuable technologies than they would otherwise. So not only are the firm's complementary technologies compatible with the standard, they may also represent the 'first best' solution in applying the standard in some way. For example, Nokia's technology for decoding voice signals functions in conjunction with its standard essential technology for sending and receiving voice and data on TDMA based wireless networks. By embedding its 'exclusive' complementary technology in its own phones, Nokia's phones achieved better sound and voice quality than rivals that had to rely on suboptimal decoding methods. This increased the consumers' willingness-to-pay for Nokia's phones. The link between its complementary technology and the standard provided Nokia an advantage in the early TDMA-based handset market.

When the firm owns complementary technologies, the firm can appropriate value from them in two general ways. Adopters need to access not only the technology and knowledge underlying the standard, but also complementary technologies that allow for optimal functionality of products that utilize the standard. The firm can license these complementary technologies to firms adopting the standard. If the firm competes downstream instead, it can embed the complementary technologies into its own products to differentiate them in downstream competition. For instance, Qualcomm combined its technologies that comprised the core of the CDMA standard with its chipsets and power management technologies, which increased their value in the CDMA-based product market.

While complementary technologies themselves become more valuable, so does the underlying knowledge. The can firm leverage this knowledge in several ways. One, future innovative search will be more certain and more productive because the firm already understands how components work with the standard and how technologies can combine with the standard to create value (Clark 1985; Cohen and Levinthal, 1990; Fleming 2001; Zahra and George, 2002). For example, Qualcomm leveraged its knowledge position in wireless standards and complementary areas to extend its technologies to the automotive, home appliance, and health care industries. Two, the firm can use its knowledge position to attract partners with valuable complementary resources (Mower, Oxley, and Silverman, 1996; Rosenkopf and Nerkar, 2001; Dushnitsky and Lenox, 2005). Because of its technological position surrounding CDMA standards as Qualcomm sought to expand its customer base to new industries, it could attract key partners with complementary capabilities.

Therefore, the knowledge behind complementary technologies enables a range of future value capture options. When knowledge is valuable, the firm will want to prevent it from spilling over to rivals. Prior work demonstrates that aggressive IP enforcement can reduce knowledge spillover (Somaya, 2003; Agarwal, Ganco, and Zidonis, 2009). Thus, I expect the firm to protect IP in the complementary area vigorously.

Demand for the standard will also increase the incidence of infringement. As implementers begin to build their own technology to link to the standard, they may find it difficult to utilize the standard effectively without infringing on the firm's complementary technologies. Inadequate attempts to invent around patented technology will drive litigation higher (Bessen and Meurer, 2006). For instance, Nokia won rulings against HTC in several countries where it alleged HTC violated several implementation patents that link chipsets to communication standards. While not 'essential' to the standard, these patents (e.g. US 7,415,247; US 6,393,260; EP0998024)[66] cover how communication signals (covered by Nokia's SEPs) interact with chipsets. The outcome of the suits spurred equity analysts to report on the potential that Nokia's complementary technologies have for generating value from its patent portfolio (for example, see Deshpande, Udeshi, Hirani, Hall, and Kesireddy 2013).

As the adoption rate of the standard increases, so will the attempts to build on the standard. This demand effect increases the number of rivals working within the proximity of the focal firm's technology area, which should result in higher incident of infringement (Bensen and Meurer, 2005). Therefore, when the firm has such well positioned complementary technologies, the incidence of infringement will be increasing with the adoption of the standard.[67]

[66] This are just several examples.

[67] At some point, the firm's strategic stakes in the technological area will be well known to market participants as the news of patent lawsuits disseminates. Thus, the probability of infringement will likely decline at some point. However, licensing rates may continue to increase as the number of implementers of the standard increase.

Based on these arguments, I layout my core hypothesis: post-disclosure, technologies complementary to the firm's disclosed IP will experience a higher rate of litigation relative to the other comparable technologies. The increase in the litigation rate will come after the technology becomes complementary to the standard.

EMPIRICAL ANALYSIS

Sample & Variables

I conduct the empirical analysis in the context of the information communications technology (ICT) industry between 1988 and 2014. I focus only on communications and information technology standards because the firms involved with these standards tend to be R&D intensive,[68] have in house IP lawyers, and relationships with IP law firms. Lawsuits between firms in the ICT industry are more common than in other industries. For example, between 2007 and 2011 over 50% of IP lawsuits involved ICT industry patents (Comino and Manenti, 2015). Therefore, lawsuits may be common enough to approximate for firms' appropriation concerns.

I use the Disclosed Standard Essential Patents (dSEP) Database (Bekkers *et al.*, 2011) to obtain information on IP disclosures to standards. This dataset includes the disclosure date, patents disclosed, firm disclosing, and information to help identify the standard. Data on patents comes from the U.S. Patent and Trademark Office (USPTO). I compile patent citations using data from National Bureau of Economic Research (NBER),

[68] Firms such as Actel, Qualcomm, and Ericsson send between 10 and 20 percent of revenues on R&D each year. As a comparison, large pharmaceutical companies (e.g. Merck, Pfizer, and Eli Lilly) typically spend 15 percent of revenues on R&D in a year.

(Hall et al., 2001) and Patent Network Dataverse (Lai *et al.*, 2013). Firms' financial data comes from the Compustat database.

To calculate my dependent variables, I collect data on IP lawsuits from Thomson Westlaw. This provides a comprehensive set of lawsuits filed in the United States. Antidotal evidence suggests that standards related IP patented abroad will often be patented in the United States, because of the size and importance of U.S. market. Therefore, major patent lawsuits if filed outside the U.S. also tend to be filed in the U.S. as well.[69] Because I am interested in the incidence of litigation and not outcomes per se, and because I restrict my analysis to U.S. patents, there is little to gain by expanding the data collection beyond the U.S. court system.

To compile the sample of disclosed IP, I use the dSEP database to identify 4,865 patent disclosures (3,089 unique patents) from ICT industry firms to 10 different SSOs between 1988 and 2010. Each disclosed patent represents IP the firm believes to be essential to a standard.

The main independent variable, *Complementary Technology*, identifies that a patent is complementary to a patent disclosed to an SSO. To identify complementarity, I rely on the established principal that inventions that draw on combinations of technologies reflect the complementarities between them (Fleming, 2001; Toh and Miller, 2017). To apply this principal, I identify all the U.S. patents that the firm discloses during a disclosure event. Then I trace all unique undisclosed patents that the firm owns that are co-cited with at least one of its disclosed patents prior to or in the year of the disclosure. I only count co-

[69] For example, Ericsson, Nokia, and Samsung all sued Apple over IP related to smartphones. All suits filed in non-U.S. domains were also filed within the U.S.

cited patents from a different technology class than the disclosed patent because patents in the same class may refer to different components of the same technology or to prior versions of the same technological concept, rather than complementarity across separate and distinct technologies (Makri *et al*., 2010; Toh and Miller, 2017).

I control for various technology, firm, and environmental factors that will influence the likelihood a patent will be litigated. To control for the importance of a technology, I use several measures based on citations. Citations a patent receives (*Received Citations*) is a commonly used measure of value in the strategy and economics literatures (Harhoff *et al.*, 1999; Jaffe and Trajtenberg 2004; Allison *et al.*, 2004; Hall *et al.*, 2005; Rysman & Simcoe, 2008; Simcoe *et al.*, 2009). *Backward Citations* measures the number of citations made by each patent, which captures the depth of knowledge used (Lanjouw and Schankerman, 2004). *Breadth of Citations* measures the number of different technology classes cited by the patent, which serves as a proxy for the diversity of knowledge used in the invention (Toh and Miller, 2017). I also use several other patent level and firm level variables, which I describe in Table 3.1. I will discuss their usage in the appropriate sections below. I use different sample selection criteria depending on the nature of the empirical tests, thus, I will describe the relevant sampling methodology prior to each analysis.

SSOs and IP Disclosures

In my sample, firms primarily disclose at 10 SSOs that manage major ICT standards. I begin by briefly describing each SSO.

- The American National Standards Institute (ANSI) coordinates standard organizations in the U.S., covering wireless cellular technologies and digital subscriber lines (DSL).
- Alliance for Telecommunications Industry Standards (ATIS) set standards for telecommunications networks and technological interoperability.
- European Telecommunications Standards Institute (ETSI) is a central SSO for major wireless cellular standards. The ETSI, along with its American counterpart the ATIS, play a key role in the 3rd Generation Partnership Project (3GPP) which managed the evolution and maintenance of the GSM, GPRS, EDGE, UMTIS, HSPA, and LTE wireless standards.
- The Institute for Electrical and Electronic Engineering (IEEE) is involved with local area network standards such as IEEE 802 LAN/MAN, 802.3 Ethernet standard, and 802.11 Wireless Networking (i.e. Wi-Fi) standard.
- Internet Engineering Task Force (IETF) focuses on internet standards and protocol.
- Joint Technical Committee (JTC) is standard setting body run jointly by the International Standards Organization (ISO) and International Electrotechnical Commission (IEC)'s for developing ICT industry standards. Example standards include smart cards and the coding and compression of audio and video data (e.g. MPEG-4 standard). Disclosures appear in the database as being to disclosed to either the JTC, ISO, or IEC.

- International Telecommunications Union (ITU) manages standards related to broadband, wireless technologies, navigation, radio astronomy, satellites, and voice-over-internet protocol.
- The Telecommunications Industry Association (TIA) helps manage standards covering transmission systems (e.g. cellular towers and satellites) and voice-over-internet-protocol.

Figure 3.1 summarizes the count of both standard essential patents (i.e. disclosed patents) and complementary patents by SSO. The ETSI has the largest count of both SEPs (2,765) and complementary patents (16,412). The IEEE and the IETF are second and third in the number of SEPs respectively.

Standards & Litigation Rates

A simple descriptive analysis demonstrates that SEPs and complementary patents exhibit litigation rates well above average. Approximately 2.7 percent of disclosed and complementary patents experience at least one lawsuit between the time of the disclosure event and 2014. To put this into perspective, consider that of all the ICT related patents granted between 1988 and 2010, only 1 percent are litigated over their observable life (i.e. application date to 2014).

Table 3.2 provides a summary for a select set of standards and firms. In Panel A, I display the number of SEPs, the number of patents complementary to those SEPs based on my *Complementary Technology* measure, the litigation rate between the disclosure date (t0) and t+5, the litigation rate between the disclosure date and 2014, and a short description of the standard. The litigation rate measures the proportion of the complementary and disclosed patents that experienced at least one lawsuit between the time they were disclosed to the standard and the designated date. Relative to the unconditional litigation rate, SEPs and complementary patents have higher litigation rates. Moreover, much of the litigation occurs in the first five years after the disclosure event, which points to the possibility that the patent's relationship with the standard contributes to the greater litigation propensity.

In Panel B, I display similar information for 15 firms active in ICT industry standard setting. Ericsson, Motorola, Nokia, and Qualcomm disclose the most IP to SSOs, much of which involves major wireless communication standards. These firms also have large portfolios of complementary technologies. Together, they have an average *Litigation Rate* in the t0 to t=2014 window of 2.3 percent. Most firms shown are litigious. Several large outliers, such as AT&T, Hybrid Networks and Stratacom, have high rates but relatively small standards related patent portfolios.

In Appendix 3.1, I provide additional statistics on the relationship between SEP and complementary patents in IP lawsuits.

Descriptive Analysis of Complementarity on Litigation

I now explore how becoming complementary to a standard affects the patent's future litigation propensity. To create the sample, I first identify 380 events in which firms disclose IP to a SSO on a given date. Next, I trace all complementary patents to each disclosure event. Then, I create a matched pair of patents by randomly selecting a complementary patent and non-complementary patent that have the same technology class and application year. For a given technology class, application, and event year, patents are select without replacement. Finally, I define the year of the disclosure event as t0 and calculate *Litigation Rate, Received Citations,* and control variables relative to t0.

The sample consists of 17,670 complementary patents that have a matched control patent. Table 3.3 provides the descriptive statistics of the complementary and control sample. Focusing on the future *Litigation Rate* in row one, complementary patents have an average litigation rate of 2.14 percent and non-complementary patents have an average litigation rate of 0.96 percent. The difference in means is statistically significant (p-value 0.000). On average, complementary patents experience higher litigation rates than the similar patents.

Table 3.3 also reveals the difference between complementary patents and the average patent. On average, complementary patents receive significantly more citations (*Received Citations*$_{t\text{-}3 \text{ to } t\text{-}1}$ of 14.42) than their matched counterparts (*Received Citations*$_{t\text{-}3 \text{ to } t\text{-}1}$ of 5.55). They also exhibit a higher *Prior Litigation Rate* (0.82 percent vs. 0.28 percent). These results suggest that the control patents provide a poor counterfactual for the complementary patents. Therefore, the following probit regression analysis (Table 3.4) should be treated as descriptive rather than causal. The results can be interpreted as the impact of a patent becoming complementary as compared to an average patent of the same age and technology class. Before proceeding to the analysis, note that the control patents tend to come from firms with significantly larger *Revenues* and *Total Assets*, but with significantly lower *Operating Margins*.

In Table 3.4, I display the regression analysis using the previously described sample. In Models 1-5 I estimate the probability of future litigation over different windows using a probit specification. I display the average partial effects (APE) in the table. The univariate analysis in Model 1 shows that becoming complementary increases the litigation rate by 1.2 percent (p-value 0.000) as compared to similar, noncomplementary patent.

In Models 2-5, I control for factors that correlate with a technology's importance (*Backward Citations*, *Breadth of Citations*, *Received Citations*). I also control for firm level factors that may influence a firm's litigiousness. Larger firms have more resources for a legal battle, so I include log of *Revenues*. However, larger IP portfolios are harder to monitor, which may reduce the likelihood that any one patent is litigated (*Total Patents)*. Firms with greater downstream assets (*PP&E, CAPX Intensity*) may be less willing to litigate because they compete through their superior manufacturing capabilities or lower production costs. *Operating Margin* proxies for the firm's profitability. To control litigation trends in the technological area, industry, environment, and by age, I include fixed effects for technology class, industry, year, and application year.

Model 2 displays the fully specified model for the $Litigation_{t0:t=2014}$. Complementary patents have a 1 percent great likelihood of being litigated as compared to the average patent. As expected, patents that have greater value before the standard have a higher instance of litigation (*Received Citations* APE 0.0004; p-value 0.000). Patents that draw on broader knowledge also see a significant increase in litigation propensity *(Breadth of Citations* 0.002; p-value 0.000). Model 3-5 show similar results.

Model 6 and 7 replicate Model 1 and 2, but use the count of future lawsuits. The Poisson model estimate for *Complementary Technology* shows that becoming complementary increases the number of future lawsuits by about 61 percent. While not shown, the count model results for the other windows are similar to the results displayed in Model 3-5.

I also estimate the likelihood that a patent had previously been litigated. From Model 8, I find that complementary patents have a 0.6 percent higher prior litigation rate than control patents. This suggests that to create a more precise counterfactual for the complementary patents, I will need to control for firms' propensity to litigate as well as the pre-complementary value of the patent.

As a robustness check, I rerun the analysis using only the first instance a patent becomes complementary and findings are similar. For example, using the specification in Model 2, I find approximately the same APE (0.01) and significance level (0.000) for *Complementary Technology*. However, *Complementary Technology* is not significant predictor of Litigation prior to disclosure (i.e., running Model 8).

Within-Firm Analysis of Litigation Rates

In this section, I employ a nearest-neighbor matching procedure (Abadie and Imbens, 2006; 2011) with tight set of exact match criteria to create a more believable counterfactual for complementary patents (Toh and Miller, 2017). To account for firm specific factors, such as litigation capability, resources, and IP monitoring costs, I restrict the potential control sample for each complementary patent to non-complementary patents from the same firm. From the within-firm set of patents, for a given complementary patent, I further restrict the set of possible control patents to ones that have the same application year, technology class, and the exact same number of prior lawsuits. This helps suppress differences in value between the complementary and control patents. It also suppresses the potential effect of notoriety that might stem from previous lawsuits. I then match for each complementary patent, all control patents that meet the criteria. For each complementary patent, I denote time t0 as the year of the disclosure event and calculate all variables for the complementary patens and control patents relative to this date. I form the counterfactual *Litigation Rate* for each complementary patent by taking the average *Litigation Rate* for all matching control patents. My sample of complementary patents consists of the first time a patent becomes complementary to the standard.

If we think of becoming complementary as a treatment, and if we are willing to assume that conditional on the matching variables, treatment is exogenous, then the imputed counterfactual from the untreated (control patents) patents can be used to calculate the patent's treatment effect on the treated (Rosenbaum and Rubin, 1983; Abadie and Imbens, 2002).[70] The treatment effect on the treated provides the effect of becoming complementary on the litigation rate compared to its counterfactual self (i.e. if it had not become complementary). The average across all such observations is the average treatment effect on the treated (ATET).

[70] We need one additional assumption, that the probability of assignment to the treatment level is lies in between zero and one. Together with the other assumption, which more formally, conditional on observables, the conditional mean of the outcome for treated and untreated observations is independent of the treatment, I have the sufficient conditions for weak 'strong ignorability' (Rosenbaum and Rubin, 1983).

Table 3.5-Test 1 displays the results of the above matching procedure. ATET is 2.84 and significant (p-value of 0.00). The results suggest that once the firm discloses IP to the standard, the future litigation rate of complementary patents increase by 2.84 percentage points (pp) over what the rate would be if the patent was not complementary.

From the regressions in Table 3.4, I find that a patent's prior citations and the citations it receives correlate with litigation. It also reasons that these factors influence the likelihood of becoming complementary to the standard. Standard essential technologies tend to be more important and valuable than other patents even before disclosure to the standard (Rysman and Simcoe, 2008). It would reason that their complementary patents may possess similar traits. Per Table 3.3, I find that a complement patent tends to draw on greater depth and breadth of knowledge (see *Backward Citations* and *Breadth of Citations*), and receive more citations (*Received Citations*) than a random non-complementary patent. Therefore, to better meet the assumption of independence conditional observables, I account for these factors.

I add *Backward Citations* and *Breadth of Citations* in Model 2. Since I do not have enough observations with exact matches, I instead use a nearest-neighbor matching procedure that chooses potential matches based on the lowest Mahalnobis Distance. To have more freedom to create matches, I drop the exact match on the *Count of Past Litigation*. Upon creating these matches, I compute the bias-adjusted average treatment effect on the treated (Abadie *et al.* 2004, Abadie and Imbens, 2011). I find a statistically significant ATET of 2.78 pp (p-value 0.00). Adding citations received in the three years prior to the event date (*Received Citations* $_{t-3:t-1}$) to better control for quality differences across patents increases ATET to 2.88 pp (Model 3).

In Table 3.5-Test 4, I reapply the strict exact matching procedure—i.e., only considering control patents that come from the same firm, application year, technology class, and that have the same *Count of Past Litigation.* I then match using *Backward Citations* and *Breadth of Citations* and *Received Citations*$_{t-3:t-1}$. I find a strong and significant ATET (2.80 pp; p-value 0.00). This is over three times larger than the unconditional litigation rate (0.9 percent) in the within-firm sample. Thus, being complementary to disclosed IP appears to be both statistically and economically meaningful. The results support my core hypothesis—that the litigation propensity for complementary technologies will be higher than similar, but non-complementary technologies after the firm discloses standard essential IP. I find similar results when I use a four-year or five-year window for the *Litigation Rate*. For example, using a five-year window, all tests from Table 3.5 are statistically significant (at the 1 percent level), but exhibit slightly lower ATETs (range 0.8 pp to 1.4 pp).

To test how the change in the litigation rate increases between the pre- and post-event period, I use the matching specification from Table 3.5-Model 3 to conduct a difference-in-difference style of analysis. The event at time t0 is when the patent becomes complementary to the standard via the firm's disclosure of SEPs. To conduct the analysis, I first estimate the ATET in the t-4 to t-1 period. To reduce ambiguity as to whether lawsuit is in the process of being filed prior to the standard, I exclude the year in which the firm discloses its SEP (i.e. t0) from the calculation. Next, I estimate the ATET in the post-event period (t+1 to t+4). Then I compare the pre- and post-ATETs, which results in my difference-in-difference matching estimate.

Table 3.6, Tests 1-3 show the estimates for the four-year windows. In the pre-event window (Test 1), the ATET is negative (-0.08) and insignificant. Conditional on observables, I find no statistical difference in the pre-event litigation rates. Test 2 displays the post-event ATET, which is positive and significant (0.87; p-value 0.001). The difference-in-difference estimate is 0.95 pp, with a p-value of 0.001. Patents that become complementary see a meaningful increase in their litigation rates as compared to their imputed counterfactual estimates. Results using three-year windows (Tests 4-6) support a similar conclusion. These results support my assentation that increase in the litigation rate for complementary technologies will only occur after the firm has disclosed to the SSO.

Patent-Level Fixed Effect Models

A firm's patents that do not become complementary to the standard may comprise a part of another technology platform that was not selected. For example, a firm may develop along two parallel technology trajectories. A standard emerges that institutionalizes one of the technology platforms; the other, rejected platform, may become worthless. If this is the case, the post-event increase in the litigation rate in the prior analyses could be inflated because the control group decreases while the treatment group increases.

To suppress this concern, I focus only on the complementary patents themselves and use their own prior litigation rate as a control group. First, I sample complementary patents using only the first instance of becoming complementary. Second, for patents with at least five-years of pre-event and five-years of post-event data, I calculate the dependent variable as the five-year litigation rate. Third, I create a patent-period panel that contains only two time periods (a five-year litigation rate for the pre-event period and five-year litigation rate in post-event period). *Complementary Technology* takes the value of one once the patent becomes complementary. Because patent value and age tend to exhibit an inverse-U shaped relationship, I control for *Age* and *Age Squared*. I start by running the analysis on *Litigation*, which takes the value of one if the patent is litigated in the five-year period and zero otherwise. I estimate the model using fixed effect logit.

Table 3.7-Model 1 displays the estimates for the five-year windows (t-5 to t-1, t0 to t+4). The coefficient for *Complementary Technology* is 0.549 and statistically significant (p-value 0.000). Fixed effect logit coefficients cannot be used to recover the marginal effects because the marginal effects depend on the fixed effects that are conditioned out of the equation. However, the average semi-elasticity can be estimated (Kitazawa, 2012).[71] Using the estimated semi-elasticity, I find that five-year litigation rate increases by 54 percent once the patent becomes complementary to the standard. The results are both economically and statistically significant.

As a robustness check, I also using a five-year model but omit the event year, (t0) from both windows (Model 2). This avoids ambiguity around whether the initial actions to

[71] If we want to estimate the average semi-elasticity of $\frac{\partial ln \Pr[y_{it}=1|x_{it},\alpha_i]}{\partial x_{it}} = \beta \frac{1}{1+\exp[\beta x_{it}+\alpha_i]}$, we find that it is a function of the fixed effect α, which has been conditioned out of the model (Chamberlain, 1980). However, Kitazawa (2012) result bypasses dealing with α because the expected value of the average semi-elasticity can be consistently estimated as $E[semi-elasticity] = \beta(1-E[y_{it}])$, where $E[y_{it}]) = \bar{y}$ $= \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T} y_{it}$

file a lawsuit preceded the disclosure in time. Results are similar. I also use a four-year window (Model 3) and find similar results.

Models 4-6 use the *Litigation Count* as the dependent variable. I estimate the models using a conditional fixed effect Poisson model estimated via quasi-maximum likelihood and calculate robust standard errors. In Model 4 I find that the coefficient for *Complementary Technology* is 0.504 and statistically significant (p-value 0.000). The patent experiences a 50 percent increase in the five-year count of lawsuits once it becomes complementary to the standard. Using the alternative windows, I find similar results (see Model 5-6). The results further support my hypothesis that litigation rates for complementary technologies will rise post-disclosure.

Separating the Incentive Effect from the Demand Effect

The prior analyses depict a positive relationship between *Complementary Technology* and the future litigation rate, which is consistent with two interpretations. One, as a technology becomes complementary to the standard, the firm has a greater incentive to protect it. Two, once the standard is set, the demand for technologies related to the standard increases, which in turn, increases the potential for infringement on these technologies. I expect that both the incentive and demand effects drive the *Complementary Technology-Litigation Rate* relationship. In this section, I try to separately identify the size of the two effects by accounting for the potential increase in demand in the *Litigation-Complementary Technology* model.

To provide a rough estimate of the two effects, I first need a measure of a patent's demand or value. I assume that received citations approximate the value of and demand for a patent. As noted before, prior literature commonly uses citations as a measure of value (Harhoff *et al.*, 1999; Jaffe and Trajtenberg 2004; Allison *et al.*, 2004; Hall *et al.*, 2005; Rysman & Simcoe, 2008). For instance, Simcoe *et al.* (2009) use citations received post-disclosure as a proxy for the increase in demand for SEPs.

I measure the post-disclosure event increase in demand for a patent as the number received citations in the t0 to t+5 period (*Received Citations*). To measure litigation, I use *Litigation Rate* in the t0 to 2014 widow. I expect that demand for a patent will be affected by the firm's litigiousness, therefore, I will need to simultaneously estimate a model for each endogenous variable. I use the within-firm patent sample used in Table 3.5.

To identity each model, I need instruments that effect one endogenous variable but not the other. In the *Litigation Rate* equation, I use the firm's total patents over the prior five years (*Total Patents 5-year*). I expect that firms in the sample have litigation related capabilities, such as in-house IP lawyers and outside law firm relationships. However, as the firm's patent portfolio grows larger, the ability to scan the environment for incidences of infringement should decrease. Using a firm-level fixed effects to control for litigation capabilities, I expect that *Total Patents* will negatively influence the *Litigation Rate* for a patent. Because I am relying on within-firm variation in *Total Patents* to identify the model, I check to see if there is sufficient within-firm variation in *Total Patents*. *Total Patents* does vary within firm, with a within-firm standard deviation of 2,600 and coefficient of variation 55 percent. I exclude *Total Patents* from the demand model because I assume that a patent's importance is not a function of the size of a firm's patent portfolio.[72]

In the demand equation, I use the patent's received citations in the t-5 to t-1 window (*Received Citations*$_{t-5:t-1}$). Using the patent's prior citations, I proxy for its pre-event importance, which should positively influence future demand. In a second specification, I also include the ratio of a patent's *Received Citations* $_{t-5:t-1}$ to the total citations received by all patents in its technology class during t-5 to t-1 window (*Relative Citations*$_{t-5:t-1}$) as an instrument. *Relative Citations*$_{t-5:t-1}$ proxies for the relative importance and visibility of the patent. If the entire technology area experiences an increase in demand after the formation of the standard, *Relative Citations*$_{t-5:t-1}$, will account for the proportional increase in the demand that the patent should experience. I exclude both variables from the litigation model because I assume that the future litigation rate is a function of the expected demand for the patent which is approximated by *Received Citations*$_{t0:t+5}$. Once I condition on expected future demand, I assume that the patent's prior importance should not affect the litigation rate. If this assumption does not hold, the litigation equation will not be identified.

I measure the effect of complementarity in both equations. *Complementary Technology* indicates the patent is complementary to IP disclosed at time t0. In the litigation equation, *Complementary Technology* should approximate the incentive effect, given that I am including the demand proxy, *Received Citations*. In the demand equation, *Complementary Technology* estimates the increase in demand due to being complementary to the standard.

[72] This should hold after conditioning on complementary technologies.

I also include a set of variables common to both equations. To control for knowledge structure of the patent, I included *Backward Citations* and *Breadth of Citations*. To control for visibility of the patent to others and the patent's importance, I included each patent's prior number of lawsuits (*Prior Litigation Count*). To suppress unobservable factors related to the firm, technological area, environment, and patents' age, I include firm, technology class, year, and application year fixed effects.

To simplify estimation of the system, I use a linear specification for both equations, which should roughly approximate the marginal effects in both models. To check this, I run both the litigation and demand equation separately using OLS. I exclude the endogenous regressors. Table 3.8-Model 1 provides the linear probability model results for the litigation equation. I find that becoming complementary increases the likelihood of future litigation by 3.7 percent (*Complementary Technology* coefficient 0.037, p-value 0.000). To benchmark, the marginal effect from a probit model suggests a 3.1 percent increase.

Model 2 displays the linear count model for the demand equation. Using linear estimates, complementary patents receive 3.06 more citations than non-complementary patents. Using a Poisson or Negative Binomial specification, I find average partial effects of 5.42 and 3.67 respectively. The linear model may underestimate the effect. Note that the instruments in both Model 1 and Model 2 are significant.

To estimate the system, I use three-stage least squares (3SLS) (Zellner and Theil, 1962). 3SLS allow error correlation across equations and provide more efficient estimation than other methods (e.g. two-stage least squares) at the cost of transmitting a specific equation specification error through the entire system. Using the less efficient 2SLS, I find similar results.

Model 3 displays the system estimation using one instrument per equation. In the demand equation, the instrument strongly predicts demand (*Received Citations*$_{t\text{-}5:t\text{-}1}$ 0.529; p-value 0.000). I find a positive and significant effect for *Complementary Technology* (2.27; p-value 0.000) and a positive but insignificant effect for the *Litigation Rate* (41.59; p-value 0.15).

To separate the demand effect from the incentive effect, I use the predicted *Received Citations t0:t+5* to account for the post-event bump in demand, which should allow the estimate of *Complementary Technology* to generate a rough approximation of the incentive to litigate. In the litigation equation in Model 3, I find a positive and significant effect for both *Received Citations*$_{t0:t+5}$ (0.0002; p-value 0.000) and *Complementary Technology* (0.015; p-value 0.000). Using the median value for the predicted *Received Citations*$_{t0:t+5}$ for complementary patents, I find that typical post-event increase in demand increases the *Litigation Rate* up by 1.87 percentage points. The *Litigation Rate* is 1.5 percentage points greater for the firm's complementary patents than for the firm's non-complementary patents. This provides a ballpark estimate of the incentive effect. Model 4 displays the estimate with the second instrument added to the demand equation, results remain similar.

I may not have enough within-firm variation in *Total Patents* for the demand equation to be identified properly. Therefore, I rerun the model on a subsample in which all observations have a within-firm coefficient of variation for *Total Patents* that is above the median. Model 5 shows the results. In the litigation equation, I find a positive and significant effect for both *Received Citations t0:t+5* (0.0001; p-value 0.000) and *Complementary Technology* (0.023; p-value 0.000), The impact of *Complementary Technology* is larger in both equations than in the full sample models. Note that *Litigation Rate* negatively affects future citations (-108; p-value 0.038), which differs from the positive and insignificant effect found in prior models. The finding is more consistent with the expectation from prior literature that litigiousness will deter rivals from your technological space.

Using the estimate for *Received Citations*$_{t0:t+5}$ in Model 5, I find that for the median complementary patent, demand increases the probability of future litigation by 0.6 pp. Not surprisingly, I find a larger effect for *Complementary Technology* (2.23 pp; p-value 0.000), than in Model 3 or Model 4.

While not shown, I also estimate the litigation model including the interaction between the *Received Citations*$_{t0:t+5}$ and *Complementary Technology*, while including both instruments *Received Citations*$_{t-5:t-1}$ and *Relative Citations*$_{t-5:t-1}$ in the demand equation. Using the sample from Model 5, I find positive and significant effects for *Received Citations*$_{t0:t+5}$ (0.0007; p-value 0.000), *Complementary Technology* (0.006; p-value 0.017), and their interaction (0.001; p-value 0.000). All instruments in the model are significant. The results suggest that even after accounting for the specific effect of demand on complementary technologies, there remains a positive incentive effect.

Overall, the system estimates allow me to suppress the effect of demand on future litigation by controlling for its endogenous nature in the model. Doing so, I find an economically and statistically significant effect of *Complementary Technology*. This points to an effect on litigation that goes beyond the 'demand effect.' Indeed, estimates suggest that the incentive effect accounts for approximately 50 percent to 85 percent of the effect of complementarity on litigation.

However, I interpret these results cautiously for several reasons. First, in the models shown in Table 3.8, I am only account for average demand, not for how demand differs in its impacts litigation across complementary and non-complementary patents. While I discuss the results of the model including the interaction of *Complementary Technology* and *Received Citations*$_{t0:t+5}$, I am may not have enough unique information from the two instruments to identify both endogenous variables. Second, linear models only crudely approximate the marginal effects in discrete choice and count models, though the results here seem reasonable. Third, I assume that *Litigation* is independent of prior demand when I condition on a proxy for expected future demand (as measured by the predicted value of *Received Citations*$_{t0:t+5}$), which may be a tenuous assumption. Four, I assume that *Complementary Technology* is uncorrelated with the error terms. However, unobserved factors that make the technology compatible with standard essential technology could correlate with litigation rates or demand. I help suppress this issue using only patents from firms that disclose and that have complementary technologies. I further suppress the effect by comparing the complementary patent to very similar patents (same firm, technology class, and age) and controlling for other important elements (*Backward Citations*, *Breadth of Citations* and *Prior Litigation Count*). Yet, the model may still provide biased estimates.

DISCUSSION & CONCLUSION

In this paper, I examine the role complementary technologies play in the firm's IP strategy. Firms actively participating in standard setting often disclose IP that becomes essential for the functionality of the standard. By doing so, they lose some measures of control over these technologies, often in exchange for licensing revenue. While prior literature focuses mostly on these standard essential technologies, instead, I use them as a starting point to unravel how they play a role in the firms' broader standards related IP strategy. I argue that firms benefit by having SEPs, not only through licensing revenue, but also through the increase in value of their portfolio of technologies complementary to the SEPs. Therefore, the firm will focus its appropriation strategy around these technologies. I trace these efforts by observing differences in patent litigation. Because of the costly nature of lawsuits, higher litigation rates should point to greater appropriation efforts on the part of the firm.

I find strong support for my predictions. As compared to a random sample of similar patents, complementary patents have higher litigation rates. To better identify the effect, I use information on very similar patents within the firm's own portfolio to create counterfactuals for the complementary patents. I find strong evidence that the firm litigates patents once they become complementary more than they likely would have otherwise. Focusing only on complementary patents, I also find that the future litigation rate and the number of lawsuits increase once the patent becomes complementary to a SEP. The fact that firms only start to focus their litigation efforts on these technologies once they become complementary provides strong evidence for a causal link between becoming complementary to the standard and a patent's future litigation rate.

However, the mechanism underlying this causal link is not clear because two interpretations are consistent with the previously discussed findings. One, firms more vigorously protect their complementary patents because these patents become more valuable and central to the firm's IP strategy. Two, the standard increases the demand for the complementary technologies—as more firms adopt the standard, the incidence of infringement, either intentional or inadvertent, increases which raises the litigation rate. Mapping back to my theory, I suggest that technology compatible with the standard will experience higher litigation rates because they become more valuable and because they represent applications of how the supply the standard, which is consistent with both interpretations. However, if complementary patents make the firm more competitive or play a central role in the firm's technology trajectory, then the firm should have a greater incentive to protect them, which emphasizes the first interpretation. To distinguish between the two, I estimate the effect of complementarity on litigation rates while accounting for the endogenous increase in demand. The tentative results suggest that demand does not account for the entire increase in the litigation rate. Rough decompositions of the overall effect using the estimates from Table 3.8, I find that the demand effect may range from 15 percent to 50 percent of the overall effect of complementarity on litigation. Therefore, the incentive effect likely accounts for a nontrivial portion (50 percent to 85 percent) of the estimated effect of complementarity.

My thesis shifts our view of how firms capture value in the technological portfolio from standard setting. Prior literature depicts SEPs as valuable assets because they often provide a stream of licensing revenue (Lerner and Tirole, 2006), elevate the firm's reputation as a technology pioneer (Lerner and Tirole, 2002; Waguespack and Fleming, 2009), or allow the firm the ability to control the pace of technological progression (Simcoe, 2012). I add to this literature by demonstrating that SEPs, through non-disclosed complementary technologies, can also enhance the firm's ability to appropriate returns in their non-disclosed technological portfolio. By doing so, I also provide a reasonable explanation why firms would disclose SEPs, even when doing so does not yield direct financial or reputational benefits.

I also extend the profiting from innovation framework by (Teece, 1986; 1996) by providing empirical support for the role complementarity plays in the firm's technology portfolio. While empirical work has mostly focused on the role of complementary downstream assets (Tripsas 1997; Arora and Coeccagnoli, 2006), I show how technological complementarity influences the firm's appropriation strategy.

Table 3.1. Variable Calculations

Patent Level Measures:	
Litigation Dummy	Whether patent is litigated over the designated window (0/1).
Litigation Count	Number of lawsuits that patent is involved in over the designated window.
Prior Litigation Count	Number of lawsuits that patent is involved prior to the disclosure event.
Complementary Technology	Co-cited with a SEP of a different technology class prior to or in the year of the SEPs disclosure.
Received Citations	Number of citations the firm receives during designated window.
Backward Citations	Number of citations the patent makes to other prior art.
Breadth of Citations	How many different, unique technology classes are covered in the patent's backward citations.
Age	Time in years from the patent's application date to time t.
Technology Class	The primary technology class assigned by the USPTO
Firm Level Measures:	
Total Patents (5-year)	Firm's total number patents in the prior five years.
Number Tech Classes (5-year)	Total number different technology classes that firm patents in during the prior five years
Patent Scope (5-year)	Take the ratio of firm's patents in each technology class to total patents in five year period. Scope is one minus the sum of the squared ratios.
Total Assets	Total assets of the firm in the prior year.
Revenues	Total revenues of the firm in prior year.
PP&E	Total property, plant, and equipment of the firm in the prior year.
CAPX Intensity	Total capital expenditures over total revenues in the prior year.
Operating Margin	Operating income over revenues in the prior year.

Figure 3.1. SEPs & complementary patents by SSO

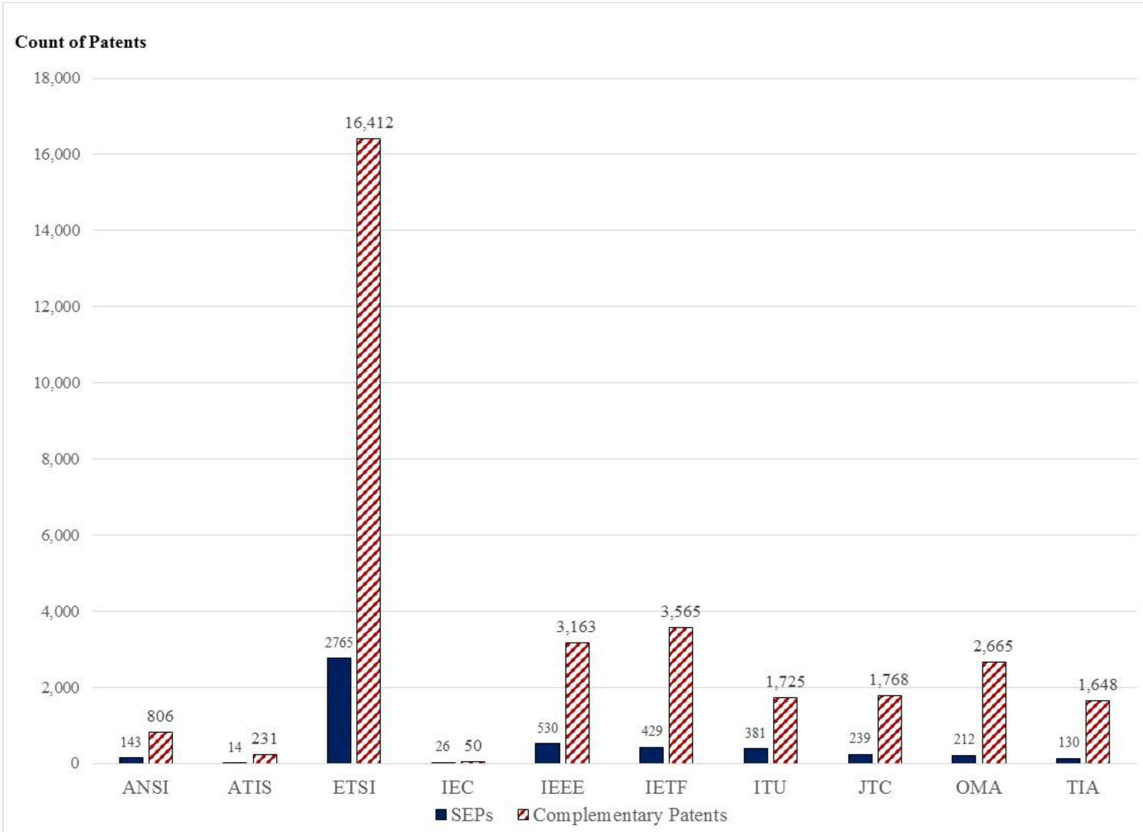

Table 3.2. SEPs, complementary patents, & litigation rates for select standards & firms

Panel A.

Example Standards	SEPs	Complementary Patents	Litigation Rate t0:t+5 (%)	Litigation Rate t0:t=2014 (%)	Description
Wireless Cellular Standards:					
3rd Generation Partnership Project (3GPP)	435	3,351	1.8	2.5	Covers cross-SSO consortia that manages the release of 3rd, 4th, and 5th generation wireless standards (i.e. W-CDMA, TDD, HSDPA, HSUPA, HSPA+, LTE) that are not broken out below.
CDMA2000	44	863	0.9	0.9	3rd generation mobile wireless standards.
General Packet Radio Service (GPRS)	540	4,744	1.0	1.5	Mobile data service standard for GSM
GSM EDGE Radio Access Network (GERAN)	232	143	1.7	1.7	Radio element of the GSM-EDGE network the specifies the interoperability of base station and control/switching systems.
Global System for Mobile Communications (GSM)	357	1,192	1.4	2.9	2nd generation TDMA based cellular standard.
Push to Talk over Cellular (PoC)	16	74	4.0	10.5	Covers technology that allows for walkie-talkie type usage over mobile cellular networks.
Universal Mobile Telecommunications System (UMTS)	504	2,599	1.2	2.1	Third generation mobile cellular standard using W-CDMA technology.
Other wireless cellular standards	435	3,351	1.8	2.5	Composite of 3rd and 4th generation wireless standards (i.e. W-CDMA, TDD, HSDPA, HSUPA, HSPA+, LTE,) that are not broken out above.
Other Communication Standards:					
Digital Enhanced Cordless Telecommunications (DECT)	22	262	0.4	1.8	Standard covering cordless telephone systems.
Local Area Networks (LAN)	343	1,912	1.6	1.6	Includes Ethernet, wireless Lan (Wi-Fi) and other
Digital private mobile radio (dPMR)	12	226	1.3	2.1	Simple common air interface standard for private networks
Universal Integrated Circuit Cad (UICC)	7	98	2.9	8.6	Smart card used in GSM and UMTS network mobile terminals
Internet & Audio-Visual Standards:					
Firewire	69	196	1.8	2.3	Interface standard for devices
Forward Link Only (FLO)	14	30	5.3	5.3	Standard coving delivery of multimedia over TV channel bandwidths
Internet Protocol televisions (IPTV)	6	58	9.4	9.4	TV content delivery using internet protocol.
MPEG-4 & associated audio visual standards	237	967	2.4	2.8	Method for compressing digital audio and visual data.
Wireless Application Protocol (WAP)	5	794	0.8	2.0	Pre-HTML wireless web browser standard for mobile devices.
vCards	2	71	1.4	11.0	Standard covering electronic business cards.

Panel B.

Example Firms	SEPs	Complementary Patents	Litigation Rate t0:t+5 (%)	Litigation Rate t0:t=2014 (%)	Description
AT&T	34	38	13.9	19.4	Internet, LAN, MPEG, transmission systems
Apple	32	261	1.4	1.4	Internet, firewire, MPEG, LAN
Broadcom	11	8	5.3	10.5	Cable networks, internet, wireless cellular
Cisco	58	702	0.7	1.3	Internet, LAN, MPEG
Ericsson	206	1,202	1.3	2.3	Internet, transmission systems, wireless cellular
Fujitsu	15	53	2.9	2.9	MPEG, voice and data
Hybrid Networks	11	5	18.8	18.8	LAN
Lucent Technologies	18	128	2.1	3.4	Transmission systems
Motorola	291	2,625	0.6	1.5	LAN, transmission systems, wireless cellular
Nokia	248	1,235	1.3	2.5	Internet, LAN, transmission systems, wireless cellular
Nortel Networks	92	447	0.2	3.6	Firewire, internet, LAN, transmission systems
Panasonic	48	168	1.0	1.9	Digital media & broadcasting, MPEG, voice and data
Qualcomm	209	1,076	1.8	2.9	IPTV, LAN, transmission systems, wireless cellular standards
Stratacom	2	21	17.4	17.4	Internet, IPTV, LAN
Toshiba	4	22	3.8	11.5	Internet, LAN, wireless cellular

In Panel A, the same patent that is disclosed to multiple standards will be included in each standard's count of SEPs. The same goes for Complementary Patents. In Panel B, I count a patent that is disclosed to or becomes complementary to multiple standards only once.

Table 3.3. Descriptive for complementary patents and random matches

Variable		Complementary Patents		Random Match Patents		
	N	Mean	Std. Dev.	Mean	Std. Dev.	Difference in means (p-value from *t*-test)
Litigation Rate t0:t=2014 (%)	17,670	2.14	14.47	0.96	9.76	0.000
Litigation Count t0:t=2014	17,670	0.05	0.53	0.03	0.82	0.013
Litigation Rate t0: t+5 (%)	15,635	1.02	10.06	0.54	7.32	0.000
Litigation Count t0: t+5	15,635	0.01	0.17	0.01	0.19	0.006
Prior Litigation Rate application date: t-1 (%)	17,670	0.82	9.02	0.28	5.31	0.000
Prior Litigation Count applicatio date: t-1	17,670	0.01	0.19	0.00	0.10	0.000
Received Citations t-3 to t-1	15,367	14.42	18.47	5.55	9.19	0.000
Received Citations t-5 to t-1	12,497	25.30	30.80	9.73	15.13	0.000
Backward Citations	17,567	12.75	19.45	10.68	17.82	0.000
Breadth of Citations	17,567	3.73	2.90	3.47	2.77	0.000
Age	17,670	7.54	5.04	7.54	5.04	1.000
Total Patents (5-year)	17,346	4,355	5,487	4,448	5,005	0.098
Number Tech Classes (5-year)	17,346	106	62	115	71	0.000
Patent Scope (5-year)	17,346	0.88	0.11	0.89	0.16	0.000
Total Assets	17,667	39,464	35,170	50,398	74,620	0.000
Revenues	17,667	33,595	26,968	38,291	33,583	0.000
PP&E	17,667	15,954	20,356	21,933	23,983	0.000
CAPX Intensity	17,658	0.05	0.04	0.06	0.12	0.000
Operating Margin	17,667	0.14	0.16	0.03	1.72	0.000

Table 3.4. Descriptive probit analysis of litigation

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Dependent Variable	Litigation (0/1)	Litigation (0/1)	Litigation (0/1)	Litigation (0/1)	Litigation (0/1)	Litigation Count	Litigation Count	Litigation (0/1)
Window	t0:t=2014	t0:t=2014	t1: t+4	t1: t+5	t0: t+5	t0:t=2014	t0:t=2014	t=application date : t-1
Method	Probit	Probit	Probit	Probit	Probit	Poisson	Poisson	Probit
Information Shown	APE	APE	APE	APE	APE	Coefficient	Coefficient	APE
Complementary Technology	0.012***	0.010***	0.004**	0.004**	0.003**	0.401***	0.608***	0.006***
	(0.000)	(0.000)	(0.0440)	(0.00623)	(0.0397)	(0.000)	(0.000)	(0.000350)
Backward Citations		-0.00001	-0.00001	-0.00001	-0.0001		-0.012***	0.00001
		(0.186)	(0.254)	(0.0701)	(0.175)		(4.81e-09)	(0.834)
Breadth of Citations		0.002***	0.001**	0.001**	0.001***		0.174***	-0.00001
		(0.000)	(0.015)	(0.000)	(0.003)		(0.000)	(0.968)
Received Citations (t-3 to t-1)		0.0004***	0.0002***	0.00001***	0.0001***		0.0148***	0.0002***
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Total Patents (5-year) in 000s		-0.0001***	-0.0004	-0.002	-0.002		-0.131***	-0.400
		(0.000)	(0.162)	(0.476)	(0.369)		(0.000)	(0.261)
ln(Revenues)		-0.004***	-0.003***	-0.003***	-0.003***		-0.0847***	-0.002***
		(0.000)	(0.000)	(0.000)	(0.000)		(0.001)	(0.000)
PP&E in 000s		-0.001	-0.001	-0.001	-0.001		0.004***	-0.001
		(0.803)	(0.704)	(0.724)	(0.956)		(0.003)	(0.796)
CAPX Intensity		-0.008	-0.010	-0.008	-0.008		0.0256	-0.025
		(0.725)	(0.604)	(0.591)	(0.644)		(0.953)	(0.140)
Operating Margin		0.008	0.008*	0.010**	0.010*		0.0226	0.004
		(0.105)	(0.087)	(0.038)	(0.070)		(0.650)	(0.202)
Application Year Fixed Effect	NO	YES	YES	YES	YES	NO	YES	YES
Technology Class Fixed Effect	NO	YES	YES	YES	YES	NO	NO	YES
Industry Fixed Effect	NO	YES	YES	YES	YES	NO	NO	YES
Year Fixed Effect	NO	YES	YES	YES	YES	NO	NO	YES
Observations	35,340	25,295	21,102	23,079	20,989	35,340	21,974	14,869
Pseudo R-squared	0.02	0.14	0.240	0.13	0.24	0.004	0.13	0.25

p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.5. Within-firm matching analysis of litigation rates

	Nearest-neighbor matching variables	Exact match	Average Treatment Effect on Treated (pp)	A&I Robust SE	p-value	Total *N*
(1)	none	Firm, Application year, Technology Class, Year, Count of Past Litigation	2.84	0.23	0.00	81,852
(2)	Backward Citations, Breadth of Citations	Firm, Application year, Technology Class, Year	2.78	0.26	0.00	80,943
(3)	Backward Citations, Breadth of Citations, Received Citations (t-3:t-1)	Firm, Application year, Technology Class, Year	2.88	0.30	0.00	68,514
(4)	Backward Citations, Breadth of Citations, Received Citations (t-3:t-1)	Firm, Application year, Technology Class, Year, Count of Past Litigation	2.80	0.30	0.00	68,311

Dependent variable is litigation rate t0:t=2014. Test statistics use Abadie & Imbens' robust standard errors. Treatment is the presence of complementary technologies. Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

Table 3.6. Within-firm difference-in-difference matching analysis of litigation rates

Test	Average Treatment Effect on Treated (pp)	A&I Robust SE	p-value	Total N
(1) Litigation Rate t-4:t-1	-0.08	0.15	0.608	39,577
(2) Litigation Rate t+1:t+4	0.87	0.25	0.001	39,577
(3) Difference-in Difference	0.95	0.30	0.001	39,577
(4) Litigation Rate t-3:t-1	0.03	0.01	0.743	55,425
(5) Litigation Rate t+1:t+3	0.72	0.16	0.000	55,425
(6) Difference-in Difference	0.70	0.09	0.000	55,425

Test statistics use Abadie & Imbens' robust standard errors. Treatment is the presence of complementary technologies. Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

Table 3.7. Fixed effect Logit and Poisson models

Dependent variable:	Model 1 Litigation (0/1)	Model 2 Litigation (0/1)	Model 3 Litigation (0/1)	Model 4 Litigation Count	Model 5 Litigation Count	Model 6 Litigation Count
Window length:	5 year	5 year (omitting t0)	4 year	5 year	5 year (omitting t0)	4 year
Method	Fixed Effect Logit	Fixed Effect Logit	Fixed Effect Logit	Fixed Effect Poisson	Fixed Effect Poisson	Fixed Effect Poisson
Sample	Full	Full	Full	Full	Full	Full
Complementary Technology	0.549***	0.349***	0.511***	0.504***	0.337***	0.468***
	(0.000)	(0.004)	(0.000)	(0.000)	(0.004)	(0.000)
Age	0.100	0.124*	0.057	0.098	0.122	0.032
	(0.125)	(0.0663)	(0.424)	(0.220)	(0.121)	(0.724)
Age Square	-0.002	-0.003	0.002	-0.002	-0.003	0.002
	(0.575)	(0.281)	(0.579)	(0.652)	(0.310)	(0.570)
Observations	1,194	1,174	1,103	1,212	1,190	1,115
Log-pseudolikelihood	-490.95	-475.37	-427.38	-868.81	-822.52	-741.04

Robust p-values calculated from standard errors that account for within firm clustering in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.8. Analysis of demand and incentive effects

	Model 1	Model 2	Model 3		Model 4		Model 5	
Method	OLS	OLS	3SLS		3SLS		3SLS	
Equation	Litigation	Demand	Litigation	Demand	Litigation	Demand	Litigation	Demand
Dependent Variable	Litigation Rate	Received Citations	Litigation Rate	Received Citations	Litigation Rate	Received Citations	Litigation Rate	Received Citations
Litigation Rate				41.59		12.90		-108.0**
				(0.150)		(0.612)		(0.038)
Received Citations t0:t+5			0.002***		0.001***		0.001***	
			(0.000)		(0.000)		(0.000)	
Complementary Technology	0.037***	3.058***	0.015***	2.267***	0.015***	2.602***	0.023***	4.798***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Patents (5-year) in 000s	-0.00001***		-0.00001***		-0.00001***		-0.0001***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Relative Citations t-5:t-1						27.81***		55.35***
						(0.000)		(0.000)
Received Citations t-5:t-1		0.529***		0.497***		0.492***		0.545***
		(0.000)		(0.000)		(0.000)		(0.000)
Backward Citations	0.0002***	0.034***	0.0003***	0.0214**	0.0003***	0.030***	0.0001	0.010
	(0.000)	(0.000)	(0.000)	(0.035)	(0.000)	(0.000)	(0.623)	(0.431)
Breadth of Citations	0.0001	0.119***	-0.0003	0.125***	-0.0003	0.115***	0.0003	0.315***
	(0.443)	(0.000)	(0.200)	(0.000)	(0.210)	(0.000)	(0.448)	(0.000)
Prior Litigation Count	0.070***	0.088	0.057***	-2.299	0.058***	-0.569	0.044***	4.184*
	(0.000)	(0.859)	(0.000)	(0.186)	(0.000)	(0.711)	(0.000)	(0.081)
Constant	-0.0424	-4.65	-0.034	-2.871	-0.034	-5.835	0.007	9.444
	(0.535)	(0.528)	(0.648)	(0.717)	(0.645)	(0.430)	(0.936)	(0.418)
Firm Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Application Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Technology Class Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Observations	67,911	67,911	67,911	67,911	67,911	67,911	32,826	32,826
R-Square	0.03	0.50	0.04	0.43	0.04	0.50	0.04	0.58

p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix 3.1. Litigation of Standard Essential Patents & Complementary Patents

In this section, I discuss the relationship between SEPs and complementary patents in patent lawsuits and how their individual litigation rates compare. Litigation of IP related to standards tends to fall into two broad categories. The first set of lawsuits tend to focus on cases where one or more parties allegedly infringes on the plaintiff's SEP by adopting the standard. Table A3.1 breaks down lawsuits that include a SEP or complementary patent. SEP focused cases tend to cover a smaller number of SEPs (see column three in Table 9), with 1.3 SEPs litigated on average. The second set of lawsuits revolve around how the defendant applies the standard in product market competition. These suits often detail how the defendant allegedly infringes on the plaintiff's IP by including it into a product that functions on a standard, such as smartphone. In Table A3.1, I find that of the 343 cases with at least one complementary patent, 25 percent of the cases also include a SEP. Cases that include both a SEP and complementary patent tend to specify a larger number of patents (4.8 SEPs and 6.6 complementary patents on average). Often, the plaintiff alleges the defendant infringes on its SEP by using the standard while not licensing the underlying IP, and then builds products that apply the standard, and by doing so, infringe on the firm's complementary IP.

Table A3.1 Lawsuits by SEP and complementary technology

	Lawsuits | SEP>=1	Lawsuits | SEP>=1, Comp. Tech.=0	Lawsuits |Comp. Tech>=1	Lawsuits |Comp. Tech>=1 & SEP=0
Number of lawsuits	238	153	343	258
SEPs				
Mean	2.55	1.3	1.19	-
Standard deviation	4.08	0.8	3.69	-
Complementary Technology				
Mean	2.36	-	4.19	3.39
Standard deviation	6.47	-	6.38	4.72

CHAPTER 4

Strong Firms, Weak Products? The Role Of Within-Firm Product Complementarities In New Market Entry Strategy

Abstract

While prior research documents the importance of pre-entry resources on the likelihood of entry and post-entry success, less studied are firms' product strategies as they enter new markets. Evidence suggests that highly capable firms often enter markets with inferior products yet thrive in the market. I address this puzzle by examining firms' product feature choices as they enter new markets, and how these choices affect performance. I argue that new product markets are embedded in ecosystems comprised of other, complementary product markets and that this influences firms' product strategy. Taking a demand-side view of complementarities, I propose that firms with existing products complementary to the new market will enter the new market with products that have lower technical performance, and that firms with complementarities will choose features and components that function with their complementary products and exclude features and components that do not. Examining entry into the nascent smartphone market, I find strong support for these conclusions. Empirical results also demonstrate that firms can achieve high market performance by relying on complementarities in lieu of high technical performance. I identify complementarities within the firm's product portfolio as an important driver of product strategy in new markets, and compatibility between complementary products as a mechanism the firm can use to achieve successful entry.

INTRODUCTION

New market entry has long been an important topic in strategy (Helfat and Lieberman, 2002). Prior research suggests that a firm's pre-entry resources influence what product markets it will enter (Penrose, 1959; Mitchell, 1989; Helfat and Lieberman, 2002; Lee, 2008). Literature also demonstrates that diversifying entrants that possess resources, such as technological knowhow, that fit the needs of the new market tend to be more successful when they enter (Klepper and Simon, 2000; King and Tucci, 2002; Franco, Sarakar, Agarwal, and Echambadi, 2009). Yet we know much less about firms' product strategies as they enter nascent markets despite the importance that key strategic elements, such as product design, play in post-entry success (Brown and Eisenhardt, 1995; Krishnan and Ulrich, 2001). Understanding what drives heterogeneity surrounding product design choices can allow us to better assess the performance of a firm's entry strategy and how entry into a market fits into the firm's overall strategy.

Our limited knowledge of product strategies in new markets is apparent in technology focused sectors. Here, common wisdom suggests that diversifying entrants with superior technological resources will choose to compete by developing products with high technical performance (Bayus and Agarwal, 2007; Franco, *et al.* 2009). However, firms with strong technological resources that compete on the technological frontier in existing markets often enter new markets with products that exhibit low technical performance or contain a limited set of features. Knowledge based theories suggest that these firms cannot adequately transfer their technological resources to the new market (Winter, 1995; Szulanski, 1996). Yet, these firms often thrive in the new market, even when competing against other firms whose products have superior technical performance. This suggests that firms may intentionally enter behind the technological frontier.[73] [74] So why would firms with strong technological capabilities enter behind the technological frontier? What drives their product strategy in new markets?

To address these questions, I depart from prior literature that typically focuses on how the firm's resources match with new market, and instead, consider how other markets the firm operates in may influence its product strategy in the new market. Indeed, a new product market is often part of an innovation ecosystem consisting of many complementary markets (Adner and Kapoor, 2010). In such an ecosystem, there is the potential for cross-market correlation in consumer preferences (Brandenberg and Nalebuff, 1996; Zander and Zander, 2005; Ye, Priem, and Alshwer, 2012; Schmidt, Makadok, and Keil, 2016) that the firm can exploit if it owns complementary products in the ecosystem. Therefore, a firm's position in other markets in the ecosystem may bear on its product strategy as it enters a new market.[75]

In this paper, I examine how the firm's portfolio of existing products influences its entry strategy and its resulting performance in the new market. I identify a key element that influences the firm's entry strategy—the potential complementarity between its existing products and its new market products. Products are complementary when consumers derive more value from using the products together than separately.[76] I assume both products exist separately and one is not just a component part of the other. I predict that firms with complementary products will enter the new market with products that exhibit lower

[73] Examples include Merrill Lynch in online brokerage and Google in smart television/digital media players.
[74] This is especially puzzling because early adopters typically prefer technological performance (Porter, 1983; Adner and Levinthal, 2001; Rogers, 2003).
[75] Prior literature on innovation incentives demonstrates that the firm's position in the current market influences its incentive to invest in new technologies (Arrow, 1962; Reinganum, 1985; Conner, 1988). Likewise, position in complementary markets can influence the firm's technological decisions in new markets.
[76] Complementary products can be thought of as Edgeworth complements in that when both can be accessed and consumed together then utility is higher than it otherwise would be (Allen, 1934; Samuelson, 1974).

technical performance or contain fewer features as compared to firms without complementary products, but achieve similar success in the market.

I conduct my empirical tests using product characteristics in the nascent stage of the global smartphone market. I collect a novel dataset on smartphone features that allows for the calculation of dependent variables that capture complexity of a product's technical performance. I use several matching and propensity score weighting techniques to address potential selection issues related to complementary products. I also account for selection into the market.

I find that firms with complementary products enter the new market with products that exhibit inferior technical performance as compared to firms without complementary products, yet perform better in terms of market share. I also unpack how firms make decisions regarding product features. Consistent with the strategy of competing on compatibility with their complementary products, evidence shows that firms include product features that correspond to their complementary products, but exclude some features that do not function with their complementary products.

The research contributes to the literature on market entry in several ways. I move beyond a single market focus, which can make some entry strategies appear puzzling or unsuccessful. Instead, by highlighting compatibility between complementary products as a mechanism through which some firms base their new market entry strategy, I can explain why firms with vast technological capabilities may choose to enter markets behind the technological frontier, and why such a strategy can be successful. Doing so also helps place entry into the broader context of the firm's value creation and capture strategy by detailing the link between the new market product and other products in the firm's portfolio. By investigating firms' choice of different product features in new product markets, I move beyond the typical binary view of entry and reveal a critical source of and reasons for heterogeneity within firms' entry strategy. Doing so provides insight into tradeoffs managers make when entering a nascent market.

The research also contributes to our understanding of complementarities in market entry research. Prior work using Teece's (1986) complementary asset framework demonstrates that diversifying entrants can redeploy downstream resources such as distribution facilities or a sales force to support the success of a new product or innovation (Mitchel, 1989; Helfat and Raubitschek, 2000). Kapoor and Furr (2014) extend this framework by suggesting that complementary asset availability influences firms' technology choices upon entry. In this extant view, complementarity is a supply-side phenomenon that plays an important supporting role in the new products success.[77] Instead, I focus on how demand-side complementarities influence product strategy. I stress that complementarities in the firm's portfolio not only allow the new product to create more value for customers and thus make the product more competitive, but they also offer additional channels to appropriate value from entry. This phenomenon is particularly important in the context of high technology ecosystems, such as mobile communications and streaming media, which encompass many, potentially interdependent product markets in which the firm's position in one could bear on its strategy in another.

THEORY & HYPOTHESES

Background

Market entry literature has moved from stylized models in which firms enter and learn about their cost efficiency (e.g. Jovanovic, 1982) to a focus on pre-entry resources

[77] A similar strand of literature investigates how complementary assets can buffer the firm from technology change (Tripsas 1997). My work differs because instead of suggesting that the path dependent firm survives technological upheaval because it owns some key complementary assets, I point out that technologically advanced firms choose to rely on complementarities instead of advancing the technological frontier.

(Helfat and Lieberman, 2002). This literature demonstrates how pre-entry resources influence if and when firms enter a market, and their subsequent performance (Penrose, 1959; Lane, 1988; Chatterjee and Wernerfelt, 1991; Mitchell, 1989; Schoenecker and Cooper, 1998; Silverman, 1999; Klepper and Simons, 2000; Lee, 2008; Bayus and Agarwal, 2007; Franco *et al.*, 2009). In general, this research finds that firms with superior resources are more likely to enter the market and perform well when they do (Lee, 2008). For example, Klepper and Simons (2000) find that firms with significant marketing, R&D, and production experience in a similar market are more likely to enter and perform well in the new market. Franco *et al.* (2009) demonstrate that only firms with strong technological capabilities benefit from moving into the market early. The product development literature draws similar conclusions. Firms succeed when they have resources that fit with the new market and thus, allow them to create high performing products that satisfy consumers (Cooper, 1979; Cooper and Kleinschmidt, 1987; Zirger and Maidique, 1990; Montoya-Weiss and Calantone, 1994; Gatignon and Xuereb 1997; Henard and Szymanski, 2001).

While prior literature documents the importance of resources for entry success, we know a lot less about firms' product strategy upon entry. Do firms always convert their superior resources into technologically superior products? Most research ignores what firms *actually do* in terms of product design (i.e. characteristics and features choices) when they enter the market,[78] despite the importance of product development decisions for firm performance (Ali, Kalwani, and Kovenock, 1993; Brown and Eisenhardt, 1995). The product development literature focuses on drivers of product success, such as technical performance or the firms' market orientation (Montoya-Weiss and Calantone, 1994; Henard and Szymanski, 2001), but ignores how development decisions fit in the firms'

[78] Benner and Tripsas (2012) provide one of the few studies to investigate product level strategy as firms enter a new market. Using product data from the digital camera market, they find substantial heterogeneity in features and characteristics, even among entrants with access to similar technological resources.

overall strategy. Therefore, prior literature offers little explanation for why highly capable firms might enter markets with products that exhibit lower technical performance. This gap can obscure our ability to accurately assess entry performance or understand how entry plays a role in the firm's broader strategy.

To shed light on this puzzle, I begin with the observation that in many high-technology industries, new product markets form in the context of a larger innovation ecosystem consisting of multiple, potentially complementary product markets. Firms often operate in many of these product markets, and in some instances, offer existing products that are complementary to the new market. Products are complementary when they can create more value for some consumers when used together. The bases for this idea has a long history in economics (e.g. Allen, 1934; Hicks and Allen, 1934a; 1934b; Samuelson, 1974). For example, a video streaming service is complementary to a smart television device.[79]

When consumers value combining the products from different markets, the firm that operates in both the new and complementary market may have a difference set of incentives than a firm that operates in only the new market. Thus, the firm's portfolio of complementary products may influence how it views the new market opportunity.[80] So how does the firm's portfolio of products influence its product strategy in new markets?

To answer this question, I consider how complementarities in the firm's product portfolio incentivize the firm to make certain product characteristic and feature choices

[79] From the point of view of a consumer, the better the streaming service that can be accessed through the device (e.g. more content or better content) the more the consumer will derive utility from the device. The better the device functions (e.g. makes searching content easier), the more the consumer will derive utility from using the streaming service.
[80] This is similar to the notion of how the firm's business model or resource base will influence how it views the new market. For example, Tripsas and Gavetti (2000) illustrate that Polaroid's business model in film based photography shaped how its executives viewed the digital photography market. Wu *et al.* (2013) theorize that complementary assets influence the way in which incumbent firms respond to technological change.

upon entry into a new market. Products are complementary when consumers derive more value from using them together than separately.[81] I assume that firms face some demand uncertainty and do not know the exact product attributes consumers' value most, which is consistent with conditions typically experienced during the early stages of a market (Utterback and Abernathy, 1975; Tushman and Anderson, 1986). I conceptualize the product as a "complex assembly of interacting components" (pg 3, Krishnan and Ulrich, 2001), which can be evaluated relative to other competing products, based on technical performance (Krishnan and Ulrich, 2001). I define technical performance as how the various product dimensions combine to influence how users experience the technology. For example, one can compare laptop computers based on technical measures such as clock speed, screen quality, random access memory, and battery life.

Complementary Products Influence on Product Design

Firms differ in the way in which they can approach the nascent stage of the market depending on whether they possess complementary products. In new high technology markets, the initial consumer pool is often comprised of what the product life-cycle literature calls early adopters[82]—consumers that tend to favor products with high technical performance. Firms without complementary products will focus on capturing a share of the early adopters by applying their technological resources to develop high performing products. However, competing on the technological frontier in the early stages of the market is difficult. Slight product performance differences can create large differences in market share and profits (Bayus, Jain, and Rao, 1997). It is also costlier, both in terms of

[81] Basically, the user has higher utility when using the two products together because the marginal benefit to the consumer of one product is enhanced when combined with the other product (Milgrom and Roberts, 1990; Siggelkow, 2002; Toh & Miller, 2017).
[82] In the product life cycle / product adoption literature, the first two sets of adopters are typically called "innovators" and "early adopters." I combine both and simply call them early adopters. Both tend to favor technological sophistication.

product development and per unit costs (Clark *et al.*, 1987; Schoonhoven, *et al.*, 1990). Building products on the frontier typically requires experimenting with unproven technology, which tends to yield more negative outcomes than proven technology (Pacheco-de-Almeida, Henderson, and Cool, 2008), and therefore, raises development costs by increasing both research effort and development time (Mansfield, 1988; Cohen, Eliashberg, and Ho, 1996). For example, Apple spent over $100 million (about 5% of total annual sales) to create the Newton, which was easily surpassed in the market by slightly better functioning offerings from Sony and Motorola.

Competing on compatibility offers an alternative strategy through which firms with complementary products can enter a new market. This strategy can benefit firms in several ways. First, the firm need not compete on the technological frontier because it does not need to target early adopters that prefer technical performance. Instead, the firm can target consumers that value compatibility between its new product and complementary products.[83] This may include growing the market by attracting the firm's current complementary product customers that are not typical early technology adopters.[84] These consumers may tradeoff technical performance for compatibility with complementary products if the new product surpasses their minimally acceptable performance threshold. In this way, complementary products increase the competitiveness of the firm's new market

[83] I assume that firms with complementary products do not incur additional development costs for these complementary products, as these products are already in existence. I also assume that firms without complementary products do not consider entering the complementary product market, at least not until after the firm's initial product development is complete and the firm has entered the market. This allows me to focus on how the firm's existing complementary products shape entry and product strategy in the new market.

[84] For example, Merrill Lynch entered the online brokerage market by targeting a subset of its current customers that valued its complementary products, such as stock market research and customized investment advice, with the ability to trade independently on an online platform. Similarly, Research in Motion's foray into the smartphone market targeted its corporate customers that wanted to combine its Blackberry Enterprise Server with a phone capable of receiving secure messages and emails. In both cases, the firms target audience was not typical early adopters in the new market, but rather current customers that would value combining the firm's complementary offerings with a product in the new market.

product. This effect is accentuated when the firm's complementary products are not compatible with rivals' offerings in the new market.

Second, complementary products offer additional channels through which to profit from entry into the new market. For each unit of the new product sold, the firm may be able to sell additional units of the complementary product. If consumers of complementary products value combining them with the new market product, launching a product in the new market can make the firm's complementary products more competitive in their existing markets. When combined with the first mechanism, complementarities within the firm's portfolio allow it to create and capture an indirect network externality[85]—complementarities increase the demand for and competitiveness of the new product which in turn, increases the demand for and competitiveness of the complementary product(s). Such positive feedback loops can be a major driver of success in the market (Katz and Shapiro, 1986; Schilling, 2002; Zhu and Iansiti, 2012).[86]

Together, these two mechanisms suggest that the firm with complementary products will find consumers who value its complementarities more attractive because it can potentially reach them at lower costs than other consumers. Moreover, these consumers will also be more profitable for the firm because they will potentially buy the firm's products in both the new and complementary markets.

The firm will also find consumers that do not value its complementary products less attractive. The firm expects that the benefit from complementarities will diminish as it

[85] The network externalities argument is often applied to standard wars (e.g., Betamax vs. VHS) and other platform competition, in which the focus is on the central technology and its success is determined by access to compatible technologies. However, in the case of within-firm complementarities, the firm owns both the central and compatible technology, and financially benefits from the success of both.

[86] It is useful to compare this argument to the concept of economies of scope. Scope based benefits accrue through cost savings via shared inputs (Clark, 1923; Panzar and Willig 1981), or the shared use of indivisible tangible or intangible resources (Penrose, 1959; Teece, 1980). Economies of scope are a driver of market entry. Furthermore, products that are complementary might exhibit cost based economies of scope. However, my core proposition regards how complementarities across the firm's product portfolio operate on the revenue function and differs from typical economies of scope arguments that typically focuses on the cost function.

tries to target consumers that prioritize technical performance. To successfully target such consumers, the firm will likely need to increase technical performance, and therefore incur higher product development and per unit production costs. At the early stages of the market, most entrants will focus on early adopters, which could increase price and technical performance competition in this segment.

Based on the above argument, the firm with complementary products is more likely to focus on consumers that value compatibility with its complementary products, and will choose features and characteristics that bring its product to the technical performance level that will allow it to maximize profit on this segment. Increasing technical performance to reach other segments of the market could potentially force the firm to shift price and/or incur higher costs that will lower total expected profits. Therefore, the strategic effect of differentiation on compatibility—focusing on the less competitive and more lucrative consumers that benefit from complementarities—will tend to outweigh the potential benefit of targeting all early adopters.[87] Firms with complementarities will compete on compatibility and thus, will tend to design lower technically performing products than they would if they did not benefit from complementarities.

Another mechanism may also influence the firm's product strategy. The firm may tradeoff technical performance for time-to-market when it believes that it either can benefit from or be harmed by network effects between the new market and its complementary product markets. By entering earlier than it otherwise would, the firm can help generate a positive network externality in its portfolio. It can also avoid a decline in the sales of its complementary product portfolio that could stem from users switching to rivals' products

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[87] Note that this logic is consistent with models of differentiation under different types of demand uncertainty (Meagher and Zauner, 2004; 2005, Meagher *et al.*, 2008).

that are compatible with the new market. This is particularly important when the cost of adapting technologies to be compatible with rivals is high (Eggers, 2012).[88]

When the firm believes that entering early will allow it to gain an advantage or avoid becoming disadvantaged in complementary markets, the firm will want to rush its new product to market. To achieve shorter time-to-market, the firm will need to tradeoff technical performance of the product. Creating innovative technology or including new components is time consuming and costly (Schoonhoven *et al.*, 1990). Many of the aspects of product development, such as knowledge of how various components function together, are subject to time compression diseconomies (Dierickx and Cool, 1989). Even for a firm with significant related resources, the time to design and launch a new product in an entirely new market can be significant because prior product development experience may be of only limited value in searching for the best solutions (March, 1991).

Apple's entry into digital media player market with their Apple TV device provides an example of how complementarities influence entry. The initial Apple TV had only basic features but provided a compatible interface to link a television to other Apple devices, and most importantly, to its iTunes content platform. Apple's intent is not to derive profits solely from the sale of the device, but instead to also profit from selling entertainment content across its iTunes platform.[89] They can achieve this goal without making the most sophisticated device. By entering the market, Apple ensures that its platform is compatible with at least one product in the market. It also avoids losing content sales if consumers choose content platforms based on their TV compatibility.

[88] For example, Palm attempted to make its Pre-series smartphones compatible with Apple's iTunes entertainment content platform after it was clear that Palm could not succeed with its own entertainment platform. However, on each successive update to iTunes, Apple made iTunes incompatible with Palm's products, forcing Palm to create an expensive update to reintroduce compatibility.

[89] Indeed, the device often sells for much less than what Apple expects consumer will purchase in content from iTunes.

Firms without complementary products do not have the same incentive structure. They neither capture value in their entire portfolio by entry, nor face the same competitive pressures linked to cross-market externalities. Instead, this type of firm is more likely to differentiate its products through superior technical performance than a firm with complementary products, because the former does not offer another source of value to customers.[90] Therefore, I predict:

Hypothesis 1: A firm with products that are complementary to the new market will enter the new market with products that have lower technical performance.

A corollary of this prediction relates to the endogenous relationship between complementarity and entry. If complementarities can allow the firm to profitably target a subset of consumers at lower costs, then complementarities lower the entry threshold. Therefore, firms with complementary products should exhibit a higher propensity to enter the new complementary market. Moreover, if the firm can benefit from or be harmed by network effects in the market, the firm will more likely enter the market to harness the benefits and stymie the threat.

It is possible that the firm with complementarities will enter the market with inferior technical performance for other reasons.[91] However, if it is rational for firms with complementary products to implement a strategy based on compatibility, and thus enter the market low performing products, then, along with support for Hypothesis 1, I should also find evidence that complementary products enhance firm performance. While I do not formally build a theory of a complementary product-performance relationship, using the same logic behind Hypothesis 1, I propose two empirically testable conjectures. First,

[90] For example, Kapoor and Furr (2014) find that start-up entrants into the solar photovoltaic industry choose higher performing technology to differentiate themselves from rivals.
[91] For example, the firms resource base makes it path dependent or the firm.

holding the new product design constant, firms with complementary products will have higher market performance than firms without complementary products. Support for this conjecture would highlight the general benefit of complementarities. Second, firms with complementary products can enter the market with inferior technical performance and achieve at least a similar level of profit (from the new market and through complementary products) as firms that have superior product technical performance but no complementary products. Empirical support for this prediction would underscore the rationality of compatibility-based strategy and explain why highly capable firms may choose to enter new markets in this manner.

Choice of Product Features and Components

When entering a new product market, firms must decide on what features to include in their products. Different features or design parameters can come with various tradeoffs (Ulrich and Eppinger, 2000). For example, to make a race car safer, the designer can include a stronger frame, additional roll bars, and airbags, however, these features will come with a weight penalty, which will reduce speed, handling, and fuel efficiency. Tradeoffs may not only affect technical performance, but also include the absence of another feature. A car can only be fitted with one type of tire at a time; software can be designed to function with only certain operating systems, but by doing so, eliminates its capability to function with others.

When weighing tradeoffs between different features, we might expect a typical firm to choose the bundle of features that it believes consumers will most likely prefer. However, in new markets, firms may not know consumers' exact preferences for different product attributes. In absence of concrete knowledge of consumer preferences, my arguments behind Hypothesis 1 suggests that having complementary products will bear on the firm's product feature choices. To capture the benefits from complementarities, the firm needs to make its new product compatible with its complementary products. The firm may also want to include features that enhance the co-functionality of the products.

Hypothesis 2: A firm with products that are complementary to the new market is more likely to <u>include</u> features in its new market product <u>that function with</u> its complementary products.

While the firm may choose to include features that help capture the benefit of complementarities, such choices may come at the expense of other features. Here, I argue that the firm may exclude features that it has the capability to include for several reasons. In line with the argument behind Hypothesis 1; the firm may want to keep costs low or reduce development time. To achieve this objective, the firm may need to omit features that do not help capture the benefit of complementarities.

Another strategic motivation may play a role in feature choice. The firm may exclude features that co-function with rivals' complementary products, so to decrease rivals' ability to appropriate returns from the firm's product. The firm is likely to do this when it plans to develop a competing complementary product or when the benefit of compatibility with the rival's complementary product is outweighed by the costs of supporting the rival's product. For example, compatibility with a rivals' complementary product could enhance rivals' positive network effects, to the detriment of the focal firm.

Hypothesis 3: A firm with products that are complementary to the new market is more likely to <u>exclude</u> features in its new market product <u>that do not function with</u> its complementary products.

EMPIRICAL ANALYSIS

Empirical Setting

I test my propositions using entry and product design data from the global smartphone market. Smartphones combine features of a mobile phone with features of a computer. Smartphones differ from feature phones in that they have an operating system that can run a variety of software applications.

Smartphones are complex products comprised of many interdependent components. Designing a smartphone involves making many decisions so to achieve both performance (such as calculation speed) and form (such as weight and thinness). A variety of technologically sophisticated firms from different industries entered the market, including current[92] market leaders Apple and Samsung, computer makers Acer and Dell, industrial conglomerates Siemens and Toshiba, and consumer electronics makers LG and Sony.

The smartphone traces its origins back to the IBM Simon Personal Communicator in 1994—a phone that had some limited ability to receive faxes and email. Between 1999 and 2002, several firms, such as Nokia, Ericsson, and Qualcomm, launched phones that included very limited computing ability. However, it was not until the mid-2000s that both advances in mobile chipset technology and the adoption of wireless networks that could support significant data transmissions (e.g. GSM's GPRS service) led to the creation of an actual market for smartphones. At the start of 2005, the smartphone market began to grow rapidly (see Figure 4.1), which intrigued computer and consumer electronics firms that had previously ignored the mobile phone market. Many firms started to develop smartphone development projects in 2005, which led to surge in entry between 2005 and 2009. Therefore, I focus my analysis in this period, when the market is still in the nascent stage.

[92] Based on 2015 sales data.

Note that this period predates the explosion in growth and subsequent maturation of app-based ecosystems that dominate the current smartphone landscape.[93]

Data Sources

To construct my sample, I use data from multiple sources. I collect data on smartphone market entry and product features primarily from two online databases: GSMArena and Phonescoop. GSMArena has been used to create a census of phones and is used by industry participants to track product characteristics (Koski and Kretschemer, 2005; Cecere, Corrocher, and Battaglia, 2015). Patents covering phone design often cite GSMArena data on phone features and design (e.g., US D636364 S1). These two sources combine to provide comprehensive coverage of all mobile phone launches between 1994 and 2015. I supplement the feature data with information from the manufacturers, four other online phone data sites (fonerena.com, gadgets.ndtv.com, mobiles-prices.com, and techradar.com), firms' websites and product brochures, and three technology and trade magazines (PCWorld, PCmag, and CNet). From these sources, I can identify over 200 features and components for each phone.

I collect information on firms' product scope and capabilities using the Corp-Tech database, annual reports, firms' websites, Mergent database, and IBM Research publications. The Corp-Tech database lists technology companies and their products. The directory contains detailed product codes for each firm and is collected directly from the firms and updated on a yearly basis (Lee, 2008; Lee and Lieberman, 2010). Information on firms' participation in wireless communication standards comes from Disclosed Standard Essential Patents (dSEP) Database (Bekkers *et al.*, 2012). I gather data on firm financials

[93] Several major mobile app stores opened in late 2008 through 2010 (e.g. Android Market/Google Play, Blackberry App World, Windows Phone Marketplace, Nokia Store, etc.). This spurred the growth of third-party developers that acted as complementors to different operating systems.

from Compustat and firms' annual reports. I acquire patent data from the U.S. Patent and Trademark Office. Data on firms' smartphone market performance comes from Statista, Inc. (who collects it from Nielsen, IDC, and Gartner) and firms' own records. Data on broadband access by country comes from the International Telecommunications Union (ITU). Because I use multiple different samples in the analysis, I discuss how I form each sample directly prior to the relevant analysis.

Dependent Variables

To test hypotheses regarding products' technical performance, I need to compare the technological aspects of smartphones. I take several approaches to this task. First, I create one all-encompassing measure that captures all the major aspects of the product, such as speed, screen quality, form, and software applications supported. The measure also reflects the tradeoffs inherent in such a complex product. For example, if the smartphone has a large, fast processor, it will be heavier and will use more power. Therefore, as one measure nears the frontier, other measures will likely regress from the frontier. The dependent variable is designed to capture these tradeoffs. Second, I create several measures that capture one or several specific aspects of the product's technical performance, for example, CPU speed or primary camera image quality. I describe these in detail below.

To capture the overall technological sophistication of the product, I create a measure called *Technical Performance*. To calculate the measure, I read over a hundred smartphone reviews and multiple articles on smartphone performance metrics from five different websites and magazines: GSMArena, CNet, PCmag, PCWorld and androidauthority. Using this information, I identify 29 different design elements that capture speed, form, and functionality of the phone and account for the phone's overall performance. I collect the component data from GSMArena and Phonescoop. I describe each of the 29 components of the measure in Table 4.1, and provide basic descriptive statistics for the raw values. For example, *CPU Speed* measures the clock rate of the processor in megahertz, where faster clock rates correlate with quicker calculation times. Other components, such as *Music-Video Features*, capture how many features the phone supports, in this instance, the ability to support music and video content. Typically, as new features arise (such as MP4 audio format) the phone will also support the prior version (e.g., MP3), therefore, counting features will adequately capture the differences between products on the dimension in question.[94]

To summarize the information on various components into one measure, I need a metric that can handle inputs with different scales (e.g., megapixels, gigahertz, and feature count). To accomplish this, I utilize Gower's distance measure (Gower, 1971). For each component, x_{ikt}, I apply a unit set normalization to create s_{ikt}. To create the measure, I take the average of all s_{ikt}. Equations (1) and (2) provide the calculations:

(1) $$s_{ikt} = \left(1 - \frac{\max(x)_{it} - x_{ikt}}{\max(x)_{it} - \min(x)_{it}}\right) w_{it}$$

(2) $$Technical\ Performance_{kt} = \frac{\sum_{i=1}^{I} s_{ikt}}{\sum_{i=1}^{I} w_{it}}$$

Where *i* is a component, *k* is a smartphone, and *t* is a year. Note that *w* takes the value of 1 if any product in year *t* has component x_i, and is 0 otherwise. If no products in year *t* have feature x_i, then x_i is ignored (i.e. *w* is 0 for that *i*). This allows the overall frontier to evolve from year to year, not only on the value of a particular component, but also with the

[94] The measure may overweight the importance of indicator and count variables (such as GPS) relative to continuous measures (such as primary' Camera megapixels). To check how sensitive the measure is to the inclusion of components measured as a binary indictor or count, I reran the calculation in equations (1) and (2), dropping all 13 of these components. The resulting measure was highly correlated with the original measure (0.96). Replacing *Technical Performance* with this new measure does not impact the significance of the results.

addition of new technological components.[95] *Technical Performance* is in [0,1], and would equal 1 only if the product were on the technical frontier for every component. *Technical Performance* measures the aggregate performance of the smartphone relative to other smartphones launched in the same year.[96]

One issue with an aggregate measure is that one must assume how much each component weighs on performance. This is subjective, as different users will weigh dimensions differently. To add some robustness around the measure, I identify several of the main components that effect user experience and are prominently featured in in product reviews. For example, *Data Speed*, describes how fast the firm can download information, such as a webpage or an email. I calculate *Data Speed*, as the phone's speed divided by the maximum speed for phones in the same year. Another example, *Camera MP*, captures the image quality of the main camera; I calculate *Camera MP* as the phone's camera quality divided by the maximum quality for phones in the same year. I also conduct some additional analyses using a weighted version of *Technical Performance*, where the weights come from a hedonic regression of smartphone price on the characteristics that comprise the *Technical Performance* measure. I discuss this further in the additional analysis section.

To test Hypotheses 2 and 3, I identify product features tied to two broad complementary product markets: the market for business software and the market for entertainment content (i.e. music, movie, and games), and create a variable based on each. To decide which features are related to each market, I use product reviews from major technology magazines. I describe the dependent variables and independent variables used in this analysis in more detail later.

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[95] For example, to make video and gaming abilities more complex, separate graphics processor units (GPU) were added in the late 2000s.

[96] Alternatively, I can calculate the dependent variable as the distance from the technical frontier (i.e., distance from max *Technical Performance* in year). All results all robust if I use this alternative calculation.

To analyze the performance conjectures, I use two dependent variables. The first, *Market Share*, is a measure of the firm's global share of sales for that year. In most years, I do not have precise information for firms with less than 1 percent market share, and thus set such firms to 0.5 percent share.[97] The second, *Top Five Performer*, takes the value of 1 if the firm has a *Market Share* in the top five during the year and is 0 otherwise.

Independent Variables

The main independent variable, *Complementary Products*, captures the extent to which the firm has products complementary to the smartphone. A product can be complementary when it creates more value when used in conjunction with the other than used alone (Milgrom and Roberts, 1990). To identify complementary product categories, I take the following steps. First, I attempt to read at least one product review for each firm per year from prominent review sites such as GSMArena, PCWorld, PCmag, and CNets. While I randomly select products to review, many products do not have a formal review article. Instead, I end up with firms' most heavily marketed products, which tend to be reviewed by technology writers.[98] Second, I supplement this information with data from Market Line Research reports, academic literature (Gebauer, 2008), and IBM Research (e.g., Matthews, Pierce, and Tang, 2009). Third, I verify my information through discussions with industry experts and through firms' own documentation (e.g., websites, product brochures).

From this research, I identify two broad types of complementary categories: business software and entertainment applications. Example entertainment complementarities include entertainment platforms (e.g. Apple's iTunes), internet search

[97] Setting firms with unit sales but missing share to 0.5 percent should have little effect as the margin of error will be very small.
[98] This is not a problem because at this stage in the collection process, I am only identifying types of complementary products.

engines, and multi-media software (e.g. Google's multi-media engine, patent US 7,286,823). Example business complementarities include enterprise communication software, operating systems, and custom enterprise software.[99]

After identifying the complementary product categories, I need to map the list not only to firms that entered the smartphone market, but also to firms at hazard of entering the market. To do this, I first map the identified complementary product categories to Corp-Tech database product groups. I use information on group name, subgroups, and discussions with a Corp-Tech database expert to map the information. To verify the mapping, I check known producers of certain products and verify that they map the Corp-Tech product group code. This matching effort results in eight different product groups in the Corp-Tech database. Example complementary products include the following: mobile internet software, local area network software for mobile devices, enterprise systems, audio players, video players, email clients, and search engines.[100] I then match the Corp-Tech product codes to the firms in my sample. Because there is not a clear product code for music and video platforms in the Corp-Tech directory, I use lists of music platforms and firms' annual reports to code the data in each sample accordingly. To calculate *Complementary Products* for each firm, I count the total number of complementary categories in which the firm competes.[101]

Products from all nine complementary categories function in conjunction with the smartphone, but exist separate from the device. This is consistent with my notation of

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[99] Note that my focus is on the nascent stages of the smartphone market, prior to the proliferation of mobile apps.

[100] I list Corp-Tech product group names and give the Corp-Tech code in parentheses: AI Systems (SOF-AI), Communications Systems Software (SOF-CS), File Management Software (SOF-DM), Media and Communication Software (SOF-ME), Office Automation Software (SOF-OA), Email Systems (TEL-EM), Internet Multi-media (TEL-IM), and Internet Search (TEL-IS). As a point of reference, there are 23 Telecom product groups and 33 software product groups in Corp-Tech. Examples of excluded categories include Health Service software (SOF-HL), Financial Management software (SOF-FM). If a financial or healthcare software application was made for a smaller device (like a PDA or smartphone) it would map to SOF-OA or SOF-AI., even if it connected to or functioned with software from the excluded categories.

[101] Complementary Products can take a maximum value of 9.

complementarity. The products also exist prior to the creation of the smartphone market. For example, an entertainment platform hosts music and videos in a separate location and integrates with a phone or device through an application. Conversely, a technological component, such as a microchip, directly integrates with the device, but does not provide value outside of its application in the device, and hence, is not counted as complementary.

Prior literature suggests that resources will affect entry strategy. I control for these resources through several variables. Firms with greater research experience might build superior products, so I control for lagged *R&D* expense.[102] *Phone Patents* captures knowledge relevant to smartphones, and covers patent applications over the past three years in technology categories such as communication technologies, screen technologies, and semiconductors. Table 4.2 provides a detailed list of these groupings. Larger firms may have superior ability to enter new markets with better products, so I control for *Firm Size*, measured as the total number of employees.[103] To capture the firm's knowledge of wireless standards and communications technology, I create a proxy (*Standards Disclosure*) for firm's technologies essential to wireless communication standards. To create *Standards Disclosure,* I use information from Disclosed Standard Essential Patents Database (Bekkers *et al.*, 2012) to calculate the cumulative number of technology disclosures the firm makes to standard setting organizations. Firms with experience in feature phones may hold an advantage in the smartphone market. To control for this (*Prior Feature Phones*), I count the cumulative number of feature phones launched by the firm. In some models, I replace this measure with the number of smartphones (*Prior Smartphones*).[104] *Computer*

[102] Note that R&D will enter most models with enough lag that it should capture spending pre-smartphone development. Thus, I can use it to control for the firm's general research intensity and experience, while avoiding it being directly endogenous in the model. Endogeneity is a concern because my theory suggests that firms may reduce development costs because of compatibility. All results remain the same if I exclude R&D.
[103] Alternatively, I can use total assets or total revenues, all provide similar results.
[104] I do this in panel models where smartphone experience is more relevant. Results are similar using either measure.

Maker, specifically controls for the firm's ability to design computers, and takes the value of 1 if the firm designs personal computers, laptops, mini-computers, servers, mainframes, or super computers. Experience in designing personal data assistants (*PDA*) could improve firms' ability to develop smartphones, as the products have similar properties. *PDA* takes the value of 1 if the firm has experience designing personal data assistants.

Downstream assets may influence firms' entry strategy (Mitchell, 1989). To account for downstream resources that relate to the smartphone market, I calculate several variables using information from Corp-Tech product categories and annual reports. *Distribution Capability*, takes the value of 1 if the firm has a retail presence and the value 0 otherwise. *Manufacturing Capability*, accounts for the firm's ability to make electronic devices and takes the value of 1 if the firm manufactures any electronic parts or components and is 0 otherwise.

I also create several variables to use in selection models and control for potential bias in *Complementary Products*. To account for selection into the market, I collect information on broadband access by country (*Broadband)* from the ITU. To measure diversification, I create two variables. *Business Segment* is the number of business segments listed in Compustat. *Product Breadth* is the number of high-technology product categories the firm competes in per the Corp-Tech database. I also use several financial variables that I describe as necessary.

To control for how the firm's industry might influence behavior, I create controls for industry effects using two-digit SIC codes (*Industry Dummies)*. Wireless standards behind the phone's network can influence some of the smartphone's functionality. I control for this using dummy variables for seven different wireless standards (*Wireless Standards Dummies)*. To control for phone price, I use GSMAarena's price tier variable. This measure places phones in a price tier each year and thus avoids complications that arise from trends in price over time. The price tiers range from 1 to 10.[105] To best control for the price effect, I use dummy variables for price (*Price Tier Dummies*). Finally, I control for phone release year (*Year Entry Dummies*).

I organize the rest of the empirical section as follows: First, I analyze firms' initial product design upon entry into the smartphone market. Next, I analyze firms' product designs in their first three years in the market. Then, I examine how the firms makes feature and component tradeoffs in their product design. Finally, I estimate the effect of complementarities on firm market share in the smartphone market.

Preliminary Analysis

I begin by noting that one puzzle presented at the beginning of the paper—highly capable firms entering with inferior performing products—is present in this context. Of the firms that entered the smartphone market, none of the top five firms by either total revenue, R&D, phone related patents, communications knowledge (as measured by *Standards Disclosure)*, or return on assets, had their initial product designs on the technical frontier. In fact, most had products with technical performance below both the median and the average.[106] Of the top five firms (by each of the aforementioned criteria) that had below average or below median designs, the vast majority had *Complementary Products*, which offers descriptive support for Hypothesis 1.

Next, I plot trends in various product features using data from firms' first three years in the market. The graphs in Figure 4.2 show that products from firms with

[105] To provide some context, on average, price tier 3 equates to 125 euros, price tier 5 is 230 euros, and price tier 8 is 440 euros. Typically, top end phones are in the 7-10 tier and entry-level phones are in the 1-3 tier. If prices are missing, I supplement the GSMArena data with historic price data from fonerena.com, gadgets.ndtv.com, mobiles-prices.com, techradar.com, phonearena.com, or the firm's MSRP information. I then map the price to the GSMAreana price tier.
[106] Using the top five firms on each criterion, I list the number below the average in parentheses: revenue (5), R&D (5), Phone patents (5), Standards Disclosure (5), return on assets (3).

Complementary Products tend to be less sophisticated than products from firms with no *Complementary Products*, which supports Hypothesis 1. For example, data download speed for firms with complementarities lag that of firms without complementarities by an average of 30% between 2006 and 2010 (see Figure 2b).

Table 4.3 provides descriptive for the sample of products from entering firms' first three years in the market. As predicted, *Complementary Products* is negatively correlated with *Technical Performance* (-0.08). Figure 4.3 provides a histogram of *Technical Performance*.

Product Analysis—First Smartphone

I begin my test of Hypothesis 1 by conducting a simple cross-sectional analysis of firms' first product in the market. I only consider firms that entered in the nascent stage of the market (2005-2009). If firms launch more than one smartphone upon entry, I use the smartphone with the highest technical performance, so to best represent the firms' ability to create a high technically performing product. I measure all independent variables in 2005, except for *Complementary Products*, which I measure two years prior so to avoid potential reverse causation. Because *Technical Performance* is continuously distributed within [0,1], I use a fractional logit model (Wooldridge, 2010).

Model 1 in Table 4.4 provides the basic estimate of the *Technical Performance-Complementary Product* relationship. *Complementary Products* has a significantly negative average partial effect[107] (APE) (-0.015; p-value 0.003). Models 2 and Model 3 provide alternative estimates using fractional probit and beta regressions respectively, with similar results.

[107] The marginal effect of variable j in the fractional logit model depends on the value of the other variables. To calculate average partial effect (APE), I take the average impact using the formula, $\overline{g(\boldsymbol{x'\beta})}\ \beta_j$, where j is the coefficient of the variable of interest and g(.) is the logit pdf.

To provide an alternative to the *Technical Performance* measure, I estimate the model using two major technological features as dependent variables: *Data Speed* and *Camera MP* (see Model 5 and Model 6). I measure these dependent variables as a ratio of the products performance on the dimension over the maximum performance achieved by any product that year. For example, I calculate *Data Speed* as a product's data download speed divided by the maximum speed achieved by any product in that year. I find a negative and significant effect for *Complementary Products* in both models, which supports Hypothesis 1.

Because entry is a strategic choice and firms that enter likely believe they can build effective products, I model the firm's entry decision using a sample of firms at hazard of entering the smartphone market. I do not find evidence that self-selection into the market effects the results. However, I find that having one additional complementary products increases the likelihood of entry by roughly 2 percentage points. Firms with complementary products are approximately four times more likely to enter than firms without. This result supports the conjecture that complementarities lower the entry threshold. Second-stage results suggest that *Complementary Products* significantly decrease *Technical Performance*. I discuss the sample selection analysis and display the results in Appendix 4.1.

Product Panel Analysis

Models in Table 4.4 have limited sample size and barely support the inclusion of all necessary controls. To expand the sample, I include all the smartphones released by the firm during its first three years in the market (i.e. a firm-product-year panel). Sources suggest that firms' initial strategy unfolds over three years.[108] I continue to limit the sample

[108] The focus of the paper is on firm's product strategy upon entry into a new market. If the window is too long, I will capture the firm's behavior as an incumbent.

to the nascent period of the market (2005-2009). To account for the product development process, I lag all independent variables except *Complementary Products* two years.[109] *Complementary Products* is calculated two years prior to entry into the market to avoid reverse causality.[110] Note that all results are robust if I include the firm's entire product history (instead of first three years) in the nascent period.

Table 4.5 provides estimates using the firm-product-year panel sample.[111] In Model 2, using the full set of control variables, I find that a negative and significant effect of *Complementary Products* (average partial effect -0.014; z-statistic -6.26; p-value 0.000). To interpret this effect, adding one complementary product decreases *Technical Performance* by approximately two thirds of a standard deviation. To understand what this means for the smartphone's performance, I simulate the effect of going from 0 to 1 on *Complementary Products* on three key elements of phone performance: CPU speed, screen resolution, and camera quality. Take for example a firm with no complementarities that has a smartphone with a 768 megahertz CPU, 268 pixels per inch screen resolution, and 5 megapixel camera. The counterfactual (i.e. treatment of *Complementary Products* equal to one) entails a 528 megahertz CPU, 155 pixels per inch screen resolution, and 3.14 megapixel camera. Therefore, a one-unit increase in *Complementary Products* represents a meaningful decline in technological performance across the three components.

[109] The lag is appropriate because I want to control for knowledge and technology that might be applied to the phone design. For example, patents applications covering technologies at the beginning of the design process might be included in the product, while a patent application that comes several months after the launch of the product will likely have no bearing on product quality.

[110] *Complementary Products* exhibits almost no variation between the pre-entry and the first several years post entry. Thus, *Complementary Products* is identified using variation across firms; however, this is consistent with my theory, which is cross sectional in nature. Of course, this rules out the use of firm fixed effects to suppress unobserved firm-level heterogeneity.

[111] The sample has 52 firms that release approximately four phones per year.

Sensitivity Analysis

The remaining models in Table 4.5 demonstrate the robustness of the result using estimates with alternative dependent variables, all yielding similar results. For example, Model 3 estimates *Technical Performance* using only the five key components that affect the speed of the phone.

Because my theory is cross-sectional in nature, I also rerun the above analysis using a between estimator. I calculate the average of the variables across all product-years and regress the firm's average *Technical Performance* on the average of independent variables. I find robust results (APE -0.02, p-value 0.000). Overall, the results in this section support Hypothesis 1.

I also analyze the sensitivity of my results to entry timing. I split the sample into two: early entrants (firms that entered in the first three years) and late entrants (firms that entered afterwards). I find results consistent with my main model, with the APE for *Complementary Products* -0.01 (p-value 0.000) and APE in late entrant model -0.02 (p-value 0.009). Results are similar if I model each entry year separately.

Selection Issues Related to Complementary Products

Firms with complementarities in their portfolio may make design choices not because of the complementarities, but because of unobservable factors related to their strategy or situation. For example, *Complementary Products* may simply pick up the effect of diversification on product design. Very diverse firms could be more prone to technological path dependence or less flexible in adopting new technologies into their product designs, especially compared to specialist firms. Alternatively, poor-performing firms may diversify in search of better opportunities, and by chance, enter product markets complementary to the smartphone market. These firms might enter the new market with inferior product designs because they lack technological capabilities. While I account for many firm capabilities, some confounding unobservable effect may remain.

Before addressing this concern empirically, I compare firms with and without *Complementary Products* to see if there are any obvious differences (see Table 4.6). Both groups are similar, differing significantly only on the breadth of their product portfolios (*Product Breadth*). Firms with *Complementary Products* tend to have broader product portfolios than firms with no *Complementary Products*.

To address potential unobservable factors in the panel analysis, I use an inverse probability weighted regression adjustment (IPWRA) model (Wooldridge, 2007; Elfenbein, *et al* 2010). This method utilizes information on the likelihood of receiving a particular treatment to create probability weights. I then use these weights in outcome-regression models for each treatment level to calculate a counterfactual so to estimate causal effect of the treatment.[112] This method requires separating the sample into treated and control groups, with *Complementary Products* (measured as 0/1) as the treatment factor. In the first stage, I run a logit regression to estimate the propensity of a firm having at least one *Complementary Products* as a function of observable covariates (I discuss the variables in this model in Appendix 4.2). The inverse of the predicted propensity is then used as a weight in two separate second stage models, one for the treated (firms with *Complementary Products*) and one for the control (no *Complementary Products*). Each second stage model uses a fractional logit regression to create a regression-adjusted estimate for treated and control observations. I specify these second stage models using the same variables as Model 1 of Table 4.5. The parameters of the second stage models control

[112] Two assumptions are needed to derive consistent estimates. First, conditional on observables, the conditional mean of disclosure for treated and untreated (control) firms is independent of the treatment. Second, for similar values of the observables, there are firms that will and will not receive the treatment (e.g. will or will not develop complementary technologies). This second assumption is referred to as the overlap or common support assumption. Together, these two assumptions provide a weak condition for what Rosenbaum and Rubin (1983) call ‘strong ignorability’.

for how each covariate impacts *Technical Performance*.[113] By comparing the computed mean values from each of the treatment level models, I can compute the average treatment effect on the treated (ATET), which is my estimate of the causal impact of *Complementary Products* on *Technical Performance*. This estimation is robust to misspecification of either the first stage model or second stage model (Wooldridge, 2007).

In Model 1 of Table 4.7, I use the propensity model from Model 1-Table B1 (in Appendix 4.2). The propensity score model predicts the likelihood of having *Complementary Products* well (Pseudo R-square of 0.54). In Model 1 of Table 4.7, I find a negative and significant ATET (-0.07; p-value 0.037). Model 2 reports ATET using the flexible form propensity score model (see Appendix 4.2, Model 2-Table A4.2.1; Pseudo R-square of 0.64). ATET is negative (-0.09) and significant (p-value 0.04). The results strongly support Hypothesis 1.

Although the propensity score models do a good job of predicting the likelihood of having complementarities, I can increase their effectiveness by constraining the sample to a set of very similar firms (Iacus, King, and Porro, 2011). To further control for potential bias, I combine the IPWRA model with a pre-model Coarsened Exacting Matching procedure. Coarsened Exacting Matching (CEM) is a nonparametric technique that allows the user to coarsen the data—effectively placing each observation into a single stratum

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[113] All three equations have logit specifications and can be thought of as a system of exactly identified equations. I estimate parameters of the propensity model using the score equations from the quasi-maximum likelihood estimator (QML). The parameters of the two second stage models are estimated using the score equations from the weighted QML estimator. The exact specifications are as follows. Let the first stage logit estimate of the propensity of the firm having complementary technologies be given by $p(z_i, c_i, \hat{\gamma}) = \left[\frac{g(z_i\hat{\gamma}')\,[\tau_i - G(z_i\hat{\gamma}')]}{G(z_i\hat{\gamma}')[1-G(z_i\hat{\gamma}')]}\right] z_i$ where the z variables are the predictors of the treatment effect, c_i is a binary indicator of the treatment, $G(z)$ is the cumulative distribution function (cdf) for the logit, and $g(.)$ is a probability distribution function given by the partial derivative of the cdf with respect to z. From the propensity score model, I derive the inverse probability weight, $w_i(c)$, which is equal to the inverse of $p(z_i, c_i, \hat{\gamma})$ in treated model and the inverse of 1- $p(z_i, c_i, \hat{\gamma})$ in the untreated model. The conditional outcomes for the treated and untreated models are estimated using the following equation: $u_c\{x_i, \hat{\beta}_i, w_i(c)\} = w_i(c)c_i\left[\frac{g(x_i\hat{\beta}')\,[c_i - G(x_i\hat{\beta}')]}{G(x_i\hat{\beta}')[1-G(x_i\hat{\beta}')]}\right] x_i$. I do not report the treated and untreated model output, as interpreting their coefficients do not directly shed light on the hypotheses.

based on a pre-specified set of variables (Blackwell, Iacus, King, and Porro, 2009). I discard any strata that only contain treated or untreated observations. CEM increases the effectiveness of propensity score models because it reduces outliers and increases common support, which enhances the propensity score model's predictive ability and reduces potential bias (Iacus *et al.*, 2011).[114]

To create the sample for Model 3 of Table 4.7, I begin by running a CEM using quartile breakpoints for three key variables, *R&D*, *Product Breadth*, and *Patent Scope*.[115] I then only retain strata that contain both treated and untreated observations.[116] This reduces the sample to sets of treated and untreated firms that are very similar on these three dimensions. With this new sample, I then run the IPWRA model (per the specification in Model 2). The predictive ability of the propensity score model increases, with Pseudo R-square up 0.18 to 0.82. Using the sample, I find a negative and significant ATET (-0.15; p-value 0.02), which supports Hypothesis 1.

Overall, as I do more to suppress endogeneity concerns, the estimated effect of complementarities become more economically meaningful while remaining statistically significant.

Product Features and Components Choice Analysis

In this section, I analyze how the type of complementary products the firm has in its portfolio influences its choice of new product features. I begin by creating two new

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[114] Note that I am not using CEM weights, instead, I use CEM to select groups of treated and untreated observations that are similar on the defined dimensions. I then use this sample in the IPWRA analysis.
[115] To demonstrate the benefit of the CEM procedure, one usually compares the Multivariate L1 statistic before and after the CEM procedure. The Multivariate L1 statistic is a multivariate version of the taxicab distance measure (see Iacus, King, and Porro, 2008). Higher values suggest greater imbalance. The pre-CEM Multivariate L1of the sample on the three variables is 0.76, the post-CEM is 0.25, representing a substantial reduction in imbalance between treatment and control groups.
[116] For example, the first stratum is comprised of observations that fall into the bottom quartile on all three variables. I drop all observations in this stratum unless there are both treated and untreated observations

independent variables. The first, *Complementary Products-Business*, takes the value of one if the firm's complementary products are business oriented[117] and zero otherwise. The second, *Complementary Products-Entertainment*, takes the value of one if the firm's complementary products are entertainment oriented, and zero otherwise.

Next, I create several dependent variables that capture either business related or entertainment related functionality, but not the other. The first business related dependent variable, *Business Features*, provides a count of business related features. To calculate *Business Features*, I sum *Business Features Other* and *Business Enterprise Software* (see Table 4.1 for these variable definitions). *Business Features* include the ability to read and write text word documents, spreadsheets, presentations, pdfs, print from the phone, send and receive faxes, use email client software, etc. As an alternative measure, *Full Office Suite*, takes the value of 1 if the phone can view and edit spreadsheets, documents, and presentations.

I also include four entertainment related dependent variables. *Camera Features* captures features that enhance the photography capability of the phone, such as smile detection (see Table 4.1). *Screen Performance* summarizes the smartphones screen quality and functionality.[118] I base the measure on the idea that better screen quality is preferred for viewing entertainment content such as videos or games. *Sound & Video Features* counts the number of sound features and browser features related to watching video or listening to music (the measure sums *Browser Features* and *Music/Video Features* from Table 4.1). Finally, *Video Camera* takes the value of one if a video camera is included and zero otherwise.

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[117] Business oriented complementary products categories include Communications Systems Software, File Management Software, Office Automation, and Email Systems. Entertainment oriented product categories include Internet Multi-media, Internet Search, and Music/Media Platforms.

[118] The features included in the calculation are size of the screen in inches, screen to body ratio, resolution in ppi, number of colors, and whether it has a special protective glass. To summarize the information, I use Gowers distance measure, the same formula used to calculate *Technical Performance*.

Table 4.8 provides estimates of these models using the same sample and set of control variables as used in Table 4.5. I begin by analyzing the business related dependent variables. In Model 1, I regress *Business Features* on the two complementary product variables and controls using a pooled negative binomial model.[119] *Complementary Products-Business* is positive (APE 0.512) and significant (p-value 0.000), which supports Hypothesis 2. *Complementary Products-Entertainment* is negative (APE -0.414) and significant (p-value 0.000), which supports Hypothesis 3. Firms with business related complementarities include significantly more business-related features in their smartphone designs, while firms with entertainment related complementarities include significantly less.

Model 2 (*Full Office Suite* as dependent variable) yields similar support for both Hypothesis 2 and Hypothesis 3. Having business related complementarities increases the likelihood of including a *Full Office Suite* in the smartphone by 17 percentage points, while having entertainment related complementarities decreases the probability by 31 percentage points.

Model 3-6 estimate firms' choice of entertainment related features. Model 3 displays the estimates for *Camera Features*. I find a positive and significant effect for *Complementary Products-Entertainment* (APE 0.484; p-value 0.001), which supports Hypothesis 2; and a negative effect, significant at the 10% level for *Complementary Products-Business* (APE -0.50; p-value 0.062), which supports Hypothesis 3. In the model for *Screen Performance* (Model 4) I find a positive and significant effect for *Complementary Products-Entertainment* and a negative and significant effect for Complementary *Products-Business*, which supports both hypotheses.

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[119] Note that there is no over dispersion so the model can be reduced to a Poisson specification. A Pooled Poisson model yields the same results.

I find mixed results in Models 5. The model of *Sound & Video Features* (Model 5) shows that a negative and significant *Complementary Products-Business,* which supports Hypothesis 3. However, *Complementary Products-Entertainment* is not significantly positive. Firms without complementarities began to increase their sound and video features mid-way through the sample period as third party music and video content providers arose. This may explain the insignificant effect of *Complementary Products-Entertainment*.

In Model 6, I find entertainment related complementary products increase the likelihood of video camera inclusion by 21.3 percentage points (0.213; p-value 0.001 for *Complementary Products-Entertainment*). I find a negative but insignificant effect for *Complementary Products-Business*. Video ability, while not widely included in smartphones from firms with business-related complementarities, was not entirely absent.

The analysis in this section demonstrates that firms include feature and components that fit with their complementarities, which supports Hypothesis 2 and 3. To tie back to the findings in the previous sections, omission of features that do not function with their complementarities only account for a portion of the lower *Technical Performance*. I want to emphasize that firms with complementarities do significantly lag firms without complementarities on many other major component performance metrics.

Firm Performance Analysis

In this section, I investigate the relationship between competition of complement products and market performance. From my theoretical argument, I conject that holding technical performance of the new product constant, complementarity provides a benefit in market competition, thus should enhance firm performance. While this may not be a surprise, finding support for this conjecture will underscore the value firms gain in a new market by having complementary products.

To control for the technical performance of the firm's products, I calculate the firm's average *Technical Performance (Average Technical Performance)* across all its smartphones released in year *t*.[120] I then estimate both the impact of *Average Technical Performance* and *Complementary Products* on *Market Share* simultaneously using a fractional logit regression. In Model 1 of Table 4.9, I estimate the effect of *Average Technical Performance* and *Complementary Products* without controlling for other relevant resources. I find that *Complementary Products* is positive (APE 0.01) and significant (p-value 0.013), and that *Average Technical Performance* is positive (APE 0.213) and significant (p-value 0.039). However, once I control for firms' resources (Model 2), *Complementary Products* stays positive (APE 0.044) and significant (p-value 0.019), while *Average Technical Performance* stays positive (APE 0.056), but becomes statistically insignificant (p-value 0.591). Adding one complementary product increases market share by almost 5 percentage points.

To make the comparison more precise, I match firms with and without complementary products based on their *Average Technical Performance* across all its smartphones released in year *t*. I then use a nearest-neighbor matching model, matching firms with complementary products to one or more firms without complementary products based on *Average Technical Performance* and *Year*.[121] I find that firms with complementary products have 4.30 percentage points greater market share, and that the difference is statistically significant (p-value 0.000).

The prior analysis assumes that there is no selection effect related to having complementarities that might cofound the market share analysis. To suppress potential selection effects, I use a nearest-neighbor matching model to match firms based on factors

[120] Results remain the same if I use a firm's maximum *Technical Performance* (i.e. best performing phone) in year t.
[121] I match the firms with complementary products to firms without based on the lowest Mahalnobis Distance on the matching variables.

that affect the likelihood of having *Complementary Products*. To create counterfactuals for the firms with *Complementary Product*, I match each firm with *Complementary Products* (i.e. 'treated' firm) to firm(s) without (i.e. 'control' firms) using the following variables that predict the likelihood of having *Complementary Products* or that might otherwise influence *Market Share*: *Firm Size*, *Business Segments*, *Product Breadth, Patent Scope, R&D, Firm Size, PDA Manufacturer,* and *Year*.[122] To suppress differences in *Average Technical Performance*, I run the procedure on two samples. The first sample is constrained to firms with below median *Average Technical Performance*, while the second sample is constrained to firms with above median *Average Technical Performance*. In the low *Average Technical Performance* sample (Model 1 of Table 4.10), I find that the ATET is positive (5.71 percentage points) and significant (z-statistic of 4.66). I find similar results in the high technical performance sample (Model 2). These results suggest that, accounting for product technical performance and suppressing some of the endogeneity related to complementary products, conditional on entering the market, complementary products have a positive impact on market share in the new market.

My theory also suggests that firms with complementary products can enter the market with inferior technical performance and achieve at least a similar level of profit (from the new market and through complementary products) as firms that have superior product technical performance but no complementary products. To adequately test this conjecture, I need to observe profits, both in the new market and in the complementary

[122] To apply the method, I use a binary version of *Complementary Products*. Treated (untreated) firms are ones with *Complementary Products* equal to 1 (0). The idea is to create a counterfactual for treated firm using almost identical untreated firm(s), and compare then compare *Market Share*. To create the counterfactual, I match control firms to the treated firm using a set of variables that I describe in the text. I match the treated firm to a minimum of one 'nearest neighbor' untreated firm within the set, based on the lowest Mahalnobis Distance on the matching variables. Upon creating these matches, I compute the bias-adjusted average treatment effect on the treated (ATET) (Abadie and Imbens 2011). This ATET essentially compares *Market Share* between each treated firm and its computed counterfactual.

markets. Unfortunately, I am unable to observe product level profits at all and do not possess systematically collected data on complementary market performance. Using *Market Share* to compare performance in the new market severely restricts how I can interpret the results. A firm with complementary products could have low market share in the new market, but entry into this market allows it to be very profitable in the complementary market. Therefore, using *Market Share*, I can find empirical patterns consistent with the conjecture. However, lack of a positive *Market Share* effect does not necessarily refute the conjecture.

With this major caveat in mind, I conduct the following test. First, I create a treated group comprised of firms with inferior products (below the median *Average Technical Performance* in year *t*) that also have *Complementary Products*. Next, I create a control group of firms with superior products (above the median *Average Technical Performance* in year *t*) that do not have *Complementary Products*. Then, I perform a basic *t*-test and find that the difference in means between the two groups (treatment minus control) is 3.45 percentage points (z-statistic of 2.72). On average, firms with inferior technical performance and *Complementary Products* have higher market share than firms with superior technical performance but no *Complementary Products*. To suppress selection effects, I use the nearest-neighbor matching model, matching on the same variables as in Model 1 and 2 of Table 4.10. In Model 3, I find a positive and significant ATET (9.29; z-statistic of 4.10). Therefore, the firm with products that exhibit inferior technical performance but has at least one complementary products has a 9.29 percentage point greater *Market Share* than it would have had if it competed with a superior product and no complementarities instead.

All results in this section remain robust if I use *Top Five Firms* instead of *Market Share*. Overall, the results demonstrate that competing on compatibility positively affects market share. Note that market share is a conservative measure of how complementarities affect the firm's overall performance because market share in the new market does not account for the additional increase in profits resulting from the increased sales of complementary products.

Identifying Mechanisms

I proposed two broad reasons that explain the *Complementary Product-Technical Performance* relationship: (1) firms use a compatibility strategy (2) complementarities induce the firm to choose speed to market over product performance. Firm performance results support the viability of compatibility as a strategy.

To provide evidence for (2), I run both a Cox proportional hazard model and an exponential survival model to identify the effect of complementarities on speed of entry (using the same variables from the first stage regression in Table 4.1A.2 of Appendix 4.1). In both models, I find that complementarities increase entry speed, which is consistent with the idea that firms want to enter early to benefit from network effects. However, if firms enter behind the technical frontier only to take advantage of early entry, then there is no reason that capable firms should continue to build products with inferior technical performance in subsequent periods. Comparing Table 4.5 with Table 4.4, the effect of *Complementary Products* on *Technical Performance* is not significantly different. If firms were only compromising *Technical Performance* initially, I would expect products to increase in relative performance over the first several years and the negative relationship between *Complementary Products* on *Technical Performance* to weaken.

To probe the effect further, I extend the three-year sample out an additional three years. In the six-year sample, I continue to find a negative effect of *Complementary Products* on *Technical Performance*. To avoid potential selection effects, I run a cohort analysis, using only firms that were in the market in 2005, and find that the APE of *Complementary Products* on *Technical Performance* is -0.023 and significant (p-value 0.000). Thus, evidence suggests that firms employ a strategy based on compatibility between the new product and complementary products. While I cannot completely rule out that firms may tradeoff technical performance for a quicker time-to-market, this mechanism alone does not appear to explain the empirical results.

Additional Analyses

My main dependent variable, *Technical Performance*, does not account for how users might weigh different smartphone components or attributes differently. To suppress this concern, I use a hedonic pricing regression to approximate the marginal willingness to pay for each characteristic (Rosen, 1974). I then use this information to weight the elements of *Technical Performance*, and then run the same specified regressions as Model 1 and Model 2 of Table 4.5. To create the weights, I regress price on the unit set normalization of all components (i.e. all the s_{ikt} from equation 1). I apply the normalization so that coefficients for all components are in the same unit. The coefficient for a component can be thought of as the marginal willingness to pay for being close to the frontier on the component. Because of multicollinearity, some components yield a negative price, so I drop them from the model.[123] Using only the components with positive coefficients, I create a willingness-to-pay weighted *Technical Performance.* Rerunning Model 2 of Table 4.5, I find that adding one additional complementary product reduces *Technical Performance* by just under 10 percent (p-value 0.019). Results are robust when using the weighted dependent variable.

[123] Camera Primary MP, Camera Secondary MP, CPU Speed, Screen Protection, RAM, Scree-to-Body Ratio, Screen Size, Business Enterprise Software, Business Features Other all had positive coefficients.

Prior literature finds that firms may view entry and technology choices differently in a new market when they make a substitute product (Conner, 1988; Mitchell, 1989). To avoid cannibalizing sales, firms with substitute products may limit the functionality of their new product. In the smartphone context, firms' that made a PDA could face similar incentives, which if they also have complementary products, could bias the analysis. However, in the main design models (Model 2 of Table 4.5), the *PDA* indicator variable is positive and significant, signaling that experience with PDAs benefits firms' designs. Rerunning Model 2 on only firms that made a PDA, I continue to find negative and significant results for *Complementary Products*. While PDA design experience benefits the firm's smartphone design, having *Complementary Products* tends to induce the same strategy—lower technical performance and a reliance on complementarities.

Successful firms with complementary products, such as Apple, could potentially skew the results. I drop Apple and rerun all analyses shown in the paper and results are robust. Results remain robust if I drop any one firm in the sample.

Another concern might be that firms competing only on price and not on compatibility drive the negative effect of *Complementary Products* on *Technical Performance*. To address this concern, I begin by noting that across nine of the ten price tiers, there are phones from firms with and without *Complementary Products*. I also use the price tier fixed effect (see Table 4.5 for example), which allows me to model within price tier. If I split the sample at the middle (fifth) price tier and rerun Model 2 of Table 4.5, I find that the effect of *Complementary Products* on *Technical Performance* is negative and significant in both the high price and low price subsamples.

It is possible that firms with complementary products only attain high market share through greater marketing spending. This is consistent with the notion that firms with complementary products are diversified marketing-centric conglomerates that target the mass market, while firms with superior designs are boutique technology specialists. However, evidence does not support this notion. Results from Table 4.6 show that both sets of firms are similar in size. Intangible assets (which account for brand value) are very similar across both sets of firms. While I only have data on advertising or selling and general administrative expenses for 60% of firms, I find no statistical difference between the two sets, with advertising spending slightly larger and selling expenses slightly lower for firms with complementary products. In addition, both sets of firms compete in a similar fashion and target the same customers in other markets in which they compete.

Complementarities could be negatively related to technical performance because firms with marginal technological resources are induced to enter the market to potentially take advantage of their complementarities. Such firms would not otherwise enter the market, because competing on their technological resources alone would not yield a positive expected profit. While I acknowledge that this could be the case in some instances, empirical evidence supports the notion that some firms with high technological resources *choose* to compete on compatibility. First, I find basic evidence that highly capable firms—strong prior financial performance, large patent totals, high R&D spending, significant communications industry knowledge—enter the market with very low technical performance. Presumably, these firms could compete on the frontier. Second, controlling for many variables related to capabilities, I find strong support for the negative effect of complementarities. Third, I show that firms with inferior technical performance and complementary products perform better in the smartphone market in terms of market share than firms with only superior technical performance. While I cannot rule out that firms with marginal capabilities enter because they have complementary products, the evidence does not support this explanation.

One concern is that consumers choose smartphones based on operating systems, and that firms' operating system choice correlates with *Complementary Products* in a way that cofounds my market share performance estimates. To account for this possibility, I rerun the performance analysis on two subsamples. The first subsample is comprised of firm-year observations in which firms primarily used Google's Android operating system. The second subsample includes all firm-year observations for firms primarily using non-Android operating system (i.e. iOS, Symbian, Windows Mobile, etc.). In both subsamples, firms with low *Technical Performance* and *Complementary Products* outperformed firms with high *Technical Performance* and no *Complementary Products.* Estimates of *Complementary Products* in both regressions remained positive and significant. Conclusions remain the same when accounting for the operating system.

I argue that firms strategically choose to exclude some components that do not function with their complementary products. However, firms may simply lack the capabilities to do so, which partially undermines my logic behind Hypothesis 3. I note that more than half of the firms with business-related complementarities that excluded camera features concurrently produced a digital camera. Similarly, about half the firms that exclude a full office suite or sound features produced other products that included such features. Sound software and mobile office software could be acquired in the typical smartphone producers supply chain. Take Hewlett Packard for instance. Hewlett Packard's first smartphone release omitted a camera altogether, while subsequent releases were well behind the curve in terms of camera features. At the same time, they designed and manufactured had digital cameras. Hewlett Packard also include most of the sound and video features in its laptops and desktops that it omitted from its smartphones. Overall, evidence for why firms with complementarities excluded features is more consistent with the strategic decision interpretation than with a lack of capabilities or access interpretation.

DISCUSSION

In this paper, I suggest that a firm's position in other markets in the ecosystem influences its product strategy in nascent markets. The main message is that we need to account for how the firm is applying its existing capabilities in these markets, as cross-market complementarities will affect product development decisions. Firms that can benefit from complementary products are more likely to enter a new market with products exhibiting lower technical performance relative to firms without complementary products. In addition, firms will tradeoff features based on whether they function with their complementary products.

My empirical results support these predictions. Firms with complementarities build products with significantly lower technical performance. I use various measures of a product's broad technical performance as well as specific attributes (e.g. speed, camera quality, etc.) to demonstrate the robustness of the core finding. My results remain robust as I attempt to suppress endogeneity related to selection into the market or selection into complementarities. Support for my feature tradeoff hypotheses also support my overall argument. Firms strategically design new products with their complementarities in mind.

I also provide some tentative evidence that complementarities impact market share in the new market. To better investigate performance, however, I need profit information on products in both the new market and complementary markets. Employing such data could allow for a more adequate test of whether the firm should rely on complementarities and enter behind the frontier when it could choose a different strategy. Moreover, I cannot rule out the possibility that differences in performance in the new market will disappear once I account for entry.

Research on how entry into one market affects performance in complementary markets can provide further support for my theory. Firms that enter the new market should experience a positive benefit in complementary markets relative to other competitors that do not enter. Analysis across multiple complementary market-new market cases could explore the heterogeneity in cross-market complementarities, compare demand and supply side complementarities, and derive more precise boundary conditions. Research in this direction could add to our knowledge of diversification and product portfolio management as well as better connect research on product design to the corporate strategy literature. I leave this to future study.

My theory differs from other perspectives existing in the literature. Cognitive views suggest that the firm, when faced with uncertainty, may select features based on its industry peer group. I separate my logic by controlling for industry and then showing that within the peer group, firms intentionally select features that correspond to their complementary products. Similarly, a firm's resource base may cause it to be inert, which could influence its entry strategy. I suggest and find that firms with substantial overlap in their resource base may differ in their product strategy because of even one potentially complementary product, which makes the inertia hypothesis less plausible in this context.

Furthermore, supply-side complementarities, either upstream economies of scope or downstream commercialization assets, could affect product strategy. However, neither supply-side mechanism suggests that the firm will exclude features in its new market product that do not function with its complementarities, especially when it includes these features in products in other markets. Empirical evidence is not consistent with supply-side interpretations.

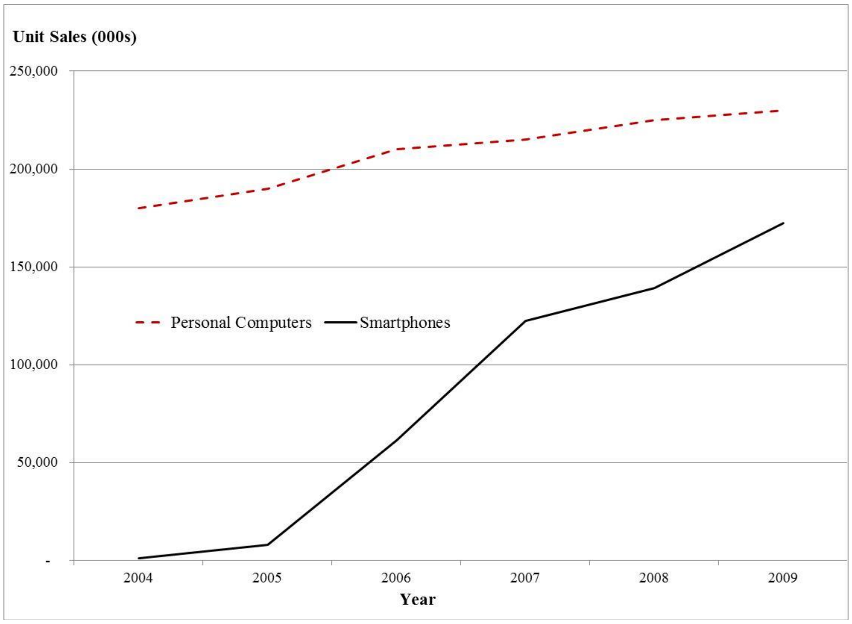
It is worth reemphasizing that my arguments in this paper concern product design in a nascent market, prior to the formation of easily observable consumer preferences and well defined market segments. As a market matures, consumers' preference for certain features become known and markets segment. I would not expect a firm to release products that do not meet certain levels of technical performance for the segment that they target. Therefore, the usefulness of my theoretical argument will likely diminish as the market becomes more mature.

However, the market segmentation process can be linked with my argument. Market segmentation may occur as firms attempt to capture cross-product complementarities. Firms, by designing their new market products to serve their customers currently using their complementary products, initiate the segmentation process.

CONCLUSION

To conclude, my findings highlight the importance of taking a systemic perspective of the firm's portfolio. Firms with complementarities have a different set of incentives than firms without complementarities. Complementarities in the firm's portfolio not only improve success in the new product market, but also offer additional means to appropriate value from market entry, and thus are a valuable resource. They also provide a useful contingency to explain why otherwise similar firms may enter the market at different times, choose different technological trajectories, grow a new market by targeting non-typical customer segments, and perform differently under a variety of circumstances. Accounting for complementarities in product design helps provide a more complete understanding of a firm's entry strategy and how such entry fits into the its overall strategy. Doing so, I contribute to the literature on market entry, product design, and complementarities.

Figure 4.1. Worldwide smartphone sales trend



Data sourced form Gartner, IDC, and Wonk.

Table 4.1. Smartphone specifications and features for technical performance calculation

Descriptives For A Sample of Smartphones From Firms' First Three Years In Market.

Design Element	Description	Mean	Standard Deviation	Max
Data Speed (megabytes per second)	Data download speed., a function of the network and the communication technology inside phone.	9.73	16.54	150
CPU Speed (clock rate in megahertz)	Measure of processor performance	921	506	2,500
CPU Core (count)	Number of processor cores.	1.00	0.85	2
RAM (megabytes)	Random-access memory.	795	7,678	256,000
Graphics Processor (indicator)	Does phone have separate graphics processor	0.73	0.45	1
Memory Storage Included (megabytes)	Total memory capacity included at sale	18,150	15,812	32,000
Memory Expansion (megabytes)	Total expandable memory	23,419	22,412	128,000
Absolute Screen Size (square inches)	Total screen size, bigger screens are desirable	3.70	1.16	7
Screen to Body Ratio (%)	Proportion of body that is made up of screen.	47.74	19.19	100
Screen Resolution (pixels per inch)	Resolution in pixels per square inch, measures quality of screen	212.17	78.39	534
Screen Color (thousand)	Greater number of colors, the better the image quality	7,245	7,942	16,000
Camera Primary (megapixels)	Image quality of main camera	5.047	3.86	23.79
Camera Secondary (megapixels)	Image quality of secondary camera	0.938	1.71	16
Camera Features (count)	Features: autofocus, red eye detection, rotating lenses, LED flash, dual LED flash, optical zoom, smile detection, geo-tagging, panorama ability	2.34	2.05	7
Video Quality (width resolution of pixels)	Measures video's resolution	654	939	3840
Browser Features (count)	Count of different formats handled, which include: HTML, WAP, XHTML, Flash, Java	2.20	1.50	5
Weight of Phone (grams)	Lighter the phone, the more desirable	108.34	60.43	375
Standby Time (hours)	Number of hours phone can be on without use before battery is depleted	269	208	1,500
Talk Time (hours)	Number of hours phone can be used in talk mode before batter is depleted	379	339	3,420
Music-Video Features (count)	Count of features: has music player, high end sound (Dolby), number of audio/video formats handled, (AVI, AAC, SS, AACP, AMP, AMR, AACPP, EAACP, HIFI, M4A, MFI, MPEG4, MP3, MP4, VDO, WAV, WMA)	5.52	1.48	9
Business Enterprise Software (indicator)	Includes package with advanced word processing, spreadsheet, presentation, and email client software	0.16	0.37	1
Business Features Other (count)	Count of other features: fax ability, pdf reader, direct print ability, projector, document reader, can handle customized java applications, can sync with PC	0.65	0.49	2
Advanced Features (count)	Count of features: predictive text, photo editing, QR reader, specialized social media applications, voice control and speech recognition	0.84	0.58	3
Basic Features (count)	Count of features: WLAN, Bluetooth, radio, USB, 3mm jack, wireless charging, flashlight, calculator, calendar, optical character recognition, organizer software)	4.63	1.01	7
Message Features (count)	Message features: ams, ems, smtp, im, push mail, email, rss, sms, specialized message application	2.02	0.29	4
GPS (indicator)	Contains GPS ability	0.72	0.44	1
Health Application Ability (indicator)	Has sensors for health based apps (like step counting and heart monitoring)	0.002	0.04	1
Television Receiver (indicator)	Has Digital TV service	0.05	0.21	1
Advanced Screen Protection / Glass (indicator)	Has specialized protective glass	0.13	0.34	1

Data range from 2005 to 2010 and include smartphones for firms' first three years in the market. Weight is reverse coded in the calculation so that lighter is better.

Table 4.2. Details on phone-related patent calculation

Variable	Description	Technology Class	Variable	Description	Technology Class (nclass)
Hardware Patents:			Screen Patents:		
	Electrical computers: arithmetic processing and calculating	708		Computer graphics processing and selective visual display systems	345
	Electrical computers and digital processing systems: multicomputer data transferring	709		Incremental printing of symbolic information	347
	Electrical computers and digital processing systems: processing architectures and instruction processing (e.g., processors)	712		Liquid crystal cells, elements and systems	349
	Electrical computers and digital processing systems: support	713	Photo Patents:		
Communications Patents:				Image analysis	382
	Wave transmission lines and networks	333		Photography	396
	Communications: electrical	340		Electrophotography	399
	Communications: directive radio wave systems and devices (e.g., radar, radio navigation)	342	Audio Patents:		
	Communications: radio wave antennas	343		Demodulators	329
	Facsimile and static presentation processing	358		Amplifiers	330
	Communications, electrical: acoustic wave systems and devices	367		Oscillators	331
	Multiplex communications	370		Modulators	332
	Error Detection/Correction and Fault Detection/Recovery	371		Electrical audio signal processing systems and devices	381
	Pulse or digital communications	375		Coded data generation or conversion	341
	Telephonic communications	379			
	Optical waveguides	385			
	Telecommunications	455			
	Data processing: speech signal processing, linguistics, language translation, and audio compression/decompression	704			
Semiconductor Patents:					
	Semiconductor Device Manufacturing: Product	437			
	Semiconductor device manufacturing: process	438			
	Superconductor technology: apparatus, material, process	505			
	Data processing: design and analysis of circuit or semiconductor mask	716			

Technology classifications come from United States Patent Office and National Bureau of Economic Research.

Figure 4.2. Comparing firms with and without complementary products on the technical performance of various smartphone features

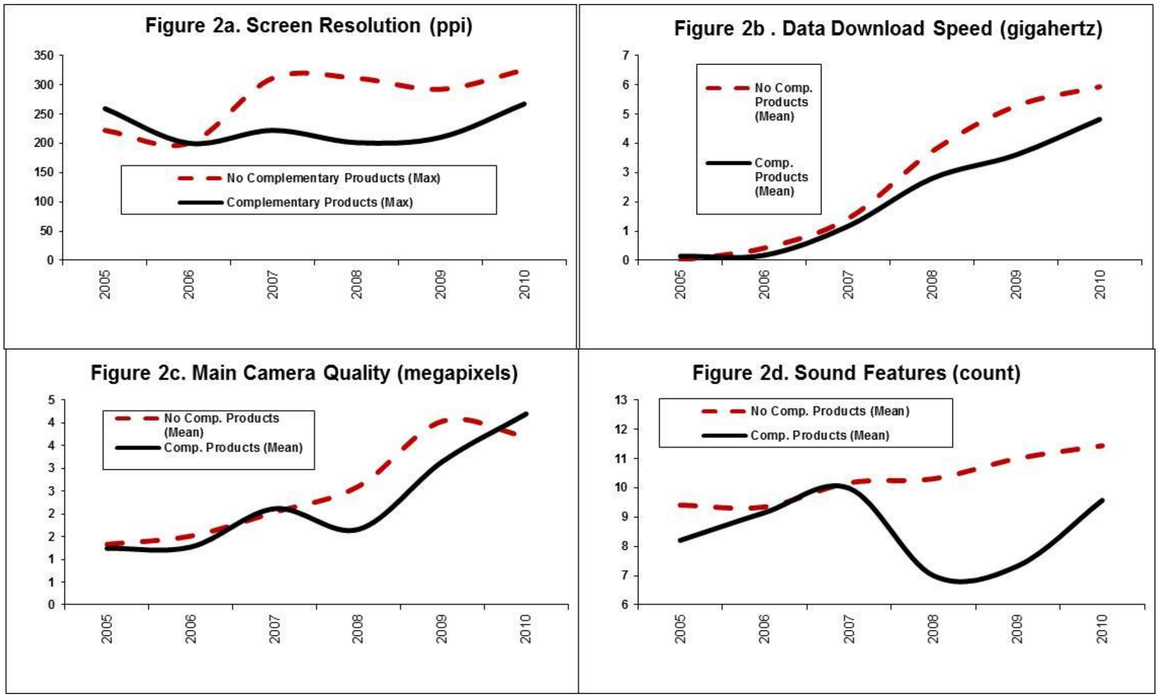


Table 4.3. Descriptive statistics and pairwise correlations for product design sample

	Variable	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Technical Performance	0.25	0.09	1												
(2)	Complementary Products	0.59	0.97	-0.08	1											
(3)	Firm Size	69.97	63.95	0.16	-0.07	1										
(4)	R&D	1,784	2,077	0.19	0.29	0.59	1									
(5)	Phone Patents	108.49	354.87	-0.21	0.24	0.17	0.28	1								
(6)	ln(Standards Disclosures)	2.15	2.76	-0.21	0.22	0.15	0.46	0.24	1							
(7)	Prior Feature Phones	31.35	43.80	-0.20	-0.09	0.15	0.34	-0.08	0.41	1						
(8)	Distribution Capability	0.00	0.06	0.05	0.29	-0.07	-0.06	-0.02	-0.03	-0.06	1					
(9)	Manufacturing Capability	0.76	0.43	0.04	0.05	0.09	0.21	0.10	0.22	0.20	0.02	1				
(10)	Computer Maker	0.36	0.48	0.24	-0.15	0.27	-0.03	-0.08	-0.46	-0.23	0.08	0.26	1			
(11)	PDA	0.48	0.50	0.34	0.16	-0.13	0.00	0.29	0.01	-0.28	0.06	0.32	0.22	1		
(12)	Business Segments	3.38	2.40	0.31	0.06	0.67	0.58	0.14	0.21	0.22	0.03	0.14	0.10	0.13	1	
(13)	Product Breadth	7.06	5.52	0.16	0.62	0.29	0.51	0.23	0.34	-0.01	0.23	0.22	-0.02	0.25	0.35	1

Figure 4.3. Histogram of *Technical Performance*

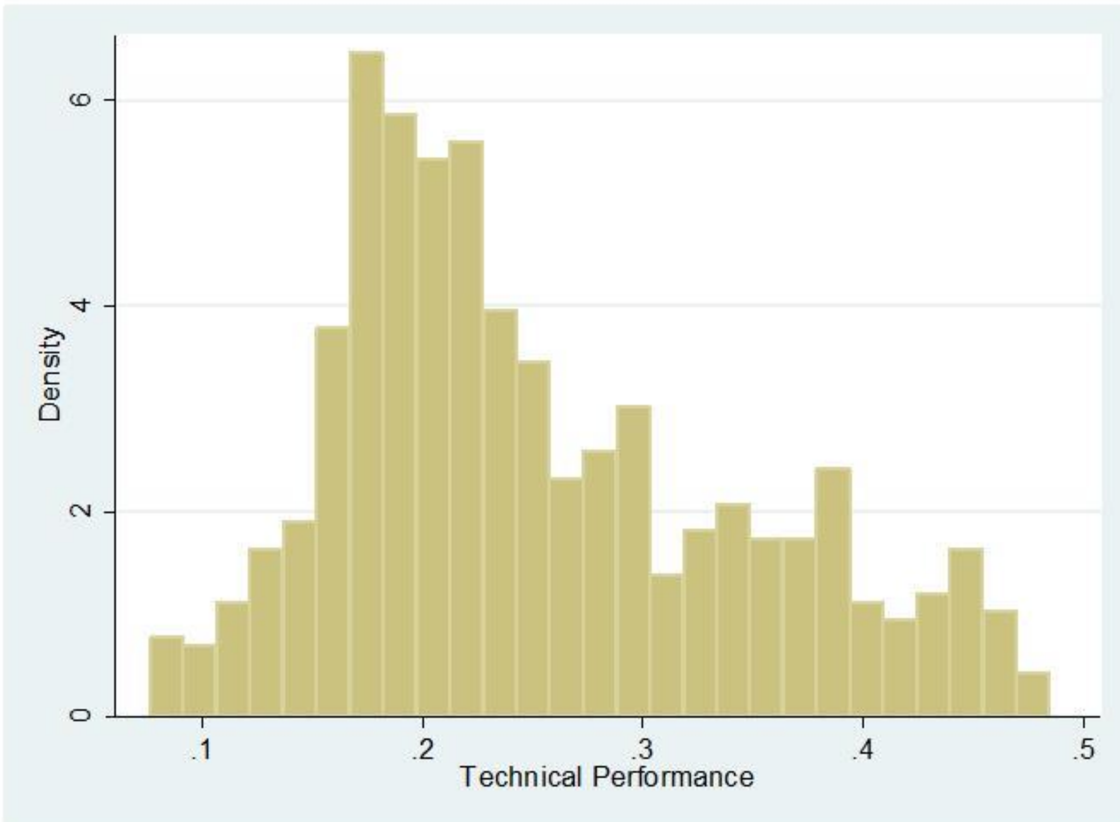


Table 4.4. Technical performance regressions for firms' first smartphone upon entry

	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent Variable:	Technical Performance	Technical Performance	Technical Performance	Data Speed/Max(Data Speed)	Camera MP/Max(Camera MP)
Model:	Fractional Logit	Fractional Probit	Beta	Fractional Logit	Fractional Logit
Information Shown:	Average Partial Effects	Average Partial Effects	Average Partial Effects	Average Partial Effects	Average Partial Effects
Complementary Products	-0.015***	-0.015***	-0.015***	-0.004**	-0.011***
	(0.003)	(0.002)	(0.002)	(0.022)	(0.003)
Firm Size (in millions)	-0.041	-0.053	-0.043	-0.009**	-0.010
	(0.617)	(0.496)	(0651)	(0.034)	(0.230)
R&D (in billions)	0.014***	0.014***	0.014***	0.0003	0.00008
	(0.006)	(0.005)	(0.008)	(0.174)	(0.187)
Phone Patents (in thousands)	-0.0007	-0.0007	-0.0006	-0.0003	-0.0001
	(0.773)	(0.746)	(0.787)	(0.386)	(0.704)
ln(Standards Disclosures)	-0.015***	-0.014***	-0.015***	0.001	-0.007***
	(0.000)	(0.000)	(0.000)	(0.481)	(0.006)
Prior Feature Phones	0.0003	0.0003	0.0003	-0.0006*	0.0004
	(0.344)	(0.359)	(0.335)	(0.0057)	(0.230)
Distribution Capability	0.084**	0.084**	0.085**	-0.077***	0.045
	(0.017)	(0.014)	(0.013)	(0.000)	(0.275)
Manufacturing Capability	0.032	0.030	0.032*	-0.004	0.056***
	(0.100)	(0.102)	(0.098)	(0.566)	(0.000)
Computer Maker	0.013	0.012	0.013	-0.0003	-0.012
	(0.340)	(0.350)	(0.343)	(0.880)	(0.287)
PDA	-0.019	-0.017	-0.018	0.017**	0.010
	(0.289)	(0.312)	(0.312)	(0.047)	(0.484)
Price Tier Dummies	YES	YES	YES	YES	YES
Year Entry Dummies	YES	YES	YES	YES	YES
Observations	52	52	52	52	52

MP stands for megapixels. Robust p-values are reported in parentheses. Scale parameter for Beta regression is 5.7. Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

Table 4.5. Technical performance regressions for firms' first three years in the market

	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent Variable:	Technical Performance	Technical Performance	Tech. Performance For: {Data Speed, RAM, CPU Speed, CPU Cores, GPU}	Data Speed/Max(Data Speed)	Camera MP/Max(Camera MP)
Model:	Pooled Fractional Logit	Pooled Fractional Logit	Pooled Fractional Logit	Pooled Fractional Logit	Pooled Fractional Logit
Information Shown:	Average Partial Effects	Average Partial Effects	Average Partial Effects	Average Partial Effects	Average Partial Effects
Complementary Products	-0.014***	-0.014***	-0.012***	-0.002***	-0.010***
	(0.000)	(0.000)	(0.004)	(0.001)	(0.000)
Firm Size (in millions)	-0.056	-0.097	-0.3340***	0.001	-0.024
	(0.338)	(0.128)	(0.008)	(0.198)	(0.620)
R&D (in billions)	0.0004*	0.0004*	0.015***	0.0001	0.0001
	(0.072)	(0.075)	(0.000)	(0.432)	(0.475)
Phone Patents (in thousands)	0.00002	0.00002	-0.0001	0.001	-0.0003
	(0.981)	(0.708)	(0.928)	(0.172)	(0.136)
ln(Standards Disclosures)	-0.002	-0.002	0.001	0.0001	0.0005
	(0.119)	(0.150)	(0.649)	(0.383)	(0.550)
Prior Smart Phones	0.002***	0.002***	0.0003	0.00005*	0.0004
	(0.000)	(0.000)	(0.605)	(0.066)	(0.117)
Manufacturing Capability	-0.002	0.0007	0.024	0.003	-0.004
	(0.865)	(0.949)	(0.173)	(0.243)	(0.685)
Computer Maker	0.003	0.009	-0.001	-0.0004	0.001
	(0.659)	(0.229)	(0.953)	(0.676)	(0.845)
PDA	0.016***	0.014***	-0.015	0.0001	0.011
	(0.009)	(0.068)	(0.324)	(0.926)	(0.139)
Distribution Capability	0.110***	0.108***	0.111***	0.007***	0.013
	(0.000)	(0.000)	(0.000)	(0.009)	(0.115)
Industry Dummies	NO	YES	YES	YES	YES
Price Tier Dummies	YES	YES	YES	YES	YES
Year Entry Dummies	YES	YES	YES	YES	YES
Observations	415	415	415	415	415

MP stands for megapixels. P-values calculated from robust standard errors that account for within firm clustering are reported in parentheses. All results remain robust if logit transformed dependent variables are used, either in a pooled model or with random effects. Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

Table 4.6. A comparison of smartphone makers with and without complementary products

Variable	Mean (standard deviation): Complementary Products	Mean (standard deviation): No Complementary Products	*t*-statistic (unequal variance)	p-value
Total Assets	32,913	28,970	0.31	0.76
	(53,771)	(30,663)		
Intangible Assets	5,940	7,893	-0.31	0.76
	(12,905)	(23,639)		
R&D	1,877	1,096	1.37	0.18
	(1,822)	(1,870)		
Patent Total (3-Year Window)	887	378	1.11	0.28
	(1530)	(1408)		
Business Segments	4.27	4.33	0.08	0.94
	(3.17)	(2.50)		
Product Breadth	9.7	4.32	2.10	0.05
	(9.1)	(5.30)		
ROA	0.14	0.13	0.45	0.66
	(0.09)	(0.08)		
Operating Margin	0.10	0.07	1.26	0.22
	(0.08)	(0.10)		
CAPX Intensity	0.05	0.09	-1.60	0.12
	(0.06)	(0.06)		

Table 4.7. Inverse probability weighted regression adjustment analysis of technical performance

Dependent Variable: Technical Performance	Average Treatment Effect on Treated	A.I. Robust Standard Errors	Z-statistic	p-value	N
Model 1. (Base Propensity Score)	-0.07	0.03	-2.09	0.037	291
Model 2. (Flexible Form)	-0.09	0.04	-2.03	0.04	291
Model 3. (Sample: Coarsened Matches Only)	-0.15	0.06	-2.35	0.02	129

The sample for Model 3 is restricted to observations from a coarsened exact matching procedure in which observations were matched using R&D, Product Breadth, and Patent Scope. Standard errors are calculated using Abadie–Imbens standard errors (see Abadie and Imbens, 2006). Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

Table 4.8. Analysis of product design tradeoffs by complementary product type

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Business Related		Entertainment Related			
Dependent Variable (DV):	Business Features	Full Office Suite Included	Camera Features	Screen Performance	Sound & Video Features	Video Camera Included
DV Mean:	0.79	0.31	1.51	0.23	4.54	0.35
DV Standard Deviation:	0.59	0.46	1.69	0.15	1.41	0.48
DV Range:	0-3	0-1	0-7	0-0.69	0-7	0-1
Description::	Pooled Neg. Binomial	Pooled Probit	Pooled Neg. Binomial	Pooled Fractional Logit	Pooled Neg. Binomial	Pooled Probit
Information Shown:	Average Partial Effects	Average Partial Effects	Average Partial Effects	Average Partial Effects	Average Partial Effects	Average Partial Effects
Complementary Products-Business (0/1)	0.512***	0.171*	-0.500*	-0.020***	-1.01**	-0.092
	(0.000)	(0.058)	(0.062)	(0.001)	(0.041)	(0.207)
Complementary Products-Entertainment (0/1)	-0.414***	-0.307***	0.484***	0.017**	0.200	0.213***
	(0.000)	(0.000)	(0.001)	(0.042)	(0.609)	(0.001)
Firm Size (in millions)	-1.68**	0.187	1.452	-0.128**	-0.784	0.056
	(0.000)	(0.779)	(0.3111)	(0.011)	(0.783)	(0.908)
R&D (in billions)	0.075***	-0.057***	-0.095**	0.002	-0.041	0.003
	(0.000)	(0.000)	(0.016)	(0.112)	(0.389)	(0.793)
Phone Patents (in thousands)	-0.171	-0.00002	0.304*	-0.003	0.426	0.086
	(0.101)	(0.998	(0.064)	(0.650)	(0.163)	(0.247)
ln(Standards Disclosures)	-0.014	-0.037*	-0.033*	-0.0001	0.038	0.014*
	(0.224)	(0.053)	(0.086)	(0.872)	(0.603)	(0.059)
Prior Smart Phones	0.002	0.003	0.012	0.002***	0.025**	0.012***
	(0.615)	(0.194)	(0.102)	(0.000)	(0.049)	(0.000)
Manufacturing Capability	-0.699***	-0.390***	0.715***	0.024*	-1.13**	0.250***
	(0000)	(0.000)	(0.002)	(0.051)	(0.047)	(0.004)
Computer Maker	-0.037	0.184***	0.030	-0.029**	0.398	-0.069
	(0.6591)	(0.011)	(0.852)	(0.013)	(0.163)	(0.159)
PDA	0.559***	0.455***	-0.028	-0.002	0.144	-0.154**
	(0.000)	(0.000)	(0.868)	(0.774)	(0.701)	(0.015)
Distribution Capability	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
Alpha (dispersion parameter)	0.000	n/a	0.000	0.000	0.000	n/a
Industry Dummies	YES	YES	YES	YES	YES	YES
Price Tier Dummies	YES	YES	YES	YES	YES	YES
Year Entry Dummies	YES	YES	YES	YES	YES	YES
Observations	380	359	380	380	380	357
Pseudo R2	0.06	0.39	0.15	0.15	0.20	0.35

Distribution Capability is omitted due to collinearity with Industry dummy variables. P-values calculated from standard errors that are robust and account for within firm clustering are reported in parentheses. Average partial effect in brackets. Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

Table 4.9. Market share regression models

	Model 1	Model 2
Dependent Variable:	Market Share	Market Share
Specification:	Fractional Logit	Fractional Logit
Information Shown:	Average Partial Effect	Average Partial Effect
Average Technical Performance	0.213**	0.056
	(0.039)	(0.591)
Complementary Products	0.010**	0.044**
	(0.013)	(0.019)
Global Smartphone Sales (in millions)	-0.00005*	-0.00005
	(0.071)	(0.136)
Firm Size (in millions)		-0.067
		(0548)
R&D (in billions)		0.007***
		(0.004)
Phone Patents (in thousands)		0.022
		(0.398)
Distribution Capability		0.074*
		(0.069)
Manufacturing Capability		0.070**
		(0.056)
Computer Maker		0.033
		(0.166)
PDA		0.017
		(0.516)
Product Breadth		-0.007***
		(0.004)
Business Segments		0.008***
		(0.007)
Observations	448	200
Industry Dummies	YES	YES
Year Dummies	YES	YES
Pseudo R-Square	0.10	0.37

Global Smartphone Sales measure the total number of smartphone units sold in the year across all firms. Results are robust if the firm's maximum Technical Performance (i.e., firm’s smartphone with highest Technical Performance in that year) is used instead of its average across its smartphones in the year. Firms with no market share data have less than 1% so are set at 0.5%. Results are similar if I use Top 5 instead of Market Share. P-values calculated from robust standard errors that account for within-firm clustering in parentheses. Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

Table 4.10. Market share analysis using nearest-neighbor matching

Dependent Variable: Market Share			
Average Treatment Effect on Treated (%)	A.I. Robust Standard Errors	Z-statistic	N
Model 1			
Treated: Low Tech. Performance & Complementary Products Control: Low Tech. Performance. Frontier & No Complementary Products			
5.71	1.23	4.66***	78
Model 2			
Treated: High Tech. Performance & Comp. Products Control: High Tech. Performance & No Comp. Products			
3.28	1.13	2.91***	122
Model 3			
Treated: Low Tech. Performance & Comp. Products Control: High Tech. Performance & No Comp. Products			
9.29	2.27	4.10***	92

The models use different treated and control samples. Observations in the sample (treated & control) are matched using Firm Size, Business Segments, Product Breadth, Patent Scope, R&D, Firm Size, PDA Manufacturer, and Year. I match the treated firm to a minimum of one 'nearest neighbor' untreated firm within the set, based on the lowest Mahalnobis Distance on the matching variables. Comp. is short for Complementary. Low Tech. Performance denotes that the firm has, on average across all of its phones, a below median Technical Performance in the given year, while High Tech. Performance denotes above median Technical Performance. Results are robust if the firm's maximum Technical Performance (i.e., firm's smartphone with highest Technical Performance in that year) is used instead of its average across its smartphones in the year. Matching method accounts for bias when matching on two or more variables using Abadie–Imbens bias correction, and standard errors are calculated using Abadie–Imbens method (see Abadie and Imbens, 2006). Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

Appendix 4.1. Sample Selection Criteria for Firms at Hazard of Entry

Because entry is a strategic choice and firms that enter likely believe they can build effective products, I model the firm's entry decision using a sample of firms at hazard of entering the smartphone market. To create a sample of firms that might be at hazard of entering the smartphone market, I begin with a cross-section of global firms in 2005, which marks the beginning of the nascent smartphone market (see Figure 1). The sample is comprised of a broad sample of global firms that satisfies any of the following criteria: (1) patented in one of the phone related patent classes in the prior five years (see Table 2); (2) main four-digit SIC code description relates to computers, communications, or electronics; (3) Corp-Tech database listed the firm as a maker of computer hardware, computer software, telecommunications and internet products, or electrical components. The result is a sample of 3,245 firms, 57% of which are U.S. headquartered. I code, *Entry*, as equal to 1 if the firm enters the smartphone market in 2005 or the following five years. To avoid reverse causality or simultaneity between *Complementary Products* and *Entry*, I measure *Complementary Products* based on information from 2003.[124] Table A1 contains descriptive statistics and correlations for this sample. Overall, 2.1% of firms enter the smartphone market. Approximately 6% of firms in the sample compete in at least one complementary product category, and of those that do, they tend to compete in 1.8 different complementary categories on average.

To analyze selection into the market, I use Heckman Selection model estimated via Full Information Maximum Likelihood.[125] To use this method, I need to transform the fractional dependent variable, *Technical Performance*, into a variable that is suitable for

[124] For example, a firm might enter a complementary product category as it launches a smartphone. To avoid this, I use information from two years prior. Antidotal evidence suggests that the time from development to launch was approximately 20 to 28 month on average.

[125] The model combines a first stage probit with a second stage linear model and uses Full Information Maximum Likelihood. Results are robust using the two-step, limited information maximum likelihood procedure.

linear regression.[126] I do this using the logit transformation: ln[y/(1-y)], where y is *Technical Performance* (Wooldridge, 2010).[127] To identify the first stage, I use an instrument partially correlated with entry, but that does not bear on *Technical Performance*. The instrument, *Broadband*, counts how many millions of customers have broadband internet service in the firm's home country during the year. In 2005, *Broadband* access was thought to be a substitute for fast wireless data standards, which could potentially limit market potential and therefore, discourage entry.[128]

Model 1 in Table A2 provides a basic ordinary least squares regression of the logistically transformed *Technical Performance* on *Complementary Products* and controls. *Complementary Products* is negative and significant as predicted by Hypothesis 1. Models 2 displays the Heckman estimates. *Broadband* is negative and significant in the first stage and *Complementary Products* is negative and significant in the second stage (coefficient -0.090; p-value 0.000), supporting Hypothesis 1. In Model 3, I add *Price Tier Dummies* in place of *Wireless Standard Dummies* and find similar results.[129] Note that sample selection does not appear to be an issue. Rho is low (0.285) and a Wald test that rho is 0 cannot be rejected (Chi-square p-value of 0.23). Also note that the coefficients from the basic regression (Model 1) and the outcome regressions from the Heckman model (Models 2 and 3) are relatively stable.

Because U.S. firms comprise a large portion of the sample, using a country level instrument in the first stage could result in biased predictions. Therefore, I re-estimate the

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[126] Otherwise, I would need to use a fractional logit or probit model and build the first stage selection model into the likelihood function.
[127] The transformed dependent variable appears normally distributed, with a mean of -1.28, standard deviation of 0.43. A skewness/kurtosis test for normality cannot reject normality (chi-square p-vale of 0.36).
[128] I use a country level measure because I can find no firm or industry level measure that could affect entry but is not potentially correlated with *Technical Performance.*
[129] The sample size is too small to control for both wireless standard and price of the phone. All results in Table 4 are robust using either specification.

model by first randomly cutting U.S. firms from the sample until the U.S. share of the total sample is the same as the second largest country's share, which removes 876 U.S. firms (see Model 3). Rerunning the specification from Model 2, I find robust results. In the first stage, Broadband is negative and significant (coefficient -0.014, p-value 0.06). In the second stage, *Complementary Products* is negative and significant (coefficient -0.089, p-value 0.001).

The prior analysis assumes that *Complementary Products* is exogenous. To suppress potential selection effects related entry as well as the likelihood of having *Complementary Products*, I combine the Heckman selection model with a propensity score-weighting model (Model 5). I begin by running a model that predicts the propensity for the firm to create *Complementary Products* (please see Appendix B for a discussion of the variables in the model). Using the inverse propensity scores, I weight the second stage of the Heckman model (e.g. the outcome model).[130] Combined, the model allows endogenous market entry and uses the propensity scores weighting to help control for firms' selection into complementary products. While not shown, *Complementary Products* is negative and significant (coefficient -0.16, p-value 0.000).[131] The result supports for Hypothesis 1.

[130] I do not weight the first stage entry model, as I am only interested in testing Hypothesis 1 and want to reduce the potential computational burden.
[131] In the previously mentioned models, I use a continuous version of *Complementary Products*. I also estimate the propensity score weighted second stage using an indicator variable (*Complementary Products* 0/1), and conclusions are similar (coefficient of -0.17 and p-value of 0.000).

Table A4.1.1. Descriptive statistics for firms at hazard of entering the smartphone market

	Variable	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	Entry	0.02	0.15	1														
(2)	Complementary Products	0.10	0.48	0.21	1													
(3)	Firm Size	5.97	24.27	0.39	0.06	1												
(4)	R&D	65.38	393.45	0.49	0.20	0.65	1											
(5)	Phone Patents	7.33	61.05	0.35	0.15	0.46	0.69	1										
(6)	ln(Standards Disclosures)	0.05	0.49	0.42	0.08	0.41	0.54	0.29	1									
(7)	Prior Feature Phones	0.26	3.37	0.45	0.20	0.20	0.40	0.24	0.48	1								
(8)	Distribution Capability	0.00	0.06	0.04	0.04	0.00	0.00	0.00	-0.01	0.00	1							
(9)	Manufacturing Capability	0.40	0.49	0.08	0.01	0.05	0.11	0.09	0.09	0.07	-0.04	1						
(10)	Computer Maker	0.03	0.18	0.16	0.06	0.08	0.12	0.20	0.02	0.05	0.02	0.22	1					
(11)	PDA	0.02	0.12	0.58	0.17	0.35	0.45	0.34	0.48	0.39	0.04	0.12	0.20	1				
(12)	Business Segments	2.08	1.68	0.45	0.00	0.57	0.54	0.38	0.35	0.22	0.09	0.13	0.24	0.41	1			
(13)	Product Breadth	4.68	4.51	0.26	0.47	0.31	0.43	0.49	0.23	0.30	0.23	0.26	0.34	0.33	0.37	1		
(14)	Mobile Penetration	72.88	19.78	0.01	-0.02	0.03	0.04	0.01	0.03	0.02	0.01	0.02	-0.02	0.01	0.06	-0.02	1	
(15)	Broadband	30.01	21.15	-0.05	0.11	-0.05	0.00	0.02	-0.03	-0.01	-0.03	0.08	0.01	-0.02	-0.15	-0.03	-0.27	1

Table A4.1.2. Sample selection models of technical performance: Firms' first smartphone upon entry

	Model 1	Model 2		Model 3		Model 4	
Model Type	OLS	Heckman FIMLE		Heckman FIMLE		Heckman FIMLE	
Sample	Full	Full	Full	Full	Full	Full	U.S. Share Reduced
Dependent Variable	Logit Transformed Technical Performance	Logit Transformed Technical Performance	Market Entry	Logit Transformed Technical Performance	Market Entry	Logit Transformed Technical Performance	Market Entry
Complementary Products	-0.100***	-0.090***	0.906***	-0.082***	1.238***	-0.090***	0.891***
	(0.007)	(0.000)	(0.000)	(0.003)	(0.000)	(0.001)	(0.000)
Firm Size (in millions)	-0.133	-0.967*	0.483**	-0.217	6.20**	-0.966*	4.31*
	(0.173)	(0.069)	(0.029)	(0.643)	(0.013)	(0.069)	(0.052)
R&D (in billions)	0.133***	0.135***	0.358	0.008***	0.186	0.135***	0.347
	(0.002)	(0.000)	(0.177)	(0.004)	(0.491)	(0.000)	(0.192)
Phone Patents (in thousands)	-0.158	-0.181	-1.94	-0.150	-1.25	-0.179	-1.90
	(0.335)	(0.152)	(0.132)	(0.289)	(0.302)	(0.155)	(0.149)
ln(Standards Disclosures)	-0.053**	-0.052***	0.261**	-0.076***	0.351***	-0.052***	0.280**
	(0.0129)	(0.000)	(0.015)	(0.000)	(0.002)	(0.000)	(0.030)
Prior Feature Phones	-0.003	-0.002	0.224***	0.001	0.221***	-0.002	0.221***
	(0.461)	(0.329)	(0.001)	(0.558)	(0.001)	(0.330)	(0.001)
Distribution Capability	0.688***	0.646***	2.099**	0.435**	0.657	0.648***	2.003**
	(0.000)	(0.000)	(0.028)	(0.032)	(0.548)	(0.000)	(0.042)
Manufacturing Capability	0.103	0.092	-0.379	0.151	-1.194***	0.093	-0.420
	(0.302)	(0.210)	(0.282)	(0.156)	(0.003)	(0.202)	(0.246)
Computer Maker	0.089	0.109	0.955***	0.141*	1.056***	0.108	0.954***
	(0.415)	(0.178)	(0.001)	(0.092)	(0.005)	(0.180)	(0.002)
PDA	0.043	0.082	2.192***	-0.0522	2.572***	0.079	2.152***
	(0.625)	(0.280)	(0)	(0.574)	(0)	(0.290)	(0.000)
Broadband			-0.019***		-0.027***		-0.0140*
			(0.004)		(0.003)		(0.060)
Constant	-2.113***	-2.181***	-6.524	-2.106***	-6.649	-2.17***	-6.315
	(0.000)	(0.000)		(0.108)		(0.000)	
Rho		0.285		0.227		0.28	
Lambda (Rho*Sigma)		0.039		0.033		0.038	
Wald test of null that Rho=0							
(Chi-Sq p-value)		0.23		0.47		0.24	
Industry Dummies	NO	NO	YES	NO	YES	NO	YES
Wireless Standard Dummies	YES	YES	NO	NO	NO	YES	NO
Price Tier Dummies	NO	NO	NO	YES	NO	NO	NO
Year Entry Dummies	YES	YES	NO	YES	NO	YES	NO
R-Square	0.92		0.71				
Pseudo R-Square			0.69		0.76		0.64
Observations	53	51	3,222	48	3,217	48	2,341

If firm released more than one phone upon entry, I use the highest performing phone in the model. P-values calculated from robust standard errors are reported in parentheses. Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

Appendix 4.2. Modeling the Propensity to Create Complementary Products

In this appendix, I provide the estimates of two different first stage propensity score models. I include a set of variables that might influence the firm to both create *Complementary Products* and enter the market. First, I include two measures of diversification, *Business Segments* and *Product Breadth*, because diversified firms are more likely to both have complementarities and to enter new markets as part of their diversification strategy. I include proxies for the firm's knowledge, scope of knowledge, and innovative effort using *Total Patents*, *Patent Scope*, and *R&D*.[132] Firms with high debt may be unable to create *Complementary Products*, to account for this, I include *Leverage*, measured as the firm's debt to equity ratio. Firms with poor performance may attempt to diversify into more product areas to reverse their poor results, and by chance, enter areas that are complementary. To account for this I include the firm's *Operating Margin*.[133] Finally, I control for whether the firm is headquartered in the U.S., as proximity to U.S. consumers that were early adopters of smartphones could lead the firm to both create *Complementary Products* and enter the market. Model 1 of Table B1 provides the basic estimates of the propensity score model using the sample from Table 5. In Model 2, I add squared terms of several key variables to capture any nonlinear effects, and thus yield a better prediction (Wooldridge, 2010). I estimate both models using a logit specification.

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[132] *Patent Scope* measures the breadth of the firm's knowledge, and thus its likelihood of potentially creating links between these knowledge elements. It is calculated as 1 minus the concentration ratio (also known as the Herfindahl–Hirschman Index). Using information of the number patents and technology classes, I make the following calculation: $1 - \sum_{k=1}^{K}(\frac{total\ patents\ in\ \ firm\ \ k\ in\ three\text{-}year\ window\ t}{total\ patents\ in\ year\ t})^2$. I use a three-year window to capture the firm's recent innovative efforts, though a one-year window or five-year window yield similar results.

[133] *Operating Margin* is calculated as operating income over total revenues. Note that other measures of performance, such as ROA, yield the same results.

Table A4.2.1. Predicting the propensity to have complementary products

Dependent Variable: Complementary Product (0/1)	Model 1 (1)	Model 2 (2)
R&D	0.0001	0.0062***
	(0.519)	(0.000)
R&D Squared		-2.99e-07*
		(0.000)
Patent Scope	3.621***	1.949
	(0.000)	(0.122)
Total Patents	-0.000103	0.00127
	(0.651)	(0.189)
Total Patents Squared		-1.31e-07
		(0.272)
Product Breadth	-0.636***	-0.430
	(0.000)	(0.542)
Product Breadth Squared		-0.0545
		(0.496)
Business Segments	-0.340***	-0.408***
	(0.095)	(0.107)
Leverage	-4.913***	-7.986***
	(0.001)	(0.000)
CAPX Intensity	-2.858	-0.831
	(0.438)	(0.866)
Liquidity	9.04e-05	0.0001
	(0.187)	(0.228)
Operating Margin	1.300*	1.249*
	(0.060)	(0.077)
US Company	-5.831**	
	(0.0222)	
Constant	1.063*	1.248
	(0.090)	(0.333)

Coefficients and p-values in parentheses shown. Significant (two-sided test) at *** p<0.01, ** p<0.05, * p<0.1.

CHAPTER 5

Conclusion

The objective of my dissertation is to examine how complementarities within the firm's portfolio of technologies and products influence its technology strategy. Through three essays, I highlight the influential role that complementarities play in several important settings.

In Chapters 2 and 3, I study value creation and capture strategy in compatibility standards. I find that firms only experience positive cumulative abnormal stock returns from disclosing technology to standards when they own technologies complementary to their disclosed technology. Firms leverage their disclosures to SSOs to increase the value of their technology portfolio. The larger the complementary technology portfolio, the more the firm can enhance its position in the technological ecosystem surrounding the standard, and the more the firm should be willing to bear the costs of disclosure.

At the technology level, I also find that complementary technologies increase in value after they become compatible with the standard. Patents covering these technologies experience an increase in citations. Complementary patents also experience a significant increase in the likelihood of litigation after their complementary standard essential patents are disclosed. The jump in the litigation rate highlights the important role complementary patents play in the firm's post-standard value appropriation strategy.

The findings and arguments from Chapters 2 and 3 have direct implications for several literature streams. I add to the literature on free revealing and disclosure (Allen 1983; Harhoff et al. 2003; Henkel, 2006) by identifying a mechanism that drives firms to disclose IP—complementarities in the firm's portfolio. By identifying complementary technologies as a way to capture value from disclosures on other technologies, I shed light on why firms may disclose or give away IP for little or no direct financial reward. I also add to the empirical work on disclosure, a literature that has thus far been weighted toward case studies and theoretical work.

My findings add to the literature on compatibility standards. Prior work focuses on the standard setting process (Farrell, 1996; Chiao *et al.*, 2007; Farrell and Simcoe, 2012; Simcoe, 2012) and standard essential technology (Rysman and Simcoe, 2008; Simcoe, Graham, Feldman, 2009; Bekkers *et al.* 2011), but rarely explicitly theorizes about firms' standard setting strategy. The scant work on standard setting strategy investigates how firms select a SSO (Lerner and Tirole, 2006) or how participation in standard setting activities fits with firm's networking strategy (Leiponen 2008; Bar and Leiponen, 2014; Ranaganathan and Rosenkopf, 2014). I extend our knowledge on standards strategies by explicitly considering how firms utilize standards for financial gain and by documenting a strategy in which they employ.

My work also informs the literature on standards policy. From a consumer's perspective, the fact that firms with complementary technologies benefit from disclosure is likely a positive finding. These complementary technologies can be used to enhance the consumers experience with products that function on the standard. Yet, the research points to potential problem: even if a firm's assertion of market power over its disclosed SEPs is curtailed, it may still be able to create socially undesirable lock-ins via its complementary technologies that are not disclosed and hence not subjected to oversight. By retaining control these complementary technologies, the firm may create distortions from socially optimal equilibrium prices. While I do not offer direct evidence as such, firms' litigiousness surrounding their complementary technologies signals the length they are willing to go to defend the advantage these technologies affords them. Overall, my findings do draw a more complete picture of firms' standard-related incentives. Potential standards-related policy should not ignore how firms utilize SEPs to capture value in the technological ecosystem surrounding the standard.

These two essays add to the empirical evidence on the importance of complementary assets. Prior research on how firms profit from innovation has demonstrated the importance of downstream complementary assets in appropriating returns from innovations (Teece, 1986; 1996). The role of complementarity between technologies has received less empirical inquiry (Teece, 1996; Somaya and Teece, 2006). I demonstrate the important role compatibility between two technologies play in value creation and appropriation. Compatible technologies can create significant complementary value for the firm when one technology holds an important position in the ecosystem (e.g. inside a standard) that then enhances the value of the strategic options for the other technology.

In Chapter 4, I examine the role that product complementarities play in the firms' product strategy as they enter new markets. I find that firms with products complementary to the new market are more likely to enter the new market, and will enter the new market with products that exhibit lower technological performance than firms without complementary products. Complementarities also influence the firms' design tradeoffs—

firms design their products to best support the functionality of their complementary products. Empirical results also demonstrate that firms can achieve high market performance by relying on complementarities in lieu of high technical performance.

My findings extend our knowledge of market entry and post-entry strategy. Prior literature typically either focuses on the antecedents of entry or post-entry survival, while leaving what firms do when they enter a market relatively unexplored. I show that complementarities not only are an antecedent to entry, they play an important role in describing post-entry behavior. Complementarities shape what consumers the firm will target and how it will position itself in the market. For instance, firms can rely on complementary products to avoid competition at the technological frontier. The relationship between either a firm's product strategy and its overall technological capabilities will be contingent on whether the firm has complementary products.

This work also expands our view of product design. I propose that demand-side complementarities influence feature selection and overall technical performance. Doing so, I highlight how the potential for bundling (i.e. complementary product and new product) influences design. For example, firms can focus on selecting features and attributes that fit with their existing complementarities and cut costs by excluding ones that do not. This adds to the existing supply-side arguments that focus on upstream economies of scope or downstream commercialization assets.

Overall, this dissertation contributes to our knowledge of complementarities and strategic advantage. Prior research highlights three broad ways in which complementarities impact the firm. First, complementarities among knowledge elements expand combinatorial possibilities, leading to more innovation. Second, complementary assets help support appropriation from these innovations. Third, the ownership of complementary assets impact innovation incentives—increasing both the overall incentive to innovate and the direction of innovation. I expand this literature to include how complementarities among technologies or products in the firm's portfolio offer different avenues for value creation and capture. By doing so, I identify complementarities as a unique and potentially hard to imitate source of advantage that can both create different strategic options and increase firm performance.

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APPENDIX

Glossary of Information and Communication Industry Terms

CDMA: Code division multiple access, a 2^{nd} and 3^{rd} generation wireless communication multiplexing technology which optimizes bandwidth by allowing numerous signals to occupy the same transmission channel.

GPRS: General Packet Radio Service. A mobile data packet service for GSM.

GSM: Global System for Mobile communication. A 2^{nd} generation digital mobile wireless communications network standard that relies on TDMA multiplexing.

HSPA: High speed packet access, a protocol for sending data on a WCDMA based network.

LTE: Long-Term evolution standard for wireless mobile communication.

MPEG-4: Moving Picture Experts Group's agreed upon method for compression of audio and visual digital data.

TDMA: Time-division multiple access. A method for frequency sharing by allocating different users different time slots on the same frequency.

UMTS: Universal Mobile Telecommunications System. A 3^{rd} generation wireless communication network standard that extended the GSM network and utilized W-CDMA technology.

WCDMA: Wideband Code Division Multiple Access. An evolution of CDMA that uses a pair of 5 megahertz wide channels.

Wi-Fi: A trademarked name for the IEEE 802.11 wireless local area networking standard that allows various devices to exchange data.