Impact of Firm Capabilities

at the Marketing / Technology Interface

by

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ABSTRACT

Firms compete for profitable positions in their technological environments by capitalizing on their design and other capabilities to conceive and realize marketplace strategies more effectively and more efficiently than rivals do. However, research on how technological environment characteristics change the payoff from these capabilities is minimal. Given that possessing superior firm capabilities is a primary source of competitive advantage for firms, this study seeks to fill these critical research gaps in the literature. This dissertation, which is composed of two essays, seeks to answer what capabilities pay off more in various technological conditions. It benefits from the most comprehensive sample to date that includes 2132 publicly traded firms in the United States (US) over 34 years. All the technological industry conditions are captured by using the entire data of utility patents in the US. The first essay shows that design is a firm capability that enhances sales growth. Its effect, however, is attenuated by technology intensity because, in markets with high technology intensity, design attributes become less salient. Moreover, technological competitive intensity and maturity amplify design capability's positive effect because when technical attributes of products provide limited differentiation, design attributes receive more attention, and consumers overweight them in decision making. The second essay examines the effect of marketing and research and development (R&D) capabilities on return on assets (ROA) in three technological market conditions: Technological turbulence, uncertainty, and acceleration. It shows that all the technological environments amplify the positive ROA performance outcomes from marketing capability, with technological turbulence having the most potent effect. R&D

capability, however, is most influential in technologically accelerating markets. Finally, the second essay unveils that marketing and R&D capabilities are complementary only in technologically turbulent markets. These studies thus provide valuable insights to researchers and managers on the payoff from these capabilities and offer new guidance on which capabilities firms should emphasize on under different technological market conditions.

DEDICATION

I dedicate this dissertation to my parents, Azar and Ali, who have always offered unwavering support and encouragement throughout my doctoral journey.

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CHAPTER 1

DESIGNED FOR GROWTH: THE INTERPLAY BETWEEN DESIGN CAPABILITY AND TECHNOLOGICAL MARKET CONDITIONS

Abstract

Firms in a variety of industries employ design to compete and enhance their sales. Notably, however, researchers have thus far overlooked the circumstances upon which investment in design could pay off more or less. Although design and technology frequently intersect with one another in practice, the academic research examining this intersection is sparse and conflicting. Therefore, I study the sales impact from design, as a firm capability, across different technological market conditions. I compile a large dataset of 539 publicly traded US firms from 2000 to 2015 to examine the impact of design capability on sales growth. Using patent data, I capture the primary technological industry conditions under which firms operate‒technology intensity (TI), technological competitive intensity (TCI), and technological maturity (TM). I show that design capability enhances sales growth, and technology intensity attenuates design capability′s impact because, in such conditions, design attributes become less salient. However, technological competitive intensity and maturity amplify design capability′s positive effect because when technical attributes of products provide limited differentiation, design attributes receive more attention, and consumers overweight them in decision making. I discuss the implications of these results for academic researchers and managers.

Keywords: design capability, technology intensity, technological competitive intensity, technological maturity, sales growth

Introduction

Aesthetics, or styling, has become an accepted unique selling point - on a global basis

- GE's head of the division of global aesthetics program (Postrel 2003)

Firms in a variety of industries employ design[1] (i.e., product form or appearance) to differentiate their products and gain competitive advantage. Home furniture, automobiles, consumer electronics, home appliances, and B2B industries such as medical devices are just a few examples. The increasing popular press devoted to design and the expanding number of design awards indicate this growing attention of practitioners toward this subject (Jindal et al. 2016).

Further, companies such as Apple, Herman Miller, OXO, and BMW continuously launch products with superior designs, while most firms operating in their industries are unable to do so. In firms with strong designs, the practices of their design departments are highly patterned and over time become embedded as organizational routines, suggesting that design is a firm capability that is difficult to copy and trade (Krasnikov and Jayachandran 2008; Levinthal 2000; Teece, Pisano, and Shuen 1997). Design as a firm capability, however, has yet to receive scholarly attention.

Looking at practice, one would have a hard time understanding where investment in design would pay off more or less. The fact that some firms strong in design can have flops (e.g., Apple's Newton) (Badal 2008) suggests that industry factors may play a role in the payoff from design. Indeed, this begs questions like: is design more effective in high-tech industries like consumer electronics or low-tech industries like home furniture?

[1] For the sake of conciseness, I simply use 'design' to refer to product form. This has also been termed ornamental design.

Is it better to employ design in contexts with more technological competition? How may the worth of design change when technologies in an industry mature? Given the prevalence of design across industries and different technological contexts, the lack of a clear understanding of the contingent effects of design warrants scholarly attention.

In this study, I focus on one of the most critical market conditions—the firm's technological environment—to study the relationship between design capability and sales growth. Beyond the strong intersection observed between technology and design in practice, two theoretical considerations motivated this focus on the technological environment.

First, academic theorists suggest that two main dimensions of end products are form (i.e., ornamental design) and function (i.e., underlying technology) (Luchs, Swan, and Creusen 2016), regardless of factors beyond the end product (e.g., price), and firms combine both elements in their products (Kuang 2015). Therefore, studying design capability and its performance consequences in the context of technology is particularly critical.

Second, research shows that technological conditions are essential in studying firm performance, especially when it comes to the outcome effects of firm capabilities (Jaworski and Kohli 1993; Song et al. 2005; Wilden and Gudergan 2015). However, as depicted in table 1.1, past studies that examined the interaction between design and technology on firm performance outcomes are typically limited to single industries and suggest conflicting results: either positive (Rubera 2014), negative (Jindal et al. 2016), or insignificant (Talke et al. 2009). As a result, both scholars and practitioners are largely blind to in what situations such intersections of design and technology are worthwhile.

I thus seek to answer the following two research questions of interest to scholars and practitioners alike: (1) does design capability enhance sales growth? (2) how may this relationship be affected by different technology industry contexts? Organizational theory identifies three primary environmental dimensions: capacity, dispersion, and instability (e.g., Dess and Beard 1984; Milliken 1987). Thus, applying these to the technological environment, I focus on technological intensity (i.e., capacity), technological competitive intensity (i.e., dispersion), and technological maturity (i.e., stability) as potential moderators of design capability's impact.

I compile a large sample of 539 firms across 28 industries (2-digit SIC codes) over 16 years (2000-2015), with 8.55 years of data for each firm on average. Following conceptions of R&D capabilities (Dutta, Narasimhan, and Rajiv 1999), I define design capability as the ability of a firm to deploy its design-related resources to achieve superior and novel designs relative to other products in the market. I assess the technological environment characteristics using yearly industry patent data and test the hypotheses employing the system GMM method. The findings are robust to allowing for heteroscedasticity of the error term in the design capability estimation, controlling for additional control variables, using various lag structure criteria in the system of equations, and accounting for outliers, providing additional confidence in my findings.

This study thus offers several contributions to theory and practice. First, I propose design is a firm capability and develop a way to measure it utilizing the SFE method. I illuminate that design capability enhances sales growth. Therefore, firms that have developed robust design capabilities can sustainably boost their sales by capitalizing on design.

Second, I identify and distinguish between the key technological environmental conditions—technology intensity, technological competitive intensity, and technological maturity. These three conditions are conceptually and empirically different and examining their specific impact within the marketing strategy domain is relevant to theory and practice. It is noteworthy that prior approaches have discretely classified industries into binary groups of high-tech vs. low-tech or into specific technological stages (e.g., growth and maturity). I, however, measure technology intensity and technological maturity as continuous factors that vary across industries and over time. This allows the technological conditions to move over the 'technology continuum' (Gardner et al. 2000), enabling me to capture the average characteristics of technologies within industries and over time.

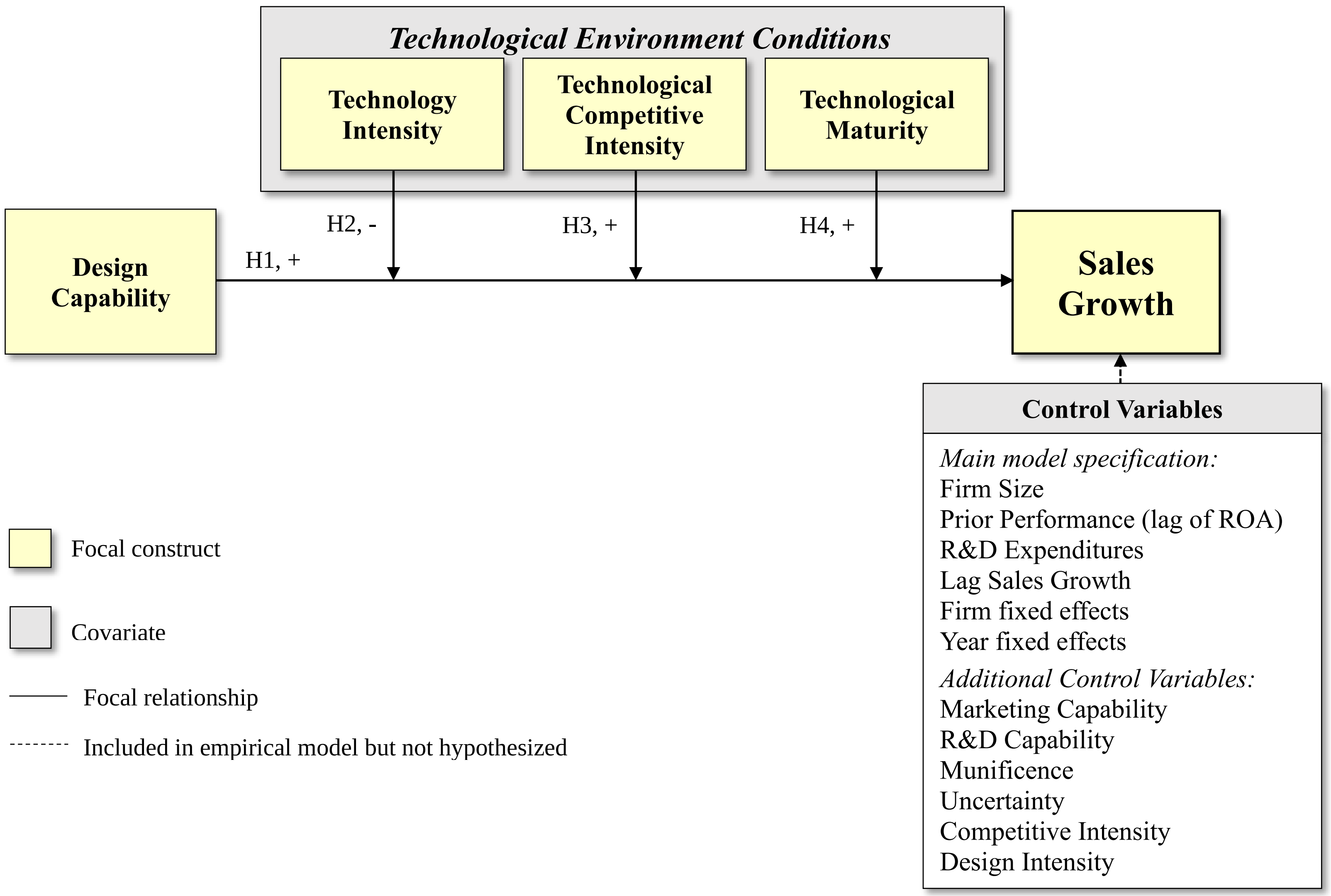
Third, by considering these three technological dimensions, I reveal the nuances in the relationship between design and technology. I show that as the technology intensity in a market increases, design capability's impact on sales growth gets weaker. This effect occurs because, in high-tech markets, technical attributes of products become more salient and receive more weight, owing to their more substantial variability (i.e., range) in high-tech markets. Moreover, new designs can increase product complexity and impede consumers' understanding of product category membership. In contrast, technological competitive intensity and technological maturity amplify the relationship between design capability and sales growth, primarily owing to the lower range and fewer number of levels of technical attributes in such markets. When firms do not have a technological edge over one another or do not offer much of technology improvement, design attributes become salient in consumer decision making and can creatively differentiate the products. Through these findings, my investigation thus provides valuable new insights to firms on how to allocate their resources to design capability in order to best compete in different technological environments.

Finally, nearly all the prior work on the performance impact of design has been limited to single industry studies of the automobile industry or centered over short time spans and reliant on subjective measures. This study benefits from the most comprehensive and strongest sample to date with 539 firms across 28 industries (2-digit SIC codes), lending more reliability and generalizability to the findings.

Theory and Hypotheses

First, I briefly review the literature on the firm capabilities-performance link. I then turn to design and discuss design as a firm capability and how it may impact firm performance (i.e., sales growth). Then, I delve into how technology intensity, technological competitive intensity, and technological maturity may affect the relationship between design capability and firm performance. Figure 1.1 presents a visualization of the conceptual framework of this study. I utilize sales growth as the focal performance measure. Sales growth captures the firm's short-term performance in gaining market positions and is one of the most used market performance variables in the innovation domain (Rubera and Kirca 2012).

Figure 1.1: Conceptual Framework



Firm Capabilities and Firm Performance

Briefly, both resource-based view (RBV) and dynamic capability theories postulate that firm capabilities drive firm performance. RBV considers firms as bundles of resources and capabilities that allow firms to capture valuable market positions. Resources are productive factors that a firm utilizes to achieve its business goals, and capabilities are a firm's ability to deploy these resources effectively. Firms differ in the endowment of their resources and capabilities (Wernerfelt 1984), and, as a result, some firms outperform others. The dynamic capability perspective also posits that in addition to resource endowment, firms must deploy and leverage their resources in ways that match their changing market environments to gain a competitive edge (Teece, Pisano, and Shuen 1997).

Design as a firm capability. Design is a widely used concept across various disciplines. Luchs and Swan (2016), in a review paper, suggest that most academic papers on design incorporate this term in three different manners: product form, function, or a combination of both.[2] Product form, the focus of this research, refers to product appearance, such as textures, shapes, colors, materials, and ornamentations (Eisenman 2013), whereas product function pertains to the engineering aspects of product and relationships among internal components, materials, and technologies delivering functional utility (Ulrich and Eppinger 2012).

[2] There are a few other studies that introduce other elements in their conception of design. For instance, Srinivasan et al. (2012) add the meaning dimension, which refers to the shared significance and memorial associations of the product, and Homburg, Schwemmle, and Kuehnl (2015) introduce the symbolic dimension, which refers to the perceived message a product communicates regarding a consumer's self-image. Jindal et al. (2016) introduce ergonomics as the third dimension of design that is more about ease of use, comfort, and user experience.

Design does not happen in isolation. Product design can enhance user-product interfaces through aesthetic and ergonomic properties while meeting the operational and cost restrictions (Ulrich and Eppinger 2012), requiring numerous back and forth iterations within the firm. Not only do firms protect their designs by means of patents, but they also build their design capabilities through interaction and collaboration among several departments, including design, marketing, R&D, engineering, and manufacturing. Therefore, design capability is deeply rooted in organizational processes and is embedded within firms in a complex mesh of interconnected actions that make it very difficult for competitors to replicate or trade (Krasnikov and Jayachandran 2008). Thus, the market positions produced through design are sustainable. As such, I define design capability as the ability of a firm to deploy its design-related resources to achieve superior and novel designs relative to other products in the market.

Design Capability's Impact on Sales Growth

Extant research on design from a marketing perspective has focused on design's intermediate behavioral outcomes (Chitturi, Raghunathan, and Mahajan 2007) and its impact on product or firm performance (Homburg, Schwemmle, and Kuehnl 2015; Jindal et al. 2016; Landwehr, Wentzel, and Herrmann 2013; Liu et al. 2017; Rubera 2014), particularly in the automobile industry and without any attention to environmental conditions. Table 1.1 provides a summary of representative research on prior studies on the market performance effects of design and how this study differs. In sum, with some exceptions, prior studies provide evidence that design enhances firm performance outcomes; however, these studies have neglected to consider whether firm performance outcomes are contingent upon environmental factors.

Table 1.1. Representative Research on Firm-Level Design Effects

Study	Objective Measurement	Environmental-Factor Moderators	Multiple Industry	Sample	Main Findings
Hertenstein Platt, and Veryzer (2005)	**No** (Expert ranking)	**No**	**Yes**	16 SICs 172 firms 7 years	D increases firm financial performance measures but does not increase sales growth
Talke et al. (2009)	**No**	**No**	**No**	14 firms 29 years	D newness persistently increases sales over time; there is no interaction between D and T newness
Rubera and Droge (2013)	**Yes** (design patents)	**No**	**No**	200 firms 6 years	D newness increases sales and Tobin's Q for only corporate brands; the interaction between D and T depends on branding
Landwehr, Wentzel, and Herrmann (2013)	**Yes** (Euclidian distance among 50 features)	**No**	**No**	German cars 7 years	Products with atypical Ds reach their sales peak at a later point than products with typical Ds
Rubera (2014)	**No** (Magazines reviews)	**No**	**No**	57 brands 26 years	D newness diminishes initial sales but increases sales over time; T newness, brand strength, and advertising enhance the effects of D
Jindal et al. (2016)	**No** (APEAL study's Style measure)	**No**	**No**	33 brands 6 years	D (i.e., form) does not affect market share; there is a negative interaction between D and T
Liu et al. (2017)	**Yes** (Morphing technique)	**No**	**No**	33 brands 8 years	D characteristics impact market share
This Study	**Yes** (SFE method)	**Yes** (TI, TCI, TM)	**Yes**	28 2-digit SICs 539 firms 15 years	D capability enhances sales growth; technological market conditions moderate the effect of D capability

D and T refer to Design and Technology

There are a number of reasons to suggest firm design capability has a positive impact on product demand and, in turn, firm sales, regardless of the firm's technological environment. First, effective designs elicit a variety of affective (Rindova and Petkova 2007) and aesthetic responses (Crilly, Moultrie, and Clarkson 2004; Hertenstein, Platt, and Veryzer 2005; Rindova and Petkova 2007), leading to positive consumer behaviors, including further product investigation, product purchase and trial, and positive word-of-mouth (Bloch 1995; Creusen and Schoormans 2005; Crilly, Moultrie, and Clarkson 2004; Homburg, Schwemmle, and Kuehnl 2015; Talke et al. 2009). These effects speed up the adoption process and increase sales (Rubera and Droge 2013).

Second, design also triggers consumer cognitive responses. It is a powerful tool for drawing consumer attention and creating perceptual cues with regard to product categories (Creusen and Schoormans 2005). Design has the potential to change the product meaning (Norman and Verganti 2014), and facilitate the social construction process by conveying and communicating what a product does (Ravasi and Rindova 2004). Thus, firms can utilize design elements to shape consumers' perception toward brand category membership and extend their product lines (Kreuzbauer and Malter 2005). Further, design provides cues about the functional values of products (Bloch 1995; Crilly, Moultrie, and Clarkson 2004; Noble and Kumar 2010; Stoneman 2010). Consumers incorporate such cues into performance judgments that are resistant even when presented with conflicting information from different sources (Hoegg and Alba 2011). Thus, effective designs enhance the perceived functional value of products.

Third, firms can utilize design to creatively differentiate their products (Hirschman 1983; Kotler and Keller 2011; Morgan, Kaleka, and Katsikeas 2004), leading to higher product involvement and triggering reward for consumers that result in product choice (Reimann et al. 2010). Indeed, past research strongly suggests that products that are creatively differentiated gain performance over competitors by meeting unique market demands in meaningful ways (Im and Workman Jr 2004).

Therefore, firms with strong design capabilities can advantageously manage their product portfolios to effectively replace their products with newer models that are differentiated only with respect to their external appearance (i.e., design) to create demand and increase their sales.

H1: *Design capability has a positive impact on sales growth*

Context Matters

A prominent topic in marketing is how the set of products and brands that consumers face (i.e., choice set) can affect consumer judgment, preferences, and decision making. The underpinning assumption in early utility models was independence from irrelevant alternatives, which states preferences among existing alternatives do not depend on additional alternatives to the choice set. This is reflected in other assumptions in early utility models: proportionality, which states that a new product takes from other products in proportion to their original shares (Luce 1959); and regularity, according to which the addition of an option to a choice set can never increase the probability of selecting an option from the original set.

The assumption of independence from irrelevant alternatives, however, has been violated by various studies. For instance, according to the similarity effect, a new product takes a greater share from similar items (Tversky 1972), therefore, potentially changing the preferences of consumers; when a new extreme option is introduced to the choice set, sometimes consumers' preferences get reversed, and they tend to choose the "compromise" option (Simonson 1989; Tversky and Simonson 1993); and interestingly, when an asymmetrically dominated option (i.e., ADE or decoy) is added to the choice set, it can help a similar option gain more share (i.e., attraction effect) (Huber, Payne, and Puto 1982; Huber and Puto 1983). The common theme across all these findings is that choice set can affect how consumers evaluate their options, which in turn influence their choice. In other words, the context in which consumers make their decision matters and preferences are dependent on it.

Originally, Huber, Payne, and Puto (1982) assert that the range of variation and frequency of attribute levels can explain why an ADE option is selected. Although later research provides different interpretations, it confirms that the dimension that is extended receives significantly more weight (Ariely and Wallsten 1995; Wedell and Pettibone 1996; Bonaccio and Reeve 2006). Similarly, the impact of the "range of variation" and "number of levels" has been well documented in the extant conjoint literature. A product attribute becomes more important as its range of variation or number of levels increases (Verlegh, Schifferstein, and Wittink 2002; Wittink, Krishnamurthi, and Reibstein 1990).

The theory of context-dependent-weighting, on which I mainly build my theory, explains how choice is dependent on the context (e.g., Ariely and Wallsten 1995; Huber, Payne, and Puto 1982; Tversky and Simonson 1993). It states that the weight or importance of product attributes (i.e., dimensions) can change predictably. Huber, Payne, and Puto (1982) assert that an increase in the variability of an attribute draws more attention to that particular attribute, and as such, it becomes more salient (Taylor and Thompson 1982) and receives more weight in consumer decision making (Bonaccio and

Reeve 2006; Bordalo, Gennaioli, and Shleifer 2013). In other words, if the variability of a dimension increases, the weight of that dimension increases. Consumers evaluate their options by aggregating information regarding different attributes and attach disproportionate weights to the product attributes (Bordalo, Gennaioli, and Shleifer 2013).

In my theoretical grounding, I consider form (i.e., design) and function (i.e., technology) the main end-product dimensions (Luchs, Swan, and Creusen 2016) that consumers jointly evaluate and weight. I theorize how the weight of design and technology may change in various conditions. Since an increase in the weight of a dimension leads to a decrease in the relative weights of other dimensions (Wedell 1998), I posit that in conditions where technology becomes more (less) salient in decision making, it receives more (less) weight, and as such, design becomes less (more) salient and receives less (more) weight.

How Technology Intensity, Technological Competitive Intensity, and Technological Maturity Moderate the Design Capability-Sales Growth Relationship

According to contingency theory (Levinthal 2000), the benefits of capabilities also depend on the context in which the capabilities are deployed (Feng, Morgan, and Rego 2017; Schilke 2014). Thus environmental factors can influence the return to a firm's resource or capability (Song et al. 2005). This notion is in line with the dynamic capabilities perspective that posits that firms must deploy and leverage their resources in ways that match their dynamic market environment (Teece, Pisano, and Shuen 1997).

As stated by organizational theory, the primary environmental dimensions are capacity, dispersion, and instability (e.g., Dess and Beard 1984; Milliken 1987). I apply these three dimensions to technology contexts to derive the technological environmental factors: technology intensity (capacity) – the extent of new product and process technologies in an industry relative to industry size; technological competitive intensity (dispersion) – the degree of dispersion of new technologies among firms competing in the same industry; and, technological maturity (stability) – the degree of standardization of technologies in an industry (Utterback 1994; Utterback and Abernathy 1975). In what follows, in theorizing each hypothesis, first, I define the particular environmental technology dimension, and what it means from a consumer's and a firm's point of view, then I theorize about how that condition can change the effect of design capability on sales growth.

Technology intensity and design capability-sales growth relationship.

Technology intensity refers to the extent of new product and process technologies in an industry relative to industry size a firm embeds (Ang 2008). It is very similar to the high- vs. low-tech typology of markets (Rosen, Schroeder, and Purinton 1998). My conception, however, is a matter of degree instead of type because there is a 'technology continuum' (Gardner et al. 2000) on which industries can shift toward either direction. The mobile phone and home furniture industries are good examples of high and low technologically intensity markets.

The impact of design capability on sales growth will likely be attenuated by technology intensity for several reasons. First, in high technology intensity markets, product attributes change rapidly, and firms continuously advance their underlying technologies – to respond to and shape consumer expectations (Rosen, Schroeder, and Purinton 1998) – as this is a critical factor for firms' survival (Ang 2008). In these markets, there is a high rate of technological change, hence the range of variability of technical performance of products is more than in markets where technology is not an essential product attribute. Therefore — as the theory of context-dependent-weighting suggests — the range of variability would draw more attention to the technical attributes (Huber, Payne, and Puto 1982), and therefore, they should become salient (Taylor and Thompson 1982) and receive more weight in decision making (Ariely and Wallsten 1995; Tversky and Simonson 1993; Bonaccio and Reeve 2006). Prior studies also suggest that consumers are generally more concerned with the technical performance of products in high-tech markets (Chitturi, Raghunathan, and Mahajan 2007; Davies and Walters 2004), and thus technology attributes of products are more salient in consumer decision making. When technology attributes become more important in decision making, design attributes receive less weight (Wedell 1998). Moreover, in these markets, consumers are more involved in purchase decisions (Gardner et al. 2000), and therefore, they tend to make more deliberate decisions. As such, immediate response to affective stimuli, such as appealing designs, is lessened.

Second, the analogical transfer paradigm (Gregan-Paxton and John 1997) demonstrates that consumer reaction to new products is a learning process in which knowledge from a familiar domain is transferred to the lesser-known new product. Wrapping new technologies, which consumers have little experience with, in a familiar product design facilitates the establishment of a mere appearance comparison, namely the knowledge transfer from a product with a similar physical appearance to the new one. Moreau, Lehmann, and Markman (2001) argue that acquiring knowledge about the new technology is necessary for consumers to recognize the relative advantage of the innovation and adopt it, suggesting that technological innovations are more accepted by consumers when they are conveyed in less novel designs. In markets where new technologies are highly incorporated in products, familiar, less novel designs can effectively facilitate the social construction process by conveying the product meaning (Ravasi and Rindova 2004), resulting in product acceptance and trial. Further, the design and the underlying technology of a product jointly determine a product's degree of complexity and novelty (Luchs, Swan, and Creusen 2016). A complex product may be incompatible with customers' existing values and experiences (Gourville 2005), requiring extensive mental effort and cognitive processing (Bloch 1995) that is not desirable from a consumer standpoint. Rindova and Petkova (2007) give the example of TiVo, which was designed to resemble a VCR physically. Even though the technology was very different, the familiar product design helped consumers make sense of the new technology.

Finally, consumers tend not to purchase products that overshoot their willingness to pay. Products with high levels of both design and technological innovation, however, prompt higher supply restrictions because they require difficult trade-offs among the product aspects (Luchs, Swan, and Creusen 2016) and a significant change in the firm's production facilities that can impart higher costs to the firm (Rubera 2014). Thereby, firms in an attempt to make up for lower profit margins may increase their prices that are higher than mainstream consumers' willingness to pay (Jindal et al. 2016), resulting in lower levels of product trial and demand.

All these arguments combined, I predict that in more technologically intense markets, while firms with greater design capabilities would still be able to execute strategies to achieve value-producing positions, the firms' ability to capitalize on these positions would be less. Conversely, markets with limited emphasis on new technologies provide a more fertile ground for firms to capitalize on their design capabilities. Therefore, the design capability's impact on sales growth is attenuated when technology intensity is high.

H2: *The greater the technology intensity, the weaker the relationship between design capability and sales growth*

Technological competitive intensity and design capability-sales growth relationship.

I define technological competitive intensity as the degree of dispersion of new technologies among firms competing in the same industry. Therefore, if technology advancement happens by a small portion of firms in an industry, technological competitive intensity is low, whereas when the majority of firms advance their technologies to a relatively similar extent, new technologies are dispersed in the industry, and technological competitive intensity is high. This creates a competitive context, generally where firms are 'structurally equivalent' (Burt 2009). As such, technological competitive intensity captures the magnitude of effect that a firm has on its competitors' chances of gaining a technological edge. Akin to competitive intensity, I use the industry concentration of utility patents published by firms in the same industry to measure technological competitive intensity.

I expect that as technological competitive intensity in a market increases, the effect of design capability on sales growth gets stronger for two primary reasons. First, products in markets with high technological competitive intensity are likely to be similar with respect to their underlying technologies and technical attributes. This similarity happens because periods of high competitiveness correspond to the rapid diffusion of new technologies among firms (Robertson and Gatignon 1986); thus, a firm can only gain a technological edge over its rivals for a short period. In these periods, imitation is a primary firm strategy (Porter and Millar 1985), and firms reverse engineer and copy their competitors' technologies at a fast pace (Zhou, Yim, and Tse 2005). Therefore, in conditions of high technological competitive intensity, firms' technological advantages are not sustainable as they match their offerings with their competitors' (Jaworski and Kohli 1993).

Thus, in both technologically intense and less technologically intense markets, this technological similarity of products—from technological competitive intensity—would lead to a fewer number of levels of technical product attributes. As the theory of context-dependent-weighting states, a product attribute becomes more salient and receives more weight as it receives more attention (Taylor and Thompson 1982; Bonaccio and Reeve 2006; Bordalo, Gennaioli, and Shleifer 2013). Prior studies vastly agree that when the number of product levels of an attribute increases, consumers tend to pay more attention to that attribute, and as such, it becomes more salient and receives more weight in consumer decision making (Verlegh, Schifferstein, and Wittink 2002; Wittink, Krishnamurthi, and Reibstein 1990). Therefore, technical attributes of products should receive less weight when their number of levels decreases in high technological competitive intensity markets, and consequently, design attributes become more salient and receive more weight (Wedell 1998). Thus, firms with strong design capabilities would be able to take advantage of these conditions effectively by capitalizing on design.

Second, competitors gain relatively similar positions concerning the level of new technologies they achieve as their offerings become technologically homogenous. Thus, consumers face a lot of clutter regarding the merits of brands' technological claims and cannot easily compare and rank them based on their functional values. Further, this slows down consumers' decision making and makes their performance judgments slower. Under these consumer-decision making circumstances, affective responses, such as those due to new or appealing designs, become more salient (Page and Herr 2002). Product designs that are novel and stand out draw consumer attention (Creusen and Schoormans 2005) and become more critical in consumer decision making (Bordalo, Gennaioli, and Shleifer 2013).

Therefore, in markets with a high degree of technological competitive intensity, design attributes become more salient and get overweighed in consumer decision making. Firms with robust design capabilities can, therefore, more effectively differentiate their products (Hirschman 1983; Kotler and Keller 2011; Morgan, Kaleka, and Katsikeas 2004) based on unique design attributes that grab consumers' attention toward their products; thus, I hypothesize:

H3: *The greater the technological competitive intensity, the stronger the relationship between design capability and sales growth.*

Technological maturity and the design capability-sales growth relationship.

I define *technological maturity* as the degree of standardization of technologies in an industry (Utterback 1994; Utterback and Abernathy 1975). As Sood and Tellis (2005) point out, there is no "single, strong, unified theory of technological evolution." The common theme across the technological evolution models, however, is that technologies go through phases of growth and maturity (Wang 2017). New technological regimes occur from radical and discontinuous technological innovations that have their own technological trajectories that lead to eras of great ferment, experimentation, and shakeouts in the market (Anderson and Tushman 2001; Tushman and Anderson 1986). Eventually, a ‘dominant design’ –in the form of key technological elements that become the industry standard– emerges, technological innovation becomes more incremental, the focus shifts from product to process innovations (Adner and Levinthal 2002; Utterback 1994; Utterback and Abernathy 1975), and consumers develop expectations about the underlying technologies of products (Eisenman 2013).

I predict that as technological maturity in the market increases, the effect of design capability on sales growth gets stronger for two reasons. In markets with high technological maturity, innovations become incremental and process-oriented (Utterback and Abernathy 1975; Eisenman 2013); therefore, technical attributes of products would have less range of variation, making the technical attributes less salient (Chitturi, Raghunathan, and Mahajan 2007; Davies and Walters 2004). Not only is there little variation of technologies in mature markets, but also firms’ offerings gravitate toward each other and become technologically homogenous (Eisenman 2013); therefore, in mature markets, there are fewer number of technical product attribute levels. Technology thus gets less weight in consumers’ decision making (Verlegh, Schifferstein, and Wittink 2002; Wittink, Krishnamurthi, and Reibstein 1990). Novel designs, however, draw consumer attention (Creusen and Schoormans 2005) and become more salient (Taylor and Thompson 1982). Further, evidence indicates that in conditions like technological maturity where all of the products in a choice set exceed functional cutoffs, consumers attach greater significance to the hedonic attributes such as design (Chitturi, Raghunathan, and Mahajan 2007).

Moreover, firms can use design to conceal the absence of any technological change that is meaningful to consumers and launch new products by exploiting the same core functions and technologies repeatedly by only changing the product design (Eisenman 2013; Hoffer and Reilly 1984). That is, in technologically mature markets, firms with design capabilities can entice their customers to replace older product models with newer ones, despite offering little technological improvement (Christensen 1995; Utterback et al. 2006). Indeed, gravitation toward competitive parity in mature markets can be averted through creative initiatives such as product design (Andrews and Smith 1996). I expect that firms with strong design capabilities can effectively use this initiative to launch new products or modify their current products to enhance their sales growth, therefore,

H4: *The greater the technological maturity, the stronger the relationship between design capability and sales growth.*

Methodology

Data

I collect the data from several secondary sources, allowing the testing of the hypotheses using a large sample of firms over a long period. I obtain all the design and utility patents published since 1995 through 2017 in the United States. Most firms – even outside of the US – tend to patent their significant innovations in the US (Tellis, Prabhu, and Chandy 2009). In 2008, the USPTO issued more patents to foreigners than to Americans, while the absolute number of patents increased (Arndt 2009). Design patents are a particular category of patents that can be granted in the US for a "new, original, and ornamental design for an article of manufacture" whereas utility patents are issued for the invention of a new machine, device, or manufactured item and refer to the functionality of a product. Design patents must be issued for the aesthetics and not the function or utility of an invention. The scope of a design patent is limited to the "overall, ornamental, visual impression." Designs that are hidden in their end-use or are necessary for the proper functioning of the device are not ornamental and, therefore, not patentable as a design patent.

This data contains 4,895,721 patents, of which 9.2% are design patents. Through extensive coding, I match the company names from the Compustat data and patent assignee names in the patent data obtained from USPTO. I account for companies using different names or business units. I were able to match 1,759,606 patents to the Compustat data, indicating a reasonable matching rate compared to that of the patent data project by the National Bureau of Economic Research (NBER), which had matched patents with Compustat data until 2006. Using the merger & acquisition data from SDC, I also track down the changes in ownership of firms. This step is crucial as a firm may acquire another firm, though the acquired firm continues to file patents using its original name. I use the matched data set, which contains of 6,736 firms over 22 years across 28 2-digit SIC codes, to calculate the capability and technological environment variables. Since five prior years of design patent data are needed to calculate DSGN_STOCK, used as an input in the SFE model to calculate design capability, the sample starts from 2000. In line with prior capability studies that use patent data, I use patent application dates instead of grant dates because once an entity applies for a patent, it is ready to use that technology/design, and most of the patent rights are granted after application. Besides, the time that it takes for a patent to get granted is out of the firm's control and varies for patents, with respectively 1.52 and 2.85 years for design and utility patents. Following Dass, Nanda, and Xiao (2017), I used the historical distribution of patents to correct for truncation bias. This correction is important because the patent application data is censored in the sense that if a patent is applied for but has not been granted by the time that data is collected, it is not included in the data. To use extra caution, I drop the last two years of the data because the data in recent years are more significantly censored. Additionally, I lose one year of data so as to perform first-differencing in the model. A firm has to have six consecutive years of patent data to be included in the final sample. Due to missing data across control variables, the final data set used for estimation comprises of 539 firms across 28 2-digit SIC codes and 4,378 firm-year observations, with 8.12 years of data for each firm on average from 2000 to 2015.

Operationalization of Variables

***Design capability*.** Design patents are applied to a wide variety of products such as consumer electronics, apparels, textiles, furnishing, and fashion products. Firms also use design patents to protect their packaging, graphic symbols, and user interfaces. Therefore, design patents can effectively show how much a firm invests in improving the design of its products.

I measure the design capability (DSGN_CAP) by using the stochastic frontier estimation (SFE) method. I use design patent stock (DSGN_STOCK) in the past five years, number of design employees (DSGN_EMP), and design expenditures (DSGN_EXP) as the inputs of design capability and the number of design patents (DO) as the output. A firm's stock of innovative design enhances its ability to develop newer generations of designs; therefore, a firm's past experiences in design innovation is a good indicator of its ability to develop newer and better designs. I utilize the Koyck lag structure (Dutta, Narasimhan, and Rajiv 2005) to calculate DSGN_STOCK, with declining weight of .5 to the power of year difference, such that more recent years receive greater weights.

Further, human resources are probably the most indicative of a firm's focus on design (Kuang 2015). I use patent inventor data to count the number of unique design inventors in each firm. There are 3,772,501 patent inventors in the data, and 333,998 of them have a record of design patent invention. If an inventor has more number of design patents than utility patents on his record, that person is considered a design inventor. Ultimately, 265,501patent inventors fall into this category, and the number of design inventors serves as my proxy for number of design employees.

Finally, as Stoneman (2010) suggests, design expenditures are most likely subsumed under R&D expenditures; therefore, I prorate firms' R&D expenditures between design and utility innovations based on design and utility patent numbers and their number of claims. The number of claims of design patents is always one, whereas utility patents almost always have multiple claims. Design expenditures in my data on average constitute 8.55% of R&D expenditures.

I use a Cobb-Douglas formulation in a 'true' random effect SFE model (Greene 2005) and specify the design capability frontier as follows:

$$\ln (DO_{it}) = \alpha_{01} + \alpha_{11} \ln (DESIGN\_STOCK_{it}) + \alpha_{21} \ln (DSGN\_EMP_{it}) + \alpha_{21} \ln (DSGN\_EXP_{it}) + \omega_{i1} + v_{it1} - u_{it1}, \quad \textbf{(1)}$$

where the scripts *i* and *t* respectively represent firms and years; ω_i represents time invariant firm heterogeneity that is not related to the production structure; v_{it} is the intrinsic randomness in a firm's frontier output level and is purely stochastic error affecting the frontier outputs; u_{it} captures the inefficiency and is the downward deviation from the efficient frontier. The 'true' random effect SFE model disentangles the time invariant firm heterogeneity from the inefficiency term. This is particularly important because the data comprises of firms from various industries that are potentially different in their design resource deployment.

I assume that random error has a normal distribution with mean of zero and that the inefficiency term has an exponential distribution (Meeusen and van Den Broeck 1977); however, as Greene (2005) points out this assumption has no major influence on the results. As a robustness analysis and following Dutta, Narasimhan, and Rajiv (1999), I allow for heteroscedasticity and model the error term as a function of firm size. Intuitively, the inefficiency term is the difference between the maximum possible output that a firm could have achieved (efficient frontier) by fully efficiently deploying its resources and the firm's actual achieved output (Dutta, Narasimhan, and Rajiv 1999). I use simulated maximum likelihood to estimate the 'true' random effect SFE model, and I transform the inefficiency term to calculate design capability using the exp[-E(u|e)] transformation.

Sales Growth. Sales growth (SG) is measured as the difference between sales in the current year and the past year divided by sales in the past year ($\frac{Sale_{it}-Sale_{it-1}}{Sale_{it-1}}$).

Control Variables. I collect a variety of variables to be included as control variables based on previous literature on the firm capability-firm performance relationship to reduce omitted variable bias to the extent possible. In particular, I control for two levels of factors: firm characteristics and technological industry conditions, whose interactions with design capability are also incorporated in the model.

Firm characteristics. Using Compustat data, I control for prior firm performance, i.e., Return on Assets (ROA), measured as income before extraordinary items divided by total assets; firm size (SIZE), measured as log of number of employees (Morgan, Vorhies, and Mason 2009); R&D expenditures (RD_EXP).

Technological industry conditions. Generally, scholars have measured technology-related market conditions, such as turbulence, either with expert ratings (e.g., Song et al. 2005) or by surveying managers (Wilden and Gudergan 2015). However, I directly utilize utility patents, as they are indicators of technological changes, to measure technology intensity, technological competitive intensity, and technological maturity. A particular advantage of utilizing such patenting activities is that I can test hypotheses across a wide range of industries over time.

I measure *technology intensity* (TI) of an industry (i.e., the extent of new product and process technologies in an industry relative to industry size) as the proportion of total number of utility patents published by firms operating in the industry in a certain year to industry size (total sales) and excluding the focal firm. By excluding the focal firm in calculation of technology intensity, I capture the technology intensity that each firm experiences facing its competitors. This measurement is similar to that of Ang (2008) where technology intensity is defined as the ratio of R&D expenditures to the firm output. Since the distribution of technology intensity is strongly right-skewed, I log-transform it.

Technological competitive intensity is defined as the degree of dispersion of new technologies among firms competing in the same industry. I rely on the 'structurally equivalent' characteristic of competitive contexts (Burt 2009) and similar to how competitive intensity is measured, I measure technological competitive intensity (TCI) by utility patent concentration index (-Σ UpS_{ijt}^2), where UpS_{ijt} is utility patent share of firms i in industry j and in year t. Therefore, if firms gain relatively similar shares of utility patents in their industry, new technologies are dispersed in the industry (i.e., low concentration) and technological competitive intensity is high.

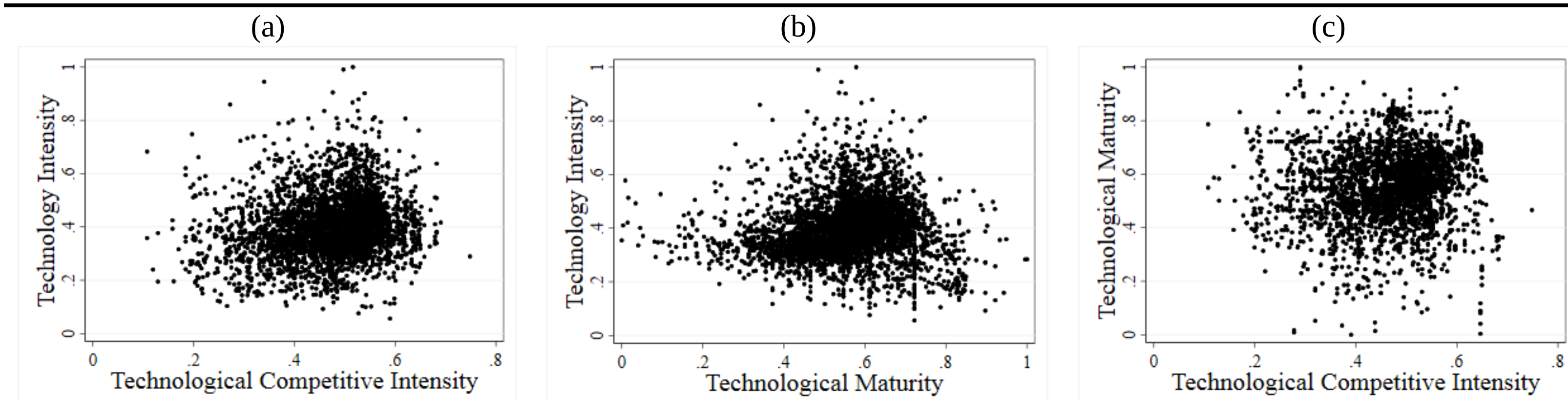
Technological maturity is measured as the ratio of process innovations to product innovations in an industry, following prior conceptions of maturity (Adner and Levinthal 2002; Utterback 1994). I use patent claim data to classify utility patents into product and process innovations. According to sections 101 and 100(b) of US patent laws, product and process are two major categories of innovations, with "the term 'process' means process, art, or method, and includes a new use of a known process, machine, manufacture, composition of matter, or material." Therefore, I parse near 36 million independent claims of utility patents issued from 2000. If a patent claim includes "method" or "process" keywords (excluding words such as processor), it is classified as process, otherwise as product. Technological maturity (TM) is then measured as the ratio of total number of process claims to the total number of product claims. The relationships between the technological environmental condition variables are displayed in figure 1.2. For information on the correlation structure and descriptive statistics, see Table 1.2.

Table 1.2
Correlation Matrix and Descriptive Statistics

	Mean	Std. Dev.	1	2	3	4	5	6	7	8
1. Sales Growth	.073	.249	1							
2. Design Capability	.833	.109	.046	1						
3. Technology Intensity	.397	.107	.007	.026	1					
4. Technological Competitive Intensity	.481	.089	.065	.002	.159	1				
5. Technological Maturity	.562	.120	.036	.009	.049	.111	1			
6. Firm Size	9.257	1.947	-.119	-.018	-.220	-.091	-.016	1		
7. Prior Performance (Lag of ROA)	3.037	19.033	-.188	-.001	-.065	-.014	.008	.240	1	
8. R&D Expenditure	897.122	1845.138	-.042	-.016	-.024	.085	.082	.523	.089	1

Correlations with an absolute value greater than .036 are significant at $p < .05$.

Figure 1.2
Technological Environmental Conditions



Model Specification

Preliminary tests confirmed the presence of heteroscedasticity and serial correlation in the panel data used. Moreover, firm capabilities are generally developed over long periods and have carryover effects on firm performance (Grewal and Slotegraaf 2007).Therefore, to account for this persistence effect and to reduce serial correlation (Wooldridge 2015), I introduce the lag of sales growth (SG), thus also controlling for otherwise omitted variable bias (Germann, Ebbes, and Grewal 2015).

I use an (Arellano and Bover 1995) and (Blundell and Bond 1998) dynamic panel estimation (i.e., system GMM). System GMM has been commonly used in the marketing strategy literature and is suited for situations where past realizations of the dependent variable affect its current state, the covariates are not strictly exogenous (i.e., covariates are correlated with the past or current realizations of the error term), arbitrarily distributed fixed individual effects are present, heteroscedasticity and autocorrelation within individuals are suspected, and finally the number of available time periods is small but the number of panel members is large (Roodman 2006). I propose the following model specifications:

$$\begin{aligned} SG_{it} = {} & \beta_0 + \beta_1 . SG_{i(t-1)} + \beta_2\, DSGN\_CAP_{it} + \\ & \beta_3\, DSGN\_CAP_{it} \times TI_{it} + \beta_4\, DSGN\_CAP_{it} \times TCI_{it} + \beta_5\, DSGN\_CAP_{it} \times TM_{it} + \\ & \beta_6\, TI_{it} + \beta_7\, TCI_{it} + \beta_8\, TM_{it} + \beta_9\, SIZE_{it} + \beta_{10}\, ROA_{i(t-1)} + \beta_{11}\, RD\_EXP_{it} + \beta_{12-26}\, YEAR + \\ & \eta_i + \varepsilon_{it} \end{aligned} \qquad \textbf{(2)}$$

where η_i is the time-invariant unobservable firm effects, ε_{it} is the i.i.d errors capturing the idiosyncratic shocks, and YEAR is a vector of time (year) dummies. The estimation challenge of this model is that the lagged dependent variable is correlated with the error term, and therefore, using linear regression results in inconsistent results. Therefore, in using linear regression models, I do not incorporate the lag of SG. I only report these results to compare them with those from the system GMM.

System GMM takes the level and first-differenced equations as a system of equations, where the lagged differences of SG are used as instruments for the level equation, and values of past realizations of SG are used as instruments for the first-differenced equation (Arellano and Bond 1991; Roodman 2006).

In summary, I control for unobserved time-invariant firm heterogeneity, carryover effects of the firm's prior status, time fixed-effects, and other factors that can affect firm performance to reduce omitted variable bias to the extent possible. I allow for heteroscedasticity at the industry level and utilize the robust or sandwich estimator of variance to produce valid standard errors.

Results and Discussion

First, I present the results of design capability estimation in the first stage, and then I turn to results from the second stage in which I test the hypotheses. I use a 'true' random SFE model to calculate design capability. Table 1.3 presents the results from the simulated maximum likelihood estimation of the design capability SFE model.

The model is statistically significant ($p < .001$), with log simulated likelihood of -2588.09 and Wald chi^2 of 5886.17. All the inputs in the SFE model are significant ($p < .001$), providing empirical support that these inputs are relevant design resources. Based on the results, the most important input is the number of design employees as it has the highest coefficient (.552) among the input set. The inefficiency and random error terms are assumed to be homoscedastic[3] as U_{sigma} and V_{sigma} only contain the constant term (p < .001). The heterogeneity term is also significant (θ = -.253; p < .001), supporting the presence of time invariant firm-heterogeneity that is not a part of the inefficiency.

Table 1.3. Design Capability

	Coefficient	Std. Err.	z	P Value	95% Conf. Interval	
DSGN_STOCK	.109	.010	1.830	.000	.089	.128
DSGN_EMP	.106	.006	18.940	.000	.095	.117
DSGN_EXP	.552	.018	3.200	.000	.517	.588
Constant	.121	.016	7.470	.000	.089	.153
U_{sigma}						
Constant	-3.487	.190	-18.310	.000	-3.860	-3.114
V_{sigma}						
Constant	-2.466	.090	-27.310	.000	-2.643	-2.289
θ	-.253	.014	-18.480	.000	-.280	-.226
σ_u	.175	.017	1.500	.000	.145	.211
σ_v	.291	.013	22.140	.000	.267	.318
λ	.600	.028	21.350	.000	.545	.655

Finally, the results indicate that the variance of the inefficiency term is statistically significant (σ_u= .175; p < .001) and as the test of λ shows, its proportion to the random error term is meaningful (.6; p < .001).

After measuring design capability in the first stage, now I incorporate it into the main model to test the hypotheses. I estimate the model using OLS, random-effect, fixed-effect, and system GMM. As discussed, the lag of the dependent variable is not included in the first three models because it is correlated with the error term and thereby leads to inconsistent results. In all these models, I relax the independence assumption and only require that the observations be independent across the industries. Therefore, I allow for

[3] As a robustness check, I allow for heteroscedasticity of the error term and model it as a function of firm size (Dutta, Narasimhan, and Rajiv 1999); the results remain unchanged.

the heteroscedasticity across industries, and as such, all the standard errors are adjusted using the robust or sandwich estimator of variance. First, I present the results from the baseline model specification without introducing any interaction terms in order to make sure the significance levels of the main effect is not due to the inclusion of the interaction terms and to capture the magnitude of the main effect. I present the results in Table 1.4.

Table 1.4. Results

	Pooled OLS	**Random Effect**	**Fixed Effect**	**System GMM**
Design Capability (H1, +)	.081***	.081***	.078***	.067***
Technology Intensity (TI)	-.077**	-.068**	-.066**	-.068*
Technological Competitive Intensity (TCI)	.138***	.045	-.051	.119***
Technological Maturity (TM)	.049	.032	.01	.035
Firm Size	-.011***	-.005	.055**	-.008**
Prior Performance (Lag of ROA)	-.002*	-.002**	-.001**	-.002**
R&D Expenditure	.000	.000	.000	.000
Lag of Sale Growth	N/A	N/A	N/A	.167***
Constant	.109***	.034	-.504**	.036
Time Fixed Effect	**Yes**	**Yes**	**Yes**	**Yes**
N	4385	4385	4385	4378
Number of Groups (i.e., Firms)	NA	540	540	539
Number of Instruments	0	0	0	93
R^2	.120	.11.8	.130	NA
F-statistic (Wald chi2)	1,736.6	(23122.5)	2,575.7	2,944.1
Degrees of Freedom	21	21	20	24
AR(II) test (p value)	N/A	N/A	N/A	.583
Hansen Overid. test (J-statistic)	N/A	N/A	N/A	5.996

*** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$

The results are very consistent across all the models. Design capability has a significant positive effect on sales growth (.067, $p < .003$), supporting hypothesis 1. The effect of design capability is also economically significant[4], providing a 10.04% increase in sales growth, on average. Now, I introduce the interaction terms to estimate the full model specification. I center the covariates before generating the interaction terms (Aiken, West, and Reno 1991). Variance inflation statistics (VIF) shows that multicollinearity is not a concern in the model as the VIF ranges from 1.01 to 2.08. I present the results in table 1.5. The results are once again very consistent across all the models. However, since controlling for lag of the dependent variable (i.e., SG) is critical for dealing with reverse causality, I focus on the results from the system GMM estimation.

The Hansen test of over-identification (J test) indicates that the moment conditions are valid, and the specification is not over-identified ($p > .99$). System GMM uses the lagged realizations of the endogenous variables as instruments for them. Since due to autocorrelation the first lags are also endogenous, higher-order lags are used. The AR(II) test indicates that the second-order lags are not correlated with the error term ($p > .56$), and therefore can be used as instrumental variables. However, to avoid over-identification and biases associated with "too many instruments" I limit the number of instrumental variables to only the second-order lags through the fifth-order lags in the estimation (Roodman 2006). All the reported results are generated with these settings.[5]

Moreover, I use the difference-in-Hansen test to examine whether the instruments of the model are empirically exogenous. These instruments include the GMM type and other covariates, including design capability and its interactions, in both first-differenced

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[4] Calculated as the standard deviation of design capability times its coefficient divided by mean of sales growth

[5] I also examine the results using different settings of lag structure and find the results to be robust

and level equations. The difference-in-Hansen test is preferred to Durbin-Wu-Hausman tests because it can report test statistics that are robust to various violations of conditional homoscedasticity (Baum, Schaffer, and Stillman 2003). The results from the difference-in-Hansen test of endogeneity reveal that both groups of instruments are exogenous (*p* ~=.99).

Table 1.5
Results

	Pooled OLS	**Random Effect**	**Fixed Effect**	**System GMM**
Design Capability (H1, +)	.070***	.065***	.059***	.058***
Design Capability × TI (H2, +)	-.242**	-.425***	-.483***	-.254**
Design Capability × TCI (H3, +)	.488**	.704***	.738***	.406**
Design Capability × TM (H2, +)	.449***	.437***	.407***	.386***
Technology Intensity (TI)	-.077*	-.068**	-.065**	-.068*
Technological Competitive Intensity (TCI)	.138***	.047	-.048	.118***
Technological Maturity (TM)	.05	.035	.013	.035
Firm Size	-.010***	-.005	.055**	-.008**
Prior Performance (Lag of ROA)	-.002*	-.002**	-.001**	-.002**
R&D Expenditure	.000	.000	.000	.000
Lag of Sale Growth	N/A	N/A	N/A	.167***
Constant	.108***	.033	-.499**	.035
Firm Fixed Effect	**Yes**	**Yes**	**Yes**	**Yes**
Time Fixed Effect	**Yes**	**Yes**	**Yes**	**Yes**
N	4385	4385	4385	4378
Number of Groups (i.e., Firms)	NA	540	540	539
Number of Instruments	0	0	0	99
R^2	.121	.121	.132	NA
F-statistic (Wald chi2)	2,158.1	(68,694.4)	16,802.5	7,567.9
Degrees of Freedom	24	24	23	27
AR(II) test (p value)	N/A	N/A	N/A	.57
Hansen Overid. test (J-statistic)	N/A	N/A	N/A	1.413

*** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$

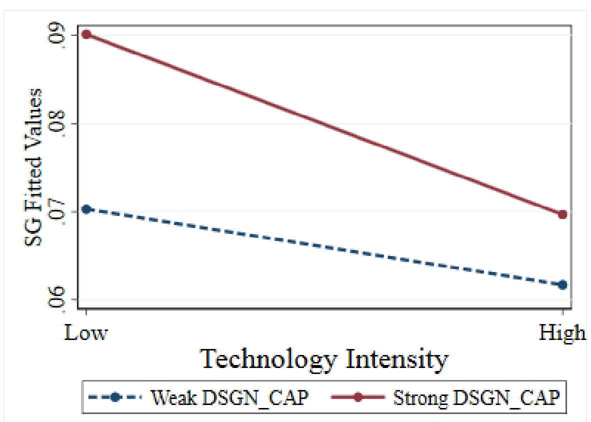
The effect of design capability on sales growth remains significant (.058, $p <$ .007) with the inclusion of the interaction terms. The interaction term between design capability and technology intensity is significant with a negative sign as predicted (-.254, $p < .013$), in support of hypothesis 2, and thus having strong design capabilities in markets with high technology intensity is less rewarding. The sign of the coefficient of technology intensity is also negative ($p < .09$), suggesting that firms operating in industries with high technology intensity on average have a harder time enhancing their sales. Further, the interaction between design capability and technological competitive intensity is also significant and, in line with my prediction, has a positive coefficient (.406, $p < .039$), in support of hypothesis 3. Therefore, the effect of design capability on sales growth is strengthened by technological competitive intensity. The effect of technological competitive intensity is also positive and significant (.118, $p < .004$), suggesting that these environments are supportive of firm growth. Finally, I find empirical support for hypothesis 4 as the interaction between design capability and technological maturity is significant with a positive coefficient (.386; $p < .003$), thus technological maturity strengthens the impact of design capability on sales growth.

Overall, my results are in support of my theory and predictions. Hypothesis 1 through 4 are all empirically supported; however, to get a more in-depth sense of the interactions, I utilize simple slope analysis, where low levels of each dimension are one standard deviation below their average values, whereas high levels of each dimension are one standard deviation above their average levels. The simple slope analysis plots are presented in Figure 1.3 (a-c).

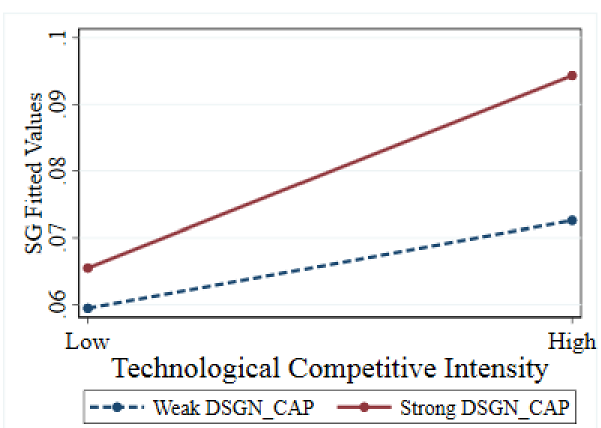
Firms with strong design capabilities gain better performance; however, design capability is a more valuable resource in industries with low technology intensity. The impact of design capability in low technology intensity condition is more than 2.6 times bigger than its impact in high technology intensity industries (economic significance of 14.4% vs 5.5%). Further, in industries with low technological competitive intensity, design capability does not make a significant difference in enhancing sales growth, whereas in industries with high levels of technological competitive intensity, design capability enhances sales growth by 14.4% on average. Finally, design capability has the strongest impact on sales growth in technologically mature industries, with a 16.4% increase in sales growth.

Figure 1.3. Simple Slope Analysis

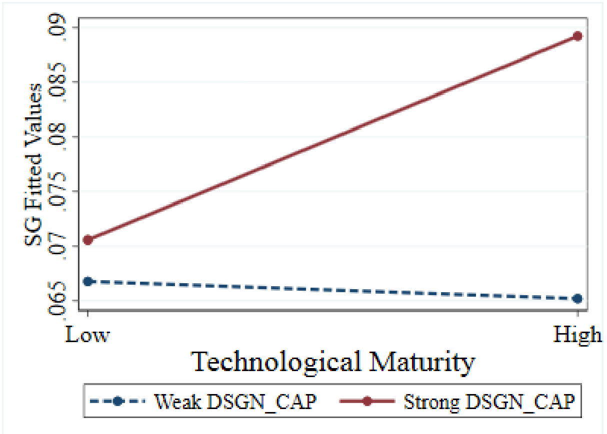
(a)



(b)



(c)



In summary, I show that technology intensity attenuates the relationship between design capability and sales growth. Design cannot make up for lack of technical excellence in high-tech markets because technical attributes of products are more salient and consumers take them more into account in their choice decisions (Chitturi, Raghunathan, and Mahajan 2007; Davies and Walters 2004). In addition, new designs may increase product complexity and impede consumers' understanding of product category membership. On the contrary, technological competitive intensity amplifies the relationship between design capability and sales growth because when products do not have a technological edge, design attributes become salient in consumer decision making, and firms with strong design capabilities can effectively use novel designs to creatively differentiate their products. Finally, technological maturity amplifies the relationship between design capability and sales growth. When technologies mature, technical advancement of products become very incremental from a consumer's standpoint; therefore, consumers develop expectations regarding the technologies embedded in products and take them for granted (Eisenman 2013). Novel designs, however, can grab consumer attention (Creusen and Schoormans 2005) and become salient in consumer decision making (Bordalo, Gennaioli, and Shleifer 2013). Moreover, design can mask the absence of any meaningful technological change (Eisenman 2013; Hoffer and Reilly 1984), and firms operating in mature industries can capitalize on their design capabilities to launch new products, albeit offering little technological improvement (Christensen 1995; Utterback et al. 2006) to boost their sales.

Robustness Checks

I provide a number of additional analyses to lend credence to my findings. I show that the findings are robust to: (1) allowing for heteroscedasticity in the calculation of design capability, (2) controlling for additional firm-level and industry-level factors, (3) other lag structure specification, and (4) accounting for outliers.

Allowing for heteroscedasticity in the calculation of design capability. I extend the SFE formulation and model the heteroscedasticity by allowing the variance of the random shock to vary across firms, with the variance as a function of firm size (Dutta, Narasimhan, and Rajiv 1999). Results of the SFE model are reported in Table 1.6. The coefficients are similar to those from the homoscedastic model. Further, firm size effectively predict the variation of error term (.69; $p < .019$). The results of the main model with the heteroscedastic design capability remain substantively unchanged. See table A.1 in Appendix A.

Controlling for additional firm-level and industry-level factors. In addition to the firm-level control variables in the main model specification, I control for marketing and R&D capabilities. Similar to the estimation of design capability, I use a ‘true’ random effect SFE model (Greene 2005) to estimate marketing and R&D capabilities. For marketing capability, I use firms’ sales and general administrative expenses, receivables

(Narasimhan, Rajiv, and Dutta 2006), and number of trademarks the firm owns (Wiles, Morgan, and Rego 2012) as the inputs and revenues as the output. I follow Narasimhan, Rajiv, and Dutta (2006) to calculate R*&D* capability, with stock of utility patents in the past five years–using koyck lag structure with declining weight of .5 to the power of year difference– and prorated R&D expenditures as the inputs and number of utility patents in a year as the output. The capability variables are once calculated with the assumption of homoscedasticity of the error term, and once with allowing for heteroscedasticity (Dutta, Narasimhan, and Rajiv 1999). See tables A.2, A.3, A.4, and A.5 in Appendix A for more details on the estimation results of marketing and R&D capabilities from the SFE models.

Table 1.6
Heteroscedastic Design Capability

	Coefficient	Std. Err.	z	P Value	95% Conf. Interval	
DSGN_STOCK	.104	.010	1.040	.000	.084	.125
DSGN_EMP	.107	.006	19.050	.000	.096	.118
DSGN_EXP	.547	.019	29.370	.000	.510	.583
Constant	.116	.020	5.840	.000	.077	.155
U_{sigma}						
Constant	-3.602	.243	-14.850	.000	-4.077	-3.127
V_{sigma}						
Firm Size	.069	.029	2.370	.018	.012	.126
Constant	-3.009	.270	-11.140	.000	-3.539	-2.480
θ	.265	.018	15.090	.000	.231	.300
σ_u	.295				.294	.295
σ_v	.165	.020	8.250	.000	.130	.209

Further, in addition to controlling for technological environmental conditions, I control for other important industry conditions: market munificence, market uncertainty, competitive intensity (Feng, Morgan, and Rego 2017), and design intensity. I use Compustat data and adapt the Keats and Hitt (1988) approach. I regress the total sales of firms in a SIC industry against the past five years to estimate munificence and uncertainty for the sixth year, as follows: $y_t = b_0 + b_1 t + e_t$, where y_t is the total sales in the industry in year *t*, *t* represents years, and *e* is the error term. I calculate industry munificence and uncertainty by dividing the year's standard error and coefficient (b_1) by the average total sales of the industry in the past five years. I use industry concentration as a proxy for competitive intensity such that higher concentration indicates lower competition and vice versa. Following prior research, I measure competitive intensity as $-\Sigma\, MS_{ijt}^2$, where MS_{jt} is the market share of firm *i* in industry *j* at year *t*. Finally, I measure design intensity in the industry in a similar fashion as technology intensity is measured; however, instead of number of utility patents, I count the number of design patents published by firms and in the industry. Therefore, it is the log transformed proportion of total number of design patents published by firms operating in the industry in a certain year to industry size (total sales) and excluding the focal firm. The results after controlling for these variables (see table 1.7.) are consistent with the results from the main model specification. It is noteworthy that the effect of marketing and R&D capabilities are significant with greater impact than that of design capability.

Lag structure setting. I run several models using different numbers of instrumental variables. I limit the number of lags, ranging from the second-order to the seventh-order. I also compere the results with the free lag restriction model. The results (Appendix A, Table A.6) are substantively similar, and therefore the findings are not sensitive to the setting of instrumental variables.

Outlier sensitivity analysis. I perform Winsorizing at various percentages (.5%, 1%, and 2%) to test for outlier influence. However, the findings mostly remain unchanged (Web Appendix A, Table A.7).

Table 1.7
Results with Additional Control Variables

	Homoscedastic Capabilities	**Heteroscedastic Capabilities**
Design Capability (H1, +)	.045**	.052**
Design Capability × TI (H2, +)	-.247**	-.318**
Design Capability × TCI (H3, +)	.387**	.472*
Design Capability × TM (H2, +)	.474***	.511***
Technology Intensity (TI)	.050*	.049*
Technological Competitive Intensity (TCI)	.104**	.107**
Technological Maturity (TM)	-.018	-.015
Firm Size	-.007**	-.006*
Prior Performance (Lag of ROA)	-.001	-.001
R&D Expenditure	.000	.000
Munificence	-.05	-.049
Uncertainty	-.035	-.019
Competitive Intensity	.011	.011
Design Intensity	-.002*	-.002*
Marketing Capability	.167***	.144***
R&D Capability	.068***	.085***
Lag of Sale Growth	.176***	.175***
Constant	.000	.000
Firm Fixed Effect	**Yes**	**Yes**
Time Fixed Effect	**Yes**	**Yes**
N	4245	4245
Number of Groups (i.e., Firms)	525	525
Number of Instruments	97	97
F-statistic (Wald chi2)	2,646.06	1,758.52
egrees of Freedom	33	33
AR(II) test (p value)	.131	.126
Hansen Overid. test (p Value)	~.99	~.99

*** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$

Limitations

There are a few limitations that offer future research opportunities. First, I use patent data to calculate the technological industry conditions. The norms and standards for deciding to file a patent and the time that it takes for patents to get published change over time. Any shift in such standards, if it occurred, may have a small biasing effect on my calculation of technological conditions. Using application dates instead of grant dates and the inclusion of year fixed effects in the models, however, mitigate this bias. Further, some patent decisions might not be completely exogenous. For instance, the choice between product versus process innovation might be affected by the reverse engineering threat that the firm feels from its competitors (Levin et al. 1987). However, allowing for firm heterogeneity and calculating technological conditions at industry level mitigate this problem.

Second, industries comprise of various product groups and technologies that may differ in terms of technological characteristics. By calculating the technological conditions at the industry level, I capture the average technological stand of industries over time. However, future research should look at the contingent effects of design initiatives at the product level to delineate a clearer pathway for gaining market positional advantage through design.

Third, I use the SFE method to calculate the capability measures, and like others utilizing this method, I assume that all the inputs are exogenous variables for SFE outputs. However, the amount of some of the design-related resources that firms devote could be determined by their expected outputs. For instance, a firm that plans to develop more new designs may tend to hire more designers and devote higher design budgets. The inherent endogeneity of the SFE inputs can raise concern in interpretation of the SFE inputs' coefficients; however, the implications for the effect of design capability remain valid as it is derived from the inefficiency term.

Fourth, my sample is based on the US publicly traded firms and utilizes US patent data. Future research should also extend this study to private firms and firms in other countries. Scholars could also extend this to look at how other performance metrics are impacted by design capability and examine how these technological environmental characteristics may moderate other capability-performance linkages.

Implications for Theory

Using a large sample of publicly traded firms in the US, this research presents an examination impact of design capability on the sales growth in various technological market conditions over a relatively long period. The findings provide several implications for theory. First, this research adds to the firm capability literature by illuminating the important role of design capabilities. Design capability is a valuable, rare, and non-imitable capability that yields positive firm performance outcomes. It provides a crucial differentiator and enhances sales growth. Firms have a design function that can operate in conjunction with—but remains separate from—marketing. For instance, IBM currently employs over 1,600 trained designers operating in 44 studios around the world. The functional structure of design within the organization can take many forms—from standalone departments to embedded design teams. Future research should look at the types and forms of marketing-design linkages and on how the different functional structures influence the quality of their relationship and the effectiveness of market outcomes.

Second, I enhance prior examinations of the impact of the firm's technological environment by distinguishing between technology intensity, technological competitive intensity, and technological maturity, adding insight on how technological environmental factors may alter the impact of firms' strategic actions on their performance outcomes. Further, I introduce an objective way to measure technological conditions based on archival data, which allows the technology conditions to be measured as continuous factors that vary across industries and over time. This advances prior measures of the technological environment, such as technological turbulence (Jaworski and Kohli 1993), based on survey data. Separating and objectively measuring these technological conditions would help better illuminate how firm capabilities impact firm performance in different technological environments; therefore, it is particularly important for future research to investigate the contingent impact of other firm capabilities, such as marketing capability, under these technological conditions. However, until then, this research provides the first attempt to depict a picture of the worth of a firm capability in various technological conditions.

Third, mostly drawing on the theory of context-dependent-weighting (e.g., Ariely and Wallsten 1995; Huber, Payne, and Puto 1982; Tversky and Simonson 1993), I theorize and empirically show how technological conditions impact the relationship between design capability and sales growth. I show that when range of variation or the number of levels of technical attributes of products decreases, they become less salient and less important, and design attributes receive more weight in consumer decision making.

Past studies offer conflicting findings on the interaction between design and technology, mainly because these studies are limited to single industries and centered over various time spans. Using the most comprehensive and most robust sample to date with 539 firms across 28 industry sectors, this study reliably reveals that the interplay between design and technology is more complicated than what the current literature suggests. Depending on what technological conditions a firm competes, design performance outcomes are reinforced or diminished.

Thus, the findings of this study potentially resolve some of the conflicting findings in the past literature. For instance, Rubera and Droge (2013) use consumer electronic industry data, and Jindal et al. (2016) use car industry data. Both studies, however, happen to use data for a similar time span (2002-2007). My data indicates that for this period, the level of technological competitive intensity and maturity of the car industry (SIC code of 3711) were low and diminishing; therefore, technical attributes of car products in this period were more important, and as such, design attributes were less important in consumer decision making. Notably, Jindal et al. (2016) did not find any effect for design (i.e., form) on market share. In contrast, the level of technological competitive intensity and maturity in the consumer electronic markets (e.g., SIC code of 3663) are high and growing, making design attributes more important. Interestingly, Rubera and Droge (2013) found that design increases sales in this environment. Thus, I provide a mechanism to explain these conflicting findings.

In sum, I reveal the interplay between design capability and sales growth is attenuated by technology intensity yet amplified by technological competitive intensity and technological maturity, contributing to the new product development literature as well as to the strategic management literature.

Implications for Practice

This research shows that market positions produced by design capability are sustainable and are a source of competitive advantage as design capability is difficult to trade or imitate, therefore, it is advantageous for managers to invest in building and enhancing design capability. I find no technological environment condition where firms with robust design capabilities perform worse than those with weak design capabilities in terms of their sales growth. This finding should support firms' efforts to create Chief Design Officers and to move the design conversation to the boardroom (Lockwood 2011). This would also suggest that firms should consider tying senior-management financial compensation to design-based metrics, such as design awards and consumer usability scores.

Further, I provide valuable new guidance for managers about the payoffs from design capability under various technological conditions. My findings indicate that design capability has less payoff when technology intensity in the industry is high (i.e., high-tech markets). Given this finding, many Silicon Valley enterprises that try to incorporate new technologies in new designs (Kuang 2015) should proceed with caution. Moreover, the results confirm that in highly technological competitive industries design effectively acts as a differentiator that helps products stand out of competition; therefore, in industries where most firms do not have a technological edge over their competitors, investing in developing robust design capabilities is more rewarding. Finally, the payoff from design capability is higher in technologically mature industries. This evidence should encourage firms in markets with slower rates of technological change to place relatively more emphasis on their design capabilities to expand their product lines by incorporating their technologies in new designs. When firms possess the know-how knowledge of the standard technology variants, exploitation of their current technologies becomes more crucial to gain competitive advantage (Tushman and Rosenkopf 1992), and firms should focus on standardization and efficiency (Lepak, Takeuchi, and Snell 2003). For instance, the mobile phone market, a high technology intensity market, went through many changes in the 1990s when various technologies, such as text messaging and touchscreen in 1993, internet access in 1996, GPS system in 1999, Mp3 player and mobile cameras in 2000, were adopted by the mobile phone manufacturers, following by a more mature phase in which manufacturers like Apple gained huge positional advantage by capitalizing on design. Combined, these results provide valuable new guidance for firms on how they should shift their focus toward design capability depending on the specific technological environment the firm faces. Moreover, managers can follow my approach and use publicly available patent data to create a dashboard to indicate the current state of their technological environment.

CHAPTER 2

PROFITING FROM TECHNOLOGICAL MARKET DYNAMICS:

THE IMPACT AND INTERPLAY OF MARKETING AND R&D CAPABILITIES

Abstract

Firms attend to their technological environment and use their capabilities to compete therein. However, little is known about how technological environment characteristics (i.e., technological turbulence, uncertainty, and acceleration) alter the payoff from these capabilities. Given that possessing superior firm capabilities is a primary source of competitive advantage for firms, this study seeks to fill these critical research gaps in the literature. I utilize the most comprehensive sample, to date, of 2132 publicly traded firms in the US over 32 years to investigate the effects of marketing and R&D capabilities on return-on-assets (ROA) in different technological environments. The findings reveal that all the technological environments amplify the positive ROA performance outcomes from marketing capability, with technological turbulence having the most potent effect. R&D capability, however, is most influential in technologically accelerating markets. Finally, I unveil that marketing and R&D capabilities are complementary only in technologically turbulent markets. This study thus provides valuable insights to researchers and managers on the payoff from these capabilities and also provides new guidance on which capabilities firms should emphasize on under different technological market conditions.

Keywords: marketing capability, R&D capability, technological turbulence, technological uncertainty, technological acceleration

Introduction

Firms vie for profitable positions in their technological environments by capitalizing on their capabilities to conceive and realize marketplace strategies more effectively and/or more efficiently than rivals do. The resource-based view (RBV) theory and accumulating evidence indicate that firm capabilities are the main drivers of firm performance (Krasnikov and Jayachandran 2008; Moorman and Slotegraaf 1999). However, extant research has mostly focused on the direct performance impact of firm capabilities, leaving gaps regarding the potential effects of market conditions in which firms operate (Feng, Morgan, and Rego 2017).

I focus on one of the most critical market conditions—the firm's technological environment. Technological change is a prime concern of the C-Suite companies. Indeed, a recent study of CEOs indicated that keeping up with technological changes is one of the CEO's most salient concerns (Feser 2017). Despite the managerial attention paid to the technological environment, there has been little empirical investigation on how firm capabilities relate to performance in different technological conditions. These prior studies are either not generalizable as their results are based on a single industry (Dutta, Narasimhan, and Rajiv 1999) or centered over short time spans and reliant on subjective measures (e.g., Song et al. 2005). Thus, knowledge on whether technological environment conditions make firm capabilities more or less valuable remains limited.

I capture technological dynamism in a market via three technological characteristics: the rate of technological change (i.e., technological turbulence), predictability of those technological changes (i.e., technological uncertainty), and changes in the speed of technological changes (i.e., technological acceleration). I attempt to fill the above-mentioned research gaps, by particularly seeking to answer whether the technological environment changes the positive performance outcomes of marketing and R&D capabilities. I then try to empirically investigate whether marketing and R&D capabilities are indeed complementary, and if so, how their joint effect varies in different technological environments.

The rationale for my selection of marketing and R&D capabilities are two-folds. First, they are among the most influential firm capabilities (e.g., Krasnikov and Jayachandran 2008). Second, product development is a spanning process that integrates inside-out (e.g., R&D) and outside-in (e.g., marketing) capabilities (Day 1994). Therefore, it is interesting to examine how these two capabilities that coexist jointly enhance firm profitability.

I compile a large sample of 2132 firms across 48 industries (2-digit SIC codes) over 32 years (1985-2016), with 5.78 years of data for each firm on average. I test these relationships by employing the system GMM method, and I assess the technological environment characteristics using yearly industry adjusted patent count data. My findings are robust to accounting for potential selection bias, various distributions of inefficiency in calculation of firm capabilities, relaxing the assumption on heteroscedasticity in the calculation of firm capabilities, accounting for outliers, and other lag structure specifications.

This study thus offers several contributions to theory and practice. First, this study is the first to distinguish between technological turbulence, uncertainty, and acceleration. This enriches scholarly research by conceptually and empirically showing that these technological dimensions are different and can change the outcomes from firms' strategic actions in different directions.

Second, this study shows that indeed the effects of marketing and R&D capabilities are contingent upon the technological environment. I reveal that all the technological environments amplify the relationship between marketing capability and ROA, and technological turbulence has the most potent effect. However, only technological acceleration amplifies the R&D capability-ROA relationship. These findings add to the strategic management literature by providing strong evidence that the technological environment is influential in the returns to a firm's capability investments. Further, finding support for a stronger effect of marketing capability in technologically uncertain markets empirically confirms the notion of causal ambiguity, adding to the RBV theories.

Third, this study enriches the literature on the interplay between capabilities by showing that marketing and R&D capabilities are only complementary in technologically turbulent markets. Therefore, the extent of fit between firm capabilities and market environment can change the value of each capability as well as those of their interactions, adding to the dynamic capability literature.

Finally, prior studies on the effect of technological conditions are very spare and very limited in scope. This study benefits from the most comprehensive and strongest sample to date with more than 2,132 firms across 48 industries over a long period, lending more reliability and generalizability to the findings.

Theory and Hypotheses

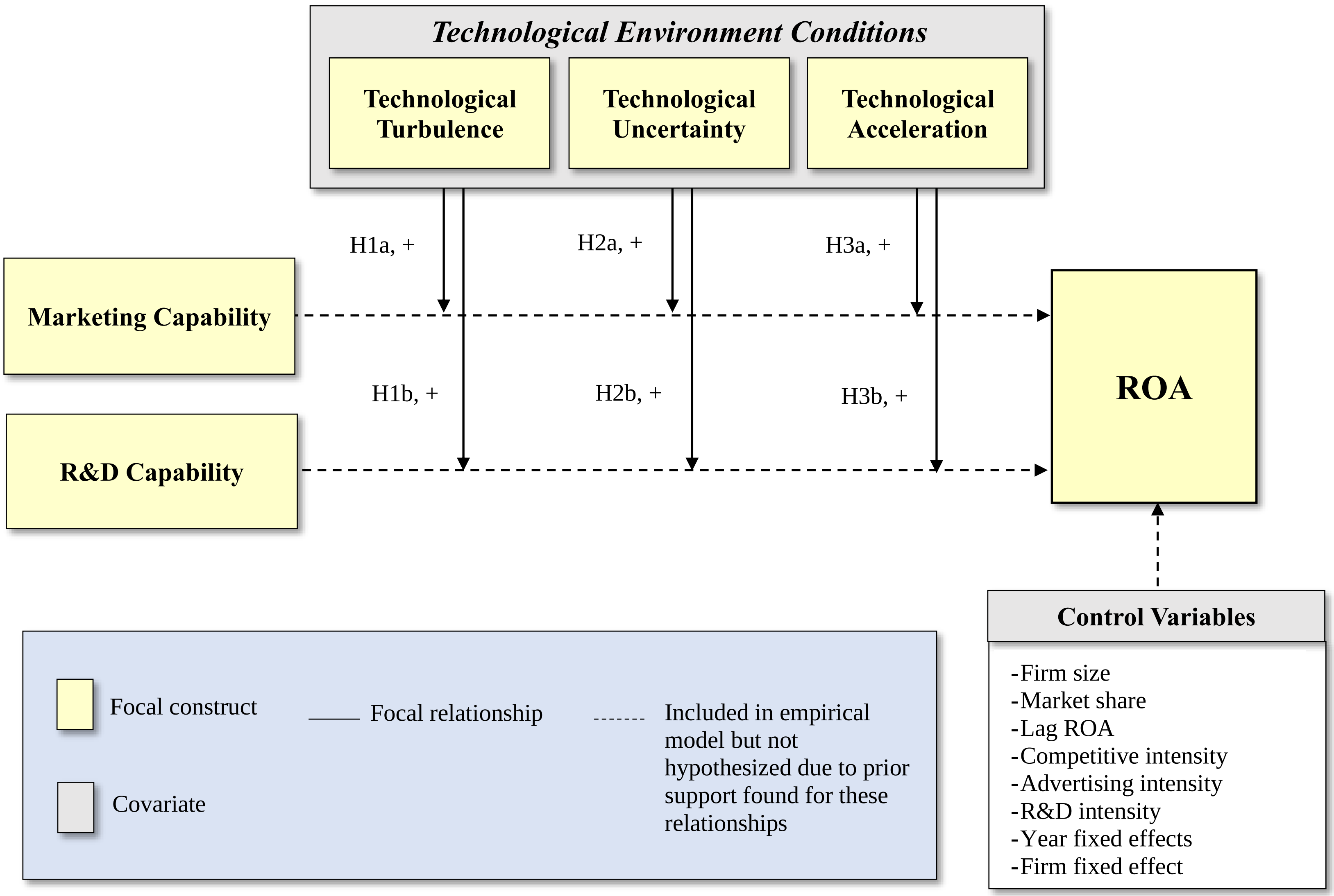
First, I briefly review the literature on the firm capabilities-performance link. Then, I introduce technological conditions (i.e., turbulence, uncertainty, and acceleration) and delve into how they may affect the relationships between marketing and R&D capabilities and firm performance. Figure 2.1 presents a visualization of the conceptual framework of this study. I utilize return on assets (ROA) as the focal performance measure. ROA has long been viewed as the firm’s short-term profitability (Narver and Slater 1990) and is the most used financial position variable that incorporates both revenue- and cost-based views on firm performance (Rubera and Kirca 2012).

Firm Capabilities and Firm Performance

The resource-based view (RBV) regards firms as bundles of resources and capabilities that drive valuable market positions. Firms differ in the endowment of their resources and capabilities (Wernerfelt 1984), and firms with more robust bundles of resources and capabilities can outperform others. The dynamic capability perspective also suggests that firms must practice resource configuration, complementarity, and integration in ways that match their changing market environments to leverage firm capabilities’ performance outcomes (Kozlenkova, Samaha, and Palmatier 2014; Teece, Pisano, and Shuen 1997). Jointly, both RBV and dynamic capability theories suggest that firm capabilities drive firm performance.

Marketing capability-performance and R&D capability-performance. Capabilities are complex bundles of skills and knowledge embedded in organizational processes that transform the firm’s available resources into valuable outputs (Day 1994; Dutta,

Figure 2.1. Conceptual Framework



Narasimhan, and Rajiv 1999). The performance effects of marketing capabilities and R&D capabilities have received the most attention in the literature. Marketing capability represents the firm's ability to understand customer needs and effectively link its offerings to customers (Krasnikov and Jayachandran 2008), whereas R&D capability is concerned with developing a continuous stream of break-through, patentable, and revolutionary new products (Feng, Morgan, and Rego 2017). The overall body of the literature suggests that firm marketing and technological capabilities are positively associated with a number of measures of firm performance (e.g., Dutta, Narasimhan, and Rajiv 1999; Morgan, Vorhies, and Mason 2009), including ROA (Feng, Morgan, and Rego 2017).

Various firm capabilities coexist within firms and are often intertwined (Feng, Morgan, and Rego 2017). Theoretically, different firm capabilities may complement one another, such that one capability enhances the effect of another on firm performance. This complementarity occurs if the firm’s efficiency and/or effectiveness in deploying its resources increases, potentially resulting in new applications of resources (Kozlenkova, Samaha, and Palmatier 2014; Teece, Pisano, and Shuen 1997). However, it is also possible that a firm capability diminishes another capability’s effect because firm resource limitation and goal conflicts across capabilities can create inter-capability trade-offs and inefficiencies (King, Slotegraaf, and Kesner 2008). Given the prior research on the relationship between marketing and R&D capabilities, which tends to report a complementary relationship (Dutta, Narasimhan, and Rajiv 1999; Moorman and Slotegraaf 1999; Song et al. 2005), I later empirically explore how the interplay between marketing R&D capabilities changes in various technological environmental conditions.

How Technological Turbulence, Technological Uncertainty, and Technological Acceleration Moderate Specific Capability (Marketing, R&D, and Design)-ROA Relationships

According to contingency theory (Levinthal 2000), the benefits of capabilities also depend on the context in which the capabilities are deployed (Schilke 2014). Thus, environmental factors can influence the return to a firm's resource or capability (Song et al. 2005). Extant research has been primarily focused on one technological environment characteristic, technological turbulence (Glazer and Weiss 1993; Hanvanich, Sivakumar, and Hult 2006; Jaworski and Kohli 1993; Moorman and Miner 1997). *Technological turbulence* is the rate of technological change (Jaworski and Kohli 1993). To this, my study adds to the literature by examining two other aspects of the firm's technological environment: *technological uncertainty*—the absence of pattern and inability to accurately forecast the changes in the underlying technology[6], and *technological acceleration*—change in the rate of such technological change. I discuss how each capability-ROA relationship may be affected by each distinct technological environmental condition.

Technological Turbulence

Technological turbulence has been defined as the rate of technological change in the industry, in which a firm embeds (Hanvanich, Sivakumar, and Hult 2006; Jaworski and Kohli 1993; Moorman and Miner 1997). Technological turbulence is high when

[6] Some authors have considered uncertainty as part of technological turbulence. However, it generally does not load with the other items designed to capture the rate of change (e.g., Jaworski and Kohli 1993; Wilden and Gudergan 2015), suggesting it is a separate dimension of the firm's technological environment. Further, while some authors have suggested that "a rapid pace of technological change creates uncertainty" (Weiss and Heide 1993, p. 221), uncertainty is not a proxy for variation or rates of change as, for instance, rapid but predictable changes create no uncertainty at all (Dess and Beard 1984).

firms operating in the same industry heavily advance their underlying technologies (i.e., product and process), and it is low when technical changes are minor and infrequent. Firms operating in high technological turbulence markets need to continuously advance the underlying technologies of their offerings to respond to customer requirements. In contrast, firms in low technological turbulence markets try to milk the long-linked technologies while having a focus on standardization and efficiency (Lepak, Takeuchi, and Snell 2003). For instance, the communications equipment and home apparel industries are high and low on technological turbulence.

Technological turbulence and the marketing capability-ROA relationship. I expect that the effect of marketing capability will be strengthened in markets with high technological turbulence for two primary reasons. First, in these markets, consumers may face a lot of clutter regarding the merits of different technological claims. Thus, firms need to adequately inform their customers concerning their technical excellence (Dutta, Narasimhan, and Rajiv 1999) and motivate them to try such new technologies. Robust marketing capabilities can help firms break through the technological clutter and competitive interference in such markets, thus increasing customer trial of new products (Wilden and Gudergan 2015).

Second, in technologically turbulent markets, the basis for competition is continually evolving. Firms with strong marketing capabilities can better identify their customers' changing needs and choice factors. In addition, product management proficiency, which is also a component of marketing capability (Morgan, Vorhies, and Mason 2009), enable firms to effectively customize their offerings to address their customer requirements (Lepak, Takeuchi, and Snell 2003). This capability is critical because firms need to balance their product portfolio in ways that their products do not cannibalize each other, but rather seek to increase their total sales. Further, such firms are also in a better position to understand which new technological features and how much customers would be willing to pay. Thus, in addition to aiming for increasing their sales, they would charge a premium price for technological features that they add on their products, increasing their profit margin as well. Therefore, I expect that technological turbulence strengthens the ROA impact of marketing capabilities.

H1a: *The higher the technological turbulence, the stronger the relationship between marketing capability and ROA.*

Technological turbulence and the R&D capability-ROA relationship. Firms in technologically turbulent markets must shift, integrate, and reconfigure their resources toward technological innovations as keeping up with the high rate of technological change in such markets is a key survival factor (Ang 2008). Therefore, firms with robust R&D capabilities may be better off in these markets than firms with weak R&D capabilities. Further, there are reasons to predict that the positive impact of R&D capabilities on ROA may be amplified by technological turbulence.

First, products have shorter life cycles in technologically turbulent markets (Dutta, Narasimhan, and Rajiv 1999). As such, firms need to continually advance the technical performance of their products by employing new technologies. Firms that have robust R&D capabilities are more adept in improving their technologies and incorporating them into their products. R&D capability enables firms to upgrade their products and launch them in their markets, which increases their sales. Furthermore, R&D capability affects how fast a company can introduce its new products to the market

(Rabino and Moskowitz 1981). Firms that do not have robust R&D capabilities may fall behind the competition and loses their share.

Second, consumers pay more deliberate attention to the technical performance of products in markets with high technological turbulence (Chitturi, Raghunathan, and Mahajan 2007; Davies and Walters 2004). Firms with robust R&D capabilities can stand out of their competition by effectively technologically differentiating their products to gain share from their competitors and increase their sales. Combining these arguments, I expect that a firm's robust R&D capability increases the sales of the firm. Since firms that have developed robust R&D capabilities are efficient in deploying their resources, an increase in their sales should result in more profitability (ROA).

H1b: *The higher the technological turbulence, the stronger the relationship between R&D capability and ROA.*

Technological Uncertainty

I define technological uncertainty as the degree of unpredictability of technological changes in a market. Markets with little technological uncertainty are characterized by evident trends in technological advancement, and firms operating in those markets can reliably anticipate such trends based on the information they have in hand. A primary reason for periods of technological uncertainty is discontinuous technological innovations with their own technological trajectories that lead to eras of great ferment, experimentation, and shakeouts in the market (Anderson and Tushman 2001; Tushman and Anderson 1986). Technological uncertainty peaks when a technological regime replaces another, but it is not evident what form of the new technology will become the industry standard (Tushman and Rosenkopf 1992).

Technological uncertainty and the marketing capability-ROA relationship. A major challenge that firms face is to predict which variant of the new technology will become the dominant design that customers prefer (Tushman and Rosenkopf 1992). Marketing capability becomes essential in technologically uncertain markets as it supports market sensing and customer linking through effective information acquisition and utilization (Day 1994). Marketing capabilities can reduce the uncertainty that the firm experiences—via frequently scanning customer demands, competitor actions, and the acceptance of new technologies in the marketplace (Li and Calantone 1998). Thus, firms with robust marketing capabilities benefit from high-quality consumer feedback (Griffin and Hauser 1993) and can reconfigure their recourses toward the next directions of technologies and to avoid wastage of resources.

Moreover, technological uncertainty may cause demand uncertainty (Anderson and Tushman 2001). Firms that have strong relationships with their customers and effective channel relationships, owing to their robust marketing capabilities, can better mitigate any demand uncertainty in technologically uncertain environments. Therefore, I theorize that when technological uncertainty increases, marketing capabilities can help guide firms' technological investments, reduce wastage of resources, and facilitate customer adoption and acceptance. Thus,

H2a: *The higher the technological uncertainty, the stronger the relationship between marketing capability and ROA.*

Technological uncertainty and the R&D capability-ROA relationship. When firms cannot predict what variants of technology will standardize in the market, the exploration of new technological opportunities becomes more crucial for them to gain competitive advantage. Firms with robust R&D capabilities can effectively and efficiently cope with such technologically uncertain conditions by continuous risk-taking, experimentation, and discovery. These firms eventually gain expertise and reach to a level of excellence in new technologies that once were not the industry standard (Tushman and Rosenkopf 1992).

Finally, causal ambiguity in how and what R&D resources firms utilize to achieve technological innovations increases in highly technologically uncertain markets (Eisenhardt and Martin 2000), creating barriers to replication. As such, a firm with robust R&D capabilities can more effectively explore technological opportunities, with less imitation treat from its rivals, when the technological environment is uncertain. For all the reasons mentioned, I posit:

H2b: *The higher the technological uncertainty, the stronger the relationship between R&D capability and ROA.*

Technological Acceleration

I define technological acceleration as the speed of change in the rate of technological change in a market. During periods of technological acceleration, opportunities for technological innovation and commercialization of new product lines rapidly arise, and technological imitation and reverse-engineering becomes more difficult as technological innovations accelerate (Davies and Walters 2004; Levin et al. 1987). For instance, the mobile phone market went through a high technological acceleration phase in the 1990s when various technologies, such as text messaging and touchscreen in 1993, internet access in 1996, GPS system in 1999, Mp3 player and mobile cameras in 2000, were adopted by the mobile phone manufacturers.

Technological acceleration and the marketing capability-ROA relationship. When technological changes accelerate, consumers pay more attention to technological trends and technical attributes of the products. For instance, this was the case when cellphone manufacturers begin employing the technology of digital photography in their products in the early 2000s. These periods are great opportunities for firms with strong marketing capability to create a lot of buzz about the new technologies of their products by effective marketing communications, another aspect of marketing capability (Morgan, Vorhies, and Mason 2009). They also make their products relatable to their customers. They can extract and convey the meaning of those newly emerged technologies and help their customers understand what the product stands for, therefore, increasing customer trials in such technologically accelerating markets.

Moreover, effective channel relationships, due to robust marketing capabilities (Morgan, Vorhies, and Mason 2009), are incredibly crucial in technologically accelerating markets as they facilitate timely product launches. Emerging technologies, when they have a clear pathway forward, generally lead to market expansion or new markets. In technologically accelerating markets, firms can capitalize on their strong channel relationships to place their products in the market in a timely manner and gain a competitive advantage over time (Moorman and Slotegraaf 1999). Moreover, If the firm has fallen behind the competition in reaching those accelerating technologies, then the strong channel management would create barriers to entry (Reve 1986) for those rivals that have reached to such technologies. For these reasons, the impact of marketing capabilities on ROA will be amplified when technological acceleration is high.

H3a: *The higher the technological acceleration, the stronger the relationship between marketing capability and ROA.*

Technological acceleration and the R&D capability-ROA relationship. The returns from R&D capabilities are expected to be amplified in markets with high rates of technological change. However, I expect to observe more benefits for R&D capabilities when technological changes are accelerating.

To compete in a technologically accelerating environment, firms must exploit knowledge faster and more effectively as time is of the essence, and fast organizational learning becomes essential as development times shrink (Rycroft 2007). Firms have to move from an old technology to a new one (Tushman and Rosenkopf 1992), and R&D capabilities facilitate this transition (Song et al. 2005) through a timely introduction of new products and replacing obsolete technologies (Wind and Mahajan 1997). R&D capabilities are also important to the speed of product development (Moorman and Slotegraaf 1999) and have been found to influence time to market (Rabino and Moskowitz 1981). When new technology areas emerge, firms that own these technological positions first can capture rents. These rents cannot be competed away as quickly because firms without strong R&D capabilities cannot keep up. Thus,

H3b: *The higher the technological acceleration, the stronger the relationship between R&D capability and ROA.*

Methodology

Data

The data is collected from several secondary sources. First, I obtain all the utility patents that are published in the US since 1975 through November of 2018. This data is collected from the United States Patent and Trademark Office (USPTO) and includes more than 6.2 million patents. Firms apply for utility patents to protect their technologies and prohibit other individuals or companies from making, using, or selling the invention without obtaining authorization. Utility patents cover the creation of a new or improvement of a useful product, process, or machine. Therefore, they are used in a variety of industries, from low-tech to high-tech markets, and most firms, even foreign firms, patent the majority of their technological innovations in the US (Tellis, Prabhu, and Chandy 2009).

Second, I use the Compustat data, which contains financial information of firms in various industry sectors. The major challenge in preparing the data is to integrate the patent data with the Compustat data as the only common variable between these two databases is company name (i.e., conm in Compustat and assignee in USPTO). However, in many cases, business units apply for patents, and as a result, a company may have multiple assignee names. Relying on software packages and the patent data project by the National Bureau of Economic Research (NBER) and through extensive coding, I standardize the assignee names and match them with company names in Compustat. Using these matched names, I integrate the patent data with Compustat data. The matched data contains 2,233,778 utility patents published by publicly traded firms in the US.

I consider patents effective since their date of application because by the time that a firm applies for a patent, it already has gained the know-how knowledge, and most of the patent rights come into effect immediately after the application. However, the patent application data is censored because if a patent is never granted, it is not included in the data. Thus, there are many patent applications that are not included in the data because they are yet to be granted, and only patent applications that are granted by November of

2018 are included. To correct this truncation bias, I dropped patents published within 2017 and 2018 as they are more intensely censored. I also employed the method offered by Dass, Nanda, and Xiao (2017) that uses the historical distribution of patents to correct for truncation bias.

Further, in many cases, the ownership of a firm changes over time due to mergers and acquisitions. Thus, using the merger and acquisition data from the SDC database, I also track down such changes in ownership. If a firm is acquired by another firm but continue publishing patents using its original name, then I consider those newly published patents for the acquiree firm.

Finally, five prior years of data are needed to calculate the technological uncertainty and acceleration variables; therefore, the first five years of data are not included in the final sample. Additionally, data-points for another year are dropped out of the final data to perform first-differencing in the model. Due to missing data across all the variables, some data points are excluded. The final data set comprises of 2,132 firms across 48 2-digit SIC codes and 12,332 firm-year observations, with 5.78 years of data for each firm on average from 1983 to 2016.

Operationalization of Variables

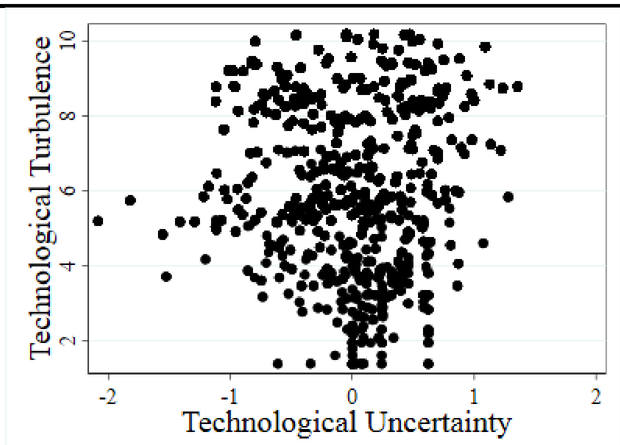
Dependent Variable. I use Return on Assets (ROA) as dependent variable in this study. ROA is income before extraordinary items divided by total assets (ib/at). I obtain this data from Compustat.

Technological Environment Conditions. I measure technological turbulence (TECH_TURB) of an industry (i.e., rate of technological change) as the total number of utility patents published by firms operating in the industry in a certain year. For technological acceleration (TECH_ACC) and uncertainty (TECH_UNC), I adapt the approach of Keats and Hitt (1988) and regress the total number of utility patents of firms in a 2-digit SIC industry against the past five years to estimate technological acceleration and uncertainty for the sixth year, as follows:

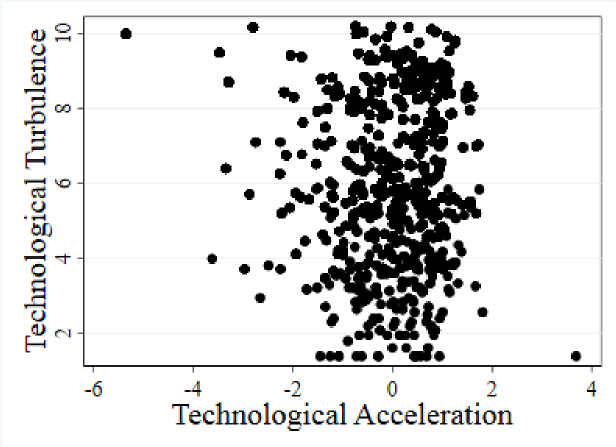
$y_t = b_0 + b_1 t + e_t$, where y_t is the sum of utility patents in the industry in year *t*, *t* represents years, and *e* is the error term. Thus, y_t is a rate and the coefficient (b_1) captures a change in rate, or acceleration. I calculate technological uncertainty and acceleration by dividing the year's standard error and coefficient (b_1) by the average total number of utility patents of the industry in the past five years. The relationships between the technological environmental condition variables are displayed in figure 2.2 (a-c). I log-transform the technological environmental condition variables because they are strongly right-skewed.

Figure 2.2
Technological Environmental Conditions

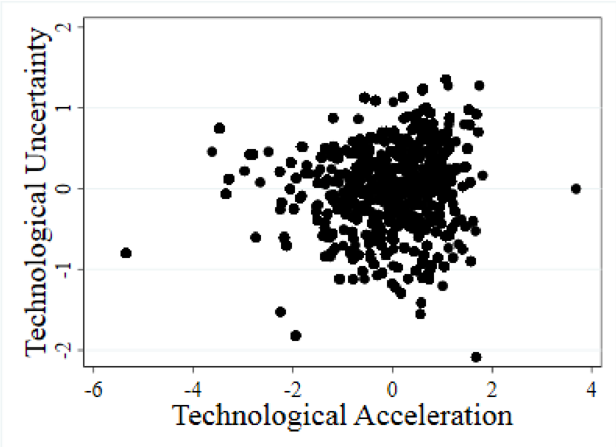
(a)



(b)



(c)



Firm capabilities. Following prior research, I measure the firm capabilities by using the stochastic frontier estimation (SFE) technique. I use firms' sales and general administrative expenses (SGA; xsga in Compustat), receivables (RECEIVABLES; rect in Compustat), and the number of trademarks[7] (TRADEMARKS) the firm owns (Narasimhan, Rajiv, and Dutta 2006; Wiles, Morgan, and Rego 2012) as the inputs for marketing capability (CAP_MKTG) frontier, while I use revenues (REVENUE; sale in Compustat) as its output. I follow Narasimhan, Rajiv, and Dutta (2006) to calculate R*&D capability* (CAP_RD), with R&D expenditures (xrd) and adjusted utility patent stock in

[7] This data collected from the United Stated Patent and Trademark Office

the past five years (TECH_BASE) as the inputs and sum of adjusted number of utility patents published in the year as the output (UO). To calculate TECH_BASE, I utilize a Koyck lag structure (Dutta, Narasimhan, and Rajiv 2005) with declining weight of 0.5[8], so that more recent years receive higher weights. To calculate operations capability (CAP_OPS), I use a cost frontier, instead of a production frontier, as the goal of operations capability is to minimize the cost of production. In line with prior research, the number of employees (EMPLOYEES; emp in Compustat), total inventories and (INVENTORIES; invt in Compustat), and total net of total plant, property, and equipment (PPENT; ppent in Compustat) are used the inputs and cost of good sold (COGS; cogs in Compustat) is the output of the operations frontier (Feng, Morgan, and Rego 2017; Mishra and Modi 2016). Following past research, I also control for year and industry fixed effects in all the frontier equations (Feng, Morgan, and Rego 2017; Xiong and Bharadwaj 2011). I use a Cobb-Douglas formulation and specify the marketing and R&D frontiers as follows:

(1) *Marketing Capability:*

$$\ln(\mathrm{REVENUE}_{it}) = \alpha_{01} + \alpha_{11}\ln(\mathrm{SGA}_{it}) + \alpha_{21}\ln(\mathrm{RECEIVABLES}_{it}) + \alpha_{31}\ln(\mathrm{TRADEMARK}_{it}) + \omega_{11}\,\mathrm{IND}_i + \omega_{21}\,\mathrm{YEAR}_t + v_{it1} - u_{it1}$$

(2) *R&D Capability:*

$$\ln(\mathrm{UO}_{it}) = \alpha_{02} + \alpha_{12}\ln(\mathrm{RD\_EXP}_{it}) + \alpha_{22}\ln(\mathrm{TECH\_BASE}_{it}) + \omega_{12}\,\mathrm{IND}_i + \omega_{22}\,\mathrm{YEAR}_t + v_{it2} - u_{it2}$$

[8] Alternatively, I used different weights (.4 and .45) to calculate TECH_BASE. Final results, however, remain unchanged.

(3) *Operations Capability:*

$$\ln(COGS_{it}) = \alpha_{03} + \alpha_{13}\ln(EMPLOYEES_{it}) + \alpha_{23}\ln(INVENTORIES_{it}) + \alpha_{33}\ln(PPENT_{it}) \omega_{13}\, IND_i + \omega_{23}\, YEAR_t + v_{it3} - u_{it3}$$

where the scripts i and t represent firms and years, respectively, IND_i represents industry dummy variables that control for unobserved heterogeneity due to market conditions, and $YEAR_t$ captures the fixed effect of years. Here, v_{it} is the intrinsic randomness in a firm's frontier output level and is purely a stochastic error affecting the frontier outputs; u_{it}, however, captures the inefficiency and is a downward deviation from the efficient frontier. Following the approach by Dutta, Narasimhan, and Rajiv (1999), I also assume that the random shock is a function of firm size, taking into account the heteroscedasticity of firms.

For all the capability calculations, the assumption is that the random error (v) is normally distributed and has a mean of zero. I also assume that the inefficiency term (u) has an exponential distribution[9] (Meeusen and van Den Broeck 1977) (note that u_{it} cannot be negative). The inefficiency captures the difference between what a firm could have maximally achieved and what the firm actually achieved (i.e., output) (Dutta, Narasimhan, and Rajiv 1999). If the firm completely efficiently deploys its resources, it will be somewhere on the efficient frontier. In contrast, when the firm is inefficient in deploying its resources, it deviates from the efficient frontier, and the inefficiency term grows.

[9] I also calculate the firm capabilities assuming the inefficiency term is half normal. The results are robust to the assumption on the distribution of the inefficiency term.

Finally, I use maximum likelihood to estimate the SFE model, and using the exp[-E(u|e)] transformation, I calculate the capabilities. Intuitively, a firm has a stronger capability when it is less inefficient in deploying its resources.

Technological environmental condition variables. In the past studies, researchers have occasionally incorporated technology-related market conditions, such as turbulence. In their measurement, however, they relied on either expert rating (e.g., Song et al. 2005) or surveys (Wilden and Gudergan 2015). In this study, I directly utilize utility patents data to measure technological turbulence, uncertainty, and acceleration. This enables me to test my hypotheses across a wide range of markets.

Additional Control Variables. I collect data from Compustat to additionally control for two firm-level variables (i.e., firm size, and market share) and three market-level variables (i.e., competitive intensity, advertising intensity, and R&D intensity[10]) that can simultaneously affect firm capabilities and ROA (e.g. Morgan, Vorhies, and Mason 2009; Rubera and Kirca 2012). I measure firm size by taking the natural log of total assets, and market share as a firm's sales in a year divided by total sales of all firms operating in the same industry.

I use industry concentration as a proxy for competitive intensity such that higher concentration indicates lower competition and vice versa. Following prior research (Dess and Beard 1984), I measure competitive intensity as 1-Σ MS_{ijt}^2, where MS_{jt} is the market share of firm *i* in industry *j* at year *t*. This index ranges from 0 to 1, with 0 representing a perfect monopoly and 1 representing a perfect competition. Advertising intensity

[10] R&D intensity has a high correlation with technological turbulence; therefore, I re-estimate the model without controlling for R&D intensity. Since the results remain substantively similar, I keep R&D intensity as a control variable.

Table 2.1
Correlation Matrix and Descriptive Statistics

	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12
1. ROA	.013	.201	1											
2. Marketing Capability	.773	.129	.354	1										
3. R&D Capability	.776	.128	.075	.007	1									
4. Operations Capability	.773	.112	-.110	-.296	.029	1								
5. Firm Size	6.834	2.190	.356	.083	.052	-.049	1							
6. Market Share	.003	.015	-.008	-.008	.008	.021	.067	1						
7. Competitive Intensity	.949	.035	.021	-.002	-.014	-.087	-.060	-.164	1					
8. Advertising Intensity	.049	.043	.039	-.049	.000	-.044	.058	-.011	.230	1				
9. R&D Intensity	.067	.025	.021	.002	-.027	-.118	-.074	-.166	.408	.148	1			
10. Technological Turbulence	8.452	1.439	.007	.027	-.018	-.077	-.045	-.206	.492	-.026	.749	1		
11. Technological Uncertainty	.032	.578	.007	-.021	-.008	-.013	-.022	-.069	.075	.096	.085	.093	1	
12. Technological Acceleration	-.043	1.113	.001	-.002	-.008	.005	-.060	.009	-.038	.142	-.020	-.046	.122	1

Correlations with an absolute value greater than .021 are significant at $p < .05$.

and R&D intensity are total advertising and R&D expenditures in an industry divided by total sales (Fang, Palmatier, and Steenkamp 2008; Rubera and Kirca 2012). Descriptive statistics and correlations are presented in Table 2.1.

Model Specification

It is crucial to control for prior performance because it may affect the firm's current performance. Therefore, I introduce the lag of ROA to control for otherwise omitted variable bias (Germann, Ebbes, and Grewal 2015), to account for inertia and persistence, and to reduce serial correlation (Wooldridge 2015), which preliminary tests confirm its presence in the data. The estimation challenge is that the lag of the dependent variable is correlated with the error term, and, thus, using a linear regression would result in inconsistent results. To address this challenge, I use system GMM dynamic panel estimation (Arellano and Bover 1995; Blundell and Bond 1998). System GMM is commonly used in the marketing strategy literature because it can tackle several estimation challenges, including the case when some covariates (e.g., lag of ROA) are correlated with the past or current realizations of the error term (i.e., not strictly exogenous). System GMM uses the level and first-differenced equations as a system of equations. The lagged differences of the dependent variable are used as instruments for the equation in level, and deep lags of the dependent variable are used as instruments for the first-differenced equation (Roodman 2006).

System GMM can also handle cases where arbitrarily distributed fixed individual effects are present. In addition to the presence of autocorrelation in the data, which is the case in this study, system GMM requires that the number of available time periods to be small, but the number of panel members to be large (Roodman 2006). The data satisfies these requirements as there are 2132 firms for which 5.78[11] years of data are available, on average. I propose the following model specifications:

$$
\begin{aligned}
ROA_{it} = \beta_0 + \beta_1\, ROA_{i(t-1)} + \\
&\beta_2\, CAP\_MKTG_{it} \times TECH\_TURB_{it} + \beta_3\, CAP\_RD_{it} \times TECH\_TURB_{it} + \\
&\beta_4\, CAP\_MKTG_{it} \times TECH\_UNCit + \beta_5\, CAP\_RD_{it} \times TECH\_UNC_{it} + \\
&\beta_6\, CAP\_MKTG_{it} \times TECH\_ACC_{it} + \beta_7\, CAP\_RD_{it} \times TECH\_ACC_{it} + \\
&\beta_{8\text{-}18} \times CONTROLS + \beta_{19\text{-}52}\, YEAR + \eta_i + \varepsilon_{it} \qquad \textbf{(4)}
\end{aligned}
$$

where η_i is the time-invariant unobservable firm effects, and ε_{it} is the i.i.d error capturing the idiosyncratic shocks. CAP is a vector of marketing, design, and R&D capabilities. CONTROLS is a vector of the control variables. It consists of firm capabilities (i.e., marketing, R&D, and operations capabilities); technological variables (i.e., turbulence, uncertainty, and acceleration), market conditions (i.e., competitive intensity, advertising intensity, and R&D intensity); and firm-level variables (i.e., firm size, market share). YEAR is also a vector of year dummies, and η represents the firm fixed effects.

In sum, I control for variables identified relevant in changing both the capability measures and firm performance (e.g., Morgan, Vorhies, and Mason 2009; Rubera and Kirca 2012). I also control for endogeneity due to unobserved time-invariant firm heterogeneity by adding the η_i term. Finally, adding the lagged dependent variable, I control for further reduce the omitted variable bias (Germann, Ebbes, and Grewal 2015) and account for carry-over effects of the firm’s past actions.

[11] Although the panel is long, I limit the number of lags in estimation to not run into overestimation

Results and Discussion

First, I present the results of the SFE models in the first stage.

I then turn to results from the second stage in which I test the hypotheses. Tables 2.2., 2.3., and 2.4 present the results from the maximum likelihood estimations of the marketing, R&D, and operations capability SFE models.

Table 2.2
Marketing Capability

	Coefficient	Std. Err.	z	P Value	95% Conf. Interval	
SGA	.290	.007	39.12	.000	.276	.305
RECEIVABLES	.748	.007	108.94	.000	.735	.762
TRADEMARK	.023	.003	7.39	.000	.017	.029
Constant	1.608	.064	24.99	.000	1.482	1.734
U_{sigma}						
Constant	-2.211	.050	-44.06	.000	-2.309	-2.112
V_{sigma}						
Firm Size	-.056	.017	-3.38	.001	-.089	-.024
Constant	-1.911	.127	-15.10	.000	-2.159	-1.663
$E(\sigma_v)$	.320				.319	.320
σ_u	.331	.008	39.86	.000	.315	.348

Table 2.3
R&D Capability

	Coefficient	Std. Err.	z	P Value	95% Conf. Interval	
RD_EXP	.086	.003	24.51	.000	.079	.092
TECH_BASE	.850	.004	22.29	.000	.842	.857
Constant	-.169	.070	-2.43	.015	-.305	-.032
U_{sigma}						
Constant	-2.409	.048	-50.10	.000	-2.504	-2.315
V_{sigma}						
Firm Size	-.071	.008	-8.64	.000	-.087	-.055
Constant	-1.139	.049	-23.09	.000	-1.235	-1.042
$E(\sigma_v)$	.448				.447	.448
σ_u	.300	.007	41.59	.000	.286	.314

Table 2.4
Operations Capability

	Coefficient	Std. Err.	z	P Value	95% Conf. Interval	
EMPLOYEES	.381	.011	33.75	.000	.359	.403
INVENTORIES	.384	.009	42.39	.000	.366	.401
PPENT	.368	.007	50.80	.000	.353	.381
Constant	.912	.064	14.34	.000	.788	1.037
U_{sigma}						
Constant	-2.311	.055	-41.640	.000	-2.420	-2.202
V_{sigma}						
Firm Size	-.157	.008	-18.690	.000	-.173	-.140
Constant	-.220	.052	-4.210	.000	-.322	-.117
$E(\sigma_v)$	.539				.538	.540
σ_u	.315	.009	36.040	.000	.298	.333

All the SFE models are statistically significant ($p < .001$). Moreover, all the inputs of the frontiers are also significant ($p < .001$), providing empirical support that these inputs are relevant to the capabilities. The coefficients can be interpreted as elasticities. The random error terms are assumed to be heteroscedasticity, where they are a function of firm size (Dutta, Narasimhan, and Rajiv 1999). In all the models, firm size is a significant factor of V_{sigma} ($p < .001$), supporting the assumption of heteroscedasticity. Finally, the results indicate that the variance of the inefficiency terms are statistically significant ($p < .001$). Overall, the results from the SFE models suggest are empirically strong and significant.

Having calculated the firm capabilities, I center the explanatory variables before generating the interaction terms (Aiken, West, and Reno 1991). Variance inflation statistics (VIF) suggest that multicollinearity is at a low level as the VIF ranges from 1.03 to 3.06, with an average of 1.76, which is within a conveniently safe level. Now, I utilize the system GMM technique to test my hypotheses.

The Hansen test of overidentification (J test) shows that the moment conditions are valid, and the estimation is not over-identified ($p > .99$). The AR(II) test indicates that the second-order lags can be used as instrumental variables as they are not correlated with the error term ($p > .297$). However, to avoid overidentification and biases associated with "too many instruments," I limit the number of instrumental variables to only from second-order to fifth-order lags in my main estimation[12] (Roodman 2006). Moreover, the difference-in-Hansen test confirms that the instruments of the model, as well as other covariates, are empirically exogenous, as the *P*-value is greater than .997 in all the subsets of variables. These instruments include the GMM type and other covariates, including firm capabilities and technological conditions, in both first-differenced and level equations. The difference-in-Hansen test is preferred to Durbin-Wu-Hausman tests because it can report test statistics that are robust to various violations of conditional homoscedasticity (Baum, Schaffer, and Stillman 2003).

Although multicollinearity is not a concern, I add the interactions of each of the technological conditions separately to use extra caution. It gives more confidence that the significance of the coefficients is not due to the inclusion of other variables. Each of models 1 through 3 adds the interactions of a technological environment variable with marketing and R&D capabilities; and, model 4 is the full model specification with all the interaction terms. In all the estimations, I account for the heteroscedasticity of the error term, and as such, all the standard errors are adjusted at the industry level. The results are presented in Table 2.5.

[12] I assess the robustness of the results using different lag structure settings

Table 2.5
Main Results

	Model 1	**Model 2**	**Model 3**	**Model 4**
Marketing Capability × Technological Turbulence (H1a, +)	$.644^{***}$			$.645^{***}$
R&D Capability × Technological Turbulence (H1b, +)	.006			.014
Marketing Capability × Technological Uncertainty (H2a, +)		$.284^{***}$		$.244^{***}$
R&D Capability × Technological Uncertainty (H2b, +)		.003		-.01
Marketing Capability × Technological Acceleration (H3a, +)			$.267^{**}$	$.213^{**}$
R&D Capability × Technological Acceleration (H3b, +)			$.158^{***}$	$.170^{***}$
Prior Performance (Lag of ROA)	$.324^{***}$	$.324^{***}$	$.324^{***}$	$.324^{***}$
Marketing Capability	$.333^{***}$	$.340^{***}$	$.348^{***}$	$.330^{***}$
R&D Capability	$.058^{***}$	$.059^{***}$	$.060^{***}$	$.059^{***}$
Operations Capability	.016	.015	.016	.016
Firm Size	$.021^{***}$	$.021^{***}$	$.021^{***}$	$.021^{***}$
Market Share	$-.202^{***}$	$-.209^{**}$	$-.197^{**}$	$-.205^{***}$
Competitive Intensity	$.118^{*}$	$.142^{**}$	$.143^{**}$	$.118^{*}$
Advertising Intensity	.06	.034	.038	.057
R&D Intensity	$.444^{**}$	$.478^{**}$	$.473^{**}$	$.446^{**}$
Technological Turbulence	$-.055^{*}$	$-.060^{*}$	$-.058^{*}$	$-.056^{*}$
Technological Uncertainty	.011	.012	.014	.01
Technological Acceleration	-.004	-.005	-.007	-.006
Constant	$-.320^{***}$	$-.329^{***}$	$-.344^{***}$	$-.303^{***}$
Firm Fixed Effect	**Yes**	**Yes**	**Yes**	**Yes**
Time Fixed Effect	**Yes**	**Yes**	**Yes**	**Yes**
N	12332	12332	12332	12332
Number of Firms	2132	2132	2132	2132
Number of Instruments	219	219	219	227
Degrees of Freedom	51	51	51	55
AR(II) test (p value)	.297	.288	.321	.289

***** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$**

The results across all the models are fully consistent, and therefore, I discuss the results of from the full model (model 4). As expected, the main effects of marketing and R&D capabilities are significant (.330, $p < .001$; .059, $p < .001$). In terms of the economic significance[13], marketing capability increases ROA by .043, and R&D capability increases it by .007. Considering the standard deviation of ROA, one can conclude that the effect sizes of these capabilities are strong as marketing and R&D capabilities increase ROA by 21.7% and 3.7% of its standard deviation. It is also noticeable that the effect size of marketing capability is more than five times that of R&D capability on short term profitability.

The interaction between technological turbulence and marketing capability is significant (.645, $p < .001$), supporting H1a. However, the interaction between technological turbulence and R&D capability is insignificant (.014, $p > .76$), rejecting H1b. Therefore, in line with my prediction, marketing capability is crucial in technologically changing environments. The stronger effect of marketing capability in technologically turbulent market occurs possibly because firms with robust marketing capability can reduce customer clutter and manage their products more proficiently. Firms in technologically turbulent markets may face a red queen competition situation in which they are forced by their rivals to participate in continuous and escalating technological development such that each firm competes just so as to stand still relative to its competitors (Derfus et al. 2008). As a result, although R&D capabilities are important survival factors in technologically turbulent markets, they do not gain additional rents.

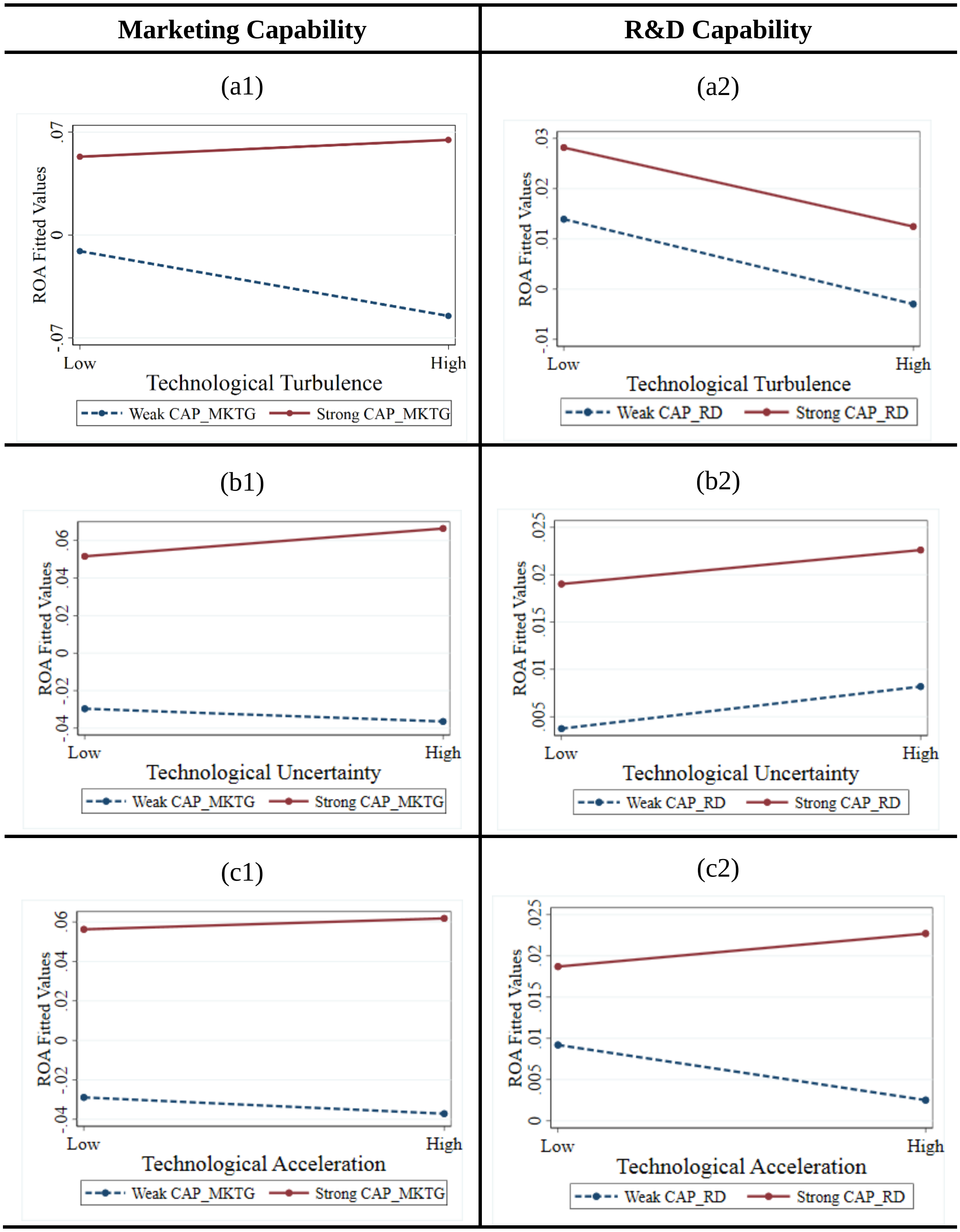
[13] Calculated as the standard deviation times coefficient

Moreover, the interaction between marketing capability and technological uncertainty is significant (.244, $p < .003$), but the interaction between R&D capability and technological uncertainty is not significant (-.010, $P > .82$). Therefore, I find empirical support for H2a and not for H2b. These findings likely owe to the significant market sensing role of marketing in technologically unpredictable markets. In contrast, firms that have robust R&D capabilities tend to explore new technology areas more that does not translate into profitability in the short-term when it is not clear what variant of new technologies will dominate the other and become the new industry standard.

Finally, I find a significant positive interaction between marketing and technological acceleration (.213, $p < .05$), supporting H3a, as well as a significant effect for the interaction between R&D capability and technological acceleration (.17, $P < .006$), in support of H3b. Therefore, when technological changes accelerate in a market, firms can capitalize on their reliable channels and entice their customers to try and purchase the new products if they have robust marketing capabilities. Firm with robust R&D capabilities can also more effectively reconfigure their resources to move fast toward mastering and deploying new technologies.

Furthermore, to understand how the effect of marketing and R&D capabilities changes in various technological conditions, I perform margin analysis. High and low levels of each variable is calculated based on one standard deviation above and below its average value. The plots of the marginal effects of marketing and R&D capabilities are presented in Figure 2.3 (a1, a2, b1, b2, c1, and c2).

Figure 2.3
Margin Analysis



Firms with strong marketing and R&D capabilities are always better off, regardless of their technological conditions in their markets. The margin analysis reveals that the positive interaction of marketing capability and technological turbulence is mainly driven by the fact that firms that have weak marketing capabilities lose more profitability in highly turbulent markets than in lowly turbulent markets. Further, the effect of marketing capability on enhancing ROA in markets with technological turbulence is almost twice as large as in markets with low technological turbulence (.11 vs. .06). Firms with strong marketing capabilities slightly perform better in technologically uncertain markets than in markets with little uncertainty (.10 vs. .07); however, there is no differential effect for R&D capability in high and low technologically uncertain markets. Finally, the effect of marketing capability in technologically accelerating markets is .10, which is slightly higher than its effect in markets with little technological acceleration (.08). However, R&D capability is crucial in these markets as its effect is twice in magnitude (.02 vs. .01). It is interesting that in technologically accelerating markets, if a firm already has a robust R&D capability, it gains performance, but if it does not, it loses profitability.

Supplementary Analysis

The results as well as the RBV theory that suggests various firm capabilities are intertwined and mutually present within firms (Feng, Morgan, and Rego 2017) motivate to explore further how marketing and R&D capabilities jointly affect firm performance, and how their joint effect changes in various technological conditions. As such, I propose the following model specifications:

$$
\begin{aligned}
ROA_{it} = \beta_0 + \beta_1\, ROA_{i(t-1)} + \beta_2\, CAP\_MKTG_{it} \times CAP\_RD_{it} \\
\beta_3\, CAP\_MKTG_{it} \times TECH\_TURB_{it} + \beta_4\, CAP\_RD_{it} \times TECH\_TURB_{it} + \\
\beta_5\, CAP\_MKTG_{it} \times TECH\_UNCit + \beta_6\, CAP\_RD_{it} \times TECH\_UNC_{it} + \\
\beta_7\, CAP\_MKTG_{it} \times TECH\_ACC_{it} + \beta_8\, CAP\_RD_{it} \times TECH\_ACC_{it} + \\
\beta_9\, CAP\_MKTG_{it} \times CAP\_RD_{it} \times TECH\_TURB_{it} + \\
\beta_{10}\, CAP\_MKTG_{it} \times CAP\_RD_{it} \times TECH\_UNC_{it} + \\
\beta_{11}\, CAP\_MKTG_{it} \times CAP\_RD_{it} \times TECH\_ACC_{it} + \\
\beta_{12\text{-}22} \times CONTROLS + \beta_{23\text{-}56}\, YEAR + \eta_i + \varepsilon_{it} \qquad \textbf{(5)}
\end{aligned}
$$

The 3-way interactions of marketing and R&D capabilities with each of the technological environment conditions (i.e., technological turbulence, uncertainty, and acceleration) are added to the main model specification. As such, I use an identical set of covariates, and akin to the main analyses, I use the system GMM to estimate this model. I present the results in table 2.6.

Again, the Hansen test of over-identification indicates that the moment conditions are valid ($P > .99$) ; the AR(II) test indicates that the second-order lags can be used as instrumental variables ($P > .291$); and the difference in Hansen test indicates that the instruments of the model are empirically exogenous ($P > .99$). The results are very consistent with those from the main analysis. Therefore, I only focus on the joint effect of marketing and R&D capabilities in various technological environment conditions. Noteworthily, the interaction between marketing and R&D capabilities is not significant (.005, $P >.97$), suggesting that, on average, marketing and R&D capabilities only have additive effects on short-term profitability. However, the joint effect of these capabilities positively interacts with technological turbulence. The 3-way interaction of marketing and R&D capabilities is statistically significant (1.381; $P < .019$), indicating that these capabilities are complementary when the rate of technological change is high in the market. The other two 3-way interactions, however, are not significant (.555, $P >.645$; -.102, $P >.890$). These results reveal that marketing and R&D capabilities show neither complementary nor substitutive effect in technologically uncertain or accelerating markets.

Table 2.6. Supplementary Analysis

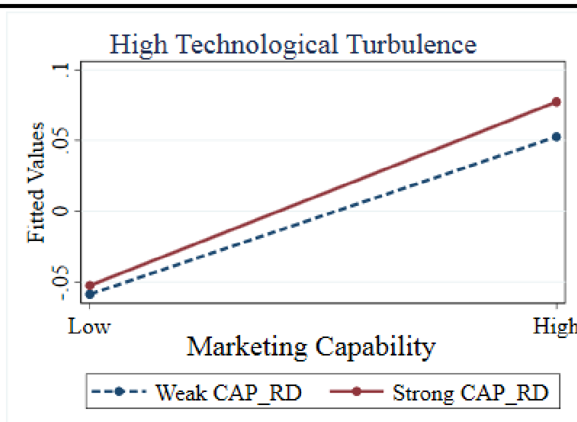
Marketing Capability × Technological Turbulence	.660***
R&D Capability × Technological Turbulence	.004
Marketing Capability × Technological Uncertainty	.245***
R&D Capability × Technological Uncertainty	-.018
Marketing Capability × Technological Acceleration	.215*
R&D Capability × Technological Acceleration	.170***
Marketing Capability × R&D Capability	.005
Marketing Capability × R&D Capability × Technological Turbulence	1.381**
Marketing Capability × R&D Capability × Technological Uncertainty	.555
Marketing Capability × R&D Capability × Technological Acceleration	-.102
Prior Performance (Lag of ROA)	.323***
Marketing Capability	.332***
R&D Capability	.058***
Operations Capability	.016
Firm Size	.021***
Market Share	-.207***
Competitive Intensity	.116*
Advertising Intensity	.058
R&D Intensity	.450**
Technological Turbulence	-.057*
Technological Uncertainty	.01
Technological Acceleration	-.006
Constant	-.303***
Firm Fixed Effect	**Yes**
Time Fixed Effect	**Yes**
N	12332
Number of Firms	2,132
Number of Instruments	235
Degrees of Freedom	68
AR(II) test (p value)	.291

***** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$**

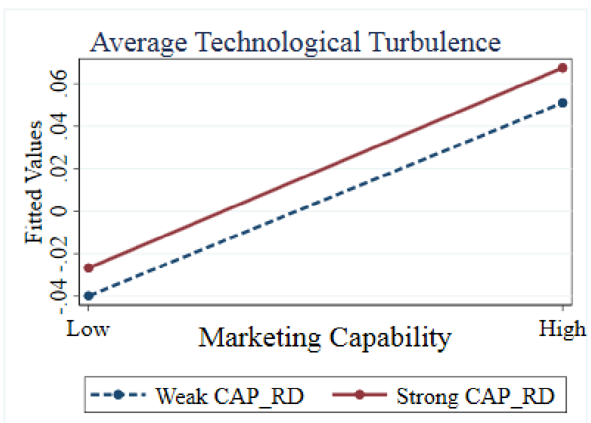
Again, I perform margin analysis to depict the average marginal effect of marketing capability, given the R&D capability and technological environmental conditions. The plots for the marginal effect are presented in Figure 2.4 (a-c).

Figure 2.4
3-Way Interactions Margin Analysis

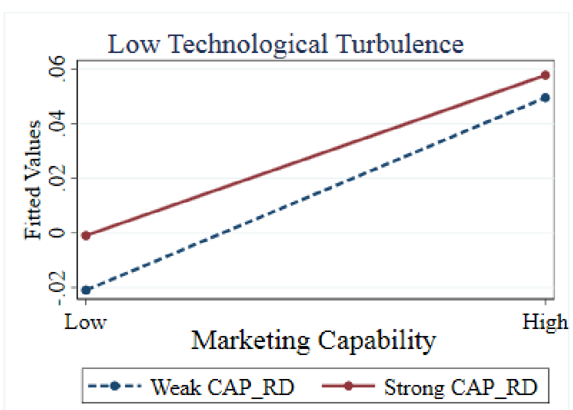
(a)



(b)



(c)



The average marginal effect of marketing capability on ROA is strongest when the firm has robust R&D capabilities and operates in a market with high technological turbulence. It is more significant than if the firm has weak R&D capabilities in that environment (.49 vs. .43). In contrast, when technological turbulence is low, the average effect of marketing capability is stronger when R&D capability is weak than when it is strong (.27 vs. .22).

Further, the best-case scenario for a firm is when it has superior marketing and R&D capabilities and performs in a technologically turbulent market. As technological turbulence decreases, the firm's profitability diminishes as well. When firms have weak marketing capabilities in a market with high technological turbulence, their R&D capabilities barely makes a difference. It suggests that R&D capability is dependent on marketing capability technological turbulence is high.

Combined, I conclude that these findings fully support the notion that marketing and R&D capabilities are complementary if technological turbulence is high in the market. I observe a similar pattern in terms of technological uncertainty, although the 3-way interaction between the capabilities and technological turbulence is not statistically significant. The average marginal effect of marketing capability is stronger if R&D capability is strong in technologically uncertain markets (.42 vs. .38) or R&D capability is weak in markets with little technological uncertainty (.31 vs. .32). Therefore, marketing and R&D capabilities only show a mere complementary relationship with one another, given technological uncertainty into account. Finally, the relationship between marketing and R&D capabilities is purely additive with respect to technological acceleration. The difference between the average marginal effect of marketing capability, regardless of R&D capability, in high and low technological acceleration markets is about .04, not supporting any complementarity or substitution effect between these two capabilities.

Robustness Checks

I perform several additional analyses to lend credence to my findings. I show that the findings are robust to: (1) correcting for potential selection bias, (2) various distributions of inefficiency in calculation of firm capabilities, (3) relaxing the assumption on heteroscedasticity in the calculation of firm capabilities, (4) accounting for outliers, and (5) other lag structure specification.

Correcting for potential selection bias. Although the Compustat database includes almost all the publicly traded firms in the US, the use of USPTO restricts the sample, which can result in selection bias. To account for this potential bias, I utilize the two-stage Heckman (1979) approach. The Heckman approach estimates a probit model in the first stage using the sample of firms that does not suffer from selection bias (i.e., Compustat in this case). The control variables in the main model specification are the covariates, and a dummy variable of whether the firm has published any utility patents is the dependent variable. I calculate the inverse Mills ratio and include it in the model as an additional control variable. The results remain substantially unchanged, lending support that the results do not suffer from selection bias (Table 2.7). The only difference is that the interaction between marketing capability and technological turbulence becomes statistically insignificant in model 4 (.183, $p > .122$), though it remains significant in model 3 (.23, $p < .047$).

Table 2.7
Accounting for Selection Bias

	Model 1	**Model 2**	**Model 3**	**Model 4**
Marketing Capability × Technological Turbulence (H1a, +)	.614***			.615***
R&D Capability × Technological Turbulence (H1b, +)	.023			.032
Marketing Capability × Technological Uncertainty (H2a, +)		.265***		.231***
R&D Capability × Technological Uncertainty (H2b, +)		-.006		-.02
Marketing Capability × Technological Acceleration (H3a, +)			.233**	.183
R&D Capability × Technological Acceleration (H3b, +)			.146***	.161***
Prior Performance (Lag of ROA)	.299***	.299***	.299***	.299***
Marketing Capability	.286***	.291***	.298***	.283***
R&D Capability	.066***	.068***	.069***	.067***
Operations Capability	.029	.028	.029	.029
Firm Size	-.498***	-.511***	-.511***	-.493***
Market Share	-.215***	-.222***	-.211***	-.219***
Competitive Intensity	.07	.091	.093	.07
Advertising Intensity	.07	.046	.05	.067
R&D Intensity	.451**	.484**	.480**	.454**
Technological Turbulence	-.055*	-.061*	-.059*	-.056*
Technological Uncertainty	.015	.016	.018*	.013
Technological Acceleration	.019	.018	.016	.017
IMR	-13.679***	-14.005***	-14.031***	-13.531***
Constant	-17.690***	.699***	-2.071***	-5.539***
Firm Fixed Effect	**Yes**	**Yes**	**Yes**	**Yes**
Time Fixed Effect	**Yes**	**Yes**	**Yes**	**Yes**
N	12332	12332	12332	12332
Number of Firms	2132	2132	2132	2132
Number of Instruments	221	221	221	229
Degrees of Freedom	52	52	52	56
AR(II) test (p value)	.229	.222	.247	.222

***** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$**

Various distributions of inefficiency in calculation of firm capabilities. Assuming the inefficiency terms have half-normal distributions, I recalculate all the capability measures and retest my hypotheses. Once again, my results remain completely unchained, suggesting that the results are robust to the assumption on the inefficiency term (Appendix B, Table B.1).

Relaxing the assumption of heteroscedasticity in the calculation of firm capabilities. I assume that the random error in the SFE models is homoscedastic and no longer model its variance as a function of firm size. I recalculate the firm capabilities and test the hypotheses again. The results remain similar, suggesting the results are robust to this assumption (Appendix B, Table B.2).

Accounting for outliers. To account for outliers, I winsorize at various percentages (.5%, 1%, and 2%). However, the findings mostly remain unchanged (Appendix B, Table B.3).

Other lag structure specification. I run several models using different numbers of instrumental variables by restricting the lags, ranging from the second-order to the seventh-order. I also compare the results with the free lag restriction model. The results (Appendix B, Table B.4) are substantively similar, and therefore, the findings are not sensitive to the setting of instrumental variables.

Limitations

There are a few limitations that offer future research opportunities. First, I use the SFE method to calculate the capability measures, and like others utilizing this method, I assume that all the inputs are exogenous variables for SFE outputs. However, the amount of resources that firms devote may be pre-determined by outputs the firm desires to achieve.

Second, I use patent data to calculate the technological environmental conditions. The norms and standards of patenting may have shifted a bit over time. For instance, the time gap from when a patent is applied for and when it gets published has changed over the years. Changes in such standards, may have a small biasing effect on my calculation of technological conditions. However, I use application dates and correct for these time lags. Also, the inclusion of time fixed effects in the models mitigates this bias.

Third, in any industry, there are multiple product groups, for which technological characteristics can be different. I measure the technological conditions at the industry level, therefore, assuming they do not vary across product groups. However, future research should use a similar approach but rather on product categories to calculate technological conditions in order to delineate a cleaner mechanism for gaining firm performance through firm capabilities.

Fourth, my sample is based on the US publicly traded firms and utilizes US patent data. Future research could also extend this analysis to private firms and possibly to other countries. Scholars could also extend this work by other performance long-term metrics, either expected or actual. However, until then, this research provides the first comprehensive picture of the worth of marketing and R&D capabilities—in various technological conditions—based on a large sample of firms and industries over thirty-two years.

Implications for Theory

This study uses a large sample of publicly traded firms in the US and examines the ROA impact of marketing and R&D capabilities in various technological market conditions. Consistent with most of the prior studies (e.g., Dutta, Narasimhan, and Rajiv 1999), I find positive main effects for marketing and R&D capabilities. Regardless of what market conditions a firm embeds in, it will always enjoy higher levels of ROA if it has robust capabilities. This study, however, provides a comprehensive picture of how the effect of each of the marketing and R&D capabilities changes with the level of the other capability and technological market conditions. Thus, this study offers several implications for theory.

First, it enhances prior examinations of the impact of the firm's technological environment by distinguishing between technological turbulence (rate of change), technological uncertainty, and technological acceleration. I also introduce an objective way to measure these based on archival data. Extant research has not previously examined technological acceleration, and it has studied the other two dimensions conjoined together (Jaworski and Kohli 1993; Song et al. 2005). Not only these dimensions are conceptually different, but the correlations among them are low. Therefore, it is crucial for future research to examine further the contingent impact of firms' strategic actions in these technological conditions. This research provides the first attempt to depict a picture of the worth of a marketing and R&D capabilities in these technological conditions.

Second, this study advances the literature by revealing the profit performance impact of marketing capabilities is amplified by technological turbulence, most likely owing to communication management and product proficiency. Importantly, without robust marketing capability, a firm can never gain performance above the market average, regardless of its level of R&D capability. And not surprisingly, those firms that have weak marketing capabilities perform exceptionally poorly in high technologically turbulent markets. This finding implies that firms must allocate their resources to and invest in developing robust marketing capabilities to achieve performance in such markets. In contrast, counter-intuitively, the effect of R&D capability does not significantly change in technologically turbulent markets. Although firms must shift, integrate, and reconfigure their resources toward technological innovations in these markets, they face a red-queen competition effect. As such, R&D capability becomes more of an essential factor that firms must develop and invest in to survive.

Third, RBV theorists have asserted that uncertain environments generally increase causal ambiguity, impede the ability of other firms to imitate resources (Eisenhardt and Martin 2000), and boost the efficacy of firms' dynamic capabilities (Drnevich and Kriauciunas 2011). I provide the first empirical test for this for technological uncertainty and find the impact of marketing capability is enhanced in technologically uncertain environments, supporting this theoretical logic. However, although R&D capability is crucial in the long-term, it does not translate into short-term profitability because firms with robust R&D capabilities tend to practice the exploration strategy to a higher extend in the periods of technological uncertainty, leading to an increase in their costs.

Fourth, this study reveals that technological acceleration marginally increases the effect of marketing capability, potentially owing to its channel management facet. However, technological acceleration significantly amplifies the ROA outcomes of R&D

capability. Firms that have developed robust R&D capabilities can exploit new areas of technology faster and capture rents that cannot be easily competed away by firms without strong R&D capabilities.

Finally, this study enriches the scant literature on the interplay between capabilities by showing that marketing and R&D capabilities are only complementary in technologically turbulent markets. This complementarity happens because the origin of the majority of new technologies is in customer requests and suggestions, and marketing capability can effectively span the bridge between the market and R&D department. A firm with strong marketing capability provides high-quality consumer feedback to its R&D department and thus benefits from desirable market-pull ideas – which start from the analysis of user needs and then lead to the development of products to satisfy those needs. Further, firms with superior R&D capabilities can continually improve the technical performance of their products and introduce new upgraded products. If they have superior marketing capabilities as well, they can more effectively expand their product portfolios, vertically and/or horizontally, to increase their revenues. However, marketing and R&D capabilities do not show any complementary or substitutive effect in other environments possibly due to firms' resource constraints.

Implications for Practice

From a managerial perspective, this research confirms that it is advantageous for managers to invest in building their marketing and R&D capabilities. Interestingly, I find no technological environment condition where having a robust marketing or R&D capability diminishes firms' ROA. This finding should support firm efforts to allocate their resources to developing these capabilities. Selecting board members from the marketing and R&D departments can empower those departments, and it potentially shifts more resources toward those departments.

On average, the payoff from marketing capability is significantly higher than from R&D capabilities. Managers, in general, should prioritize investing in developing marketing capabilities as they are crucial for gaining a competitive advantage. Firms that have weak marketing capabilities, always perform more poorly than an average firm in their market.

Further, I provide valuable new guidance for managers concerning where their firm capabilities are more rewarding. In technologically turbulent and/or uncertain markets, marketing capability is more rewarding. This evidence should encourage mangers, especially those whose companies are in markets with fast rates of technological change and/or in with unpredictable technological trends, to capitalize on their marketing capabilities more to gain profitability.

In contrast, having strong R&D capabilities in technologically turbulent markets only keeps firms in the game and serves as a minimum condition. It is likely, however, that firms that have exceptional R&D capabilities still gain additional rents in turbulent markets. R&D capability can open new opportunities for firms in technologically accelerating markets. When firms can swiftly move along new technology trends, they enjoy a pioneering effect and gain huge market shares in new emerging markets due to those accelerating technologies. This is clearly the case for many technology start-ups.

Finally, marketing and R&D capabilities are complementary in only markets with high technological turbulence. This complementarity should encourage managers to increase resource integration and synergetic interactions between their marketing and

R&D departments to gain additional rents. In sum, this study provides valuable new guidance for firms on how they should shift their focus between their strategic capabilities depending on the technological environment the firm faces.

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APPENDIX A

SUPPLEMENT TO CHAPTER 1

Table A.1
Effect of Heteroscedastic Design Capability

Design Capability (H1, +)	.058***
Design Capability × TI (H2, +)	-.254**
Design Capability × TCI (H3, +)	.406**
Design Capability × TM (H2, +)	.386***
Technology Intensity (TI)	-.068*
Technological Competitive Intensity (TCI)	.118***
Technological Maturity (TM)	.035
Firm Size	-.008**
Prior Performance (Lag of ROA)	-.002**
R&D Expenditure	.000
Lag of Sale Growth	.167***
Constant	.035
Firm Fixed Effect	Yes
Time Fixed Effect	Yes
N	4378
Number of Groups (i.e., Firms)	539
Number of Instruments	99
F-statistic (Wald chi2)	7,567.90
Degrees of Freedom	27
AR(II) test (p value)	.57
Hansen Overid. test (J-statistic)	1.413

*** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$

Table A.2
Homoscedastic Marketing Capability

	Coefficient	Std. Err.	z	P Value	95% Conf. Interval	
SGA	.724	.022	33.250	.000	.681	.767
RECEIVABLES	.228	.035	6.510	.000	.159	.297
TRADEMARKS	-.008	.005	-1.590	.112	-.018	.002
Constant	2.572	.278	9.250	.000	2.027	3.117
U_{sigma}						
Constant	-3.134	.211	-14.860	.000	-3.547	-2.721
V_{sigma}						
Constant	-5.696	.399	-14.290	.000	-6.478	-4.915
θ	.829	.060	13.710	.000	.710	.947
σ_u	.209	.022	9.480	.000	.170	.257
σ_v	.058	.012	5.020	.000	.039	.086
λ	3.601	.032	112.640	.000	3.538	3.664

Table A.3
Homoscedastic R&D Capability

	Coefficient	Std. Err.	z	P Value	95% Conf. Interval	
TECH_STOCK	.804	.020	4.020	.000	.765	.844
TECH_EXP	.092	.012	7.730	.000	.068	.115
Constant	-.620	.084	-7.400	.000	-.784	-.455
U_{sigma}						
Constant	-2.33642	.096963	-24.1	.000	-2.52647	-2.14638
V_{sigma}						
Constant	-2.140	.085	-25.200	.000	-2.307	-1.974
θ	.243	.021	11.520	.000	.202	.284
σ_u	.311	.015	2.630	.000	.283	.342
σ_v	.343	.015	23.550	.000	.316	.373
λ	.907	.027	34.130	.000	.855	.959

Table A.4
Heteroscedastic Marketing Capability

	Coefficient	Std. Err.	z	P Value	95% Conf. Interval	
SGA	.709	.012	58.800	.000	.686	.733
RECEIVABLES	.265	.014	19.320	.000	.238	.291
TRADEMARKS	-.005	.004	-1.410	.159	-.013	.002
Constant	2.100	.149	14.130	.000	1.809	2.392
U_{sigma}						
Constant	-3.236	.185	-17.520	.000	-3.598	-2.874
V_{sigma}						
Firm Size	-.385	.093	-4.120	.000	-.568	-.202
Constant	-2.676	.736	-3.630	.000	-4.119	-1.233
θ	1.121	.018	61.710	.000	1.086	1.157
σ_u	.064				.063	.064
σ_v	.198256	.018311	1.83	0	.165429	.237597

Table A.5
Heteroscedastic R&D Capability

	Coefficient	Std. Err.	z	P Value	95% Conf. Interval	
TECH_STOCK	.822	.021	39.050	.000	.781	.863
TECH_EXP	.087	.013	6.920	.000	.062	.111
Constant	-.649	.088	-7.340	.000	-.822	-.476
U_{sigma}						
Constant	-2.412	.107	-22.520	.000	-2.622	-2.202
V_{sigma}						
Firm Size	-.180	.033	-5.540	.000	-.244	-.116
Constant	-.670	.232	-2.890	.004	-1.123	-.216
θ	.226	.022	1.270	.000	.183	.269
σ_u	.348				.347	.350
σ_v	.299	.016	18.680	.000	.270	.333

Table A.6
Various Lag Structure Settings

	(2-2)	(2-3)	(2-4)	(2-5)	(2-6)	(2-7)	(2-.)
Design Capability (H1, +)	.059***	.062***	.063***	.063***	.063***	.063***	.064***
Design Capability × TI (H2, +)	-.212**	-.207**	-.205**	-.205**	-.205**	-.205**	-.205**
Design Capability × TCI (H3, +)	-.402	-.398	-.397	-.397	-.397	-.397	-.397
Design Capability × TM (H2, +)	.378***	.387***	.390***	.389***	.389***	.389***	.390***
Technology Intensity (TI)	-.054	-.056	-.056	-.056	-.056	-.056	-.056
Technological Competitive Intensity (TCI)	-.03	-.031	-.031	-.031	-.031	-.031	-.031
Technological Maturity (TM)	.04	.043	.044*	.044	.044	.044	.044
Firm Size	-.008***	-.009***	-.009***	-.009***	-.009***	-.009***	-.009***
Prior Performance (Lag of ROA)	-.002**	-.002**	-.002**	-.002**	-.002**	-.002**	-.002**
R&D Expenditure	.000	.000	.000	.000	.000	.000	.000
Lag of Sale Growth	.203***	.174***	.165***	.167***	.167***	.167***	.163***
Constant	.034	.000	.045	.044	.044	.044	.000
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4378	4378	4378	4378	4378	4378	4378
Number of Groups (i.e., Firms)	539	539	539	539	539	539	539
Number of Instruments	63	76	88	99	109	118	154
F-statistic	40,029.88	8,107.13	5,328.06	4,699.04	4,650.86	5,021.11	14,713.88
Degrees of Freedom	27	27	27	27	27	27	27
AR(II) test (p value)	.735	.597	.556	.57	.569	.566	.549
Hansen Overid. test (J-statistic)	.083	4.494	4.527	4.44	3.96	3.96	3.957

*** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$

Table A.7
Outlier Sensitivity Analysis

	% Winsorized Obs.		
	.5%	1%	2%
Design Capability (H1, +)	.061***	.064***	.066***
Design Capability × TI (H2, +)	-.274**	-.297***	-.323***
Design Capability × TCI (H3, +)	.399*	.408*	.416*
Design Capability × TM (H2, +)	.423***	.466***	.506***
Technology Intensity (TI)	-.068*	-.069*	-.069
Technological Competitive Intensity (TCI)	.119***	.119***	.119***
Technological Maturity (TM)	.037	.039	.041
Firm Size	-.008**	-.008**	-.008**
Prior Performance (Lag of ROA)	-.002**	-.002**	-.002**
R&D Expenditure	.000	.000	.000
Lag of Sale Growth	.163***	.163***	.163***
Constant	.000	.000	.000
Firm Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
N	4378	4378	4378
Number of Groups (i.e., Firms)	539	539	539
Number of Instruments	154	154	154
F-statistic	16,094.94	17,100.61	17,168.51
Degrees of Freedom	27	27	27
AR(II) test (p value)	.549	.548	.546
Hansen Overid. test (J-statistic)	3.244	3.189	3.085

*** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$

APPENDIX B

SUPPLEMENT TO CHAPTER 2

Table B.1
Half-Normal assumption on the Distributions of Inefficiency

	Model 1	Model 2	Model 3	Model 4
Marketing Capability × Technological Turbulence (H1a, +)	.627***			.625***
R&D Capability × Technological Turbulence (H1b, +)	.017			.025
Marketing Capability × Technological Uncertainty (H2a, +)		.319***		.256***
R&D Capability × Technological Uncertainty (H2b, +)		.009		-.005
Marketing Capability × Technological Acceleration (H3a, +)			.308**	.264**
R&D Capability × Technological Acceleration (H3b, +)			.157***	.164***
Prior Performance (Lag of ROA)	.320***	.320***	.320***	.320***
Marketing Capability	.305***	.313***	.320***	.305***
R&D Capability	.054***	.055***	.056***	.055***
Operations Capability	-.027	-.026	-.025	-.025
Firm Size	.023***	.023***	.023***	.023***
Market Share	-.224***	-.221***	-.212**	-.226***
Competitive Intensity	.126*	.146**	.146**	.125*
Advertising Intensity	-.021	-.036	-.031	-.025
R&D Intensity	.468**	.493**	.487**	.473**
Technological Turbulence	-.053	-.057*	-.055*	-.054
Technological Uncertainty	.008	.009	.010	.007
Technological Acceleration	-.005	-.007	-.008	-.007
Constant	-.339***	-.359***	-.357***	-.337***
Firm Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
N	12332	12332	12332	12332
Number of Firms	2132	2132	2132	2132
Number of Instruments	219	219	219	227
Degrees of Freedom	52	52	52	56
AR(II) test (p value)	.256	.251	.275	.253

*** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$

Table B.2
Relaxing the Assumption of Heteroscedasticity in Calculation of Capabilities

	Model 1	Model 2	Model 3	Model 4
Marketing Capability × Technological Turbulence (H1a, +)	.653***			.653***
R&D Capability × Technological Turbulence (H1b, +)	.026			.035
Marketing Capability × Technological Uncertainty (H2a, +)		.270***		.230***
R&D Capability × Technological Uncertainty (H2b, +)		.004		-.012
Marketing Capability × Technological Acceleration (H3a, +)			.259**	.208*
R&D Capability × Technological Acceleration (H3b, +)			.182***	.195***
Prior Performance (Lag of ROA)	.324***	.324***	.323***	.324***
Marketing Capability	.338***	.346***	.353***	.335***
R&D Capability	.064***	.065***	.067***	.064***
Operations Capability	.005	.003	.003	.006
Firm Size	.021***	.021***	.021***	.021***
Market Share	-.198**	-.205**	-.194**	-.201***
Competitive Intensity	.116*	.142**	.143**	.116*
Advertising Intensity	.065	.040	.043	.063
R&D Intensity	.435**	.467**	.463**	.439**
Technological Turbulence	-.054*	-.059*	-.058*	-.055*
Technological Uncertainty	.011	.013	.015	.010
Technological Acceleration	-.004	-.006	-.008	-.007
Constant	-.316***	-.341***	-.341***	-.314***
Firm Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
N	12333	12333	12333	12333
Number of Firms	2133	2133	2133	2133
Number of Instruments	219	219	219	227
Degrees of Freedom	52	52	52	56
AR(II) test (p value)	.302	.291	.326	.292

*** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$

Table B.3
Accounting for Outliers

	.5%	1%	2%
Marketing Capability × Technological Turbulence (H1a, +)	.672***	.685***	.688***
R&D Capability × Technological Turbulence (H1b, +)	.015	.022	.034
Marketing Capability × Technological Uncertainty (H2a, +)	.265***	.264***	.251**
R&D Capability × Technological Uncertainty (H2b, +)	-.014	-.002	.003
Marketing Capability × Technological Acceleration (H3a, +)	.242**	.287**	.350***
R&D Capability × Technological Acceleration (H3b, +)	.205***	.220***	.255***
Prior Performance (Lag of ROA)	.326***	.327***	.328***
Marketing Capability	.327***	.324***	.318***
R&D Capability	.058***	.058***	.058***
Operations Capability	.018	.018	.017
Firm Size	.021***	.021***	.021***
Market Share	-.202***	-.201***	-.201***
Competitive Intensity	.115*	.112*	.111*
Advertising Intensity	.057	.053	.048
R&D Intensity	.449**	.449**	.443**
Technological Turbulence	-.056*	-.058*	-.059*
Technological Uncertainty	.009	.01	.011
Technological Acceleration	-.009	-.011	-.013
Constant	-.300***	-.311***	-.292***
Firm Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
N	12333	12333	12333
Number of Firms	2133	2133	2133
Number of Instruments	227	227	227
Degrees of Freedom	55	55	55
AR(II) test (p value)	.292	.318	.361

*** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$

Table B.4

Various Lag Structure Settings

	(2-2)	(2-3)	(2-4)	(2-5)	(2-6)	(2-7)	(2-.)
Marketing Capability × Technological Turbulence (H1a, +)	.611***	.636***	.641***	.645***	.651***	.654***	.663***
R&D Capability × Technological Turbulence (H1b, +)	.013	.014	.014	.014	.014	.014	.015
Marketing Capability × Technological Uncertainty (H2a, +)	.231***	.241***	.243***	.244***	.246***	.247***	.251***
R&D Capability × Technological Uncertainty (H2b, +)	-.012	-.01	-.01	-.01	-.01	-.01	-.009
Marketing Capability × Technological Acceleration (H3a, +)	.204*	.210*	.212**	.213**	.214**	.215**	.217**
R&D Capability × Technological Acceleration (H3b, +)	.166***	.169***	.170***	.170***	.171***	.171***	.172***
Prior Performance (Lag of ROA)	.365***	335***.	.329***	.324***	.317***	.314***	.302***
Marketing Capability	.311***	.325***	.328***	.330***	.333***	.335***	.340***
R&D Capability	.055***	.058***	.058***	.059***	.059***	.060***	.061***
Operations Capability	.016	.016	.016	.016	.016	.016	.016
Firm Size	.020***	.021***	.021***	.021***	.021***	.021***	.022***
Market Share	-.198***	-.203***	-.205***	-.205***	-.207***	-.207***	-.209***
Competitive Intensity	.111*	.116*	.117*	.118*	.119*	.119*	.121*
Advertising Intensity	.059	.058	.057	.057	.057	.057	.056
R&D Intensity	.422**	.440**	.444**	.446**	.451**	.453**	.460**
Technological Turbulence	-.053*	-.055*	-.055*	-.056*	-.056*	-.056*	-.057*
Technological Uncertainty	.010	.01	.01	.01	.01	.01	.01
Technological Acceleration	-.006	-.006	-.006	-.006	-.006	-.006	-.007
Constant	-.285***	-.298***	-.301***	-.303***	-.321***	-.308***	-.328***
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12333	12333	12333	12333	12333	12333	12333
Number of Firms	2133	2133	2133	2133	2133	2133	2133
Number of Instruments	134	166	197	227	256	284	658
Degrees of Freedom	55	55	55	55	55	55	55
AR(II) test (p value)	.366	.313	.298	.289	.273	.266	.244

*** significant at $p < .01$; ** significant at $p < .05$; * significant at $p < .1$