THE EFFECT OF ACQUISITIONS ON ACQUIRING FIRM PERFORMANCE: EVIDENCE FROM DIGITAL PRODUCT AND SERVICE INDUSTRIES

By

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ABSTRACT

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In this study, I examine the effect of acquisition on digital firm performance in the form of product differentiation, innovation capability, and stock abnormal return. By using archival data of M&A, financial, and a unique 10-K textual analysis-based measure of product differentiation, I test the effect of completing significant acquisition on digital firms' firm performance using a difference-in-differences specification where a control group is matched using propensity score based on a variety of factors that are suggested to influence the M&A decision in the literature. I also study the heterogeneous effects of acquisition across different subgroups in the digital industry and other firm-, industry-level and M&A portfolio characteristics. I find that acquisition can cause higher level of production differentiation, however, this effect is only evident in the subsample of hardware manufacturers, and is stronger when firms make internal R&D investment to complement the acquisition. Only high *Tobin's Q* firms in hardware sector are found to perform better after M&A in terms of patent quantity, but not in terms of patent quality. Also I find that stock market investors generally react negatively to M&A behavior, however firm's *Tobin's Q* and M&A portfolio size can mitigate some of the negative impact, and investors' attitude toward M&A tend to change over time. For software firms, I find that M&A has no positive effect or even reversed impact on product differentiation and no positive effect on innovation capability and financial performance is found. Target age has been found to moderate the effect of M&A on product differentiation. Additional analyses are also conducted to examine differential effect of M&A during different time periods.

This dissertation is dedicated to my family.

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INTRODUCTION

Mergers and Acquisitions (M&A) is an important means of integration of knowledge, technology, talent and product for firms seeking those capabilities from external resources. M&A has been extensively studied in economics, finance, and strategic management in the past several decades. Empirical studies by financial economists typically examine the M&A performance in the form of stock market reaction. Those studies typically examine the short term stock market abnormal return around the M&A announcement and suggest that M&A did not create acquiring firm's value (Andrade, Mitchell, and Stafford, 2001). Alternative performance measures such as longer term accounting-based and non-financial performance measures were also used and findings have been mixed (Loughran and Vijh, 1997; Rau and Vermaelen, 1998; Mitchell and Stafford, 2000; Ravenscraft and Scherer, 1989; Healy, Palepu, and Ruback, 1992). In the strategy literature, more attention has been put to the study of motivation of M&A and the antecedents of successful M&As (Haleblian et al., 2009).

Even though M&A is not a new topic, little attention has been on M&A among digital product and services industry. M&A as a mechanism of digital firm growth is particularly worth studying since those industries are very different from others. Shorter-than-normal product and technology life cycle, more frequent new entrants, and disruptive nature of the new technology/product all make those industries extremely fast growing and hypercompetitive. As a result, digital firms need to keep innovating in order to survive and grow in this dynamic environment. As one of the easiest and fastest ways to gain innovation, M&A becomes especially effective and efficient way to obtain technology and product in a short period of time, and sometimes at lower cost. That is why M&A has become the most important means of growth in digital industry, and as a matter of fact, technology companies accounted for the majority of

M&A deal makings. A *Business Insider* article suggests that high technology M&A accounted for $214 billion of the $3.5 trillion of all M&A deals in 2014, near the records of 1999 and 2000. Over the past 15 years, the technology industry has experienced a high volume of M&A activity. In fact, technology M&A has exceeded any other industry, largely fueled by a constant demand for innovation and a decade-long period of consolidation.

For M&A initiated by digital firms, product and technology are the two most important objectives. As discussed earlier, because of the high competition, digital firms need to be innovative in their product offerings. Theories from industrial organization suggest that market power is the key for firms to generate supernormal economic rents, and firms' competitiveness in product offerings plays a vital role in getting market power. Back in 1930's, researchers have shown that product differentiation is related to market power and profitability (Hotelling, 1929; Chamberlin, 1933). Though there are plenty of researches on how M&A create values for firms in terms of both financial and operational performance, there has yet been any empirical study that focuses on the outcome of product differentiation. As for innovation and financial performance, even though this is not the first paper studying them, previous studies focus on firms of all industries or general technology-intensive industries (including IT, chemical, pharmaceutical, etc), there has not been any study that is specifically focusing on digital industry and examining differential effect of M&A on firms in different sectors of digital industries (software developers and hardware manufacturers), which is of IS researchers' and IT firm managers' interest.

In this study, I try to answer a fundamental yet important question: does M&A create value for digital (hardware and software) firms in the forms of product differentiation, innovation capability and stock market abnormal return? By analyzing a unique data set combining both public and proprietary resources, I empirically show that M&A has differential impact on product differentiation across different sectors in digital industry. I am able to build the causal relationship by using an approach called difference-in-differences to handle potential endogeneity problem. My findings suggest that hardware firms are able to increase its level of product differentiation among its competitors via M&A, while software firms tend to use M&A to close the technology gap which actually decreases product differentiation. Secondly, in order for a company to benefit from M&A in product market, it needs to invest in internal research and development (R&D) as well. I also find other heterogeneous effect of M&A on product differentiation across different firm, industry and M&A portfolio level characteristics. In addition to product differentiation, I also test the effect of M&A on digital firms' innovation capability and how stock market investors react to M&A decisions of digital firms.

This paper contributes to the literature in three ways. First, it extends the M&A literature by examining an important but understudied outcome variable of product differentiation. Product differentiation is crucial to firms in digital industries, therefore it is also one of the most common strategic reasons for acquirers to take over other companies. Although this is not the only and first paper to study M&A in high technology industry (Makri, Hitt and Lane, 2010; Bena and Li, 2014; Seru, 2014), this is the first one to examine M&A from the product perspective. The second contribution of this study is the methodology I use. The unit of analysis of this study is firm, meaning that I aggregate M&As in the same year initiated by the same firm as a portfolio and I only examine the firm years where significant M&A are completed. This approach is different from previous studies which predominately use M&A deal as the unit of analysis. Also, by adopting a difference-in-differences approach to analyze data with both firms with M&A completed and a matched sample of control firm years, I am able to tease out as much unobserved heterogeneities as possible to build the causal relationship between M&A and firm performance. Last but not the least, I shed new lights on M&A's value for acquiring firms in several specific industries and sectors, which provide different results and/or additional insights upon other M&A studies which focus on generic firms or general high tech industry. This study provides managerial implications for decision makers of digital firms on (1) if M&A actually creates value for them (2) contingencies of those value upon characteristics that are specific to digital product and service industries and/or that have not been examined in prior studies.

The rest of the paper is organized in the following way. In the literature review section, I summarize the major findings from studies of M&A from both finance and strategic management literature. In the next section, I discuss the underlying theory I base this study on, which are mainly from strategy and industrial organization economics. The methodology section describes the process of data collection, variable operationalization and sampling techniques I use. Lastly, I demonstrate my statistical analyses results and provide interpretations to them, followed by a conclusion section.

LITERATURE REVIEW

M&A has been an extensively studied phenomenon for researchers in economics, finance, and strategic management literature since 1980s because it has become increasingly popular mechanism of corporation growth since 1970s (Lamont and Anderson, 1985). In earlier works by financial economists, stock market reaction to the M&A was preferred as a measure of M&A performance because of the assumption that capital market is sufficient enough to reflect the quality or at least the perception of the M&A quality and thus is recommended as the best way to capture M&A value. Some M&A studies examine the M&A participants' stock market abnormal return around the announcement period (Asquith, 1983; Malatesta, 1983; Jarrell and Poulsen, 1989), while others focus on longer term abnormal return over three to five years after M&A (Langetieg, 1978; Asquith, 1983; Jensen and Ruback, 1983; Magenheim and Mueller, 1988; Agrawal, Jaffe, and Mandelker, 1992). Those studies generally suggest that acquirers experience negative abnormal return after M&A, both in short run and over one to three years after it. Some other studies use longer term M&A performance such as accounting and productivity data but are criticized for their lack of control group (Halpern, 1983), and results have been mixed. Some scholars find that merged firms show significant improvements in asset productivity relative to their industries, leading to higher operating cash flow returns (Healy, Palepu, and Ruback, 1992), while others' found the opposite direction (Ravenscraft and Scherer, 1987). In later works, researchers examine the differential effect of M&A based on types of acquirers and payment methods. Rau and Vermaelen (1998) find that low book-to-market (high *Tobin's Q*) "glamour" or "growth" firms underperform compared with their "value" counterparts with high book-to-market ratio (low *Tobin's Q*). They also find that bidders in tender offers outperform those in mergers, and similarly, Loughran and Vijh (1997) show evidence that firms that complete stock mergers earn significantly negative excess returns of -25% whereas firms that complete cash tender offers earn significantly positive excess returns of 61.7%. Recent works focus on other factors that differentiate the M&A effect including firm size (Moeller, Schlingemann, and Stulz, 2004), prior relationship with target firm (Higgins and Rodriguez, 2006), industry competition (Masulis, Wang, and Xie, 2007), and product market similarity (Hoberg and Phillips, 2010) among others. More recently, studies investigate alternative form of performance other than market return and accounting measure. Ornaghi (2009) studied the impact of M&A on R&D of pharmaceutical firms, and similarly, Seru (2014) shows evidence that conglomerates M&As decrease the scale and novelty of corporate R&D activities.

In strategic management literatures, researchers more focus on the antecedents of M&A performance of acquirers. Relatedness and similarity between acquirer and target firm have been the most studied deal characteristics that are argued to be impact the M&A value creation. Montgomery and Singh (1987) conceptualize and find evidence that acquisitions which are related in product/market or technological terms create higher value than unrelated acquisitions. Based on resource-based view, Barney (1988) argues that relatedness is not a sufficient condition for acquiring firms to earn abnormal returns. Rather, only when bidding firms enjoy private and uniquely valuable synergistic cash flows with targets, inimitable and uniquely valuable synergistic cash flows with targets, or unexpected synergistic cash flows, will acquiring a related firm result in abnormal returns for the shareholders of bidding firms. Seth (1990), on the other hand, shows evidence that value is created in both unrelated and related acquisitions and related acquisitions do not appear to create more value than unrelated acquisitions on average. From another perspective, Ramaswamy (1997) examines the impact of strategic similarities between target and bidder firms on changes in post-merger performance and finds that mergers between banks exhibiting similar strategic characteristics result in better performance than those involving strategically dissimilar banks. Similarly, other researchers conceptualize and find empirical evidences to support that similarity and complementarity between two merging businesses is positively related with M&A performance (Larsson and Finkelstein, 1999; Finkelstein and Haleblian, 2002). Ahuja and Katila (2001) show that relatedness of acquired and acquiring knowledge bases has a nonlinear impact on innovation output. In addition to stock market abnormal return and longer-term accounting performance (e.g. ROA), R&D and innovation performance have been also used to evaluate M&A performance, especially for technological firms. Ahuja and Katila (2001) distinguish between technological and non-technological acquisitions and find that within technological acquisitions absolute size of the acquired knowledge base enhances innovation performance, while relative size of the acquired knowledge base reduces innovation output. They also find that the non-technological acquisitions do not have a significant effect on subsequent innovation output. In a closely related study, Cloodt, Hagedoorn, and Kranenburg (2006), non-technological M&As are found to have even negative impact on the acquiring firm's post-M&A innovative performance. In more recent work, scholars examine the role of technological and knowledge complementarity in post-M&A performance in terms of innovation (Makri, Hitt, and Lane, 2010), and find significant and positive relationships.

Table 1A and 1B show the literature review of key M&A papers both in the finance and strategy literature. This study will build upon the existing literature and propose hypotheses about the effect of M&A on firm performance in three forms. I will use theories from strategy and industrial organization as my theoretical foundations. Also my unique context of digital firm may extend or even change part of the existing theory in explaining how M&A create values for acquiring firms.

Table 1A. Review of Major M&A Studies in Finance Literature

Study	Main Findings
Agrawal, Jaffe, and Mandelker (1992)	Stockholders of acquiring firms suffer a statistically significant loss of about 10% over the five-year post-merger period.
Healy, Palepu, and Ruback (1992)	Merged firms show significant improvements in asset productivity relative to their industries, leading to higher operating cash flow returns, this performance improvement is particularly strong for firms with highly overlapping businesses. Mergers do not lead to cuts in long-term capital and R&D investments.
Loughran and Vijh (1997)	During a five-year period following the acquisition, on average, firms that complete stock mergers earn significantly negative excess returns of -25.0 percent whereas firms that complete cash tender offers earn significantly positive excess returns of 61.7 percent.
Rau and Vermaelen (1998)	Bidders in mergers underperform while bidders in tender offers over perform in the three years after the acquisition. The long-term underperformance of acquiring firms in mergers is predominantly caused by the poor post-acquisition performance of low book-to-market "glamour" firms.
Andrade, Mitchell, and Stafford (2001)	1) Mergers occur in waves, within a wave, mergers strongly cluster by industry.
	2) The most statistically reliable evidence on whether mergers create value for shareholders comes from traditional short-window event studies, where the average abnormal stock market reaction at merger announcement is used as a gauge of value creation or destruction.
	3) Mergers seem to create value for shareholders overall, but the announcement period gains from mergers accrue entirely to the target firm shareholders. In fact, acquiring firm shareholders appear to come dangerously close to actually subsidizing these transactions.

Table 1A (cont'd)

	4) It is important to separate the stock-financed mergers from the others before making final judgement on the value effects for shareholders, especially for the acquiring firms.
	5) Firms classified on the basis of high book-to-market are commonly referred to as "value" firms, and tend to have higher returns on average. Firms identified as low book-to-market are referred to as "growth" or "glamour" firms, and have relatively low returns on average.
Moeller et al. (2004)	The announcement return for acquiring-firm shareholders is roughly two percentage points higher for small acquirers irrespective of the form of financing and whether the acquired firm is public or private.
Higgins and Rodriguez (2006)	This study examines the performance of 160 pharmaceutical acquisitions from 1994 to 2001 and find evidence that on average acquirers realize significant positive returns. These returns are positively correlated with prior acquirer access to information about the research and development activities at target firms and a superior negotiating position.
Masulis, Wang, and Xie (2007)	Acquirers with more antitakeover provisions experience significantly lower announcement period abnormal stock returns. Acquirers operating in more competitive industries or separating the positions of CEO and chairman of the board experience higher abnormal announcement returns.
Savor and Lu (2009)	Overvalued firms create value for long-term shareholders by using their equity as currency.
Ornaghi (2009)	Merged companies have on average, worse performances than the group of non-merging firms.

Table 1A (cont'd)

Hoberg and Phillips (2010)	Transactions are more likely between firms that use similar product market language. Transaction stock returns ex post cash flows, and growth in product descriptions all in-crease for transactions with similar product market language, especially in competitive product markets.
Li (2013)	Acquirers increase targets' productivity through more efficient use of capital and labor.
Bena and Li (2014)	Companies with large patent portfolios and low R&D expenses are acquirers, while companies with high R&D expenses and slow growth in patent output are targets. Further, technological overlap between firm pairs has a positive effect on transaction incidence. Acquirers with prior technological linkage to their target firms produce more patents afterwards.
Seru (2014)	Firms acquired in diversifying mergers produce both a smaller number of innovations and also less-novel innovations, where innovations are measured using patent-based metrics.

Table 1B. Review of Major M&A Studies in Strategy Literature

Study	Main Findings
Singh and Montgomery (1987)	Related acquisitions are found to have greater total dollar gains than unrelated acquisitions. Acquired firms in related acquisitions have substantially higher gains than acquired firms in unrelated acquisitions.
Hitt et al. (1991)	Acquisitions had negative effects on "R&D intensity" and "patent intensity".
Ramaswamy (1997)	Mergers between banks exhibiting similar strategic characteristics result in better performance than those involving strategically dissimilar banks.
Hitt, Hoskisson, and Kim (1997)	This study provides evidence of the importance of international diversification for competitive advantage but also suggest the complexities of implementing it to achieve these advantages in product diversified firms.
Capron (1998)	This paper examines how value is created in horizontal mergers and acquisitions. More specifically, it examines the impact of post-acquisition asset divestiture and resource redeployment on the long-term performance of horizontal acquisitions.
Ahuja and Katila (2001)	This study distinguishes between technological acquisitions and nontechnological acquisitions and finds that within technological acquisitions absolute size of the acquired knowledge base enhances innovation performance, while relative size of the acquired knowledge base reduces innovation output. The relatedness of acquired and acquiring knowledge bases has a nonlinear impact on innovation output. Nontechnological acquisitions do not have a significant effect on subsequent innovation output.
King et al. (2004)	This meta-analysis shows that acquiring firms' performance does not positively change as a function of their acquisition activity, and is negatively affected to a modest extent. Also, unidentified variables may explain significant variance in post-acquisition performance,

Table 1B (cont'd)

Krishnan, Joshi, and Krishnan (2004)	This study examines whether multi-product firms use mergers as a strategic tool to reconfigure their product-mix toward high-profit products. Finding suggests that mergers facilitate product-mix reconfiguration by relaxing institutional and organizational constraints on resource redeployment.
Cloodt, Hagedoorn, and Kranenburg (2006)	This study finds that companies should target M&A 'partners' that are neither too unrelated nor too similar in terms of their knowledge base.
Haleblian, Kim, and Rajagopalan (2006)	This study finds that (1) prior acquisition experience, (2) recent acquisition performance, and (3) the interaction between acquisition experience and recent acquisition performance are all positively related to the likelihood of subsequent acquisition.
Kapoor and Lim (2007)	This study shows how knowledge-based and incentive-based perspectives complement each other to explain the effects of acquisitions on the productivity of inventors from acquired firms. Incentive-based theories account for their lower productivity relative to that of inventors at nonacquired firms, and both perspectives jointly explain why their productivity converges with that of inventors from acquiring firms.
King, Slotegraaf, and Kesner (2008)	This study finds that acquiring firm marketing resources and target firm technology resources positively reinforce (complement) each other; meanwhile, acquiring and target firm technology resources negatively reinforce (substitute) one another. Implications for management theory and practice are identified.
Ransbotham and Mitra (2010)	This study finds evidence that supports acquiring early in the face of uncertainty. Analytical model and empirical analysis uncover two characteristics of young targets that drive benefits from early acquisitions—flexible growth options that provide greater opportunities for synergistic fit, and greater valuation uncertainty that leads to lower prices.

Table 1B (cont'd)

Makri, Hitt, and Lane (2011)	This study finds that complementary scientific knowledge and complementary technological knowledge both contribute to post-merger invention performance by stimulating higher quality and more novel inventions.
Laamanen, Brauer, and Junna (2014)	This study finds that acquisitions of divested assets outperform acquisitions of privately held firms, which in turn outperform acquisitions of publicly held firms.
Bauer and Matzler (2014)	This study develops a comprehensive model of M&A success. It integrates fundamental constructs of different schools and discuss their interdependencies with M&A success. M&A success is a function of strategic complementarity, cultural fit, and the degree of integration. Strategic complementarity also positively influences cultural fit and the degree of integration.

THEORY AND HYPOTHESES

Resource-based View

The phenomenon of M&A can be explained by a theory of corporate expansion by Rubin (1973) who also defines a resource as a fixed input which allows a firm to perform a particular task. The definition of input includes human capital and physical assets. The rationale of that M&A may change firm performance comes from the fact that M&A enables bidding firms acquire certain new resources (technology, physical assets and human capitals) for them to be able to perform tasks differently than they normally do, which might have impacts on firm performance. In strategic management literature, the resource-based view (RBV) has been an extensively used theory to justify M&A decisions. Originally developed by Barney (1986), RBV argues that in order to improve firm performance and maintain advantage among its competitors, a firm needs to possess resources that are hard to or at least costly to copy as sources of economic rents. According to this perspective, a firm's ability to obtain and keep profitable market positions depends on its ability to gain advantageous positions in resources that are important to production and distribution (Conner, 1991). King, Slotegraaf, and Kesner (2008) suggests that the foundation of RBV identifies resources as the drivers of firm heterogeneity (Penrose 1959). Barney (1986) defines firm resources as "all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness."

This study focuses on the digital industry, in which product and services are their core competencies. Wernerfelt (1984) mentioned that resources and products are two sides of the same coin. Based on his view, valuable and inimitable resources help firms acquire or develop new or different products that its competitors are not able to introduce. From a product perspective, Penrose (1959) view a firm is a ‘collection of productive resources’ which are combined with the choice of processes resulted in a product (Montgomery and Singh 1987). There are two ways to expand the product portfolio – expansion and diversification. Expansion refers to the improvement or enhancement of current product lines to be able to charge higher prices, by acquiring complementary products to the existing ones. Product diversification, on the other hand, is a strategy to enter into a new product market where the firm does not offer products in. The reason for a firm, to seek product line expansion and diversification is to differentiate it from its competitors. As discussed earlier, high technology especially digital firm industry is hypercompetitive thus product innovation and differentiation is of more importance and is more urgent for them than it is for other non-technology firms. By obtaining valuable, inimitable technical and human resources, firms are able to expand and/or diversify their product offerings, and eventually differentiate themselves from their competitors in the product market.

Product Differentiation Theory

Another theoretical lens this study bases upon is the product differentiation theory. A fundamental theory in industrial organization economics suggests that firms earn great profits by having market power. Market power is the ability to set the price and the quantity or the nature of the products sold (Seth, 1990), which generates supernormal profits. For example, *Glaxo* was able to set the price of *Zantac* very high though the unit product cost is close to zero, however they did not lose many customers because of their pricing. Similarly, *Xerox* developed the technology of plain-paper photocopying and patented it, which gave it the legal protection through patents. As a result, *Xerox* could raise prices to a significant level without attracting competition. Those two examples illustrate the concept of product uniqueness. The reason why

Glaxo did not lose market share even they charge a high premium is because they offer a product that is not obtainable from its competitors. As a matter of fact, after the patent expires, when competitors are able to produce generic "*Zantac*", *Glaxo* lost the market power and the right to set the price, simply because their *Zantac* is not unique anymore. Hotelling (1929) and Chamberlin (1933) famously show that product differentiation is fundamental to profitability in the theories of industrial organization (Hoberg and Phillips, 2015). By enhancing the existing product offerings or diversifying the product lines, a firm is able to differentiate it from its competitors and thus gain higher market power, which ultimately leads to higher profits (Shocker, Srivastava, and Ruekert, 1994). The effect of product differentiation on firm's financial performance is more salient for technology industry, simply because those industries are more dynamic, hypercompetitive and fast growing. Being able to stay in front of the competitors and constantly provide new product and solutions is vital for digital firm's ability to maintain market power and generate economics rents.

Acquisition and Product Differentiation

Product uniqueness seems to be vital to a high technology firm to be able to be competitive. But how can a firm actually create and maintain this value-maximization strategy? For either product line extension or diversification, a firm can choose between internal growth and acquisition from external resources. Organic growth may be a good option for firms, while it takes longer and sometimes costs more. Therefore M&A is very popular in high technology industry when the motives for acquiring a company are product and technology. Montgomery and Singh (1987) suggests that there are three main reasons that acquisition is favored over internal growth: (1) internal development requires long time for accrual of returns, (2) internal development can be more expensive than the purchase of an ongoing business, (3) in concentrated product markets where incumbent has high market power, acquisition of incumbent may be more efficient.

There are two mechanisms through which M&A increases product differentiation for the acquiring firms. In her model of long-term performance of horizontal acquisition, Capron (1999) hypothesize that the first mechanism through which M&A creates value is market coverage, which includes geographic market extension and product market extension (Aaker, 1996; Srivastava, Shervani and Fahey, 1998). In this study, I emphasize on how M&A creates value through extended product market. According to Capron (1999) and others' arguments, M&A can help with firms obtain products to complement or diversify their existing portfolio, as well as acquiring proprietary and patentable technologies for future product development, which ultimately leads to product differentiation as well. This is consistent with what I find in most of the annual reports and press releases about many high tech firms' acquisition, where CEOs discuss about their objectives of M&As being certain product or proprietary technologies of the target firm. Therefore, I hypothesize that:

> ***Hypothesis 1A****: Acquisition increases product differentiation for firms in the digital product and service industries.*

However, the effect of M&A on product differentiation is not necessarily homogenous across all digital firms. Product differentiation is more important for some digital firms than others. For example, M&As in hardware sectors are more product- or innovation-driven whereas software vendors always leverage acquisitions to gain new customers, geographic coverage, new licenses and to achieve economies of scale (Ransbotham and Mitra, 2010). Therefore, I speculate that product is a more important competence to hardware manufacturers than to their counterparts in software and service sectors, for instance, *Accenture* or *Cognizant*. Therefore, I hypothesize that:

Hypothesis 1B*: The positive effect of acquisition on product differentiation is stronger in hardware manufacturers than that in software service providers.*

Acquisition and Innovation Capability

The relationship between M&A and innovation capability is not a new question, however different contexts and methodologies have been used and findings on this question have been mixed in the previous literature. In Hitt et al. (1991), M&A is found to have negative impact on both R&D input and output (measured by patent-based metrics). Other works focus on the antecedents of post-acquisition innovation performance. For example, Ahuja and Katila (2001) differentiate technological M&A from non-technological one and find that only M&A with technology component has impact on innovation capability. A follow up study by Cloodt, Hagedoorn, and Kranenburg (2006) find that non-technological M&As even have negative impact on the acquiring firm's post-M&A innovative performance. In more recent works, researchers use more advanced statistical techniques to build causal relationship between M&A and innovation performance. In Ornaghi (2009), the researcher study the pharmaceutical industry and finds that merged companies have on average, worse performances than the group of non-merging firms. Bena and Li (2014) used matched sample of failed deals and find that M&A does increase the innovation performance after the acquisition, and the effect is stronger when there is technology overlap between the acquirer and target. Seru (2014) used the similar technique to examine the impact of M&A on target's innovation performance and find that there is a negative relationship especially when the acquirer has a conglomerate organizational format. My study focus on the impact of M&A on acquirer's innovation capability, in terms of patent quantity and patent quality, in the digital industry. Ornaghi (2009) and Seru (2014) have a similar research design and setting as mine. I try to uncover the overall impact of firms' M&A behavior on its innovation capacity.

The story is two-folded. On one hand, since most of M&A in digital firms are initiated for the purpose of product and technology innovation, sometimes acquiring firms choose a particular target for its proprietary and in-process technology and technical know-hows who can continuously invent. I speculate that M&A should bring those knowledge and resources to the acquirer, which help enhance their innovation capability measured by patent application and citation. Capron (1999) suggests that innovation is another channel through which high technology firms enhance market power and increase revenue. Though innovation capability is not the ultimate goal for a company, it is the most important thing for a high technology firm to rely on for product improvement and diversification. Therefore, technological innovation is a key capability over the long run, especially for digital industries. The core competence of a technology firm is product, and the core element of a good product is technology and innovation. If a firm is able to obtain proprietary technology and patent it, it gains competitive advantages over its competitors because technological innovation is a repertoire and incubator of future product. Taken together, M&As in digital industry mostly aim for target companies' product or technology. The purpose of many takeovers is to integrate the target firm's knowledge, technology and know-how into its own team to fully exploit target firm's capability in certain existing product market, and/or to explore their potentials in other product markets by leveraging their proprietary, patented or in-process technologies. I, therefore, hypothesize that:

> ***Hypothesis 2****: Acquisition increases innovation capability (both quantity and quality) for firms in digital product and service industries.*

On the other hand, however, M&A might lower the innovation capability. Hitt and colleagues (1991) proposed that acquisitions have a negative effect on managerial commitment to innovation, defined as managerial willingness to allocate resources and champion activities that lead to the development of new products, technologies, and processes consistent with marketplace opportunities. If M&A, especially significant one, distracts management team's attention too much, it might hamper management's innovation commitment, even though they might not intend to do so. From the target firm's perspective, M&A may also decrease its innovation productivity. In their study of inventors' productivity after acquisition, Kapoor and Lim (2007) suggest that acquiring firm might not be able to acquire as much knowledge asset (especially intangible assets) as expected from target firm because of information asymmetry, agency problem, and routine disruption of the participating firms. This is also consistent with the prior literature on post-acquisition integration which generally suggests that if the acquirer does not provide appropriate level of autonomy for newly acquired firm, the innovation outcome will be negatively impacted (Puranam, Singh, and Zollo, 1996). Therefore I propose a competing hypothesis that:

Hypothesis 2 ***(competing)****: Acquisition decreases innovation capability (both quantity and quality) for firms in digital product and service industries.*

Acquisition and Financial Performance

Financial performance has been the most commonly used performance metric in the M&A literature both in finance and strategic management literature. In earlier works by financial economists, stock market reaction to the M&A was a preferred measure performance because of the assumption that capital market is sufficient enough to reflect the quality or at least the perception of the M&A quality and thus is recommended as the best way to capture M&A value, whereas other accounting-based performance measures are criticized having methodological problem such as lack of control group and method of accounting. Some M&A studies examine the M&A participants' stock market abnormal return around the announcement period (Asquith, 1983; Malatesta, 1983; Jarrell and Poulsen, 1989), while others focus on longer term abnormal return over three to five years after M&A (Langetieg, 1978; Asquith, 1983; Jenson and Ruback, 1983; Magenheim and Mueller, 1988; Agrawal, Jaffe, and Mandelker, 1992). Those studies generally suggest that acquirers experience negative abnormal return after M&A, both in short run and over one to three years after it. In this longer term event study, longer term stock return is favored over short term abnormal return because I am more interested in "realized" abnormal return rather than "expected" return. But literature suggest that long term stock performance is subject to methodological issues since many things can happen during this period and any changes in stock abnormal return may not be due to the M&A. Therefore I use one year window pre- and post-event year. One year is not too long to be impacted by confounding factors, but is also long enough for investors to assimilate the information and react accordingly. Also I overcome the problem of endogeneity by including the control sample and using difference-in-difference specification.

As far as investors' reaction to digital firms' acquisitions, the story is also two folded. On one hand, since digital firms rely on product innovation and differentiation to survive and thrive, it is of the shareholders' best interest to look for opportunities for growth and try to bring in changes and enhancement to existing product and technology portfolio. In that sense, investors should positively react to M&A decisions by digital firms. Therefore I hypothesize that:

> ***Hypothesis 3****: Acquisition increases stock abnormal return for firms in digital product and service industries.*

On the other hand, investors may think that M&As are risky decisions for firms because statistics show that most M&As end up not performing as well as expected, and among many reasons, post-acquisition integration is a major cause. Since M&A is big investment, and failure of M&A will not only hamper firm's financial stability, but also influence their strategic planning in the long run. If the company's strategic goal is to beat its competitors by acquiring another firm and integrating its existing product and technology portfolio in a short period of time, failure in M&A integration will impact its competitiveness, then market share and ultimately profitability because firms who rely on acquisition might not have sufficient attention and resources for organic growth and internal investment. Therefore, I have a competing hypothesis that:

> ***Hypothesis 3 (competing)****: Acquisition decreases stock abnormal return for firms in digital product and service industries.*

Heterogeneous Effects of Acquisition

I also explore the heterogeneous effects of M&A across different acquirers and M&A portfolio characteristics for all dependent variables. The first important firm characteristic is the level of internal R&D. As discussed earlier, digital firms can choose to grow organically or grow via acquisition. I argue that acquisitions are favorable over organic growth because of efficiency and easiness, but that does not mean that firms could ignore internal R&D at all. Actually I speculate that firms need to make some initial investment internally and get to know what they really need and then select targets appropriately. Also, even after the acquisition, the acquiring firm still needs to continuously invest in it to fully leverage acquired assets. Thus, I think that R&D investment is crucial for M&As to work, and the level of R&D complements the M&A. Therefore I hypothesize that:

> ***Hypothesis 4****: Acquirer's internal R&D intensity positively moderates the relationship between acquisition and firm performance if any.*

Another firm characteristic that I think will have interaction effect with M&A on firm performance is *Tobin's Q*, which is a measure of market-to-book ratio which captures overvaluation and growth opportunity. In literature, *Tobin's Q* has been studied as a contingency of M&A performance. Lang, Stulz, and Walkling (1989) reported that high *Tobin's Q* bidders gained more than low *Tobin's Q* bidders. Servaes (1991) found that bidders' abnormal returns were also higher when their *Tobin's Q* ratios were higher. Rau and Vermaelen (1998) call firms with high *Q* as "glamour" firms. Therefore I speculate that if firms are valued as "glamour" firms, they have more potential growth opportunity and tend to perform better in mergers and acquisitions in terms of acquiring and integrating new product ideas and technologies. Also, investors tend to trust those "glamour" firms more and value more on their M&A decisions. Therefore, I hypothesize that:

Hypothesis 5*: Acquirer's Tobin's Q positively moderates the relationship between acquisition and firm performance if any.*

I also consider focal firm's industry environment as another moderator. Industry sales concentration captures the competitiveness of the industry. Higher sales concentration means lower competition because the whole industry is dominated by several big players. On the other hand, industry gets competitive when the market is shared by many smaller companies. I argue that industry competitiveness can moderate the relationship between M&A and firm performance. For example, if the industry is very competitive, it is very hard for the focal firm to make progress in product differentiation, even with the help of M&A. While in a less competitive environment where not many firms are competing, it is relatively easier for firms to make M&A work. Therefore, I hypothesize that:

Hypothesis 6*: Acquirer's industry concentration positively moderates the relationship between acquisition and firm performance if any.*

As for the M&A portfolio characteristics, I argue that deal size will positively moderate the effect of M&A on product differentiation. Size of the portfolio can be measured either by the total number of M&As or total transaction value of M&As. Size matters because the bigger target(s) and/or more targets always means that more, and presumably more useful knowledge and resources can be obtained via M&A which more benefits the firm performance in all kinds. Also, larger and/or more deals mean more significance so that management team of acquirer will pay more attention and commitment to those deals to make sure that deals go through well and target firm(s) can be integrated as soon as possible so that they can contribute to acquirer's product portfolio right away. Therefore I hypothesize:

> ***Hypothesis 7****: M&A portfolio size positively moderates the relationship between acquisition and firm performance if any.*

Relatedness has been an important antecedent of M&A success in the previous literature. Montgomery and Singh (1987) conceptualize and find evidence that acquisitions which are related in product/market or technological terms create higher value than unrelated acquisitions. Ahuja and Katila (2001) show that relatedness of acquired and acquiring knowledge bases has a nonlinear impact on innovation output. In more recent work, Makri, Hitt, and Lane, (2010) examine the role of technological and knowledge complementarity in post-M&A performance in terms of innovation and find significant and positive relationships. Relatedness simply means that the acquisitions made by firms are more relevant to their own product portfolio and technology advancement. Therefore they will be positively related their product and innovation performance. Also investors will positively value relatedness of M&A because they think firms will do better and get more of what they need out of related acquisition deals. Therefore I hypothesize:

Hypothesis 8*: Number of related M&As in the portfolio positively moderates the relationship between acquisition and firm performance if any.*

I also suggest that the degree to which the M&A portfolio is international will have interaction effect on firm performance. It can be measured by the number of acquisitions that are targeted on an international firm. Foreign company may bring new perspective, technologies, people and ideas to the focal firms when it comes to product innovation and innovation. Investors may also perceive M&A across the border as a signal of firm's diversification, which is good for digital firm's differentiation. Therefore, I hypothesize:

Hypothesis 9*: Number of international M&As in the portfolio positively moderates the relationship between acquisition and firm performance if any.*

Last but not the least, I examine the moderating effect of target firms' incumbency (i.e. established firm vs. new startups). Literature suggest that acquisitions targeted on firms with different incumbency status tend to perform differently. This phenomenon is especially relevant and important in my context of digital firms. In digital industries, new innovations can quickly create new market and value network that can eventually disrupt existing ones. Therefore, significant numbers of startups are founded every year and many of them get acquired by incumbents after 2-3 years of establishment to assimilate their new innovations or product offerings. Then, from the acquiring firm's perspective, whether to acquire newer startups that presumably have newer technology or product or a more established, older firms or even public firm with more established customers and market coverage, becomes a very important decision to make. In a similar study by Ransbotham and Mitra (2010), researchers analytically model the decision on whether to acquire younger or older targets with the assumptions that younger firms are cheaper to acquire while have more uncertainties for buyer in terms of their value creation, while older, more established targets have proved success but are more expensive to acquire. The focus of that study, though, is on the shareholders' reaction to the announcement of acquisitions targeted on firms with different ages. Their empirical results suggest that acquisition with older target tend to have lower performance measured by stock abnormal return around announcement days. In my study, I extend Ransbotham and Mitra (2010) to examine the effect of age of M&A portfolio on firm performance. Since older firms tend to have less disruptive technology and/or product, they might not be as helpful to the acquirers in terms of product differentiation and innovation capability as younger startups, thus I argue that average target age of M&A portfolio will negatively moderate the effect of M&A on product differentiation and innovation quantity/quality if any. As for stock market abnormal return, the argument is two-folded. On one hand, shareholders may react negatively to acquisitions of older targets because of their lack of disruptive innovation and relatively higher price. On the other hand, as I discussed, older firms are more likely to have proved success and more established customer relationships and network, so shareholders may have position reaction to M&As targeted on older firms. Therefore, I hypothesize:

> ***Hypothesis 10A****: Average age of M&A targets in the portfolio negatively moderates the relationship between acquisition and product differentiation if any.*

Hypothesis 10B*: Average age of M&A targets in the portfolio negatively moderates the relationship between acquisition and patent quantity and quality if any.*

Hypothesis 10C*: Average age of M&A targets in the portfolio positively moderates the relationship between acquisition and stock abnormal return if any.*

Hypothesis 10C (competing)*: Average age of M&A targets in the portfolio negatively moderates the relationship between acquisition and stock abnormal return if any.*

Figure 1 shows my theoretical framework of this study and Figure 2 shows the research model.

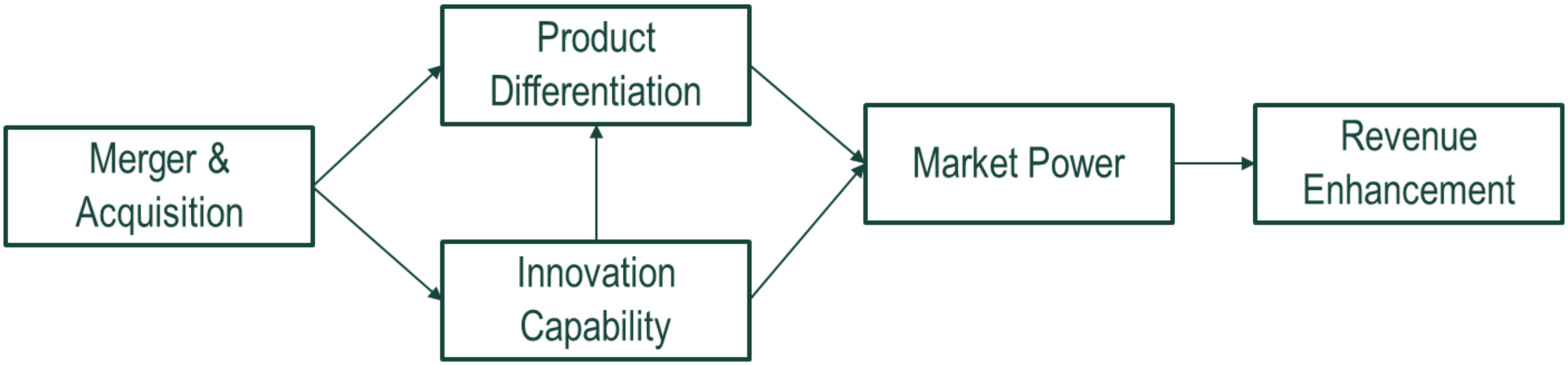

Figure 1: Theoretical Framework

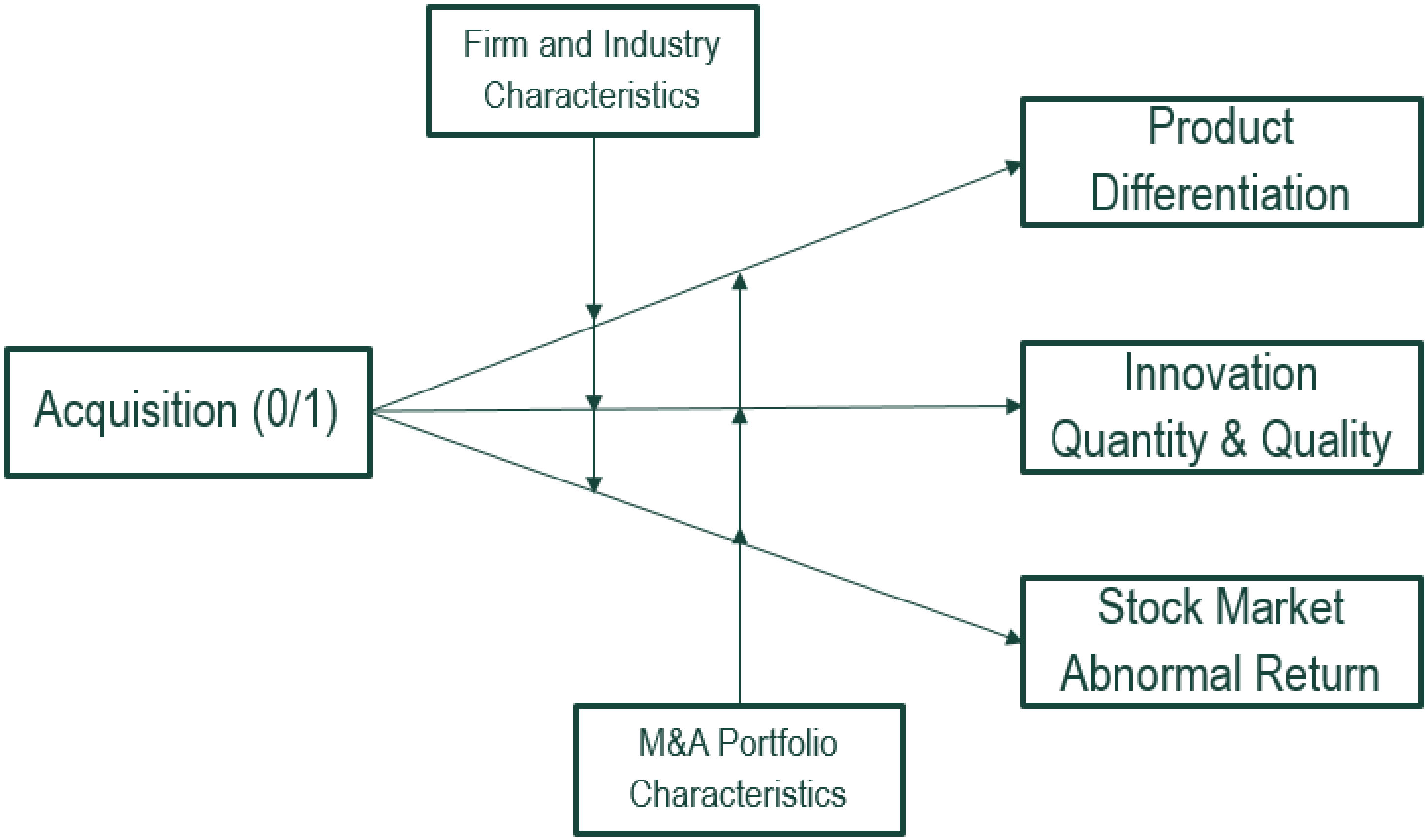

Figure 2: Research Model

METHODOLOGY

Variables Definitions

Empirical data for this study comes from various public and proprietary resources. I obtain M&A records from the *Thomson One* database, and match them with annual firm level financial information derived from *Compustat.* For the first dependent variable, I adopt Hoberg and Philips (2015)'s unique 10-K textual analysis-based measure of firm's product market similarity compared to its competitors (higher value indicates lower product differentiation). The second dependent variable of interest is annual stock abnormal return benchmarked with *S&P* 500 index return using *Fama-French* three-factor (*FF3*) model. Data on stock return and *FF3* model comes from the *Center for Research in Security Prices (CRSP)* and *Fama-French* proprietary data library, respectively. The last outcome variable of innovation capability is measured by patent quantity and quality. Those data are from the library prepared by Kogan et al. (2012) based on original patent application and citation data from the *United States Patent and Trademark Office (USPTO).* This section describes the data collection and sampling process in details.

Mergers and Acquisitions

I obtain M&A data from *Thomson One* database (previously referred as *SDC Platinum U.S. M&A* Database). I start with all M&As with announcement dates between January 1, 1984 and December 31, 2014 since information in that database is less reliable before 1984 (Bena and Li, 2014). As suggested in the finance literature, I use the following criteria for important and significant M&A deals to be included in my sample (Masulis, Wang, and Xie, 2007; Bena and Li, 2014):

1. The value of the transaction is no less than $10 million.
2. The status of the deal is completed.
3. The form of deal is merger, acquisition of majority interest or acquisition of assets[1].
4. The acquirer owns less than 50% of the target's share before the announcement and owns more than 90% after.

I begin with 104,900 M&A deals that match above criteria. Since most of the performance outcomes are only available for public firms, I restrict acquirers to be only U.S. publicly traded firms whose financial and product market information can be obtained. Then I match them with financial data from *Compustat* using common firm identifiers. After merging with *Compustat*, there are 29,800 deals initiated and completed by 8,556 unique public U.S. firms left in my M&A sample. Among those deals, I only included those M&As that are initiated by firms in the digital product and service industry[2]. Those firms are mostly technology- and innovation-intensive, thus product differentiation and technological innovation are among the most important performance indicators, as well as their most important objectives of merger and acquisition. Also, emphasizing on one big industry comprising several small sectors help us alleviate the possible bias in result interpretation due to industry heterogeneity. My final M&A sample in the digital industry has 8,133 deals initiated by 2,232 unique firms. Table 2 depicts summary statistics of the M&A deals completed by U.S. public digital firms during 1993 – 2013. There was a monotonically increasing trend in number of completed significant M&As from

[1] All M&A deals in my sample are acquisition deals (i.e. the target firm is purchased by the acquirer and operates as a subsidiary or part of the acquiring firm afterwards).
[2] Digital product and service industry is consisted of firms in Computer & Office Equipment: (SIC: 3570, 3571, 3572, 3576, 3577, 3578, 3579), Telecommunications & Semiconductors: (SIC: 3661, 3663, 3674), Instruments & Equipment: (SIC: 3812, 3822, 3825, 3826, 3827, 3842, 3845, 3861), Telephone, Telegraph & Television Equipment and Services: (SIC: 4812, 4813, 4822, 4832, 4833, 4841, 4899), and Computer Programming, Data Processing: (SIC: 7370, 7371, 7372, 7373, 7374) following the definition by Kim, Gopal, and Hoberg (2015).

1993 to 2000 and it reached a historically high number of 787 as shown in Figure 3. Similarly, total transaction value in 2000 is more than $440 billion as shown in Figure 4. The number and value of transactions significantly dropped in 2001 and suffers continuous decline after that. This trend is consistent with the dot-com bubble covering pre-2000 years followed by a collapse of bubble from 2000 to 2001 when some IT and dot-com firms completely failed and many others lost a large portion of their market value.

Lastly I collect financial data on all firms in my defined digital industry from *Compustat* over the period of 1992 to 2014. The final unbalanced panel data with 34,364 observations consists of 3,369 firms' financial data along with aggregated M&A information derived from my M&A sample.

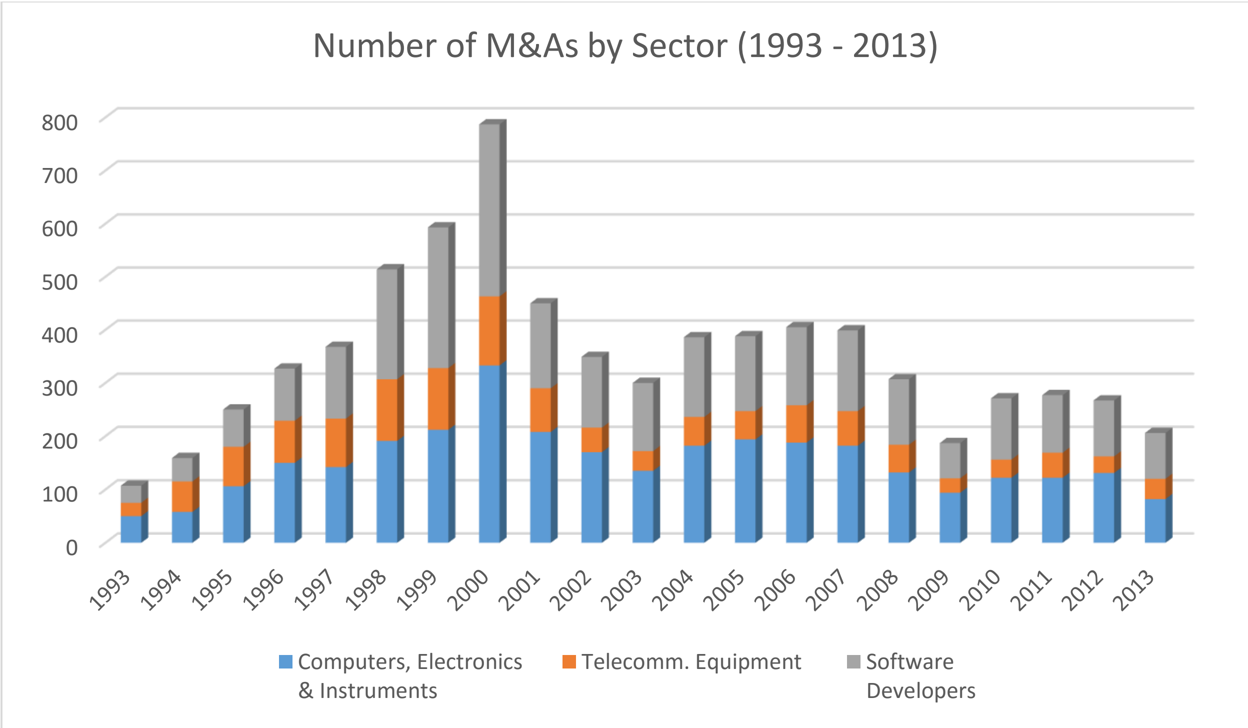

Figure 3: Number of M&As by Sector (1993 – 2013)

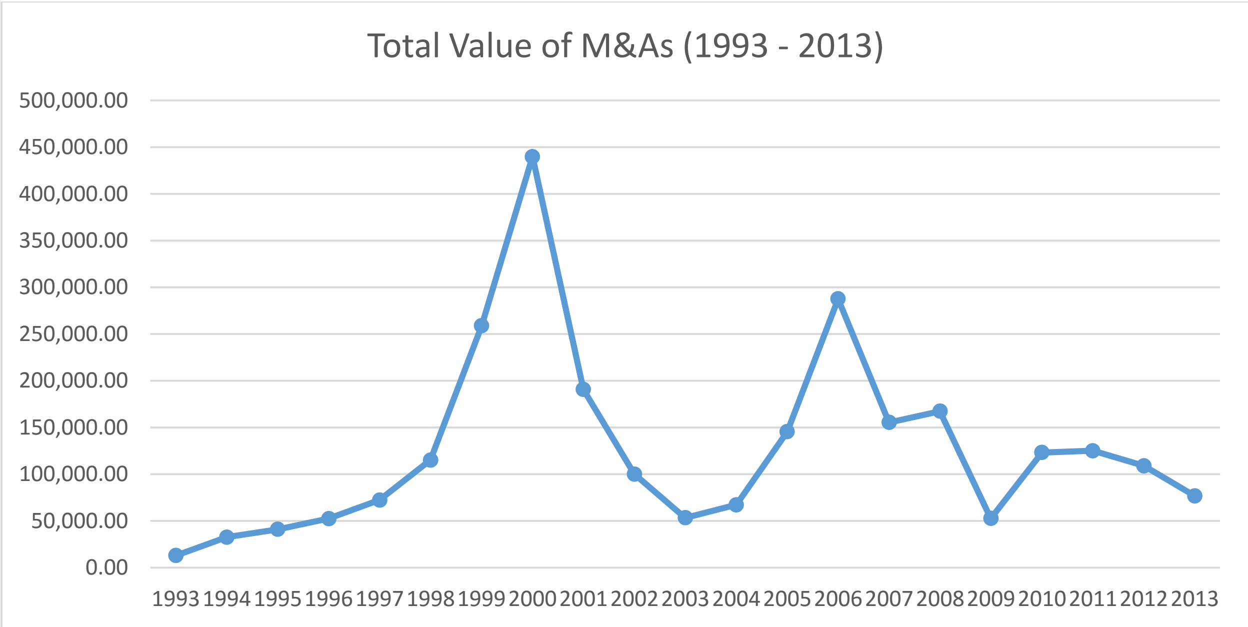

Figure 4: Total M&A Values (1993 – 2013)

Table 2. Descriptive Statistics of M&A Deals Completed by U.S. Public Digital Firms

Year	Number of M&A				Deal Value ($Million)		
	All	Computers, Electronics & Instruments	Telecomm. Equipment	Software Developers	Sum	Mean	Median
1993	107	50	25	32	12,918.81	120.74	33.00
1994	159	58	57	44	32,607.11	205.08	36.00
1995	250	106	74	70	40,923.85	163.70	40.04
1996	327	150	79	98	52,450.17	160.40	35.76
1997	368	142	91	135	72,336.66	196.57	38.03
1998	514	191	116	207	115,067.43	223.87	40.94
1999	593	212	116	265	258,756.78	436.35	55.94
2000	787	333	130	324	439,750.51	558.77	85.00
2001	450	208	82	160	190,668.76	423.71	56.60
2002	349	170	46	133	100,014.37	286.57	48.00
2003	300	135	37	128	53,311.74	177.71	40.99
2004	386	182	54	150	67,145.69	173.95	50.00
2005	388	194	53	141	145,523.57	375.06	50.00
2006	405	188	70	147	287,607.90	710.14	57.69
2007	399	182	65	152	155,445.94	389.59	60.00
2008	307	132	52	123	167,292.67	544.93	62.00
2009	187	94	27	66	52,698.58	281.81	42.31
2010	271	122	34	115	123,119.98	454.32	80.00
2011	277	122	47	108	125,028.78	451.37	71.34
2012	267	131	31	105	108,986.26	408.19	76.79
2013	206	82	38	86	76,753.05	372.59	119.17
Total	**7,297**	**3,184**	**1,324**	**2,789**	**2,678,408.60**	**367.06**	**53.20**

Note 1: All M&As are completed, significant deals whose values are at least $10 million.
Note 2: All acquirers are U.S. public firms and targets are either public or private firms.

Independent Variable

I examine the treatment effect of M&A on longer term firm performance, as opposed to short term effect. Therefore the unit of analysis in this study is firm-year, when M&A records are aggregated and the effect is evaluated at the year level. As for the treatment, I create a dummy variable *Treatment* to indicate if a firm has completed an acquisition whose value exceeds 10% of its average market capitalization of current year or previous year. Market capitalization at a given year is calculated by multiplying the stock’s close price at the end of the fiscal year by the number of common shares of outstanding. The reason why I have a threshold of 10% is because too small deals might not have significant impact on firm’s resource deployment, thus has little or no effect on product differentiation. This criteria is also similar to that of Yim (2013) when the researcher studies the effect of M&A on CEO compensation.

Dependent Variable

Product Differentiation

To measure the degree of product differentiation, I adopt a measure of firm-level product uniqueness developed by Hoberg and Phillips (2015, HP hereafter) based on textual analysis of 10-K product description. HP use text parsing algorithms that process the text in the business descriptions of 10-K annual filings on the SEC in which firms by law are required to describe the significant products they offer to the market accurately. For each product description section they parse for each firm year, a vector of product key words (after removing the common words and stop words in the description) is constructed, which is analogous to patent technology-based space of Jeffe (1986). Then they, for a given year, calculate firm-by-firm pairwise similarity scores by calculating the cosine similarity score of the two vectors representing the product space of the two firms in that year. For any two firms *i* and *j*, there is a product similarity score, which is a real number in the interval [0,1] describing how similar the words used by firms *i* and *j* are. After calculating the product market similarity score for every possible pair of firms, HP construct a *Text-based Network Industry classification (TNIC)* based on those pairwise similarity scores. *TNIC* records firms having pairwise similarities with a given firm *i* that are above a threshold as required based on the coarseness of the three digit SIC classification data. Finally, for each *TNIC* industry, HP calculate a *Total Product Similarity* (*TPS*) score which is the sum of the pairwise similarities between the given firm and all other firms in its *TNIC* industry. A higher *TPS* indicates that the focal firm has more product overlap with its competitors, thus lower product uniqueness. The *TPS* is available for U.S. publicly traded firms from 1996 – 2013 and being updated every year. HP published data for public use on their website for download, data is merged with my main dataset using *gvkey* and *year*. My sample period for this dependent variable is 1997 to 2012 because of data availability. Since *TPS* measures how focal firm's product offering is similar to its competitors, I need to reverse code it to be able to measure product differentiation. I use TPS_{it} to denote the degree of product similarity for firm *i* at year *t*.

Innovation Capability

I use patent-based metrics for proxies of firms' innovation capability. Paten t-based measures are commonly used to measure innovation in the literature of economics, finance and information systems. Most of previous studies rely on the *National Bureau of Economic Research (NBER)* patent database that is constructed by Hall, Jeffe, and Trajtenberg (2001, HJT hereafter) who collect patent grant and citation data from the *USPTO* and make them for public use. In M&A literature, Zhao (2009), Bena and Li (2014) and Seru (2014) are the most recent papers that use *NBER* patent data for innovation variable. However, since *NBER* patent database does not get update very frequently, it only covers patent and citations data up to 2006. More recently, Kogan et al. (2012) collect additional data and extend the data coverage to 2010. They also clean up ambiguous and misspelled naming conventions of patent assignees and match them with firms in *CRSP* using *permno*. I adopt their database for innovation quantity and innovation quality, measured by patent counts and citation received, respectively. Patent count measure is based on application year (i.e. the number of successfully applied patents represent the innovation capacity of that year). Similarly, number of citations a firm received on its patents that were filed in a year also indicate its innovation quality in that year. Patent and citation data are subject to truncation bias, i.e. only patents granted and citations received will be reported in the database. Also, patent application takes time (on average 2 years), thus at the time of data collection, there are still pending patents that will be granted later. Because of that truncation, there is declining number of patents toward the end of the sample period (Zhao, 2009). HJT (2001) and Seru (2014) also suggests that both patenting and citation intensities vary across industries, thus I adjust them by dividing the number of patents (citations per patent) for each firm by the mean of number of patents (citations per patent) in the same cohort to which the patent belongs to (Seru, 2014). Specifically, I scale the count of successfully granted patent in technology class k filed by firm i at year t by the mean number of patents of all firms granted at t in class k, and sum up them across all different technology classes. Similarly, citation per patent applied by firm i in year t is divided by the total number of citations received by all patents in the same year in the same technology class. Technology class information is obtained from *Google Patents*. After those normalization processes, for each firm i at year t, I have the adjusted patent number denoted as $PatNumAdj_{it}$ and adjusted number of citations denoted as $CitesAdj_{it}$ to measure innovation quantity and innovation quality, respectively.

Financial Performance

There has been debate over which measure is a better one for firm performance in previous M&A studies in the literature of strategic management. Some M&A research focus on accounting based metrics such as return on asset, however based on Ravenscraft and Scherer (1987), and King, Slotegraaf, and Kesner (2008), they can be biased by the method of accounting for an M&A. Another common measure of M&A performance is short-window stock market performance (usually several days around the announcement). I choose not to use that measure as well because short-term stock return, compared with longer-term return, represents more of "expected return" than the actual "realized return". Previous studies utilizing it examined M&A in a slightly different context from ours. As discussed earlier, this study examines the longer term effect of M&A on firms over the years, therefore I rely on long term abnormal return to evaluate the effect of M&A on acquirers' financial performance. Following King, Slotegraaf, and Kesner (2008), I use *Jenson's Alpha* to measure the annual stock abnormal return. Developed by Jenson (1968), *Alpha* compares a focal firm's average abnormal return with its benchmarked investment, such as *S&P* 500 index in my case. For each of the 12 months of the year after the M&A effective year, I collect stock return and *S&P* 500 index return data from *CRSP*. In a traditional two-parameter market model such as:

$$R_{it} = \alpha_i + \beta_i (R_{mt}) + \varepsilon_{it}$$

where R_{it} is the monthly rate of return of firm i during month t, R_{mt} is the monthly rate of return of the benchmark investment portfolio, α_i is *Jenson's Alpha*. Fama and French (1993) suggest that in additional benchmark portfolio, return difference between small and big portfolio (SMB, Small Minus Big) and that between high- and low-value portfolio (HML, High Minus Low) should also be included in the market model to more accurately predict the relationship between individual stock return and market return. I adopt Fama-French three factor to calculate my *Jenson's Alpha*. For every firm-year, I run the following regression and get the intercept as the measure of alpha:

$$R_{it} - R_f = \alpha_i + \beta_i (R_{mt} - R_f) + b_s\, SMB + b_v\, HML + \varepsilon_{it}$$

Where R_f is risk-free return. The predicted α_i captures the focal firm's annual abnormal return after comparing benchmark (*S&P* 500 index) as well as SMB and HML. I use $Alpha_{it}$ to denote the abnormal stock return of firm *i* at year *t*.

Moderating Variable

In order to examine heterogeneous effects of the M&A treatment on firm performance, I collect data on acquirer's characteristics at the event year and aggregate information of its M&A portfolio if there was a significant deal completed in that year. Acquirer's firm and industry characteristics include *R&D Intensity*, *Industry Concentration*, and *Tobin's Q*. As for M&A portfolio characteristics, I follow the literature and measure: (1) *# of M&A*; (2) *Total M&A Value* to measure the total deal size; (3) *# of Related M&A* to measure the number of the related M&A (i.e. acquirer and target are in the same 2-digit SIC industry) the focal firm has completed to measure overall similarity between the focal firm and those it acquired in a given year; (4) *# of International M&A* is the number of M&A transactions whose targets base in a different country as the focal firm; (5) *Average Target Age* is the average age of target firm in the portfolio. Age is calculated by subtract founding year from the year when the acquisition was effective. I manually collect all founding year information from public resources such as *Bloomberg BusinessWeek*, *LinkedIn*, and news report or press releases from acquiring firms.

Those moderating variables summarize the firm's characteristics and annual M&A portfolio, and are expected to provide more insights in addition to the treatment effect of making significant M&A. They will be used to create interaction terms with treatment variable and the coefficient can be interpreted as the contingency of the treatment effect of M&A on firm performances.

Table 3 summarizes the variable definitions and operationalizations.

Table 3. Variable Definitions

Variable	Operationalization
Dependent Variables	
Product Differentiation	*Hoberg and Phillips (2015)*'s measure of the degree to which the focal firm's product market is similar to its competitors' based on textual analysis of 10-K product description (lower value means more differentiation)
Stock Abnormal Return	Annual Jenson's Alpha of the regressions of focal firms' monthly return on *Fama-French* three-factor models using *S&P 500* index benchmark
Innovation Quantity	Number of filed patents that are eventually granted by the *United States Patent and Trademark Office (UPSTO)* adjusted for truncation bias
Innovation Quality	Number of citations received on patents filed that are eventually granted by *USPTO* adjusted for truncation bias
Independent & Interaction Variables	
Acquisition (Treatment)	Dummy variable of 1 if the focal firm completed an acquisition whose value exceeds 10% of its average ending *market capitalization (MC)* at *t-1* and *t*, and 0 otherwise. *MC* is calculated as *Price close at the end of fiscal year (PRCC_F) * common shares of outstanding (CSHO)*
Acquirer's R&D Intensity	Focal firm's *research and development expenditure (XRD)* scaled by *total assets (AT)*
Tobin's Q	Sum of *market value of book asset (AT)* and the *market value of common equity (CSHO*PRCC)*, minus the sum of *common equity (CEQ)* and *deferred taxes (TXDB)*, all divided by *AT* in *t-1*
Industry Concentration	*Herfindahl-Hirschman* index of sales concentration in *Text-based Network Industry Classification (TNIC)*-based industry developed by *Hoberg and Phillips (2015)*
# of M&A	Number of M&As completed by the focal firm
Total M&A Value	Total transaction values of all M&As completed by the focal firm
# of Related M&A	Number of M&A transactions whose targets are in the same two-digit SIC industry as the focal firm
# of International M&A	Number of M&A transactions whose targets base in a different country as the focal firm
Average Target Age	Average age of target firms (from founding year to acquisition year)
Matching Variables	
Year *t*	Year when the treatment variable is coded at *t*
Industry	Three-digit SIC codes of 357 (Computers), 366, 367 (Electronics), 381, 382, 384, 386 (Instruments), 481, 482, 483, 484, 489 (Telecommunications Equipment) and 737 (Software)
Firm Size *t-1*	Natural logarithm of focal firm's *total assets (AT)* in *t-1*
Tobin's Q *t-1*	(See above)

Table 3 (cont'd)

ROA *t-1*	Focal firm's *earnings before interest, taxes, depreciation, and amortization (EBITDA)* scaled by *total assets (AT)* at *t-1*
Cash *t-1*	Focal firm's *cash and short-term investment (CHE)* scaled by *total assets (AT)* at *t-1*
Leverage *t-1*	Focal firm's *total debt (DT)* scaled by *total assets (AT)* at *t-1*
Prior M&A *t-3* ~ *t-1*	Number of M&As completed in the past three years by the focal firm from *t-3* ~ *t-1*

Treatment and Control Group

This study is trying to uncover the causal relationship between digital firms' merger and acquisition behavior and firm performance. Randomized experiment is key to causal inference, however, randomization is not possible in a social science study like this. Acquirers do not randomly choose to acquire or not, thus any change between pre-merger and post-merger can be confounded by other factors that might influence firms' M&A decision in the first place and/or other unobserved heterogeneity of the firm., i.e. the change of performance may not be due to the treatment itself. Therefore it is important to select a comparable control group of firm years for each firm year in the treatment group to make it proximate to a natural experiment. In order to choose comparable group close to the counterfactuals (Hartford, 2005), I need to match on firms' characteristics that might influence their M&A decision (Li, 2013). In other words, I want to compare the performances of merging firm with those of non-merging firms, which have similar likelihood of merging. In recent M&A studies, researchers use various natural experiment designs. For example, Seru (2014) and Bena and Li (2014) use withdrawn M&A deals as control group to match with completed transactions. Li (2013), on the other hand, manually match control samples based on year, industry, size and pre-event total factor productivity. In my context, Li (2013)'s method is more appropriate, thus I adopt it and add additional pre-event firm level characteristics to match on. The reason I reply on multiple characteristics to match control sample is because I know that, from the literature, M&A is a complex decision and may not be motivated by only one or two factors. Since I am matching based on different factors, propensity score matching is a better approach.

Propensity Score Matching

Rosenbaum and Rubin (1985) propose a method of matched sampling called propensity score matching. It is a method for selecting units from a large reservoir of potential controls to produce a control group of modest size that is similar to a treated group with respect to the distribution of observed covariate. The key idea of propensity score matching is that I can create a single score based on multiple covariates and match control samples on that score. Next, I look at the M&A literature and find out the firm characteristics that might influence its M&A decision. Previous studies suggest that larger firms (Li, 2013) and firms with higher *Tobin's Q* more likely to engage in M&A (Bena and Li, 2014). *Tobin's Q* (also referred as market-to-book ratio) is included as a matching character because previous literature suggest that it captures growth opportunity (Andrade, Mitchell, and Stafford, 2001), overvaluation (Shleifer and Vishny, 2003) and asset complementarity (Rhodes-Kropf and Robinson, 2008), which are important drivers of M&As. In addition to that, I also consider return on asset (ROA), cash flow and leverage as important factors to consider when making M&A decision. Last but not the least, I find that some firms are serial acquirers, i.e. firms with previous merger experience are likely to engage in more M&As. Therefore previous M&A experience is also one of the matching variables in my model. *Prior M&A* is defined as the total number of M&As a firm has completed in the past three years. I start with my whole sample firm years of 34,364 observations to estimate the propensity score of having a significant M&A completed. As mentioned earlier, the unit of analysis of this study is firm year, i.e. two observations of the same firm at different years are treated as different observations. Among all firm year observations, there are 1,669 firm years when there was a significant M&A completed (i.e. *Treatment* = 1). Before using propensity score to match control sample, I examine the descriptive statistics of those pre-treatment firm characteristics. As shown in Table 4A, I conduct mean and median different tests for those variables across treatment and unmatched "control" groups. Significant difference in mean and/or median indicates that pre-treatment characteristics are not balanced between those two groups. If I use the whole population to infer causal relationship, and the result could be biased because the effect may be due to those factors instead of treatment itself. As seen in Table 4A, mean of *Size*, *ROA*, and *Prior M&A* of treatment group is significantly higher than that of non-merging group. Median difference test shows that *Tobin's Q* and *Leverage* are also greater in treatment group. I also test the pre-event dependent variable and find that *Total Similarity* at *t-1* is also higher in treatment. Table 5A shows the regression results of various models to find relationship between firm characteristics and M&A incidence. I first run a standard *Logit* model to regress *Treatment* on those firm characteristics, and store the predicted value as the propensity score of *Treatment*. Column (1) shows the results with pooled *Logit* model with the dependent variable of whether or not there was a significant M&A completed. All firm characteristics are found to be positively correlated with *Treatment* except *Leverage*. It suggests that my hypothesis is confirmed: larger, more profitable, firms with more cash, firms with higher *Tobin's Q*, and firms with more previous M&A experience are more likely to complete a significant M&A. As shown in Column (2), I also run a *Logit* model with firm random effect and results hold. Column (3) – (6) show the results of models with different dependent variables and they are consistent with Model (1) and (2).

Table 4A. Descriptive Statistics of Pre-Treatment Firm Characteristics Before Matching

	Significant M&A = 1				Significant M&A = 0				Difference	
	N	Mean	Std. Dev.	Median	N	Mean	Std. Dev.	Median	Mean	Median
Firm Size $_{t-1}$	1,633	5.518	1.751	5.369	24,793	4.638	2.172	4.327	0.88***	1.042***
Tobin's Q $_{t-1}$	1,460	3.082	6.329	1.841	20,820	2.903	8.19	1.748	0.179	0.093***
ROA $_{t-1}$	1,621	0.042	0.3	0.096	24,632	-0.086	1.41	0.07	0.128***	0.026***
Cash $_{t-1}$	1,633	0.296	0.244	0.243	24,782	0.293	0.242	0.239	0.003	0.004
Leverage $_{t-1}$	1,626	0.173	0.253	0.054	24,683	0.18	0.489	0.051	-0.007	0.003**
Prior M&A	1,669	0.92	1.65	0	30,351	0.253	0.793	0	0.667***	0***
PMS $_{t-1}$	1,178	3.956	3.402	2.808	14,162	3.656	3.315	2.431	0.3***	0.377***
SAR $_{t-1}$	1,446	0.883	8.311	1.146	19,385	1.153	6.369	1.112	-0.27	0.034
IQ $_{t-1}$	1,639	1.573	11.112	0	27,055	1.812	16.473	0	-0.239	0***

Note 1: Mean and median difference tests are conducted. Significant difference of mean and/or median indicates that pre-treatment characteristics are not balanced between treatment and "control" groups.

*Note 2: *, **, *** indicates the significance level of 10%, 5%, and 1%, respectively.*

Table 4B. Descriptive Statistics of Pre-Treatment Firm Characteristics After Matching

Panel A: Matched on propensity score of firm characteristics and product market similarity score at t-1

	Treatment				Control				Difference	
	N	Mean	Std. Dev.	Median	N	Mean	Std. Dev.	Median	Mean	Median
Firm Size $_{t-1}$	557	5.261	1.505	5.072	1,045	4.99	1.634	4.764	0.271***	0.308***
Tobin's Q $_{t-1}$	557	3.021	4.437	1.959	1,045	2.931	4.086	1.891	0.09	0.068
ROA $_{t-1}$	557	0.055	0.166	0.09	1,045	0.044	0.201	0.082	0.011	0.008
Cash $_{t-1}$	557	0.341	0.247	0.309	1,045	0.361	0.246	0.335	-0.02	-0.026
Leverage $_{t-1}$	557	0.121	0.218	0.018	1,045	0.1	0.17	0.01	0.021**	0.008
Prior M&A $_{t-3 \sim t-1}$	557	0.438	0.788	0	1,045	0.262	0.603	0	0.176***	0***
Product Market Similarity $_{t-1}$	557	3.853	3.064	2.793	1,045	3.786	3.039	2.703	0.067	0.09

Panel B: Matched on propensity score of firm characteristics and stock abnormal return at t-1

	Treatment				Control				Difference	
	N	Mean	Std. Dev.	Median	N	Mean	Std. Dev.	Median	Mean	Median
Firm Size $_{t-1}$	767	5.332	1.608	5.108	1,685	5.2	1.8	4.951	0.132*	0.157*
Tobin's Q $_{t-1}$	767	2.958	5.403	1.899	1,685	2.848	4.34	1.874	0.11	0.025
ROA $_{t-1}$	767	0.072	0.162	0.1	1,685	0.07	0.194	0.103	0.002	-0.003
Cash $_{t-1}$	767	0.322	0.246	0.28	1,685	0.339	0.243	0.306	-0.017	-0.026
Leverage $_{t-1}$	767	0.123	0.205	0.02	1,685	0.117	0.184	0.02	0.006	0
Prior M&A $_{t-3 \sim t-1}$	767	0.468	0.919	0	1,685	0.187	0.519	0	0.281***	0***
Stock Abnormal Return $_{t-1}$	767	0.932	5.396	1.04	1,685	0.844	4.706	1.037	0.088	0.003

Table 4B (cont'd)

Panel C: Matched on propensity score of firm characteristics and innovation quantity at t-1

	Treatment				Control				Difference	
	N	Mean	Std. Dev.	Median	N	Mean	Std. Dev.	Median	Mean	Median
Firm Size $_{t-1}$	669	5.131	1.589	4.911	1,333	4.842	1.828	4.602	0.289***	0.309***
Tobin's Q $_{t-1}$	669	3.7	7.251	2.066	1,333	2.94	3.7	1.906	0.76***	0.16**
ROA $_{t-1}$	669	0.046	0.309	0.098	1,333	0.057	0.207	0.091	-0.011	0.007
Cash $_{t-1}$	669	0.327	0.255	0.281	1,333	0.346	0.258	0.318	-0.019	-0.037
Leverage $_{t-1}$	669	0.129	0.212	0.025	1,333	0.129	0.206	0.021	0	0.004
Prior M&A $_{t-3 \sim t-1}$	669	0.5	0.922	0	1,333	0.244	0.648	0	0.256***	0***
Innovation Quantity $_{t-1}$	669	0.638	2.242	0	1,333	0.394	1.64	0	0.244***	0***

Table 5A. Regressions of M&A Incidence on Pre-Treatment Characteristics Before Matching

	Significant M&A (0/1)		Count of M&A (#)		ln (Total M&A Value)	
	Pooled Logit	Logit RE	Pooled Neg. Bin.	Neg. Bin. RE	Pooled OLS	OLS RE
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Size $_{t-1}$	0.129***	0.169***	0.309***	0.409***	0.203***	0.215***
	(0.017)	(0.022)	(0.011)	(0.016)	(0.006)	(0.007)
Tobin's Q $_{t-1}$	0.004**	0.008**	0.032***	0.016***	0.012***	0.012***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)
ROA $_{t-1}$	0.559***	0.597***	0.703***	0.796***	0.022**	0.021*
	(0.116)	(0.133)	(0.082)	(0.109)	(0.011)	(0.016)
Cash $_{t-1}$	0.632***	0.83***	0.78***	0.897***	0.307***	0.369***
	(0.132)	(0.152)	(0.09)	(0.101)	(0.045)	(0.05)
Leverage $_{t-1}$	0.024	-0.11	-0.099	-0.629***	-0.047*	-0.065**
	(0.106)	(0.151)	(0.088)	(0.121)	(0.028)	(0.028)
Prior M&A $_{t-3 \sim t-1}$	0.303***	0.222***	0.243***	0.019***	0.34***	0.244***
	(0.021)	(0.025)	(0.011)	(0.006)	(0.008)	(0.009)
Observations	22,107	22,107	24,081	24,081	24,081	24,081
Number of Groups	-	3,020	-	3,057	-	3,057
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
$\chi 2$	641.56***	437.36***	3243.35***	1279.24***		3042.05***
F					142.42***	
R^2	0.06		0.13		0.18	0.18

*Note 1: *, **, *** indicates the significance level of 10%, 5%, and 1%, respectively.*

Table 5B. Regressions of M&A Incidence on Pre-Treatment Characteristics After Matching

	Significant M&A (0/1)					
	Matched on TPS		Matched on Alpha		Matched on Patent	
	Pooled Logit (1)	Logit RE (2)	Pooled Logit (3)	Logit RE (4)	Pooled Logit (5)	Logit RE (6)
Firm Size t-1	0.053	0.076	-0.02	-0.01	0.091***	0.123***
	(0.042)	(0.053)	(0.034)	(0.042)	(0.035)	(0.044)
Tobin's Q t-1	0.01	0.009	0.005	0.006	0.031***	0.035***
	(0.014)	(0.016)	(0.01)	(0.012)	(0.011)	(0.013)
ROA t-1	0.156	0.209	0.018	0.145	-0.402	-0.443
	(0.319)	(0.389)	(0.274)	(0.332)	(0.252)	(0.291)
Cash t-1	0.072	0.126	-0.094	-0.001	-0.368	-0.412
	(0.263)	(0.32)	(0.226)	(0.271)	(0.232)	(0.275)
Leverage t-1	0.314	0.268	-0.081	-0.206	-0.302	-0.364
	(0.346)	(0.422)	(0.286)	(0.345)	(0.284)	(0.335)
Prior M&A t-3 ~ t-1	0.355***	0.301***	0.636***	0.624***	0.406***	0.396***
	(0.085)	(0.101)	(0.076)	(0.087)	(0.069)	(0.08)
Observations	1,602	1,602	2,452	2,452	2,002	2,002
Number of Groups	-	994	-	1,428	-	1,306
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
$\chi 2$	39.730	26.320	96.07***	64.31***	81.49***	60.86***
R^2	0.02		0.03		0.03	

Note 2: TPS is the Total Product Similarity score, Alpha is the stock abnormal return, and Patent is innovation quantity

Control Group

Next step is to form a control group of firm years that have similar pre-event characteristics as those who had significant deals completed. I follow Li (2013) and adopt a semi-automatic approach to match control samples. Since I have three dependent variables of interest, I match three different control samples for them. Following Li (2013), I first sort my data by year, 3-digit SIC code because literature suggests that M&As occur in waves and cluster in industries (Andrade, Mitchell, and Stafford, 2001), thus for each treatment firm year I need to find control samples within the same industry and in the same year. Then I create four equal-size quartile groups within each industry-year group based on the predicted propensity score, which ranges from 0 to 0.999 with a mean of 0.072 covering 24,081 firm year observations. The last variable I match control samples on is the pre-merger dependent variable of interest in each model, therefore I use TPS_{it-1}, $Alpha_{it-1}$, and $PatNumAdj_{it-1}$ to match control sample for my models of product differentiation, abnormal return, and innovation quantity, respectively. I nested sort the panel data by year, 3-digit SIC code, propensity score quartile group and one of the lagged dependent variables. For every treatment firm year with a significant M&A completed, I include up to two of its neighboring firm years immediately before and after the focal observation, if they meet the following requirements:

1. There was not any M&A completed in that firm year.
2. It is in the same industry-year group as the treatment firm year.
3. It is in the same propensity score quartile group as the treatment firm year and its propensity score is no greater than 25% different from that of the treatment firm year.
4. Its one-year lagged dependent variable is not missing and is no greater than 25% different from that of the treatment firm year.

5. Its one-year leading dependent variable is not missing.

By doing this, I can match up to four non-merging counterparts for each treated firm year observation as controls, and they are in the same industry and year as the treatment and are similar in terms of the likelihood of completing a significant M&A and previous performance. Non-missing requirement for lagged and leading dependent variable assures that I at least have data for observation one year before and one year after the event year because of my panel design. Also, in order to make sure that any performance change before and after the event year is due to the treatment itself, I require that there is no significant M&A completed in pre- and post-event years along the panel. Therefore I have a problem when there are firms who made significant deals in consecutive years. For example, *Firm A* – 2005 is selected as a treatment firm year and I need to build a panel of at least from 2004 – 2006 (preferably 2002 – 2008) for that firm year to observe the performance change. However, the fact that there was also a significant M&A completed in 2004 may confound the impact of the treatment in 2005, if any. Thus I cannot included 2004 in the panel, so I have to abandon that treatment firm year, as well as *Firm A* – 2004. In this case, I abandon both firm years and their corresponding matched control firm years. Another possible conflict is that a selected control firm year neighbors with this firm's another treatment firm year. For example, *Firm B* – 2000 serves as a treatment firm year, while *Firm B* – 2001 is selected as a control firm year for other treatment firm year. In this case, I prioritize the treatment firm year by abandoning the control firm year, and it does not confound the treatment firm year because there was no M&A completed in 2001 so it still can be included in the panel.

I test the balance of pre-treatment characteristics again to make sure that my match procedure works. Table 4B shows the mean and median different test results. Panel A of Table

4B shows the results of treatment/control group for my dependent variable of product differentiation. All characteristics except *Size* and *Prior M&A* are equal in mean/median across groups. This result suggests that my matching strategy balances most of the covariates, but the difference in size and prior M&A experience is too much to be eliminated. Similarly, Panel B and Panel C present the results of mean/median tests for my model of abnormal return and innovation quantity, respectively. Prior M&A seems to be unbalanced across all models, and innovation quantity at *t-1* for my third model seems to be unbalanced. I also run three Logit models for *Treatment* on pre-treatment covariates for different dependent variables. Table 5B shows the results of *Logit* models and the lack of significant relationship between covariates and *Treatment* confirms that my matching procedure helps balance most of the pre-treatment characteristics that may be confounding my causal inference of treatment variable. For all unbalanced covariates, I will include them in the regression models as controls. As soon as control samples are selected for each treatment firm year, I first check if every treatment firm year has a corresponding control firm years. My design requires at least one but up to four control firms for each treatment. For the product differentiation model, each treatment firm year has 1.88 control firm years on average, and average number of control firm years for abnormal return model and innovation capability model is 2.19 and 1.69, respectively.

Difference-in-Differences

My research design is called difference-in-differences (DID), meaning that I am comparing the dependent variable not only across the treatment/control group, but also over time. For example, *Firm A* completed significant M&A in 2005, I look at its dependent variable score over 2002 to 2008 (if available) and compare them with observations of other control firm years (e.g. *Firm B*) for the same or shorter period of time (at least 2004 to 2006). One of the advantages of this approach is that it teases out outcome variable's time series trend out of the treatment effect, if any. Also by observing multiple years before and after the event year, it provides more robust result. The third advantage of my research design is that it allows me to perform analysis of heterogeneous effects of treatment by including interaction terms in the model. In order to perform DID analysis, I need to build panel dataset for each treatment and control observation. For each of them, I included the observations in the range of [T-3, T+3] when T is the event year. I exclude observations along the panel when there was a significant M&A completed to avoid confounding impact. Therefore for some of my focal observations, they may only have observation of dependent variable for [T-1, T+1], or [T-1, T+2], or [T-2, T+1], [T-2, T+2] and so on. I build a panel of up to 6-year observations for model of product differentiation and innovation capability, however for abnormal return, I only build 2-year panel [T-1, T+1] because stock price can be confounded by so many factors, therefore I only observe the difference in stock return for one year before and one year after the event year.

Descriptive Statistics

I first winsorize all variables at the 99% level to avoid the estimation bias due to extreme values in those variables (Tukey, 1962). Table 6A reports summary statistics of the treatment and moderating variables for model of product differentiation. The mean of treatment is 0.348 meaning that 34.8% of my cross-sectional samples are treatment firm years. It is worth noting that the max value of *# of M&A* is 5 for this model. In reality, some firms may have acquired up to 21 firms a year (e.g. *Cisco*). Those firm years are excluded from my sample because my matching procedure cannot find corresponding control firm years based on their characteristics.

Table 6B presents the descriptive statistics of the dependent variable of *TPS* over the length of panel. By looking at the trend of mean and median over time, I can see there has been a decline in both control and treatment group. My DID model tries to tease out this trend and find out the impact only due to the treatment itself. Table 7A-8B are summary statistics of the same set of variables for my other two models of abnormal return and innovation capability. The mean and median of each variable stays almost the same across my different samples. In my model of abnormal return, I only show the dependent variable mean and median from [T-1, T+1] because I only include observation of one year before and one year after the event year.

Table 6A. Descriptive Statistics of Main Variables for Model of Product Differentiation

Variable	N	Mean	Std. Dev.	Median	Min	Max
Acquisition (Treatment)	1,602	0.348	0.476	0	0	1
R&D Intensity	1,317	0.121	0.126	0.09	0	1.632
Tobin's Q	1,570	2.239	2.392	1.658	0.31	55.729
Industry Concentration	1,593	0.228	0.198	0.159	0.022	1
# of M&A	1,602	0.425	0.665	0	0	5
ln (Total M&A Value)	1,602	1.595	2.349	0	0	11.194
# of Related M&A	1,602	0.25	0.528	0	0	4
# of International M&A	1,602	0.066	0.269	0	0	3

Table 6B. Descriptive Statistics of Total Product Similarity

Timing	Total Product Similarity							
	Treatment				Control			
	N	Mean	Std. Dev.	Median	N	Mean	Std. Dev.	Median
T-3	338	3.871	3.409	2.696	667	3.803	3.448	2.563
T-2	424	3.763	3.128	2.665	846	3.699	3.259	2.538
T-1	557	3.853	3.064	2.793	1,045	3.786	3.039	2.703
T	554	3.714	3.02	2.607	1,039	3.493	2.752	2.523
T+1	557	3.499	2.612	2.576	1,045	3.363	2.656	2.376
T+2	424	3.449	2.641	2.562	828	3.303	2.634	2.311
T+3	317	3.292	2.505	2.452	664	3.171	2.526	2.242

Table 7A. Descriptive Statistics of Main Variables for Model of Innovation Capability

Variable	N	Mean	Std. Dev.	Median	Min	Max
Acquisition (Treatment)	2,002	0.334	0.472	0	0	1
R&D Intensity	1,550	0.126	0.136	0.092	0	1.632
Tobin's Q	1,968	2.322	2.226	1.703	0.264	30.398
Industry Concentration	1,486	0.229	0.206	0.152	0.017	1
# of M&A	2,002	0.424	0.728	0	0	10
ln (Total M&A Value)	2,002	1.537	2.351	0	0	10.366
# of Related M&A	2,002	0.267	0.599	0	0	8
# of International M&A	2,002	0.077	0.306	0	0	4

Table 7B. Descriptive Statistics of Number of Patent

Timing	Number of Patent							
	Treatment (Significant M&A = 1)				Control (Significant M&A = 0)			
	N	Mean	Std. Dev.	Median	N	Mean	Std. Dev.	Median
T-3	508	0.63	2.591	0	1,097	0.419	1.714	0
T-2	590	0.6	2.504	0	1,224	0.38	1.4	0
T-1	669	0.638	2.242	0	1,333	0.394	1.64	0
T	669	0.636	2.124	0	1,333	0.398	1.66	0
T+1	669	0.647	2.303	0	1,333	0.439	1.982	0
T+2	519	0.674	2.259	0	1,097	0.463	2.224	0
T+3	392	0.752	2.913	0	868	0.521	2.707	0

Table 7C. Descriptive Statistics of Number of Citation

Timing	Number of Citation							
	Treatment (Significant M&A = 1)				Control (Significant M&A = 0)			
	N	Mean	Std. Dev.	Median	N	Mean	Std. Dev.	Median
T-3	508	0.023	0.134	0	1,097	0.009	0.053	0
T-2	590	0.014	0.065	0	1,224	0.008	0.042	0
T-1	669	0.019	0.099	0	1,333	0.01	0.065	0
T	669	0.02	0.104	0	1,333	0.01	0.068	0
T+1	669	0.013	0.061	0	1,333	0.01	0.063	0
T+2	519	0.015	0.067	0	1,097	0.011	0.061	0
T+3	392	0.017	0.083	0	868	0.01	0.066	0

Table 8A. Descriptive Statistics of Main Variables for Model of Stock Abnormal Return

Variable	N	Mean	Std. Dev.	Median	Min	Max
Acquisition (Treatment)	2,452	0.313	0.464	0	0	1
R&D Intensity	1,991	0.114	0.118	0.087	0	1.726
Tobin's Q	2,410	2.3	2.673	1.679	0.31	89.996
Industry Concentration	1,892	0.229	0.203	0.156	0.023	1
# of M&A	2,452	0.386	0.679	0	0	10
ln (Total M&A Value)	2,452	1.451	2.317	0	0	11.194
# of Related M&A	2,452	0.227	0.524	0	0	8
# of International M&A	2,452	0.069	0.271	0	0	3

Table 8B. Descriptive Statistics of Jenson's Alpha

Timing	Stock Abnormal Return							
	Treatment (Significant M&A = 1)				Control (Significant M&A = 0)			
	N	Mean	Std. Dev.	Median	N	Mean	Std. Dev.	Median
T-1	767	0.932	5.396	1.04	1,685	0.844	4.706	1.037
T	767	0.984	10.5	1.158	1,683	1.188	2.358	1.094
T+1	767	1.431	2.117	1.272	1,685	1.19	2.355	1.129

EMPIRICAL RESULTS

In this section, I present and interpret empirical results from econometrics models for the effect of M&A on three dependent variables: product differentiation, innovation capability, and stock market abnormal return. Please note that all my analyses use panel regressions which include up to 6-year observations for every treatment and control firm year. The length of the panel of each firm year depends on the data availability as I discuss in the method section. For model of product differentiation and innovation capability, I at least require a 2-year panel (one year before and one year after). For the model of stock abnormal return, I restrict my panel to be only 2-year long. All models control for firm and year fixed effect, and cluster the heteroskedastic-robust standard errors at the firm level. My main sample of digital firms include sub-samples of software developers (with a three-digit SIC code of 737) and hardware manufacturers (with a two-digit SIC code of 35, 36, 38, and 48). My main analyses on the results across whole, software and hardware samples. Additional results are also provided for sub-sectors under hardware manufacturers, which includes manufacturers of computers, electronics and instruments (*CEI*) products (SIC: 35, 36, and 38, respectively) and telecommunication equipment manufacturers (SIC: 48) if there are different findings in those sectors that do not present in combined hardware manufacturer sample. In results table, I use *, **, and *** to denote the significance level of 10%, 5%, and 1%, respectively. I consider 10% as marginally significant.

Product Differentiation

In order to examine the effect of M&A on product differentiation of the acquiring firms, I compare the *Total Product Similarity (TPS)* score of treatment firm years relative to those of control firm years over up to three years before and three years after the event year. I perform a difference-in-differences analysis for acquirers and control firm years in an unbalanced six-year panel data (excluding the event year T).

$$\mathrm{TPS}_{it} = \beta_0 + \beta_1 \mathrm{After}_{it} + \beta_2 (\mathrm{After}_{it}*\mathrm{Acquisition}_i) + \sum \beta (\mathrm{After}_{it}*\mathrm{Acquisition}_i*\mathrm{Interaction}_i) + \mathrm{Firm\ FE} + \mathrm{Year\ FE} + \varepsilon_{it} \quad (1)$$

In Equation (1), the dependent variable TPS_{it} is the *Total Product Similarity* score of firm *i* at year *t*. $After_{it}$ is a dummy variable that equals one if the observation is after-event (T+1, T+2, and T+3), or zero otherwise. $Acquisition_i$ is a dummy variable that equals one if firm *i* is a treatment firm (with significant M&A), or zero otherwise. $After_{it}*Acquisition_i$ is the interaction of time and treatment status, and its coefficient β_2 can be interpreted as the difference in outcomes for treatments relative to controls across up to three years before and three years after the merger, and therefore the main effect of M&A on product differentiation. $After_{it}*Acquisition_i*Interaction_i$ are interaction terms of treatment and firm-, industry-level and M&A portfolio characteristics and their coefficients provide insights on differential effects of M&A. I run the panel regression with firm and year fixed effect controlled and cluster under firm level to have robust standard error.

Main Effect of Acquisition

The first column of Table 9A shows the coefficient estimations of Equation (1) for the whole sample, and Column (2) – (3) show the results for sub-samples as indicated in labels. Results of Table 9A show that none of the coefficients of *After* is significantly different from zero for the whole sample and any sub-samples, suggesting that overtime digital firms do not differentiate their product offerings. Also, there was no overall effect of M&A on digital firms' product differentiation except for a marginally significant and positive effect on software developer sub-sample. For software firms, the direct effect of M&A on *TPS* is marginally positive (negative on product differentiation) with a coefficient of 1.066 ($p < 0.1$) indicating that acquisitions actually make firms worse off from the product differentiation perspective. Interestingly, this is consistent with my Hypothesis 1B that software firm's acquisition does not necessarily differentiate product offerings. Instead, it supports my conjecture that some firms acquire other companies to close the gap between its product offerings and its competitors'. In other words, the effect of M&As in software industry seems to be on the defense side, i.e. they acquire other firms not for the purpose of product differentiation, but for keeping up with new entrants. Since this is effect is not significant enough, I cannot make strong argument that software developers become less differentiated in product offerings after acquisition, though it is enough to argue that there is no positive main effect of M&A on product differentiation across all digital firms.

Heterogeneous Effect of Acquisition

Even though I do not find main effect, the first column of Table 9A shows that for whole sample of digital firms, the only significant result is at the coefficient of *After*Acquisition*Industry Concentration* is -0.78 ($p < 0.05$) suggesting that for the whole sample, the focal firm's M&A will have significant and positive impact on product differentiation (lower the total product similarity score) if it is in a highly concentrated (i.e. less competition) industry. Also, there is positive interaction between *Treatment* and industry concentration meaning the more concentrated the focal firm's industry is, more positive impact M&A has on its product differentiation. This supports my Hypothesis 6.

As for hardware manufacturers, the story is completely different. In my sub-samples of hardware manufacturers, the main effect of M&A is not evident. However, the effect of *After*Acquisition*R&D Intensity* is negative on *TPS* (positive on product differentiation) and significant at 1% with a coefficient of -1.74 ($p < 0.01$). This finding suggests that for hardware firms, M&A causes more product differentiation, but only for firms with its internal R&D investment in place. Furthermore, there is positive complementarily between R&D and M&A meaning that the more dollars a firm spends on its internal R&D, the higher impact M&A will have on its product differentiation. This is consistent with my Hypothesis 1B that hardware manufacturers are more product and innovation oriented and the product differentiation among competitors is a more important motivation of engaging in M&As. The finding about the interaction effect between M&A and R&D intensity is supporting my Hypothesis 4, which is especially interesting because it shows that firms with internal R&D are actually "wiser" acquirers in terms of targets selections, because they already know what they want. Also firms which already made R&D investments on some projects are more committed to them thus are more likely to succeed in integrating target firm's product and technology. No other interactions are found to be significant in this sub-sample. I further separate my hardware sub-sample to *CEI* and telecommunication sector. The interaction effect of M&A and R&D is even stronger in the *CEI* sector where the coefficient is -2.075 ($p < 0.01$) and in the sector of telecommunication equipment manufacturers where the coefficient is -50.636 ($p < 0.01$). In telecommunication sectors, I also find that the coefficient of *After*Acquisition*# Related M&A* and *After*Acquisition*# International M&A* is -0.455 ($p < 0.01$) and -1.493 ($p < 0.01$), respectively, indicating that M&A is most beneficial for product differentiation when more of those acquisitions are targeted on related and firms located in a different country. The finding about

Table 9A. Effect of M&A on Product Differentiation of Digital Firms (1993 – 2013)

	Total Product Similarity				
			Hardware Manufacturers		
	All Digital Firms	Software Developers	All	Computers, Electronics & Instruments	Telecomm. Equipment
After	-0.057	-0.068	-0.028	-0.061	0.066
	(0.071)	(0.106)	(0.083)	(0.094)	(0.115)
After * Acquisition	0.486	1.066*	0.338	0.339	-0.155
	(0.327)	(0.58)	(0.328)	(0.386)	(0.649)
After * Acquisition * R&D Intensity	-0.698	-0.503	-1.74***	-2.075***	-50.636***
	(0.549)	(0.693)	(0.72)	(0.763)	(6.539)
After * Acquisition * Tobin's Q	0.019	0.081	-0.006	0.005	-0.066
	(0.07)	(0.122)	(0.057)	(0.064)	(0.076)
After * Acquisition * Industry Concentration	-0.78**	-0.129*	-0.37	-0.292	0.496
	(0.402)	(0.767)	(0.289)	(0.304)	(0.957)
After * Acquisition * Total M&A Value	-0.052	-0.132	-0.062	-0.069	0.068
	(0.056)	(0.088)	(0.066)	(0.09)	(0.094)
After * Acquisition * # Related M&A	-0.049	-0.129	0.143	0.298*	-0.455***
	(0.122)	(0.21)	(0.15)	(0.174)	(0.166)
After * Acquisition * # International M&A	-0.055	-0.239	0.042	0.059	-1.493***
	(0.176)	(0.293)	(0.199)	(0.209)	(0.44)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Other Controls	Included	Included	Included	Included	Included
Number of Groups	994	423	571	487	84
Observations	7,711	3,346	4,365	3,767	598
R^2 *(within)*	0.13	0.26	0.07	0.07	0.26
R^2 *(between)*	0.02	0.13	0.00	0.00	0.21
R^2 *(overall)*	0.03	0.14	0.01	0.01	0.26

*Note: *, **, *** indicates the significance level of 10%, 5%, and 1%, respectively.*

relatedness can be explained in a way that related acquisition are more relevant for acquirers in terms of product offerings and related acquisitions are relatively easier to integrate. Therefore acquiring firms engaged in related M&As are more likely to integrate new product and technology from target firms easily and quickly. The result of international transaction makes intuitive sense because foreign targets might bring acquirers different perspectives and knowledge/resources that are different from those they possess in their own country. Acquiring human capitals and technology from foreign companies may provide more benefits for acquiring firms when it comes to product differentiation. All of those findings are consistent with my hypotheses. Interestingly, I only see those effects in the sub-sector of telecommunication equipment manufacturers.

Timing Effect

Next, I conduct additional analyses to explore if there is any difference in the effect of M&A during different time periods. I separate my sample into three sub-samples on the timing dimensions: 1993 – 2000, 2000 – 2007, and 2007 – 2013. There are two reasons for choosing those cutoff years. First, they make three almost equal sized blocks across my whole observation period. Secondly, year 2000 was when dot.com bubble collapsed after which many digital firms failed. Year 2007 is another important year after which the worldwide economy was severely hit because of the financial crisis. Therefore, examining the differential effect of M&A on outcomes across these three different time blocks help provide additional insights. Table 9B shows the results for M&A deals completed during 1993 – 2000. The only significant coefficient is *After * Acquisition * Tobin's Q* for the sub-sample of software developers (-0.308, $p < 0.05$) and it is significant at 10% level for the whole sample. This result suggests that in pre-2000 years, M&A helps product differentiation for software developers, but only those with high *Tobin's Q*

Table 9B. Effect of M&A on Product Differentiation of Digital Firms (1993 - 2000)

	Total Product Similarity		
	All Digital Firms	Software Developers	Hardware Manufacturers
After	0.087	0.032	0.046
	(0.207)	(0.416)	(0.223)
After * Acquisition	0.625	-0.061	1.109
	(0.763)	(1.737)	(0.743)
After * Acquisition * R&D Intensity	-0.206	-0.455	-1.015
	(0.991)	(1.564)	(1.142)
After * Acquisition * Tobin's Q	-0.182*	-0.308**	-0.218
	(0.099)	(0.142)	(0.168)
After * Acquisition * Industry Concentration	-0.176	-0.141	-0.234
	(0.652)	(2.769)	(0.588)
After * Acquisition * Total M&A Value	-0.065	0.297	-0.154
	(0.161)	(0.454)	(0.168)
After * Acquisition * # Related M&A	0.247	0.06	0.105
	(0.255)	(0.377)	(0.287)
After * Acquisition * # International M&A	0.243	2.519	-0.202
	(0.561)	(1.776)	(0.537)
Firm Fixed Effect	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Other Controls	Included	Included	Included
Number of Groups	281	119	162
Observations	1,260	505	755
R^2 *(within)*	0.11	0.19	0.10
R^2 *(between)*	0.00	0.02	0.00
R^2 *(overall)*	0.01	0.03	0.01

software companies. No effect of M&A is found for hardware manufacturers. As for the period of 2000 – 2007 when the market of digital firms was saturated and grows gradually since then, before hitting another economic hardship, the effect of M&A on product differentiation is completely different. As shown in Table 9C, during that period, M&A does not help software developers at all, whereas for hardware manufacturers, M&A helps increase acquiring firms' product differentiation only if there are internal R&D investment in place (-3.031, $p < 0.05$). This effect is consistent with the overall effect I find for the whole time period. During the last time period of post-2007 years, the effect of M&A on product different seems to be stronger, and without contingency. Table 9D shows that for in the whole sample and sub-sample of hardware manufacturers, there is main effect of M&A on product differentiation. The coefficient of *After * Acquisition* in sub-sample of hardware manufacturers is -1.756 and it is significant at 1% level. In conclusion, I find that the effect of M&A on product differentiation for software companies is almost zero or even contrary to my expectation to some degree, except for the period of 1993 – 2000 when "growth" software vendors seem to be able to leverage acquisitions to differentiate their product offerings. While for hardware manufacturers, M&A has been found to be consistently helpful to their product differentiation, especially when acquiring firms' internal R&D intensity is high, and for certain sectors of hardware companies, relatedness and internationalization of M&A even further increases the level of product differentiation.

Table 9C. Effect of M&A on Product Differentiation of Digital Firms (2000 - 2007)

	Total Product Similarity		
	All Digital Firms	Software Developers	Hardware Manufacturers
After	0.054	0.087	0.007
	(0.132)	(0.184)	(0.156)
After * Acquisition	0.791	1.229	0.495
	(0.522)	(0.897)	(0.575)
After * Acquisition * R&D Intensity	-3.271**	-3.299	-3.031**
	(1.412)	(2.641)	(1.327)
After * Acquisition * Tobin's Q	0.051	0.046	0.092
	(0.105)	(0.243)	(0.065)
After * Acquisition * Industry Concentration	-0.395	-1.043	0.179
	(0.588)	(1.087)	(0.512)
After * Acquisition * Total M&A Value	-0.13	-0.175	-0.174
	(0.092)	(0.158)	(0.114)
After * Acquisition * # Related M&A	0.087	0.069	0.451*
	(0.189)	(0.275)	(0.27)
After * Acquisition * # International M&A	-0.304	-0.471	-0.174
	(0.248)	(0.455)	(0.274)
Firm Fixed Effect	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Other Controls	Included	Included	Included
Number of Groups	617	267	350
Observations	3,508	1,551	1,957
R^2 *(within)*	0.17	0.28	0.12
R^2 *(between)*	0.02	0.03	0.00
R^2 *(overall)*	0.04	0.07	0.02

Table 9D. Effect of M&A on Product Differentiation of Digital Firms (2007 - 2013)

	Total Product Similarity		
	All Digital Firms	Software Developers	Hardware Manufacturers
After	-0.03	-0.003	-0.061
	(0.089)	(0.116)	(0.131)
After * Acquisition	-0.869**	0.228	-1.756***
	(0.45)	(0.492)	(0.72)
After * Acquisition * R&D Intensity	0.347	1.367	0.562
	(1.466)	(1.674)	(1.919)
After * Acquisition * Tobin's Q	0.203	0.083	0.323
	(0.131)	(0.104)	(0.286)
After * Acquisition * Industry Concentration	-0.049	-0.493	0.522
	(0.445)	(0.526)	(0.657)
After * Acquisition * Total M&A Value	0.125	-0.014	0.233**
	(0.077)	(0.072)	(0.116)
After * Acquisition * # Related M&A	-0.213	-0.256	-0.204
	(0.156)	(0.204)	(0.228)
After * Acquisition * # International M&A	0.11	0.114	0.031
	(0.306)	(0.262)	(0.479)
Firm Fixed Effect	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Other Controls	Included	Included	Included
Number of Groups	399	175	224
Observations	2,384	1,059	1,325
R^2 *(within)*	0.05	0.07	0.07
R^2 *(between)*	0.00	0.02	0.02
R^2 *(overall)*	0.00	0.03	0.01

Effect of Target Age

I am also interested in how target age plays a role in the effectiveness of M&A in terms of acquiring firms' product differentiation. Since there is some missing data on the age variable, I choose not to include the term *After * Acquisition * Average Target Age* in the main models to fully use my available data. In Table 10A, I show the results of a separate model with main effect of M&A and its interaction term of average age of target firm(s) in the M&A portfolio. The first column of Table 10A shows that the coefficient of *After * Acquisition * Average Target Age* is positive at 10% level. Column (2) shows that there is no main effect nor interaction effect for software developers. Column (3) shows that regression result for the sub-sample of hardware manufacturers. The coefficient of *After * Acquisition* is negative and significant (-0.289, $p < 0.05$) indicating that there is main effect of M&A on product differentiation for hardware manufacturers, and more interestingly, the coefficient of *After * Acquisition * Average Target Age* is 0.008 ($p < 0.05$) suggesting that there is a negative moderation effect of target age on M&A's effect on hardware companies' product differentiation. This is consistent with my Hypothesis 10A that older targets are less helpful for the acquiring firms' product differentiation compared with younger targets or new entrants. This effect is found be to be consistently present in my subsample of 2000 – 2007 and 2007 – 2013, but not in the pre-2000 years as shown in Table 10B and 10C.

Table 10A. Moderating Effect of Target Age on Product Differentiation (1993 - 2013)

	Total Product Similarity				
			Hardware Manufacturers		
	All Digital Firms	Software Developers	All	Computers, Electronics & Instruments	Telecomm. Equipment
After	-0.082	-0.107	-0.033	-0.054	-0.028
	(0.08)	(0.123)	(0.089)	(0.1)	(0.121)
After * Acquisition	-0.139	0.222	-0.289**	-0.262	-0.375
	(0.138)	(0.242)	(0.15)	(0.173)	(0.286)
After * Acquisition * Average Target Age	0.007*	-0.003	0.008**	0.009*	0.007
	(0.004)	(0.012)	(0.004)	(0.005)	(0.004)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Other Controls	Included	Included	Included	Included	Included
Number of Groups	898	378	520	445	75
Observations	6,764	2,881	3,883	3,371	512
R^2 *(within)*	0.13	0.27	0.07	0.07	0.21
R^2 *(between)*	0.03	0.15	0.00	0.00	0.30
R^2 *(overall)*	0.04	0.15	0.02	0.02	0.30

Table 10B. Moderating Effect of Target Age on Product Differentiation (2000 - 2007)

	Total Product Similarity				
			Hardware Manufacturers		
	All Digital Firms	Software Developers	All	Computers, Electronics & Instruments	Telecomm. Equipment
After	0.104	0.114	0.048	0.056	-0.008
	(0.147)	(0.213)	(0.167)	(0.182)	(0.25)
After * Acquisition	-0.256	0.001	-0.281	-0.197	-0.469
	(0.201)	(0.322)	(0.223)	(0.247)	(0.356)
After * Acquisition * Average Target Age	0.01**	-0.002	0.007	0.002	0.019***
	(0.005)	(0.01)	(0.006)	(0.006)	(0.004)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Other Controls	Included	Included	Included	Included	Included
Number of Groups	564	238	326	285	41
Observations	3,164	1,348	1,816	1,608	208
R^2 *(within)*	0.17	0.31	0.11	0.12	0.26
R^2 *(between)*	0.03	0.06	0.02	0.02	0.06
R^2 *(overall)*	0.05	0.09	0.04	0.04	0.09

Table 10C. Moderating Effect of Target Age on Product Differentiation (2007 - 2013)

	Total Product Similarity				
			Hardware Manufacturers		
	All Digital Firms	Software Developers	All	Computers, Electronics & Instruments	Telecomm. Equipment
After	-0.119	-0.053	-0.153	-0.216	-0.012
	(0.093)	(0.134)	(0.124)	(0.148)	(0.152)
After * Acquisition	-0.226	-0.074	-0.404*	-0.459*	-0.169
	(0.163)	(0.247)	(0.229)	(0.255)	(0.406)
After * Acquisition * Average Target Age	0.011**	0.014	0.014***	0.019***	0.001
	(0.005)	(0.013)	(0.005)	(0.005)	(0.005)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Other Controls	Included	Included	Included	Included	Included
Number of Groups	364	152	212	183	29
Observations	2,130	897	1,233	1,036	197
R^2 *(within)*	0.05	0.07	0.07	0.08	0.27
R^2 *(between)*	0.00	0.01	0.02	0.02	0.22
R^2 *(overall)*	0.00	0.02	0.01	0.01	0.24

Stock Abnormal Return

As for my second dependent variable of stock abnormal return, I perform similar empirical investigations to test the treatment effect of completion significant M&A by running the following model:

$$\text{Alpha}_{it} = \beta_0 + \beta_1 \text{ After}_{it} + \beta_2 (\text{After}_{it}\text{*Acquisition}_i) + \sum \beta (\text{After}_{it}\text{*Acquisition}_i\text{*Interaction}_i) + \text{Firm FE} + \text{Year FE} + \varepsilon_{it} \quad (2)$$

In Equation (2), I first test the timing effect and the main effect of M&A on firm's stock abnormal return.

Main Effect of Acquisition

For the whole digital firm sample and the sub-sample of hardware manufacturers, the coefficient of *After* is 0.301 ($p < 0.01$) and 0.336 ($p < 0.01$) respectively, meaning that regardless of treatment, firms tend to get better abnormal return over the period of my study, however no such effect is found in the software firms sub-sample. As for the main effect of M&A, the coefficients of *After*Acquisition* for the whole sample is significant (-0.714, $p < 0.05$) indicating that M&A actually decreases stock market abnormal return, and such effect is even stronger and more significant in the sub-sample of hardware manufacturers (-1.156, $p < 0.01$). Those results suggest that compared to hardware firms that have not completed significant acquisitions, firms with M&A perform worse in terms of stock return. In other words, investors generally have negative reaction toward M&A decisions. An explanation for those findings is that from investors' perspective, M&As are very risky moves because it costs much but they have no idea

Table 11A. Effect of M&A on Stock Abnormal Return of Digital Firms (1993 - 2013)

	Jenson's Alpha (S&P 500 Benchmarked Fama-French 3-factor Model)				
			Hardware Manufacturers		
	All Digital Firms	Software Developers	All	Computers, Electronics & Instruments	Telecomm. Equipment
After	0.301***	0.276	0.336***	0.215**	0.6
	(0.11)	(0.186)	(0.13)	(0.1)	(0.469)
After * Acquisition	-0.714**	0.079	-1.156***	-0.703	-2.551*
	(0.353)	(0.645)	(0.434)	(0.535)	(1.49)
After * Acquisition * R&D Intensity	1.799	2.198	0.498	0.063	-27.77
	(1.323)	(1.821)	(1.713)	(1.684)	(30.834)
After * Acquisition * Tobin's Q	0.11	0.02	0.231**	0.215**	0.47
	(0.119)	(0.173)	(0.105)	(0.106)	(0.533)
After * Acquisition * Industry Concentration	-0.194	-1.326	-0.088	-0.53	2.097
	(0.61)	(1.295)	(0.77)	(0.837)	(2.277)
After * Acquisition * # of M&A	0.68***	0.136	1.022***	1.063**	0.673
	(0.28)	(0.372)	(0.388)	(0.534)	(0.838)
After * Acquisition * # of Related M&A	-0.227	0.355	-0.589**	-0.84***	-0.076
	(0.265)	(0.457)	(0.285)	(0.316)	(0.618)
After * Acquisition * # International M&A	-0.183	-0.31	-0.151	-0.241	-0.592
	(0.283)	(0.627)	(0.299)	(0.313)	(1.256)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Other Controls	Included	Included	Included	Included	Included
Number of Groups	1,428	554	874	683	191
Observations	4,902	1,916	2,986	2,411	575
R^2 *(within)*	0.02	0.04	0.02	0.05	0.09
R^2 *(between)*	0.01	0.01	0.00	0.00	0.01
R^2 *(overall)*	0.02	0.03	0.01	0.03	0.05

if the firm will be able to successfully integrate the new firm and gain what they want out of those deals, which is consistent with my Hypothesis 3 (competing). Those findings seem to be consistent with prior literature that most acquirers experience negative return after M&A, both in the short term or long run setting. Again, I do not find any average effect of M&A on software developers' stock abnormal return in the whole period.

Heterogeneous Effect of Acquisition

I next explore heterogeneous effects of M&A by looking at interaction terms. The coefficient of *After * Acquisition * Tobin's Q* for hardware manufactures sub-sample is 0.231 ($p < 0.05$) indicating that the acquiring firms with higher market-to-book ratio tend to perform better in stock market, which means that *Tobin's Q* mitigates some of the negative impact of M&A, and this is especially true in the *CEI* sectors of hardware manufacturers (0.215, $p < 0.05$). *# of M&A* is another moderator in which I find interaction effect with M&A. For all digital firms (0.68, $p < 0.01$), and particularly hardware manufacturers (1.022, $p < 0.01$), the interaction effect of M&A portfolio size is positive, suggesting that even if the main effect of M&A on stock abnormal return is negative, M&A portfolio size offsets some of the negative effect. The last moderation effect that has been found to be significant is the relatedness of M&As in the portfolio. The coefficients of *After*Acquisition*# of Related M&A* for hardware firm sample is negative and significant at 5% level (significant at 1% level for *CEI* firms with even higher magnitude). This surprising result is not consistent with prior literature which generally suggests that related acquisition is better for acquirers. However this may be an interesting part of this study and what differentiates it from previous studies. Since most of previous studies do not focus on a specific industry or sector, their results are general. One of the explanation of my result can be that investors of hardware manufacturers have different criteria for good M&As as

Table 11B. Effect of M&A on Stock Abnormal Return of Digital Firms (1993 - 2000)

	Jenson's Alpha (S&P 500 Benchmarked Fama-French 3-factor Model)		
	All Digital Firms	Software Developers	Hardware Manufacturers
After	0.09	-0.136	0.049
	(0.196)	(0.383)	(0.199)
After * Acquisition	-1.013**	-1.635**	-1.31*
	(0.53)	(0.85)	(0.789)
After * Acquisition * R&D Intensity	0.558	1.101	0.598
	(1.026)	(1.564)	(1.885)
After * Acquisition * Tobin's Q	0.239	0.312	0.379
	(0.204)	(0.258)	(0.281)
After * Acquisition * Industry Concentration	2.662*	2.773	2.004
	(1.596)	(2.117)	(1.805)
After * Acquisition * # of M&A	0.472*	0.372	0.733
	(0.292)	(0.319)	(0.479)
After * Acquisition * # of Related M&A	-0.502*	-0.15	-0.597
	(0.312)	(0.423)	(0.395)
After * Acquisition * # International M&A	-0.509	-1.474	-0.686
	(0.513)	(1.675)	(0.511)
Firm Fixed Effect	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Other Controls	Included	Included	Included
Number of Groups	625	215	410
Observations	1,514	512	1,002
R^2 *(within)*	0.03	0.11	0.05
R^2 *(between)*	0.00	0.02	0.00
R^2 *(overall)*	0.01	0.06	0.01

those who invest in a non-tech firm. For digital firms, especially hardware producers, related acquisition may not be as appealing as that in other industries. A possible reason for that is consistent with what I discussed earlier in terms of product differentiation. One of the most important performance indicators of those firms are innovation and differentiation, however related acquisition might not able to contribute many opportunities for innovation and differentiation, rather they might be more beneficial for scale economies and efficiency (Singh and Montgomery, 1987). I also run a separate model to examine the moderating effect of target age, but do not find any significant relationship.

Timing Effect

I also separate my samples into three sub-samples over the years and explore if the effect of M&A on stock abnormal return is different during different time periods. Table 11B shows the similar negative overall effect of M&A for all digital firms. However, unlike what I find in the whole period sample, the negative effect is significant in the sub-sample of software developers (-1.635, $p < 0.05$), whereas that of hardware manufacturers is only significant at 10% level. In the sub-sample of 2000 – 2007, I only find negative effect for hardware manufacturers, but it is only significant at 10% level. In addition to that, I also find that similar effects for the interaction terms of *Tobin's Q* and M&A portfolio size. During 2007 – 2013, I find that M&A has positive effect on stock abnormal return. With a positive and significant coefficient of *After * Acquisition * R&D Intensity* (4.492, $p < 0.05$), M&A is found to positively impact Alpha when internal R&D intensity is higher, and that effect is stronger for hardware manufacturers (4.896, $p < 0.05$). In conclusion, I find that M&A generally decreases stock abnormal return over the longer period, and it is only evident for hardware manufacturers. However *Tobin's Q*, M&A portfolio size can mitigate some of that negative impact. The time trend analyses show that investors actually change their attitude toward M&A over time. In early years (pre-2000), investors tend to negatively react to M&A while in recent years (post-2007) M&A by hardware manufacturers seems to boost stock return if internal R&D is also in place.

Link between Product Differentiation and Stock Performance

It is worth noting that I also find a link between the effect of M&A on product differentiation and the effect of M&A on stock abnormal return. As discussed earlier, during the period of 2000 – 2007, digital firms, especially hardware manufacturers with significant M&As tend to perform better in terms of product differentiation if they also invest in their internal R&D. Interestingly, I find that during the period of 2007 – 2013, the later years, investors tend to react positively to the same groups of acquiring firms with R&D investment. This link shows a lagged effect of stock market performance in later years as an reaction to product market performance in early years, i.e. investors realize that even though M&As are risky moves (which is why they have been negative on that), M&As carried out by firms who have more intensive internal R&D (those who are more serious about and more into it) actually tend to perform well in product market, therefore investors gradually changed their attitude in later time period and start to react positively for those acquisitions initiated by firms with higher internal R&D because they think those firms know better about what they want and might be more committed to what are doing because they already made initial investment to complement potential acquired product and/or technologies.

Table 11C. Effect of M&A on Stock Abnormal Return of Digital Firms (2000 - 2007)

	Jenson's Alpha (S&P 500 Benchmarked Fama-French 3-factor Model)		
	All Digital Firms	Software Developers	Hardware Manufacturers
After	0.449*	0.379	0.379
	(0.256)	(0.507)	(0.261)
After * Acquisition	-1.37	0.956	-2.221*
	(1.185)	(1.924)	(1.281)
After * Acquisition * R&D Intensity	1.112	4.216	-3.574
	(4.018)	(6.593)	(3.347)
After * Acquisition * Tobin's Q	0.08	-0.344	0.458**
	(0.199)	(0.318)	(0.187)
After * Acquisition * Industry Concentration	-1.291	-3.898	-1.664
	(1.261)	(2.61)	(1.778)
After * Acquisition * # of M&A	1.623	0.073	2.361**
	(1.032)	(1.456)	(1.23)
After * Acquisition * # of Related M&A	-0.362	1.01	-1.295*
	(0.654)	(1.064)	(0.765)
After * Acquisition * # International M&A	0.096	-1.119	0.585
	(0.622)	(1.163)	(0.76)
Firm Fixed Effect	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Other Controls	Included	Included	Included
Number of Groups	725	303	422
Observations	1,956	848	1,108
R^2 *(within)*	0.03	0.05	0.04
R^2 *(between)*	0.00	0.00	0.00
R^2 *(overall)*	0.01	0.02	0.01

Table 11D. Effect of M&A on Stock Abnormal Return of Digital Firms (2007 - 2013)

	Jenson's Alpha (S&P 500 Benchmarked Fama-French 3-factor Model)		
	All Digital Firms	Software Developers	Hardware Manufacturers
After	0.125	0.191	0.069
	(0.116)	(0.178)	(0.151)
After * Acquisition	-0.319	-0.558	-0.04
	(0.477)	(1.022)	(0.553)
After * Acquisition * R&D Intensity	4.492**	6.403	4.896**
	(2.25)	(4.812)	(2.57)
After * Acquisition * Tobin's Q	-0.078	0.147	-0.171
	(0.198)	(0.253)	(0.288)
After * Acquisition * Industry Concentration	-0.393	-1.914	1.244
	(0.997)	(1.889)	(0.819)
After * Acquisition * # of M&A	0.318	0.298	0.029
	(0.319)	(0.675)	(0.38)
After * Acquisition * # of Related M&A	0.207	0.2	0.313
	(0.235)	(0.352)	(0.295)
After * Acquisition * # International M&A	-0.332	-0.282	-0.509
	(0.307)	(0.816)	(0.321)
Firm Fixed Effect	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Other Controls	Included	Included	Included
Number of Groups	545	201	344
Observations	1,432	556	876
R^2 *(within)*	0.04	0.08	0.06
R^2 *(between)*	0.00	0.00	0.02
R^2 *(overall)*	0.01	0.04	0.01

Innovation Capability

I next examine the impact of M&A on firm's innovation capability measured by number patents and number of citations received in a given year. Using the same empirical method, I first test the following models:

$$PatNumAdj_{it} = \beta_0 + \beta_1 \text{After}_{it} + \beta_2 (\text{After}_{it}\text{*Acquisition}_i) + \sum \beta (\text{After}_{it}\text{*Acquisition}_i\text{*Interaction}_i)$$
$$+ \text{Firm FE} + \text{Year FE} + \varepsilon_{it} \quad (3)$$

Main and Heterogeneous Effect of Acquisition on Patent

I first examine the main effect of M&A on patent. As shown in Table 12A, I find that there is no main effect in the whole sample and the sub-sample of hardware manufacturers. However in the sub-sample of software developers, the main effect of M&A is negative and significant (-0.241, $p < 0.05$) indicating that on average, software developers will file less patents after M&A. After looking at the interaction terms, I find that only "growth" or "glamour" hardware firms tend to perform better in patenting after M&A.

Timing Effect

Results from analyses on sub-samples of 1993 – 2000 show that there is a very strong negative effect of M&A on software developers' patenting (-0.801, $p < 0.01$), however the level of internal R&D investment can mitigate some of the negative effect. This can be explained by the same rationale as discussed earlier. Additionally, M&A portfolio size offsets some of the negative impact (0.256, $p < 0.01$). On the other hand, *Tobin's Q* and relatedness even deteriorate the innovation quantity. During 2000 – 2007, the main effect of M&A on innovation quantity has been found to be negative, especially for hardware manufacturers, but the *Tobin's Q* mitigates

Table 12A. Effect of M&A on Innovation Quantity of Digital Firms (1993 - 2013)

	Number of Patent				
			Hardware Manufacturers		
	All Digital Firms	Software Developers	All	Computers, Electronics & Instruments	Telecomm. Equipment
After	0.079*	0.008	0.126	0.162	0.056
	(0.047)	(0.025)	(0.079)	(0.107)	(0.05)
After * Acquisition	-0.109	-0.241**	-0.152	0.022	-0.007
	(0.202)	(0.119)	(0.368)	(0.524)	(0.063)
After * Acquisition * R&D Intensity	-0.341	0.13	-0.871	-0.817	-4.003
	(0.443)	(0.159)	(0.972)	(1.047)	(3.629)
After * Acquisition * Tobin's Q	0.029	-0.007	0.143**	0.153**	0.02
	(0.027)	(0.013)	(0.063)	(0.067)	(0.018)
After * Acquisition * Industry Concentration	-0.09	-0.007	-0.25	-0.341	0.073
	(0.176)	(0.103)	(0.306)	(0.348)	(0.074)
After * Acquisition * Total M&A Value	-0.004	0.05*	-0.03	-0.075	-0.017
	(0.043)	(0.03)	(0.07)	(0.128)	(0.013)
After * Acquisition * # of Related M&A	0.01	0.03	-0.06	-0.124	0.013
	(0.06)	(0.04)	(0.114)	(0.148)	(0.009)
After * Acquisition * # International M&A	-0.077	-0.009	-0.122	-0.139	0.008
	(0.076)	(0.07)	(0.121)	(0.169)	(0.02)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Other Controls	Included	Included	Included	Included	Included
Number of Groups	1,306	540	766	577	189
Observations	9,508	4,112	5,396	4,058	1,338
R^2 *(within)*	0.03	0.03	0.04	0.05	0.02
R^2 *(between)*	0.07	0.07	0.07	0.23	0.04
R^2 *(overall)*	0.05	0.06	0.05	0.16	0.03

Note: To avoid truncation bias, patent-based variables are scaled by average number of patents and citations in the same industry within patent classes.

Table 12B. Effect of M&A on Innovation Quantity of Digital Firms (1993 - 2000)

	Number of Patent		
	All Digital Firms	Software Developers	Hardware Manufacturers
After	0.146	0.056	0.192
	(0.143)	(0.037)	(0.217)
After * Acquisition	0.135	-0.801***	0.495
	(0.532)	(0.33)	(0.759)
After * Acquisition * R&D Intensity	0.599	0.477***	0.763
	(0.435)	(0.163)	(1.024)
After * Acquisition * Tobin's Q	-0.03	-0.021**	-0.014
	(0.037)	(0.01)	(0.158)
After * Acquisition * Industry Concentration	-0.164	-0.445	-0.282
	(0.45)	(0.625)	(0.565)
After * Acquisition * Total M&A Value	-0.077	0.256***	-0.224
	(0.134)	(0.099)	(0.18)
After * Acquisition * # of Related M&A	-0.027	-0.142***	0.056
	(0.091)	(0.056)	(0.181)
After * Acquisition * # International M&A	-0.271	-0.182	-0.228
	(0.214)	(0.17)	(0.287)
Firm Fixed Effect	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Other Controls	Included	Included	Included
Number of Groups	576	204	372
Observations	3,101	1,027	2,074
R^2 (within)	0.05	0.07	0.07
R^2 (between)	0.08	0.20	0.07
R^2 (overall)	0.07	0.15	0.07

Table 12C. Effect of M&A on Innovation Quantity of Digital Firms (2000 - 2007)

	Number of Patent		
	All Digital Firms	Software Developers	Hardware Manufacturers
After	0.05	0.056	0.024
	(0.042)	(0.039)	(0.086)
After * Acquisition	-0.442**	-0.136	-0.969**
	(0.221)	(0.164)	(0.425)
After * Acquisition * R&D Intensity	-0.049	-0.06	0.074
	(0.287)	(0.218)	(0.505)
After * Acquisition * Tobin's Q	0.066	-0.043	0.186***
	(0.056)	(0.027)	(0.054)
After * Acquisition * Industry Concentration	-0.24	-0.127	-0.144
	(0.201)	(0.185)	(0.345)
After * Acquisition * Total M&A Value	0.084*	0.049	0.166*
	(0.05)	(0.042)	(0.09)
After * Acquisition * # of Related M&A	-0.025	0.048	-0.178
	(0.07)	(0.048)	(0.146)
After * Acquisition * # International M&A	-0.172**	-0.063	-0.281**
	(0.082)	(0.088)	(0.135)
Firm Fixed Effect	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Other Controls	Included	Included	Included
Number of Groups	743	360	383
Observations	4,749	2,424	2,325
R^2 *(within)*	0.02	0.04	0.04
R^2 *(between)*	0.08	0.05	0.07
R^2 *(overall)*	0.05	0.06	0.04

some of the negative impact. However, internationalization seems to be even worse for firms' patenting.

Effect on Citation

Lastly, I run the following model to examine the impact of M&A on innovation quality of digital firms:

$$CitesAdj_{it} = \beta_0 + \beta_1 \, \mathrm{After}_{it} + \beta_2 \, (\mathrm{After}_{it}{*}\mathrm{Acquisition}_i) + \sum \beta \, (\mathrm{After}_{it}{*}\mathrm{Acquisition}_i{*}\mathrm{Interaction}_i) + \mathrm{Firm\ FE} + \mathrm{Year\ FE} + \varepsilon_{it} \quad (4)$$

I run the model in Equation (4) and find that, as shown in Table 12D, over time firms tend to perform better in terms of innovation quality regardless of treatment, because the coefficients of *After* for the whole sample, sub-sample of hardware manufacturers and sectors of CEI in hardware firms are all positive and significant at 5% level. However, I do not see any main effect of M&A on citation received. Moreover, the coefficient of *After * Acquisition * Total M&A Value* even shows that there are negative impact of M&A on citation received if the M&A portfolio size is bigger. I do not find different results for different time periods and there is no effect of target age on that main relationship.

Taken together, analyses on innovation capability show that M&A on average, does not lead to either higher innovation quantity or quality, sometimes it even lowers acquiring firm's innovation capability. Those findings support my conjecture in Hypothesis 2 (competing), and the possible explanation is that M&A distracts lots of management attention, so less effort is put on innovation and patent application. Integration might be another reason for the lower innovation productivity.

Table 12D. Effect of M&A on Innovation Quality of Digital Firms (1993 - 2013)

	Number of Citation				
			Hardware Manufacturers		
	All Digital Firms	Software Developers	All	Computers, Electronics & Instruments	Telecomm. Equipment
After	0.002***	0.001	0.004**	0.006**	0.0001
	(0.001)	(0.0005)	(0.002)	(0.003)	(0.0002)
After * Acquisition	0.011*	0.007	0.011	0.028*	0.0003
	(0.006)	(0.005)	(0.011)	(0.015)	(0.0005)
After * Acquisition * R&D Intensity	-0.015	-0.005	-0.026	-0.019	-0.005
	(0.011)	(0.006)	(0.023)	(0.024)	(0.006)
After * Acquisition * Tobin's Q	0.001	-0.0001	0.003	0.004*	0.000
	(0.001)	(0.0003)	(0.002)	(0.002)	(0.000)
After * Acquisition * Industry	-0.023	-0.004	-0.034	-0.036	0.000
Concentration	(0.017)	(0.004)	(0.026)	(0.028)	(0.000)
After * Acquisition * Total M&A Value	-0.003***	-0.0006	-0.005**	-0.01***	-0.000
	(0.001)	(0.0008)	(0.002)	(0.004)	(0.000)
After * Acquisition * # of Related M&A	0.005	-0.003	0.008	0.009	0.000
	(0.004)	(0.002)	(0.007)	(0.009)	(0.000)
After * Acquisition * # International M&A	-0.007	0.004	-0.011	-0.011	0.000
	(0.007)	(0.003)	(0.01)	(0.013)	(0.000)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Other Controls	Included	Included	Included	Included	Included
Number of Groups	1,306	540	766	577	189
Observations	9,508	4,112	5,396	4,058	1,338
R^2 (within)	0.01	0.01	0.01	0.02	0.02
R^2 (between)	0.01	0.01	0.01	0.03	0.02
R^2 (overall)	0.01	0.01	0.01	0.02	0.02

DISCUSSION AND CONCLUSION

Summary of Findings

In this paper, I study M&A, one of the most important knowledge acquisition mechanisms for high technology firms, especially those in digital industries. I extend the current literature of M&A by proposing a study to find out causal relationship between acquisition and firm performance which uses new and unique metrics.

Specifically, I examine the effect of M&A on firm performance in the forms of (1) product differentiation, (2) innovation capability and (3) stock market abnormal return of firms in digital product and service industries. Drawing theories from strategy and industrial organization economics, I argue that product differentiation is one of the most important strategic competitiveness for firms in digital industry to survive and grow, as well as the objective of most M&A transactions. I use data from public and proprietary resources and use matched sample method to test econometric models in a difference-in-difference approach. I am able to build causal relationship between M&A and firm performance. Empirical results suggest that M&A increases product differentiation for hardware manufacturers, but only for those firms who have internal R&D in place. As for software developer and service providers, M&A has no effect or even reversed effect on their level of product differentiation. Then I find that stock market investors tend to react negatively to M&A behavior, however firm's *Q* and M&A portfolio size are found to offset the negative impact. Also, investors' attitude toward M&A tend to change over time in accordance with firms' product market performance after M&A in previous years. Lastly, as for the innovation performance, only high *Tobin's Q* firms in hardware sector are found to perform better after M&A in terms of patent quality. Moreover, I find that M&A make firms worse off when it comes to patent quality.

This paper makes contributions to the academic literature in both strategy and information systems fields. Theoretically, this study argues that product differentiation is an important yet understudied key performance indicator for many high technology companies and this paper is the first one to empirically study product differentiation as a dependent variable. Methodologically, this design is robust to endogeneity of the choice of acquisition which is common in studies like this. By employing advanced econometrical and statistical techniques to build a difference-in-differences model to test the causal effect of acquisition on the change of firm performance, I am able to rule out the alternative explanation. For the IT management literature, this paper makes contribution by focusing on digital industries including hardware manufacturing and software and service providers and finding differential effects of acquisition across different industry sectors and across firm and industry-level contingencies.

Managerial Implications

From practitioners' perspective, this paper is also valuable. It provides managerial implications for digital firm managers on the effectiveness of acquisition on firm performance in different forms, and circumstances under which those effects might appear/disappear or strengthen/attenuate. Empirical results generally suggest that for hardware companies, acquisition makes a difference, however internal R&D plays an important role in complementing the acquisition(s), and effects differ depending on firms' market valuation and deal characteristics. As for software service providers, acquisitions might not work the way it was intended to be. Acquisition does not lead to higher level of product differentiation, nor help firms increase their innovation capabilities and stock performance, therefore acquisition actually makes software companies worse off. Managers of digital firms can make wiser decisions about M&A with the help of this study's results and implications.

Limitations and Future Research

There are several limitations in this study. First, before 1996 there was no available data on product differentiation. Thus I limited my analysis for that variable to 1996 – 2013. The similar problem occurs in database of patent quantity and quality. Since the patent database developed by Kogan et al. (2012) only covers public firms, I am not able track patent information of private firms, which most of the target firms are. Instead, I only measure the patent number and citations of focal firms which are all public firms. In order to make it work, I assume that all private firms who get acquired will file patents using their parent firms' name. The third limitation of this study comes from the matching procedure I choose. Since every control firm is matched with the treatment firm using "exact matching" strategy, meaning that the treatment and control observations should be in the same year and both companies are in the same industry, the number of treatment firms year that can find matched control firms years significantly decreased, meaning that it is harder to find matches, therefore the sample size of the study is decreased. However, except for the downside of this matching strategy, the good part of it is that it makes the treatment and control firm years to be as comparable as possible.

For future research, I will focus on the outcome of product differentiation and study the antecedents of product differentiation. This study answers the question of whether acquisition helps with product differentiation and when. In future study, I will get deeper into this "when" question and uncover the relationship between the characteristics of acquisition deals and the degree of product differentiation. Therefore future study will use M&A deal as the unit of analysis. Characteristics of deals to be explored include product market relatedness between acquirer and target, acquired intangible assets such as developed technology and in-processed R&D, degree of post-M&A integration, and environmental characteristics.

REFERENCES

REFERENCES

Aaker, D. A. (1996). Measuring brand equity across products and markets. *California Management Review*, 38(3), 103.

Agrawal, A., Jaffe, J. F., & Mandelker, G. N. (1992). The post-merger performance of acquiring firms: a re-examination of an anomaly. *The Journal of Finance*, *47*(4), 1605-1621.

Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, *22*(3), 197-220.

Andrade, G., Mitchell, M., & Stafford, E. (2001). New Evidence and Perspectives on Mergers. *Journal of Economic Perspectives*, *15*(2), 103-120.

Asquith, P. (1983). Merger bids, uncertainty, and stockholder returns. *Journal of Financial Economics*, *11*(1), 51-83.

Barney, J. B. (1986). Types of competition and the theory of strategy: Toward an integrative framework. *Academy of Management Review*, *11*(4), 791-800.

Barney, J. B. (1988). Returns to bidding firms in mergers and acquisitions: Reconsidering the relatedness hypothesis. *Strategic Management Journal*, *9*(S1), 71-78.

Bena, J., & Li, K. (2014). Corporate innovations and mergers and acquisitions. *The Journal of Finance*, *69*(5), 1923-1960.

Capron, L. (1999). The long-term performance of horizontal acquisitions. INSEAD.

Chamberlin, EH. 1933. *The Theory of Monopolistic Competition* (Harvard University Press: Cambridge).

Cloodt, M., Hagedoorn, J., & Van Kranenburg, H. (2006). Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries. *Research Policy*, *35*(5), 642-654.

Conner, K. R. (1991). A historical comparison of resource-based theory and five schools of thought within industrial organization economics: do we have a new theory of the firm? *Journal of Management*, *17*(1), 121-154.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56.

Finkelstein, S., & Haleblian, J. (2002). Understanding acquisition performance: The role of transfer effects. *Organization Science*, *13*(1), 36-47.

Haleblian, J., Devers, C. E., McNamara, G., Carpenter, M. A., & Davison, R. B. (2009). Taking stock of what we know about mergers and acquisitions: A review and research agenda. *Journal of Management*.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). *The NBER patent citation data file: Lessons, insights and methodological tools* (No. w8498). National Bureau of Economic Research.

Halpern, P. (1983). Corporate acquisitions: A theory of special cases? A review of event studies applied to acquisitions. *The Journal of Finance*, 297-317.

Harford, J. (2005). What drives merger waves? *Journal of Financial Economics*, *77*(3), 529-560.

Healy, P. M., Palepu, K. G., & Ruback, R. S. (1992). Does corporate performance improve after mergers? *Journal of Financial Economics*, *31*(2), 135-175.

Higgins, M. J., & Rodriguez, D. (2006). The outsourcing of R&D through acquisitions in the pharmaceutical industry. *Journal of Financial Economics*, *80*(2), 351-383.

Hitt, M. A., Hoskisson, R. E., Ireland, R. D., & Harrison, J. S. (1991). Effects of acquisitions on R&D inputs and outputs. *Academy of Management Journal*, *34*(3), 693-706.

Hoberg, G., & Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies*, *23*(10), 3773-3811.

Hoberg, G., Phillips, G. (2015). Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy*, Forthcoming

Hotelling, H. (1990). *Stability in competition* (pp. 50-63). Springer New York.

Jaffe, A. B. (1986). *Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value* (No. w1815). National Bureau of Economic Research.

Jarrell, G. A., & Poulsen, A. B. (1989). The returns to acquiring firms in tender offers: Evidence from three decades. *Financial Management*, 12-19.

Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of Finance*, *23*(2), 389-416.

Jensen, M. C., & Ruback, R. S. (1983). The market for corporate control: The scientific evidence. *Journal of Financial Economics*, *11*(1), 5-50.

Kapoor, R., & Lim, K. (2007). The impact of acquisitions on the productivity of inventors at semiconductor firms: A synthesis of knowledge-based and incentive-based perspectives. *Academy of Management Journal*, *50*(5), 1133-1155.

King, D. R., Slotegraaf, R. J., & Kesner, I. (2008). Performance implications of firm resource interactions in the acquisition of R&D-intensive firms. *Organization Science*, *19*(2), 327-340.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2012). *Technological innovation, resource allocation, and growth* (No. w17769). *National Bureau of Economic Research*.

Lamont, B. T., & Anderson, C. R. (1985). Mode of corporate diversification and economic performance. *Academy of Management Journal*, *28*(4), 926-934.

Lang, L. H., Stulz, R., & Walkling, R. A. (1989). Managerial performance, Tobin's Q, and the gains from successful tender offers. *Journal of Financial Economics*, *24*(1), 137-154.

Langetieg, T. C. (1978). An application of a three-factor performance index to measure stockholder gains from merger. *Journal of Financial Economics*, *6*(4), 365-383.

Larsson, R., & Finkelstein, S. (1999). Integrating strategic, organizational, and human resource perspectives on mergers and acquisitions: A case survey of synergy realization. *Organization Science*, *10*(1), 1-26.

Li, X. (2013). Productivity, restructuring, and the gains from takeovers. *Journal of Financial Economics*, *109*(1), 250-271.

Loughran, T., & Vijh, A. M. (1997). Do long-term shareholders benefit from corporate acquisitions? *The Journal of Finance*, 1765-1790.

Magenheim, E. B., & Mueller, D. C. (1988). Are acquiring firm shareholders better off after an acquisition. *Knights, raiders and targets*, 171-193.

Makri, M., Hitt, M. A., & Lane, P. J. (2010). Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. *Strategic Management Journal*, *31*(6), 602-628.

Malatesta, P. H. (1983). The wealth effect of merger activity and the objective functions of merging firms. *Journal of Financial Economics*, *11*(1), 155-181.

Masulis, R. W., Wang, C., & Xie, F. (2007). Corporate governance and acquirer returns. *The Journal of Finance*, *62*(4), 1851-1889.

Mitchell, M. L., & Stafford, E. (2000). Managerial decisions and long-term stock price performance*. *The Journal of Business*, *73*(3), 287-329.

Moeller, S. B., Schlingemann, F. P., & Stulz, R. M. (2004). Firm size and the gains from acquisitions. *Journal of Financial Economics*, *73*(2), 201-228.

Montgomery, C., & Singh, H. (1987). Corporate acquisition strategies and economic performance. *Strategic Management Journal*, *8*(4), 377-386.

Ornaghi, C. (2009). Mergers and innovation in big pharma. *International Journal of Industrial Organization*, *27*(1), 70-79.

Penrose, E. T. (1959). The Theory of the Growth of the Firm. *Great Britain: Basil Blackwell and Mott Ltd.*

Puranam, P., Singh, H., & Zollo, M. (2006). Organizing for innovation: Managing the coordination-autonomy dilemma in technology acquisitions. *Academy of Management Journal*, *49*(2), 263-280.

Ramaswamy, K. (1997). The performance impact of strategic similarity in horizontal mergers: evidence from the US banking industry. *Academy of Management Journal*, *40*(3), 697-715.

Rau, P. R., & Vermaelen, T. (1998). Glamour, value and the post-acquisition performance of acquiring firms. *Journal of Financial Economics*, *49*(2), 223-253.

Ravenscraft, D. J., & Scherer, F. M. (1987). Life after takeover. *The Journal of Industrial Economics*, 147-156.

Ravenscraft, D. J., & Scherer, F. M. (1989). The profitability of mergers. *International Journal of Industrial Organization*, *7*(1), 101-116.

Ransbotham, S., & Mitra, S. (2010). Target age and the acquisition of innovation in high-technology industries. *Management Science*, *56*(11), 2076-2093.

Rhodes-Kropf, M. A. T. T. H. E. W., & Robinson, D. T. (2008). The market for mergers and the boundaries of the firm. *The Journal of Finance*, *63*(3), 1169-1211.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, *39*(1), 33-38.

Rubin, P. H. (1973). The expansion of firms. *The Journal of Political Economy*, 936-949.

Seru, A. (2014). Firm boundaries matter: Evidence from conglomerates and R&D activity. *Journal of Financial Economics*, *111*(2), 381-405.

Servaes, H. (1991). Tobin's Q and the Gains from Takeovers. *The Journal of Finance*, *46*(1), 409-419.

Seth, A. (1990). Sources of value creation in acquisitions: an empirical investigation. *Strategic Management Journal*, *11*(6), 431-446.

Shocker, A. D., Srivastava, R. K., & Ruekert, R. W. (1994). Challenges and opportunities facing brand management: An introduction to the special issue. *Journal of Marketing Research*, 149-158.

Shleifer, A., & Vishny, R. W. (2003). Stock market driven acquisitions. *Journal of Financial Economics*, *70*(3), 295-311.

Srivastava, R. K., Shervani, T. A., & Fahey, L. (1998). Market-based assets and shareholder value: a framework for analysis. *The Journal of Marketing*, 2-18.

Tukey, J. W. (1962). The future of data analysis. *The Annals of Mathematical Statistics*, 1-67.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, *5*(2), 171-180.

Yim, S. (2013). The acquisitiveness of youth: CEO age and acquisition behavior. *Journal of Financial Economics*, *108*(1), 250-273.

Zhao, X. (2009). Technological innovation and acquisitions. *Management Science*, *55*(7), 1170-118