ABSTRACT

Title of Document:	Enemies at the Gate? Essays on New Entry Threats in the U.S. Information Technology Industry
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The Information Technology industry is characterized by constant technological changes, fast clock speed, and hypercompetitive markets. A significant part of this fast-moving dynamic is fed by the high rate of new entry in the form of entrepreneurial ventures. In recent decade, digital platforms accelerate these threats from startups by providing financial and marketing resources. While these developments have led to a significant increase in new entry threats faced by incumbent firms, there is little empirical research that has addressed the consequences of these threats on incumbents. This dissertation aims to fill this gap in the literature. In the first essay, I develop and validate an innovative measure of new entry threat. Then, I show that in the presence of new entry threat, firms tend to reduce their investments in innovation systematically. Further, firms that have a diversified product or technology portfolio, operate in industries with strong network effects, or face high levels of technological cumulativeness invest relatively more in R&D when facing greater new entry threats. The second essay focuses on the impact of new entry threat on the operational performance of firms in the IT industry, and studies how features of the incumbents' board may help moderate the effects of new entry threat. I provide strong empirical evidence for the theoretical predication of the negative relationship between new entry threats and firm performance. I also show that facing high NET, firms with more independent directors are better able to withstand these threats. In the third essay, I examine the influence of new entry threats on the incumbent's information disclosure in the IT industry. I find evidence consistent with theoretical prediction that high new entry threats faced by the firm indeed leads to a decrease in the incumbent's information disclosure. Interestingly, I also find the effect is less pronounced in highly concentrated sub-industries, where actual entry barriers are higher, and more pronounced in the software and services sectors, where proprietary information is more vulnerable. Overall, the three essays contribute to the literature by first creating and validating a measure of new entry threats and linking this measure to specific firm-related strategic decisions within the IT industry.

ENEMIES AT THE GATE: ESSAYS ON NEW ENTRY THREATS IN THE U.S. INFORMATION TECHNOLOGY INDUSTRY

By

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Introduction to Dissertation

"Silicon Valley is coming. There are hundreds of startups with a lot of brains and money working on various alternatives to traditional banking. … We are going to work hard to make our services as seamless and competitive as theirs. And we also are completely comfortable with partnering where it makes sense."

- Jamie Dimon,
Chairman and Chief Executive Officer
JP Morgan Chase

In recent decade, incumbent firms have been increasingly realizing the threats from new entries, especially from technology entrepreneurial startups. The concept of threat of new entry is raised by Porter (1979) as a disruptive force that constantly challenges incumbents within an industry. New entry threat (hereafter, NET) has become particularly salient in recent years where the pace of digital innovations is altering the nature of competition even in traditional industries. New ventures such as Uber, Airbnb, and Snapchat are increasingly leveraging social media, business analytics, mobile channels and cloud platforms to disrupt traditional business models by dramatically reducing costs, improving efficiency, creating personalized experiences, and offering great product variety. In addition, recent developments in crowdfunding platforms and alternative funding models have further lowered barriers to entry within the high-tech industry, making it easier for new ventures to jump-start the process of growth and resource acquisition (Aggarwal et al. 2013; Kim et al. 2014) via channels beyond the model of venture capital funding (Aggarwal et al. 2015; Kim et al. 2016).

The impact of new entry threats is particularly keenly felt within the IT industry. A significant component of this fast-moving dynamic in the IT industry is the high rate of new entry in the form of entrepreneurial ventures (McAfee et al. 2008); technology startups are constantly introducing new products to the market and transforming existing business models (Giarratana 2004). Indeed, over 70% of all venture-capital funded startups tend to be associated with the IT industry (Gompers et al. 2001). The presence of intense entrepreneurial activity in the product market of an IT incumbent firm can cause significant turbulence – entrepreneurs incorporating new and innovative technologies, backed by influential venture capitalists, to compete with incumbents for resources on the supply side and for customers on the demand side. Inasmuch as new entry threats contribute to the uncertainty of an IT firm's future income and profitability, strategic managerial decisions must account for their influences. My dissertation addresses this relatively under-studied aspect of how NET shape IT incumbent's strategic decisions. I aim to bridge this gap in the literature by first quantifying NET from technology entrepreneurial startups, and then empirically investigating its impacts on incumbents in the IT sectors.

In the first study, I start with constructing and validating a measure of NET based on product descriptions of startups and incumbents through text-mining techniques. I capture NET faced by the incumbent firm by comparing the overlap in words in the incumbent's product description and the aggregated product descriptions, representing macro-level entrepreneurial activity, from all startups that receive first-round venture capital funding in a specific year. Conceptually, this is akin to examining how similar the incumbent's product market description is to the overall movement within the entrepreneurial ecosystem. Effectively, this captures the *threat* of new entry, rather than diversifying entry (entry from incumbents) and contemporaneous competition. In order to establish the validity of this measure, I perform a series of tests. First, I examine whether the text-based approach accounts for technology trends shifting within the startup space as reflected in the "hottest" words used in product descriptions of new entrant firms across years in the sample. Second, I test whether a firm's NET is associated with the changes in its competitive landscape, such as number of close competitors (Hoberg et al. 2016), in the following years. Third, I contrast firms with high NET values and those with low NET values to investigate the likelihood of experiencing turbulent events, such as filing bankruptcy, announcing significant downsizing or layoffs, or being acquired or merged by other companies in the five years following the measurement of NET. Fourth, I validate NET by showing the sudden increase (or decrease) in industry-level demand because exogenous event disrupts the relationship between supply and demand, and therefore encourages (or discourages) entry.

Having validated the measure of NET appropriately, in my first essay, I also study the R&D investment strategies of IT firms when they face new entry threats, using the theoretical lens of real options. Using a sample of U.S. IT firms over the period 1997-2013, I show that incumbent firms on average reduce R&D spending when facing greater new entry threats. More importantly, I show that the effect is not uniform – consistent with real options theory, firms that have a diversified product or technology portfolio, operate in industries with strong network effects, or face high levels of technological cumulativeness invest relatively more in R&D when facing greater new entry threats.

In the second study, building on the foundation of the novel measure that I constructed in essay one, I empirically study whether NET leads to performance deterioration of the incumbents in the high-tech industries. I argue that the threats from startups are likely to lead to performance deterioration for the incumbents in both product and labor markets, due to NET-induced dynamic environment and high volatility. Further, I argue that firms are different in their abilities of recognizing the dynamics in their competitive environment, the speed and effectiveness with which they respond to new entry threats, and therefore the likelihood of surviving disruptions caused by new entries. One significant resource that firms may draw upon in order to respond appropriately to NET arises from the valuable monitoring and advising capabilities that come with the incumbent's *independent board* of directors (Hillman et al. 2000). Thus, I hypothesize *board independence* helps mitigate the negative impact of NET from two perspectives – internal monitoring and external resources provisioning. First, independent and external members of the board are instrumental in providing resources and expertise that is hard to substitute within the firm (Pfeffer et al. 2003). Second, the role of governance and oversight is more likely with independent board members rather than those that are associated with the firm (Hermalin 2005). Consistent with the theoretical perdition, I find that a higher level of NET indeed leads to a drop in the incumbent's performance. I also show that facing high NET, firms with more independent directors are better able to withstand these threats. To address the endogeneity issues associated with board independence, I use the enactment of the Sarbanes-Oxley Act and related changes to the NYSE/NASDAQ listing rules as exogenous shocks to create instruments, and the results are robust to the instrumental variable regressions.

In the third study, I examine the influence of new entry threats on the incumbent's information disclosure in the information technology (IT) industry. I argue that firms facing high new entry threats, which also enhance the likelihood of future competition as well as the potential for technological spillover effects from the incumbents, are more likely to withhold proprietary information from public. I empirically show that higher new entry threats faced by the firm indeed leads to a decrease in the incumbent's information disclosure. Interestingly, I also find evidence showing the effect is less pronounced in highly concentrated sub-industries, where actual entry barriers are higher, therefore incumbent firms operating in high concentrated industries are more likely to be inertia on the response of new entry threats. Furthermore, this effect is more pronounced in the software and services sectors relative to hardware sectors, since proprietary information in the former is more vulnerable to misappropriation. In sum, these findings significantly augment the extant work on firms' disclosure decision-making facing new entry threats by exploring the underlying mechanism of proprietary information disclosure. Moreover, this work has implications for investors and stake-holders, and broader concerns for policy-makers interested in well-functioning financial markets and entrepreneurial ecosystems.

Overall, this dissertation is motivated by the need to extend theoretical and practical understanding of the effects of the substantial increase in new entry threats from technology entrepreneurial ventures firms on strategic decision making in the digital age. While prior research has suffered from lacking appropriate way to quantify the threats from new entry, a key contribution of my work is providing a systematic and validated measure for new entry threats from the startup ecosystem for incumbent firms, so that further testing and validation of the measure can be carried out at broader strategy and entrepreneurship community. The availability of a standard measure will help benchmark across models and theories. By examining the responses of incumbents when facing high new entry threats from three strategic perspectives, R&D investment, operational performance, and information disclosure, I am able not only to examine the follow up response which decision maker must take when reacting to new entry threats, but also test various boundary conditions to delve into the underlying mechanisms suggested by theory. The dissertation offers novel insights into the relationship between new entry threats and incumbent firms' strategic decision making, provides the foundation for future work on new entry threats, and opens plenty of opportunities for further work on studying important topics on impacts of the competitive dynamics from startups.

Essay 1: New Entry Threats and R&D Investments in the U.S. IT Industry

Abstract

The threat of new entry by startups has often been argued to influence the decisions made by incumbent firms, especially in the fast-moving information technology (IT) industry. However, empirical analysis of this relationship is limited in the literature, largely due to the absence of a reasonable measure of new entry threats. In this work, we make two contributions to this literature. First, we develop and validate a measure of these threats through text mining, using product descriptions provided by incumbent firm 10-K filings and business descriptions provided by start-ups. This novel measure of NET differs significantly from observed entry which is backward-looking and from competition, which is contemporaneous. Second, we study the R&D investment strategies of IT firms when they face new entry threats, using the theoretical lens of real options. Using a sample of U.S. IT firms over the period 1997-2013, we show that incumbent firms on average reduce R&D spending when facing greater new entry threats. More importantly, we show that the effect is not uniform – consistent with real options theory, firms that have a diversified product or technology portfolio, operate in industries with strong network effects, or face high levels of technological cumulativeness invest relatively more in R&D when facing greater new entry threats. We discuss the implications for research and practice.

Keywords: *new entry threats, text mining, R&D investment, uncertainty, real options, innovation, disruptive technology*

1.1 Introduction

The Information Technology (IT) industry has played a central and critical role in driving economic growth over the last two decades, especially in the United States (Jorgenson et al. 1999; Jorgenson et al. 2000). This contribution to economic growth is partly a product of the constant technological changes and fast clockspeed (Fine 1998) that define the industry. The rate of change in the industry's external environment, including the development of new technologies, shifts in consumer preferences, and fast-moving market dynamics far exceeds those seen in other industries (Brynjolfsson et al. 2011; Mendelson et al. 1999). The result is a shorter product life-cycle (Mendelson et al. 1998), volatility in the market structure marked by high levels of uncertainty, and a hyper-competitive context where advantages, if any, tend to be short-lived (Wiggins et al. 2005). In such contexts, the ability to navigate uncertainty and respond to the changing environment becomes a key driver of a firm's competitive advantages.

A significant component of this fast-moving dynamic in the IT industry is the high rate of new entry in the form of entrepreneurial ventures; technology startups are constantly introducing new products to the market and transforming existing business models (Giarratana 2004). Indeed, over 70% of all venture-capital funded startups tend to be associated with the IT industry (Gompers et al. 2001). The presence of intense entrepreneurial activity in the product market of an incumbent firm can cause significant turbulence – entrepreneurs incorporating new and innovative technologies, backed by influential venture capitalists, compete with incumbents for resources on the supply side and for customers on the demand side. Inasmuch as new entry threats contribute to the uncertainty of a firm's future income and profitability, managerial decisions involving risky yet important capital investments, such as those in R&D and innovation, must account for their influences. The importance of R&D investments by the firm, as an input to the innovation process and a key enabler of competitive advantage within the IT industry (Sambamurthy et al. 2003) has been highlighted within the extant IS literature (King et al. 1994). However, there is a conspicuous gap in the literature in terms of understanding how critical decisions about R&D spending are affected by the perception of new entry threat emerging from entrepreneurs. This is the specific research question we address in this paper: *to what extent is R&D spending of the incumbent IT firm affected by new entry threats? Moreover, are there unique contextual factors relating to IT firms or IT industry subclasses that may moderate these effects?*

A large part of the difficulty in addressing this question empirically relates to the difficulty of measuring new entry threats emerging from the entrepreneurial ecosystem. By definition, threats from entrepreneurial startups represent *forward-looking* estimations of the extent to which the potential entry of new competition may influence cash flows or product market performance; therefore, these threats have not manifested as yet but may materialize at some point in the future. In addition, threats from new entry often embody systematic shifts in the technological landscape and changes in the assumptions and routines upon which the incumbents operate. However, it is unclear if all such perceived shifts in the technological landscape do indeed lead to realized transformations of incumbents' markets. Therefore, the challenge lies in the ability to measure these dynamics in an effective and theoretically rigorous manner.

It is tempting to adopt measures of entry that have been used in the literature as a starting point. However, the threat of new entry, as we explain in details later, differs markedly from *actual entry* (Aghion et al. 2009; Becker-Blease 2011), as well as *contemporaneous competition*, which captures the existing pressures on incumbents through the use of measures built around industry classification systems such as the NAICS and SIC (Aghion et al. 1992; Becker-Blease 2011). From a methodological perspective, extrapolating from measures of (contemporaneous) market competition or realized entry into industry subclasses in order to measure new entry threat is problematic for several reasons. First, measuring how incumbents are potentially affected by entrepreneurial entry into their industries would require that an analog of the SIC / NAICS codes exist for new ventures, so that the appropriate threats are matched to the right industry segment. Unfortunately, no such coding scheme exists for startups. Second, entrepreneurial new ventures, by definition, tend to bend or straddle multiple existing classifications (Sarasvathy 2001), making their association with a specific industry subclass ambiguous. Fundamentally, the use of static SIC and NAICS codes themselves in fast-moving industry contexts is limiting. Firms, once associated with a specific subclass, are rarely reclassified even when they diversify or transition into different industries. Moreover, these measures lack temporal variation both within industries and across industries, rendering them somewhat inaccurate for the measurement of new entry threats, which crucially relates to varying effects across firms within the same industry as well as over time. Thus, notwithstanding the importance of new entry threat in theoretical analyses (Spence 1977), the absence of an established measure represents a significant gap in the literature.

In this paper, we address this challenge by developing and validating, for the purposes of our empirical testing, a new measure of new entry threat. While we formally define the new entry threat (NET) measurement later in the paper, intuitively we measure the extent to which an incumbent firm's description of its product markets in its 10-K filings overlaps with the business descriptions of new entrepreneurial firms that receive first-stage funding from venture capitalists (VCs) during the same period. In order to capture the extent of potential *de novo* entry, we extract business descriptions of startups receiving first round VC funding from VentureXpert. The focus on very early-stage startups is particularly appropriate here since these firms collectively represent movement in the incumbent firm's product space towards possible future competition. At the same time, most of the early stage startups are still in a proof-of-concept phase in developing their product/service prototypes, and therefore are still years away from becoming realized entry. The fact that they were funded by VCs makes these threats relevant and credible because these entrepreneurs are likely to be innovative, thereby representing a higher likelihood of becoming a realized threat to incumbents in the near future. Beyond the development of this measure, we also conduct a series of tests to validate the measure, establishing that variation in the measure does indeed relate to increased competition as well as lower profitability in the future. We also show that firms facing high new entry threat are likely to experience greater turbulence in the form of layoffs and bankruptcies in the future, dynamics consistent with prior theory (Becker-Blease 2011).

Having established the validity of the measure, we address the central research questions – how does new entry threat faced by incumbents in the IT industry affect firm-level investments in R&D? In order to answer this question, we use the theoretical lens of real options, a recognized framework for modeling investments under uncertainty (Dixit and Pindyck 1994). Within the IT context, where a significant proportion of new entry emerges from VC-funded startups (Gompers et al. 2001), firms can use their R&D investments as a strategic tool in respond to these threats. However, R&D spending is risky, since it is not clear if these investments will first, result in positive outcome and second, succeed in creating new products or services that will withstand the test of the market. Thus, the real options reasoning approach is particularly applicable here in examining firm decision making (Huchzermeier et al. 2001).

In addition to uncertainty about their future payoffs, R&D investments are often subject to imperfect reversibility (i.e. money invested cannot be fully recovered upon disinvestment) and costly expandability (i.e. making the same investment in the future is more difficult). Particularly, if acquiring the same R&D capital in the future is as easy as in the current period, the firm benefits from the ability to defer investments in R&D until the uncertainty is lifted, leading to a higher *call* option value (Abel et al. 1996). Alternatively, if disinvestment is costless – or the investment is highly reversible (Abel et al. 1996) – the firm may benefit from investing in R&D immediately, since by investing the firm acquires a *put* option to resell the assets in the event of disinvestment. The firm's decision to invest in R&D is therefore driven by the net values of the *put* and *call* options, and by contextual factors that, on the margin, drive the reversibility and expandability of the underlying investments. Using this reasoning, we examine the impact of a set of firm and industry characteristics specific to the IT industry as boundary conditions that influence the relative values of the call/put options, and therefore the relationship between NET and the incumbents' R&D investments. We test these predictions using panel data methods on firms in the U.S. IT industry over the period of 1997-2013. We find that incumbent firms, on average, reduce their R&D investments when they face high NET. More importantly, consistent with real options reasoning (Gunther McGrath et al. 2004), we show that IT firms that have a diversified product or technology portfolio, operate in an industry with strong network effects, or face high levels of technological cumulativeness, tend to respond to high NET by investing *more* in R&D than their counterparties.

Our work provides several contributions to the Information Systems (IS) literature. First, we help deepen the understanding of IT firms' R&D investment decisions when facing fast-changing environments, particularly when these changes emerge from the entrepreneurial space. The rapid rate of technological change observed in IT and the associated volatility in product markets (Brynjolfsson et al. 2011) necessitates a deeper evaluation of how incumbent firms respond to such threats. In addition, a societal focus on innovation-related IT entrepreneurship and the development of entrepreneurial ecosystems (e.g., in the forms of incubators and accelerators) have radically improved the abilities of new ventures to threaten incumbent firms. In these contexts, it is important to understand how new entry threat may be accurately measured, and to understand how incumbents react to these threats. Our work here directly contributes to these gaps in the literature. The implications of our work extent beyond understanding the impact of new entry threats on R&D investments, to also evaluating how these responses may vary depending on a set of boundary conditions that are particularly salient in the IT industry. We thus contribute to the broader literature on how IT-related elements interact with R&D investments (Bardhan et al. 2013) in a significant manner.

Second, we advance the literature of applying real options reasoning in the understanding of IS phenomena. Prior IS research has adopted this framework in investigating IT platform adoption (Fichman 2004), IT project evaluation and risk analyses (Benaroch 2002; Benaroch et al. 1999), and the degree of consistency between managerial intuition and prescriptions (Lankton et al. 2008). While most of these studies model IT investments as generating various types of real options, few have systematically investigated how firm and industry characteristics that are specific to the IT industries – such as technology diversification, network effects, and technological cumulativeness – alter managerial decision making by changing the relative value of the different types of real options. Our study provides a richer theoretical conceptualization in the application of real options reasoning in IS research.

Beyond the theoretical implications, we also contribute by devising and validating a new way of measuring new entry threat from entrepreneurial ventures using text analysis, whose potential domains of application extend beyond the IS field. We build on work in finance and marketing that has used text analysis to construct measurement schemes that are then applied to studying competitive dynamics (Hoberg et al. 2010; Tetlock et al. 2008). Our measure of new entry threat is particularly suitable for capturing emerging threats from the collective entrepreneurial space, rather than focusing on single entrepreneurs that are easy to ignore or discount. The use of such a measure thus represents considerable value in analyzing fast-moving technology contexts, such as the IT industry. We believe that many empirical questions in the literature relating to new entry threats and competitive dynamics can be addressed through the usage of the measure we provide.

1.2 Theoretical Background

1.2.1 New Entry Threats

All firms face *product market threats*, defined as sources of instability and uncertainty in a firm's product market, which threaten the sustainability of the firm's future earnings as well as the viability of its current product portfolio (Hoberg et al. 2014). These threats are particularly pronounced and influential in the IT industry (Fontana et al. 2009), where firm survival is often in question as a result of these competitive dynamics. Within the domain of product market threats, we distinguish *new entry threats* specifically from two other forms of threats, namely *contemporaneous* *competition* and *observed (actual) entry*. We argue that there is considerable depth in the academic literature in addressing the latter two constructs while new entry threat *per se* has been relatively understudied.

This gap in the literature is not trivial, especially in fast-moving industry contexts, given that NET has been viewed as an important theoretical construct since the early days of industrial organization economics (Porter 2008). There are several critical differences between *new entry threats*, and the more frequently studied constructs of *contemporaneous competition* and *observed entry*. First, contemporaneous competition is usually measured by temporally concomitant market outcomes, such as market share/concentration (Blundell et al. 1999) or Lerner Index (Aghion 2003), while new entry threats are, by definition, forward-looking since they imperil the "stability and sustainability of future earnings" (Brav et al. 2005). Therefore, there are industries, such as the airline industry, that are characterized by high levels of competition – with large numbers of competitors and low profit margin – but relatively low threats of new entry. In addition, while competition describes equilibrium market outcomes, new entry threat is inherently about disequilibrium, which often leads to changes in competitive dynamics (Cockburn et al. 2011) and creative destruction (Aghion et al. 1992). New entry threat is also different from observed entry, which is measured by the extent to which a new competitor is viewed to emerge in the same marketplace (in the current time-frame), as opposed to the *threat* of entry in the future. From a technology lifecycle standpoint, a high level of NET is associated with the *introduction* stage of a technology's development when fundamental scientific or technological problems need to be solved; in contrast, a high level of observed entry is associated with the *growth* stage in the technology lifecycle when a broad range of market applications based on the technology has been developed and uncertainty about the technology is reduced (Haupt et al. 2007). Furthermore, observed entry is deterministic, in that there is no uncertainty about the actual entry process. In contrast, new entry threat is, by definition, uncertain since not all threats materialize (Goolsbee and Syverson 2008). Thus, new entry threat refers to the probabilistic perception of future entry, as opposed to deterministic observed entry (Hoberg et al. 2014).

Second, given the probabilistic nature of new entry threats, the potential impact of this construct is far more difficult to gauge, relative to observed entry or contemporaneous competition (Goolsbee and Syverson 2008). In the IT context, new entry threats emerge significantly from the startup space (Gompers and Lerner 2001); however, most startups tend to be in the early stage of experimenting with product prototypes and business models, lack a customer base, have lower visibility, and are not fully sustainable at this stage (Sarasvathy 2001). Therefore, a clear evaluation of their long-term ability to enter the incumbent firm's market is difficult. However, due to their innovativeness, if and when these threats do materialize, the new products or services introduced by the entrepreneurial firms may significantly reduce costs, improve efficiency, or create better customer experience (Gompers and Lerner 2001). In some cases, radically innovative solutions by startups may completely alter the assumptions and routines upon which incumbent firms built their business models. More to the point, the conceptualization of new entry threat is distinct from observed entry and contemporaneous competition, in that the locus of the threat is located much earlier in time and its potential adverse effects are far-reaching.

The ability to threaten future earnings, especially in the IT sector, is closely linked to technological changes and product innovation (Coad et al. 2008), thereby making prior work in industry lifecycles of particular relevance (Abernathy et al. 1978). Industry lifecycles describe the processes that unfold in technologically progressive industries as they evolve from birth to maturity (Klepper 1996). In general, when new industries form, there is considerable new entry into the field, firms offer many varieties of similar products, prices are typically high and there is a high level of product innovation that occurs within the nascent industry (Jovanovic et al. 1994; Klepper 1996). Over time, despite steady market growth, new entry into the field ceases, prices drop and there is a shakeout in the number of firms. At this stage, a dominant design emerges in the industry (Jovanovic et al. 1994) and incumbent firms shift to process innovations that improve upon the dominant design, leading again to increased competition in the industry. Thus, industry lifecycles are characterized by successive waves of product and process innovations that introduce high volatility within the technology industry.

New entry threats are particularly salient in the IT sector for a number of reasons. *First*, unlike many other industries, such as retail (Thomas 1999), hotel (McCann et al. 2010) or airline industries (Goolsbee et al. 2008) where the predominant entry mode is lateral, diversifying entry by mature competitors or foreign companies, firms in the IT industry constantly face *de novo* entry from startup firms. As a result, IT firms may employ a different set of strategic variables in response to entry threats than those typically employed in other industries, such as pricing, capacity, product market expansion/contraction, or advertising, which are effective in combating *de alio* entry. Within the IT sector, one of the key strategic responses to new entry threat is innovation (Sambamurthy et al. 2003; Kim et al. 2016), since new entrants typically tend to lead the attack on incumbents with new and innovative products and services. *Second*, prior work in technology-based industries has indicated that in fast-moving contexts, there is likely little separation between periods of product and process innovation (Klepper et al. 1993). Effectively, product and process innovations emerge concurrently from different players in the industry, thereby generating considerable product market threats from new venture firms (Abernathy et al. 1978). Evidence indicates that the pace at which industry lifecycles emerge and stabilize, even briefly, in the last two decades has increased in the IT industry (Carrillo 2005; Fine 1998; Mendelson et al. 1998). As industry clockspeed quickens, there is thus systematically an enhanced threat of new entry for incumbents.

High levels of new entry threat create significant uncertainties over the stability of an incumbent firm’s future earnings, which has important implications for capital investment decisions. Among these decisions, “the analysis of R&D investments is surely one of the most difficult problems of investment under uncertainty” (Schwartz et al. 2000). However, the relationship between new entry threats, measured at the level of the firm, and R&D spending, representing a critical strategic response within the IT sector, has not been studied in the IS or innovation literature. We address this specific gap in the literature. In the next section, we present the theoretical framework of analyzing investments under uncertainty from a real options lens (Dixit et al. 1994), with a particular focus on R&D investments because they are highly irreversible (Pindyck 1991) and sensitive to the threat of new entry in the IT industry. Building on this framework, we then propose hypotheses that pertain to a set of important and relevant boundary conditions moderating the relationship between NET and R&D spending.

1.2.2 A Real Options View of R&D Investments under Uncertainty

When firms operate under uncertain environments, such as those brought by heightened new entry threats, the firm can choose to invest into R&D or withhold such spending until uncertainty is reduced. In this context, there are two sources of uncertainty that the firm has to address. First, there is uncertainty on whether the new entry threat is viable and will result in observed entry in later years. Second, there is residual uncertainty on whether investments in R&D will actually result in the introduction of new products and services, which may be decomposed into technological uncertainty (the future viability of the technology being introduced) and operational uncertainty (budgeting, schedule, personnel, product performance) (McGrath and Nerkar 2004; Huchzermeier and Loch 2001). Prior work also argues that decisions on R&D face uncertainty about future demand for the firm's products, representing market uncertainty (Oriani and Sobrero 2008); in our context, many of these uncertainties are partly associated with new entry threats as well, since these threats can, on materializing, affect future demand for the incumbent's products. As a result of these factors, the future returns from R&D are stochastic, which render a naïve net present value (NPV) analysis inadequate (Dixit and Pindyck 2004). When viewed through real options reasoning, therefore, investment decisions in R&D in the current period must take into consideration (a) the ability to defer the investments in R&D, representing expandability, (b) the extent to which investments made in the current period are reversible.

More formally, Abel et al. (1996) argue that with the presence of uncertainty, capital investment decisions are associated with two forms of options: a *put* option, wherein investments made in the current period can be sold at a later date upon disinvestment, and a *call* option, where the investment can be deferred to a later period, to be acquired at a later time point when the uncertainty is lowered. The factors that affect the values of these two options are *reversibility* and *expandability* (Abel et al. 1996). Reversibility refers to the extent to which a given investment can be reclaimed, either in terms of reselling the acquired assets or through reversing the investments in part. Expandability captures the ability to make or expand on the investment in the future when uncertainty is lifted without paying a much higher price, thereby representing the attractiveness of investing in the asset in the future. Expandability thus addresses the implications of waiting to invest. Using a dynamic model set-up, Abel et al. (1996) argue that under costly expandability (when the future investments in the asset may be difficult or pricier) and costly reversibility (when the future resale price of the underlying capital asset may be lower than its current price), making the investment to acquire the asset creates a *put* option, namely the option to disinvest or sell the surplus asset in the future, and extinguishes a *call* option, i.e., the option to buy the asset in the future when uncertainty is reduced and the firm tries to adjust its capital asset stock to the optimal level. The optimality condition for capital investment in this model is determined by

$$N(K) = b - \gamma P'(K) + \gamma C'(K) \tag{1-1}$$

Where K is the amount of capital purchased, N is the naïve NPV of future incomes generated by the capital, b is the cost of capital, γ is the discount rate, $P'(.)$ is the *marginal put* option, and $C'(.)$ is the *marginal call* option.

The marginal value of the put option P' depends on the degree of *reversibility* of the underlying capital asset, such that higher reversibility of the investment makes the put option marginally more valuable, implying that the firm should acquire the asset quickly. In the extreme case where capital investment is sunk or completely irreversible, the put option has a zero value. Similarly, the marginal value of the call option *C'* depends on the degree of *expandability* of the capital investment, indicating the extent to which the investment can be deferred without paying a higher price in the future. Here again, if the capital investment is completely un-expandable, i.e. if the firm does not undertake the investment now, it will not be able to do so in the future, the call option has a zero value.

Depending on the twin factors of reversibility and expandability, the required threshold for the marginal return on the investment of the asset changes, thereby inducing the firm to choose the amount and timing of investment (Huchzermeier and Loch 2001). With the increased value of the put option, driven by greater reversibility, the required threshold for the marginal return is lower, leading to the decision to increase investment in the current period. In contrast, when the value of the call option increases, due to higher degree of expandability, the required threshold of return on the investment is higher, leading to lower investment in the asset in the current period and deferred investments. Therefore, the reversibility (put) option increases the incentive for current investment because the firm acquires this option by purchasing capital, and the expandability (call) option decreases the inventive for current investment because the firm acquires this option by delaying the investment (Czarnitzki et al. 2011).

While expandability and reversibility affect the propensity to invest or defer investment, we also need to consider the role of uncertainty, emerging from new entry threat, for instance. Abel et al. (1996) show that an increase in the level of uncertainty in future payoffs leads to an increase in the values of both the put option and the call options facing the firm, and has an ambiguous effect on the naïve NPV. Consistent with the literature, we treat R&D spending as a decision to invest capital into an asset under uncertainty (Huchzermeier and Loch 2001). Hence, the net relationship between uncertainty, such as those emerging from new entry threats, and R&D investment is unlikely to be monotonic, and may depend on idiosyncratic industry characteristics and the nature of the uncertainty (Czarnitzki et al. 2013; Oriani et al. 2008). Therefore, rather than modeling the direct effect of new entry threat on R&D investment, we use this stylized model to motivate a set of boundary conditions that relate a set of firm and industry-level characteristics to the *relative* shift in the marginal values of the put/call options. By arguing for these relative shifts in the values of these options, we can infer the effects of NET on the firm's R&D investments and thereby formulate hypotheses that can be empirically tested. We describe these hypotheses next.

1.2.3 Research Hypotheses

In this section, we propose hypotheses relating to the moderating effects of three sets of factors that are of particular relevance in the IT industry since the specific relationship between NET and R&D spending is likely to be idiosyncratic. To that end, we focus on the extent to which the IT incumbent is diversified in its technology and product portfolios, the role of network effects in the firm's product market, and extent to which the technological progress in the firm's industry is prone to cumulativeness.

Firm diversification

R&D investments are often described as highly irreversible, as a large part of the R&D spending is used to pay the salaries of research personnel that cannot be recouped at a later stage (Dixit et al. 1994). In addition, the purchased lab equipment and materials are usually project-specific or firm-specific, and therefore has little alternative use (Goel et al. 2001). As a result, the disinvestment of R&D outlays made by the firm at a later date is often subject to the familiar "lemons problem" (Pindyck 1991). However, we argue that these issues are likely to be less critical to firms that have diversified product lines or possess technological assets that are diversified in nature.

A diversified firm may have greater flexibility in terms of capacity utilization and the ability to extract synergies between seemingly disparate but related investments, including their R&D investments. In other words, the notion of alternative use of R&D resources (whether personnel, equipment, or facilities) reduces the extent to which R&D investments may be viewed as completely sunk or irreversible. For example, with concurrent, interrelated R&D projects, a firm with a diversified product portfolio has the flexibility to shift R&D personnel and equipment across projects within the boundary of the firm, in the face of changing market conditions (Czarnitzki et al. 2013). In addition, with a broader technology portfolio that includes knowledge assets in diverse domains, a firm may be able to reuse some of the intermediate outputs generated by earlier R&D investments in related technology areas, even when these earlier investments did not result in positive outcomes in their primary intended domains. Using real options reasoning, diversified firms are likely to face reduced irreversibility with respect to R&D investments. With reduced irreversibility, the higher marginal value of the put option drives a lower threshold for the marginal return on capital. This would lead to higher R&D investments in the current period when the firm faces high levels of new entry threats. Note that the combination of reversibility and NET does not affect the marginal value of the call option (Abel et al. 1996). Thus, the net effect of NET on diversified firms is likely to lead to greater R&D investments in the short term. Hence, we propose:

H1: Facing high levels of NET, a firm with a) a diversified product portfolio or b) a diversified technology portfolio is likely to invest more in R&D relative to specialized firms.

Network effects

Many IT product markets are associated with varying degrees of direct or indirect network externalities, where the utility a user derives from a product or service depends on the number of other users who are in the same network (Katz et al. 1985). In addition, multi-sided platforms that serve two or more different groups of customers who are subject to indirect network effects are common in the IT industries (Evans 2003). In industries with high network effects, there is a significant first-mover advantage, and being late to the game may foreclose the opportunity to invest or enter the marketplace in the future. In the extreme case, the presence of network effects may simply lock out late entrants (McGrath 1997).

From an real options perspective, firms operating in such markets face very costly expandability because the difficulty of acquiring the R&D capital and other necessary resources at a later stage, due to the winner-takes-all nature of competition (Weeds 2002). The cost of deferring investments, therefore, is very high. With a low level of expandability, the value of the call option is diminished, leading to a lower trigger threshold for marginal return of capital. The presence of network effects may also positively impact the put option, in the sense that if winner-takes-all dynamics exist in the marketplace, investing in appropriate R&D assets in the current time period is likely to generate higher resale value in the future. Therefore, a firm that operates in an industry with strong network effects is more likely to make higher, and earlier, R&D investments when it faces high levels of NET.

H2: Facing high levels of NET, a firm operating in an industry with strong network effects is likely to invest more in R&D relative to firms operating in industries with weak network effects.

Technological cumulativeness

Innovations in the IT industries often depend on technological cumulativeness, which is defined as "the degree of serial correlation among innovations and innovative activities" (Breschi et al. 1997). Cumulativeness represents the extent to which earlier innovations are needed for building the next generation of innovative products, thereby capturing an element of path dependence by which technology progresses sequentially. For example, prior research shows that in industries such as semiconductors and computers, technological advances often build on and interact with elements of existing technologies (Ham Ziedonis et al. 2001; Merges et al. 1990). In technological fields that display high level of cumulativeness, the success of R&D effort hinges on the relevant continuities with prior innovative activities. Firms that do not have control over earlier inventions and innovations are unlikely to be able to exploit subsequent ones (Green et al. 1995), which may be the result of a failure to develop relevant absorptive capacity (Cohen et al. 1990), or simply being locked out of the market (Hill et al. 2003).

The lock-out effect associated with high technological cumulativeness is likely to influence the decision of R&D investments under uncertainty because it is important for a firm to secure a foothold of the relevant technological competence in the early stage of the technology's lifecycle (Oriani et al. 2008). From a real options perspective, the value of the call option (or the option to delay) is dramatically reduced when subsequent innovations need to be built on earlier ones and undertaking the same investment in the future is more expensive. Additionally, prior research notes that high level of technological cumulativeness is often associated with high appropriability of innovations (Breschi et al. 1997), which further reduces the option value of delaying the investments due to the lack of spillover benefits. Technology cumulativeness is also likely to influence the put option positively, since even if the investments are partially irreversible, the purchased assets are likely to be of greater resale value in the future because of the ability to lock out competition. Therefore, we hypothesize:

H3: Facing high levels of NET, a firm operating in a field with high technological cumulativeness is likely to invest more in R&D relative to firms operating in fields with low technological cumulativeness.

Note that we have explicitly chosen to not provide a direct effect hypothesis of NET on the extent of R&D investments, since this equilibrium behavior depends on the relative marginal values of the call and put options, as well as the NPV of the investment, in relation to uncertainty as discussed above. The presence of NET is typically an off-equilibrium event, given technology lifecycles in specific industries. Therefore it appears more reasonable to provide formal hypotheses for boundary conditions that explain how firm responses are moderated by industry-level factors. The analysis we describe next will allow us to examine the direct effect of NET as well, providing guidance on the direct effect of NET. We start by describing, in the next section, the development of a new text-based measure for new entry threats.

1.3 A Text-Based Measure of New Entry Threats

As discussed above, an empirical measurement of new entry threat has remained elusive in the innovation literature, given the forward-looking nature of this construct. Most existing work has used current competitive intensity or observed (actual) entry to account for these effects (Aghion et al. 2009; Chen et al. 1992) but these are approximations at best and do not address the construct as discussed in earlier theoretical works (Caves et al. 1977; Porter 2008b). When facing *de novo* entry, the challenge for the incumbent is to spot the disruptive entrepreneurial firms that constitute such a threat early on and respond adequately (Rigby et al. 2002). Although spotting the specific disruptor is imprecise and uncertain (Markides 2006), broad movements within the entrepreneurial space into markets that intersect with the incumbent's product markets can still be recognized as significant threats. In other words, while an incumbent may not observe a specific startup with a particular product innovation, it will surely observe and respond to shifts across the *larger entrepreneurial landscape* into certain specific markets or technologies. Prior work studying technology fads/cascades has discussed these broader trends as being significant predictors of firm and individual behavior (Abrahamson 1991; Bikhchandani et al. 1998). We argue that such large-scale new venture formation within a certain product market is a valid representative of new entry threat, leading potentially to impending competition in the future. New techniques using text analysis may be used to measure such threats in a novel manner. We utilize these options to construct measures for new entry threats emerging from startups, described in the remainder of this section.

1.3.1 Methodology: From Words to New Entry Threats

The use of text analysis requires reasonably descriptive text corpora from firms in order to construct appropriate measures. A considerable body of work has used firm public filings provided by the firms, specifically firm annual reports (10-Ks) in the US, to create measures of firm fundamentals such as competitive intensity, industry classes and firm strategy (Hoberg et al. 2010; Tetlock 2011; Tetlock et al. 2008). These documents are useful as sources of data for two reasons. First, public firm product descriptions must be representative and accurate as required by financial market regulations. Thus, product descriptions of public firms contain timely information about their products, markets and competitors that are consistent with the firm's perceptions. Second, as firms evolve, these descriptions are modified and updated to reflect the changing nature of their businesses, thereby providing longitudinal variation. Thus, for incumbents, we are able to utilize their annual 10-Ks as sources of text.

We still require a source of valid text describing the entrepreneurial ecosystem that can be used to characterize the extent to which they represent credible threats. For this purpose, we use the VentureXpert dataset and focus on startups that are backed by venture capital funding. Using VentureXpert data allows us to focus on IT entrepreneurs that have received venture capital funding, and therefore are of baseline quality and represent credible threats to incumbents. It is important to note that individual new ventures included in VentureXpert are typically too small and early-stage to count as competitors or threats to incumbent firms. Therefore, we refine our definition of new entry threat from startups in two ways. First, we observe that the threat of new entry from new ventures does not appear from any single entrepreneur but from broad, collective movements in the startup space, i.e. evidence of systematic entrepreneurial movements into a specific area or sub-industry are more representative of new entry threat for an incumbent. Following Hoberg et al. (2014), we identify new entry threats at the level of the "industry"; for the purposes of our analysis, we treat the whole set of entrepreneurial ventures in VentureXpert that receive funding as the relevant "industry", since they represent collectively the new entry threat that is faced by incumbents. Second, it is unlikely that all entrepreneurial firms represent emerging, *new* entry threat to the incumbent. Therefore, we consider those entrepreneurs that receive *first-stage funding* in a given year as posing new entry threat to incumbents in that year. If the entrepreneurial ecosystem observes value in a specific industry subclass or technology space and systematically invests in new ventures at the early funding stage, there is likely to be a groundswell of new ventures associated with this industry subclass entering the VentureXpert dataset in a given year, which could then potentially lead to significant realized entry in 2-3 years, thereby representing new entry threat for the incumbent. In summary, the new entry threat measure here is based on (a) new ventures that receive new *first stage* venture capital funding, and (b) collective body of *all* entrepreneurs who receive first-stage funding, rather than individual entrepreneurs.

This collective body of startups represents varying levels of new entry threats to different incumbents, depending on how closely the entrepreneurial ventures are related to the primary market of that incumbent. We therefore require a measure of the similarity between the product portfolios observed in the VC-funded startup space and the incumbent's product market. More to the point, we need to measure the similarity between the text from the incumbent describing its product market, on the one hand, and text from the entrepreneurial space representing threats, on the other. We use the cosine text similarity approach to capture this similarity (Sebastiani 2002). The primary building block used to construct the text cosine similarity metric is the set of unique words that firms use to describe their products in their business descriptions. For publicly traded incumbents, the source of business descriptions is Section 1 of their 10-K annual filings. For startups, we use their business description from VentureXpert database. We extract all detailed business descriptions from start-ups that received first-stage funding and aggregate these descriptions for each year t; these individual business descriptions are short, with the typical description consisting of 4-5 sentences. Aggregating these for a given year provides a more representative and useful document of entrepreneurial entries in a particular year. Cosine similarity between this collective entrepreneurial document and an incumbent's business description forms the basis for measuring new entry threat, effectively by calculating their overlap in word usage.

Specifically, once the respective text documents are available, we parse semantics at a sentence level with the Natural Language Processing Toolkit (Bird et al. 2009) and retain the nouns and proper nouns, which are the most meaningful elements in product descriptions. We remove commonly used English stop-words. We also omit geographical words such as country, state and city names, as well as the words describing time periods such as months and dates, following Hoberg et al. (2016). Our results are robust to the inclusion of these stop-words. Figure 1-1 presents a histogram of frequencies of the number of unique words used in the product descriptions of the incumbent firms, showing that the typical firm uses roughly 700 unique words. Figure 1-2 displays the number of startups that received first-round funding, which range from 522 to 2299; and the number of unique words used in the collective startups' product descriptions across the years, which range from 3,020 to 6,508 words per year.

[Insert Figure 1-1 and Figure 1-2 about here]

Next, we define all incumbents' business descriptions and the aggregated start-up document as a cumulative document corpus (or collection) for each year *t* (that is, the corpus includes *n+1* documents in total, with *n* being the number of incumbents in year *t*). Subsequently, we build document vectors for each incumbent's text and the aggregated start-up text in year *t*. Let J_t denote a scalar equal to the length of the words dictionary, which includes all unique words used in document corpus of year *t*. Let W_{it} represent an ordered vector of length J_t describing the pattern in which the J_t words are used in document *i* (*i* = 0 represents the aggregated file from the startup ecosystem) in year *t.* We use *Term Frequency times Inverse Document Frequency (TF-IDF)* (Tata et al. 2007) as the weight for each word in the document vector. In this case, each element *j* in W_{it} captures the relative importance of word (or term) *j* in document *i*, given its within-document and cross-document frequency. *Term Frequency* (f_{it}) is defined as the number of occurrences of words *j* in document *i*. The normalized term frequency is defined as:

$$TF_{ji} = \frac{f_{ji}}{\max_k f_{ki}} \tag{1-2}$$

That is, the term frequency of term *j* in document *i* is f_{ji} normalized by the maximum number of occurrences of any term in document *i*. This normalization process helps correct for biases caused by the length of a document (i.e. term frequency gets inflated in longer documents). *Inverse Document Frequency* (IDF_{ji}) for a term is defined in following fashion. Suppose term *j* appears in n_j of the N documents in the collection, then IDF_j = log(N/n_j). Naturally, a term that appears in many documents, such as "service", gets a lower *IDF* weight (and therefore is treated as less important), while a term that occurs in only a few documents, such as "encryption", gets a higher *IDF* weight. The weighting score of *TF-IDF* for term *j* in document *i* thus defined to be $TF_{ji} \times IDF_j$. Intuitively, words with high within-document frequency obtain higher weighting and those with high cross-document frequency are weighted less. Lastly, since our main interest lies in the similarity between the document representing an incumbent and the aggregate document representing start-ups in that year, we operationalize the text-based measure of new entry threats for incumbent firm *i* in year *t* as:

$$NET\_TFIDF_{i,t} = SIMc(\overrightarrow{W_{i,t}}, \overrightarrow{W_{0,t}}) = \frac{\overrightarrow{W_{i,t}} \cdot \overrightarrow{W_{0,t}}}{\left|\overrightarrow{W_{i,t}}\right| \times \left|\overrightarrow{W_{0,t}}\right|} \tag{1-3}$$

where W_{it} denotes incumbent firm *i*'s document vector in year *t* ($i = 1,2,3 \ldots n$) and W_{0t} represents the aggregated start-ups' business descriptions document vector. By construction, the cosine TF-IDF-based measure of new entry threat NET_TFIDF_{it} is bounded between [0, 1]. Higher values represent greater threat of new entry for the incumbent (since the two word vectors are closer in unit vector space).

There are several reasons for why the cosine similarity score calculated by using TF-IDF weighted words vector is a good measure of new entry threat in our study. First, the properties of TF-IDF are well understood given its wide use in the studies of information processing and text analysis (Aizawa 2003; Aral et al. 2011; Hiemstra 2000). Second, the measure is intuitive given its consideration of words frequency within as well as between documents. Third, the method is only moderately computationally burdensome, making it scalable to replicate or extend to large datasets. Finally, the cosine similarity's normalization builds in a natural control for document length, since it measures the angle between two word vectors on a unit sphere.

1.3.2 Validation of the Measure of New Entry Threat

On the basis of the methodology defined above, we calculate NET for all public firms found in Compustat within the high-tech industries (of which IT industries form a subset) from 1997 to 2014. The high-tech industry is formed using the 46 4-digit NAICS codes defined by Hecker (1999). Since NET is a new measure based on text mining, in this section, we aim to illustrate the validity of our measure through a series of tests. These include assessing whether our text-based measure captures changing trends in the startup space over time; examining how NET is associated with the changes in the competitive dynamics of the incumbent's industry in subsequent years; comparing the turbulence experienced by high-NET firms with those experienced by low-NET firms in subsequent years; and examining how NET in a selected number of industries are influenced by industry-level demand shocks caused by well-known and major exogenous events. We believe these tests collectively provide sufficient validation for the measure, and describe these in some detail below.

Capturing Changing Trends in the Entrepreneurial Space

As a first step to validating our NET measure, we examine whether our approach of using text indeed accounts for shifting technology trends within the startup space, as reflected in the "hottest" words used in product descriptions of startup firms across years in our sample. In Table 1-1, we present the list of 20 words with the highest TF-IDF weights in the collective startup product descriptions document in three selected years – 2000, when the dot-com bubble was at its peak; 2003, when the stock market reached the lowest point after the dot-com collapse; and 2006, when the economy had recovered from the dot-com bubble.

[Insert Table 1-1 about here]

We observe several interesting patterns. First, there is significant longitudinal variation in the most influential words that venture-funded startups use to describe their products and services. Second, the changes in the vocabulary reflect systematic shifts in technology trends that are consistent with observations in high-tech. For example, in 2000, the VC-funded entrepreneurial space was dominated by firms related to the Internet or software industries: words such as "online", "Internet", "software", "web", "email", "broadband", "ecommerce" and "portal" were among the most frequently used in their product descriptions. In fact, all but 2 among the top 20 words are related to information and communication technology industries in 2000. However, in 2003, we observe a significant change in the vocabulary used to describe funded startups. The use of Internet-related words are dramatically reduced, to be replaced by words such as "disease", "patient", "drug", "treatment", "therapy", "protein", "biotech", and "antibody". These changes show that the VC-funded startup space had shifted systematically from Internet/software to pharmaceutical and biotech industries after the dot-com bubble. Interestingly, in 2006, we see the word list reflecting a balance between IT and biotech industries. While some software and Internet-related terms resurface, they do so with a completely different emphasis. Terms such as "search", "cloud", "blog" "advertising", "video" and "game" become more influential, reflecting a trend toward cloud computing, social media, online advertising and video games in the IT industry. Overall, Table 1-1 provides evidence for the significant longitudinal variation in the words that are used to describe the entrepreneurial firms in different years, and shows that our text-based measure of new entry threat captures and builds on these underlying trends within the startup space with fidelity.

New Entry Threat and Competitive Dynamics

If the NET measure does indeed capture the extent to which incumbents face potential new entry, one way to validate the measure is to examine how a firm's NET is associated with the changes in its competitive landscape in the following years. This would imply that firms with higher values of NET are likely to face, in the subsequent 2-3 years, an increase in the number of direct competitors, all else being equal. This is likely to happen through a number of mechanisms. To start with, some fraction of the new startups may eventually go public and become a real rival for the incumbent. In other cases, existing incumbents may form various types of alliances or joint ventures with the startups, or acquire technology licensing from them, and invade the product space of the focal incumbent (Mitchell et al. 1992). We present in Figure 1-3 a scatter plot depicting the correlation between the numbers of rivals of an incumbent defined by text-based network industries classification (TNIC)[1] (Hoberg and Phillips 2010) in

[1] Only text-based network industries classification provide us time-varying rival numbers in the same industry Hoberg, G., and Phillips, G. M. 2016. "Text-Based Network Industries and Endogenous Product Differentiation," *Journal of Political Economy* (124:5), pp 1423-1465.. Therefore, we use this classification rather than the static SIC or NAICS codes to define industry classes.

years $t+2$ and $t+3$ and the NET measure for the firm in year t. From the scatter plot, we clearly observe that a higher level of NET is positively associated with number of rivals an incumbent faces in the next few years, indicating that some of the entry threats do indeed materialize in the subsequent years. While these plots show univariate relationships, we also estimated regressions with the number of competitors as the dependent variable and NET as independent variable, including a full set of control variables. These results, available upon request, show a significant positive relationship between NET and the number of competitors in subsequent years for the incumbent firm.

[Insert Figure 1-3 and Figure 1-4 about here]

Relatedly, prior literature has shown that one of the direct consequences of rampant new entry is the reduction of profitability in the industry as a whole, due to increased competitive intensity (Audretsch et al. 1995). Some view entry as a mechanism through which profits in excess of long-run equilibrium are eroded (Mueller 1990). To test these expectations, we again show in Figure 1-4 a scatter plot relating NET in year t to a commonly used profitability measure, Return on Assets (ROA), in years $t+2$ and $t+3$. As a validity check, firms with higher NET values should experience deteriorating profitability in the years ahead, as the threats materialize. As expected, the slope of the fitted line of the scatter plot is negative, showing that higher levels of NET are correlated with decreased operating performance of the firm in the subsequent years, adding further validity to the NET measure.

Turbulence Experienced by High NET vs. Low NET Firms

One of the defining characteristics of new entry threat is that it threatens the sustainability of the firm's future earnings and the viability of its product portfolio (Hoberg et al. 2014). As a result, if a fraction of the threats do indeed materialize, firms with high levels of NET are more likely to suffer from deteriorating operational performance due to heightened competition, and therefore more likely to experience turbulent events such as liquidation or downsizing during the difficult time period that follows. We test these eventualities here. We contrast high-NET firms with those with low-NET values to study the likelihood of experiencing turbulent events such as filing for bankruptcy, announcing significant downsizing or layoffs, and being acquired by or merged with other companies in the five years following the measurement of NET.

Specifically, for each year in our time frame (1997 – 2014), we select ten firms with the highest and lowest NET scores, respectively, and put them into *high group* and *low group* respectively. This results in a total of 103 unique firms in the *low group* and 82 unique firms in the *high group* during the sample frame (the number is less than 10 times number of years, because a firm may appear in a given group in multiple years). For each observation in the *high group* and the *low group*, we conduct a search in the Lexis/Nexis database to identify news releases that are related to turbulent events associated with the firm in the subsequent 5 years, using a Boolean query combining the company name and keywords such as "bankruptcy", "liquidation", "layoff", "cut jobs", "merger", and "acquisition". Sources are limited to four types: Newspapers, Business and Industry News, U.S. Newspapers, Web news. Through this exercise, we identify turbulent events associated with the firm in the subsequent five years, and collect information such as the exact time of the events, other companies involved in the event of a merger, and so on. We also search through news releases from the firm to confirm the dates and details of events thus identified. We report the frequency of such events across the two sets of firms, representing high and low rates of new entry threats. As an illustration, in Section 1.6.2 Appendix II to Essay 1 we present a summary of these events for the two groups of firms in 2009. Figure 1-5 reports the comparison of these groups in terms of the rates of incidents for three critical events: bankruptcies, layoffs, and acquisitions/mergers. As expected, companies facing high levels of NET have much greater likelihood of experiencing turbulent events in the next few years. For companies in the *high group*, 8.5% (7 companies) of 82 companies filed bankruptcy, 40.2% (33 companies) announced significant layoffs, and 29.3% (24 companies) were acquired by or merged with other firms in the subsequent 5 years. In comparison, among the companies in the *low group*, only 4.8% (5 companies) of 103 companies filed bankruptcy, 7.8% (8 companies) announced layoffs and 15.5% (16 companies) were acquired or merged. Two-sided t-tests show that the probability of "Layoffs" and "M&A" are significantly different between the groups ($p<0.05$, $p<0.01$, respectively). Companies facing low NET fared much better than those facing high NET in subsequent years, providing evidence that the measure is forward-looking and correlates with firms' future competitive dynamics.

[Insert Figure 1-5 about here]

New Entry Threat and Industry-level Exogenous Demand Shocks

A further source of validation for NET arises from being able to observe higher values in NET when an exogenous event creates the potential for new entry into that industry; in this section, we assess these effects. The underlying argument here is that a sudden increase (or decrease) in industry-level demand due to exogenous event disrupts the relationship between supply and demand, and therefore encourages (or discourage) entry. As a result, incumbents in the industry will likely face increasing (or decreasing if demand shock is negative) levels of NET following the events. We consider 4 selected high-tech industries and their associated exogenous events as exemplars. The first is the military armored vehicle manufacturing industry[2] following the terrorist attacks on September 11, 2001. The second event we consider is changes in the Internet services provider and web search portal industry following the dot-com collapse in March 2000. Third, we consider changes in the software publishing industry after Apple's announcement of a major and critical SDK release for iOS, which drove hundreds of app developers into the mobile apps market. Finally, we trace changes in the biotechnology industry which experienced a demand boost following the complete sequencing of the human genome. We choose these events due to their importance in shaping the trajectory of these high-tech industries, thereby potentially offering new opportunities for entrepreneurial firms.

[Insert Figure 1-6 – Figure 1-8 about here]

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[2] Military Armored Vehicle Manufacturing industry is the only one that is closely related to military goods and services industry in the high-tech sector Hecker, D. 1999. "High-technology employment: a broader view," *Monthly Lab. Rev.* (122:6), pp 18-28..

Military Armored Vehicle Manufacture (NAICS 336992). Historical data suggests that the U.S. military spending reached a peak of nearly 6% of GDP during the Reagan defense buildup, and declined in the 1990s, bottoming out at 3.5% of GDP in 2001.[3] But the terrorist attacks on September 11, 2001 reversed that trend sharply, and defense spending began a substantial increase in the years following the attack, eventually reaching 4.6% of GDP by 2005 during the Iraq invasion. Spending stabilized after 2005, but increased further to 5.7% of GDP in 2010 and 2011 with the stepped up effort in Afghanistan.[4] We expect the 9/11 attacks to dramatically boost demand for the military and defense industries, which should lead to more new entry by entrepreneurial firms in the following years. Figure 1-6 plots average NET faced by incumbents in the military armored vehicle manufacturing industry over our sample period (the vertical line represents the exogenous event of 9/11). We find strong support for our conjecture – we observe a sudden surge in NET in the industry after 2001, indicating that our measure is responsive to industry-level exogenous events that provide demand shocks. These dynamics provide some support for the thesis that new entry follows exogenous demand shocks.

Internet Related Industries (NAICS 5181, 5161, and 5182). We next consider the dot-com collapse and examine its influence on Internet-related industries, which include Internet Service providers and Web Search Portal (NAICS 5181), Internet Publishing (NAICS 5161), and Data Processing (NAICS 5182). In contrast to the previous case, this event generated a significant negative demand shock. The stock market collapsed in March 2000, causing plunges in stock prices of large e-commence and Internet companies, including Amazon, eBay, and Cisco, while making investors reconsider the valuation of Internet service companies (Wheale et al. 2003). As a result, we expect VCs to shy away from investments in Internet-related firms, thereby reducing new entry threat faced by firms in this industry. Figure 1-7 provides evidence

[3] http://www.usgovernmentspending.com/defense_spending

[4] http://www.usgovernmentspending.com/spending_chart_1990_2020USp_XXs2li011tcn_30f_Recent_Defense_Spending

in support of this expectation. The average NET of Internet related firms (the solid line) reached its peak in 2000, and dropped significantly in 2001. The negative trend continued until year 2003 when the market started to recover from the dot-com bust.

Software Publishers (NAICS 5112). In Figure 1-7 we also present the average NET experienced by firms in the software industry (in dashed line). We find that the level of NET for software publishers also dropped following the dot-com bust. However, the decline in NET is smaller for software publishers than for Internet related firms, suggesting that software publishers are less severely influenced by this particular demand shock. In addition, we observe a strong increase in NET values for incumbent software publishers more recently, starting from 2009. We partly attribute this to Apple's launch of SDK3 (Software Development Kit 3) for iOS, which ignited exponential growth in its app ecosystem. Although Apple's AppStore opened in July 2008, the functionalities of earlier versions of SDK were too restrictive and hindered real innovation.[5] With the introduction of SDK3, Apple offered over 100 new features to the framework and more than 1000 new APIs. Some of these features, such as Map API, Payment API, and push notifications, were critical for developers to operate profitably in this ecosystem (Ghazawneh et al. 2010). Thus, we see a corresponding increase in entrepreneurial software developers joining the mobile app ecosystem, and a concomitant increase in NET values for the industry.

Biotechnology Research and Development (NAICS 5417). Lastly, we turn to a milestone event in the biotech industry– the completion of the human genome sequence – and examine how it shaped new entry threat. Due to widespread international cooperation and advances in the field of genomics (especially in sequence analysis), as well as major advances in computing technology, an initial sequencing of the human genome was finished in 2000, announced jointly by President Bill Clinton and Prime Minister Tony Blair on June 26, 2000.[6] In addition, in 2001, the sequence of the human genome was published in *Science* and *Nature*,[7] making it possible for researchers

[5] http://whydoeseverythingsuck.com/2008/03/apples-iphone-sdk-prohibits-real-mobile.html
[6] http://web.ornl.gov/sci/techresources/Human_Genome/project/clinton1.shtml
[7] https://www.genome.gov/10002192

across the world to begin developing treatments. These two events led to the entry of a large number of biotechnology startups. As seen in Figure 1-8, we see the average level of NET for incumbents in the biotechnology R&D services industry increased dramatically in 2001, a trend that continues to 2002 and 2003, thus again verifying that our NET does track closely with external demand shocks that affect new entry threats. In summary, we find that the longitudinal variation in the NET measures in selected industries are consistent with demand shocks following well-known, industry-wide exogenous events, which further adds to the validity of this measure. We now turn to addressing the primary research question of interest, pertaining to the influence of NET on the incumbent's R&D investments.

1.4 Data and Empirical Analyses

In this section, we start by describing the sample and other variables we use in our empirical investigations. While we do not explicitly hypothesize the first order relationship between NET and R&D investments, for completeness, we present a panel data model that reveals a negative association between NET and R&D in the specific industrial context we study, and show that the effect of new entry threats is robust to endogeneity issues by employing a number of techniques such as dynamic panel GMM estimations and instrumental variables regressions. We then proceed to hypotheses testing, and examine how the proposed boundary conditions (firm diversification, the strength of network effects, and technological cumulativeness) moderate the relationship between NET and firm R&D investments.

1.4.1 Data and Variables

We restrict our analyses to the set of firms in the IT industries, using the 24 4-digit NAICS industry codes that include IT software, hardware, and services industries over the period 1997-2013 (Kim et al. 2016). We list the NAICS codes, as well as their text descriptions in Section 1.6.1 Appendix I to Essay 1. Figure 1-9 shows the distribution of firms among the IT industry subsectors. We obtain financial data and other firm characteristics from Compustat. Our primary dataset consists of 2101 publicly traded firms over a 17-year period with 14,410 firm-year observations, representing an unbalanced panel. The sample period includes years when there was considerable turbulence in the IT industry (e.g., during the Internet boom and bubble burst) as well as the less volatile years. The long panel also includes the period of the global financial crisis in 2008 and the period of recovery afterwards, which significantly affected IT-related venture capital funding and entrepreneurial activities in general. Together, the dataset provides considerable longitudinal variation in our measure of new entry threats that allows us to use firm-level fixed effect models to control for many unobserved firm heterogeneities. We describe the variables in our main analyses in the following.

[Insert Figure 1-9 about here]

R&D Investments

Following prior literature, we measure R&D investments using R&D intensity, defined as R&D expenditures over firm's total asset (Blonigen et al. 2000; Hall 1988). R&D expenditures reflect contemporaneous managerial decisions that are closely associated with a firm's investment strategy. The mean value of R&D intensity in our sample is 12.88%.

Firm Diversification

We measure a firm's diversification along two different dimensions – the diversification of a firm's product portfolio, and the diversification of its technology portfolio. A firm's *product diversification* is constructed following Jacquemin et al. (1979)'s entropy measure of sale shares in different lines of business. This measure has been used widely in prior literature (Wiersema et al. 2008). Entropy is computed using data on firm sales in each 6-digit NAICS businesses as reported by the Compustat Segment database. Mathematically, *Entropy* for firm *i* in year *t* is defined as following:

$$Entropy_{it} = \sum_{s=1}^{n} P_{sit} \cdot \ln \frac{1}{P_{sit}} \tag{1-4}$$

where *n* denotes the total number of 6-digit NAICS business sectors reported by firm *i* in year *t*, and P_{sit} is the share of sales from business sector *s* over the total sales of firm *i* in year *t*. Since not all Compustat firms report sales by lines of business, we are able to calculate this variable for 954 firms in our sample. We define a firm's *product diversification* as the within-firm mean of $Entropy_{it}$ over the sample period.

We use a firm's portfolio of patent applications to measure its *technology diversification.* In particular, this variable is measured using the shares of patent applications filed by the firm in different patent subclasses. We employ two different form of this variable: first, an entropy-based (Jacquemin et al. 1979) measure, similar to that defined in equation (1-4), is constructed, with P_{sit} replaced by the share of patent applications in subclass *s* among all the patent applications filed by firm *i* in the five years prior to *t*. As an alternative measure, we also calculate Blau's heterogeneity index (Blau 1977) in the following fashion:

$$Heterogeneity\_index_{it} = 1 - \sum_{j=1}^{J} p_{jit}^{2} \qquad (1\text{-}5)$$

where *J* denotes the total number of patent subclasses for firm *i* during the five years prior to *t*, and p_{jit} is the share of patent applications in subclass *j* over the total number of patent applications by firm *i* during year *t-5* to year *t.*[8]

Network Effects

We adopt the measure of network effects invented by Srinivasan et al. (2004) and Wang et al. (2010). Specifically, the authors in these studies identified 45 product categories that are characterized by varying degrees of network effects, as well as the pioneers (leading firms) in each of the product categories. These products range from computer hardware (e.g., workstations, mainframe computers, and personal computers), computer software (e.g., database, personal finance software, word processing software, and spreadsheet software), consumer entertainment electronics devices (e.g., home VCRs, DVD players, videogame, and color TV), to telecom equipment (telephones, fax machines and wireless telephones) and other office suppliers (such as printer and scanners). Two groups of raters – academic experts and MBA students with background in high-tech marketing strategies – were asked to rate separately the degrees of direct and indirect network effects associated with each product category on

[8] Due to the limited availability of NBER patent data, technology diversification is only available up to 2006.

a 1 (no network externality) to 7 scale (very high externality) (Srinivasan et al. 2004). The strength of network effects is then computed by adding scores for both direct and indirect network externalities (range of 2 to 14).

We match the 45 product categories to 4-digital NAICS industry by referencing the industry classifications of the pioneers identified in each product category (Wang et al. 2010). As a result, we successfully identify network effects for 15 4-digital NAICS industries.[9] Based on this matching, we constructed two different forms of the measure of network effects: a continuous score associated with each 4-digital NAICS industry,[10] and a binary measure of high network effects industries, whose value is set to 1 for industries in which the score of network effects is higher than the median value of 8.4 among the 45 product categories (Wang et al. 2010), and 0 otherwise.

Technological Cumulativeness

Patent self-citation, or citation referring to previous patents owned by the same patentee, has been employed as an indicator of the degree of cumulative, sequential invention by a firm in prior research (Lanjouw et al. 2001). Following this interpretation, Oriani et al. (2008) defined a measure of the degree of technological cumulativeness by referring to the average percentage of patent self-citations at the industry level. We adopt a similar definition and use the NBER patent data to calculate the backward self-citation rate for each patent, which is the number of backward citations made to a patent with the same assignee code (self-citations) divided by the total number of backward citations (see Hall, Jaffe, and Trajtenberg (2001) for a full details). Using the patent self-citation data, we first compute a continuous measure of *technological cumulativeness* as the average percentage of self-citations at firm level, using the firm's

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[9] The 15 4-digital NAICS industries include machinery manufacturing, communication and audio/video equipment manufacturing, semiconductor equipment manufacturing, software publishers, computer and peripheral equipment manufacturing, Internet service providers and Web search portals, data processing, hosting and related services, etc. The highest three network effect industries are: Data processing, Computer design and Scientific related services (with a score of 10.7), Telecommunications Resellers (10), and software Publishers (9.05); the lowest three network effect industries are: Commercial and Service Industry Machinery Manufacturing (3.9), Industrial Machinery Manufacturing (4.1), and Navigational, Measuring, Electromedical, and Control Instruments Manufacturing (5.8).

[10] We use the median value if multiple network effects indexes from different products are mapped to same industry.

patent portfolio during the period of 1996-2006 when the patent data is available. Second, following Oriani et al. (2008), we also construct an industry-level, binary indicator of *technological cumulativeness*. In particular, we calculate the average percentages of patent self-citation at the industry level using all the patents filed by the patentees in the focal industry, and then identify a set of high technological cumulativeness industries, for which the variable *High Tech-Cumulativeness Industries* is set to 1 when the average percentage of self-citations of the industry is in the top quartile among all the industries in our sample, and 0 otherwise. We use 4-digit NAICS based Industry Classification to define *High Tech-Cumulativeness Industries.* Because of the static industry membership used by NAICS, the variable *High Tech-Cumulativeness Industries* is constant over time.[11]

Control Variables

Following prior literature (Atanassov 2013; Becker-Blease 2011; Kaplan et al. 1997), we control for a vector of firm characteristics that may affect a firm's R&D investment decision, including firm size, firm age, profitability, asset tangibility, leverage, capital expenditure, product market competition, growth opportunity, and financial constraints. We control for contemporaneous competition for the incumbent firm by Herfindahl-Hirschman index based on the increasingly popular Text-based Network Industry Classification (TNIC) scheme created by Hoberg and Phillips (2010). We choose TNIC over NAICS because TNIC classifications are updated every year as firms file 10-K reports, allowing for a more accurate measure of contemporaneous competition (Kim et al. 2016). We present a summary of the variable definitions in Table 1-2, and summary statistics and correlations of the variables in Table 1-3.

[Insert Table 1-2 and Table 1-3 about here]

1.4.2 Baseline Analysis of NET on R&D Investments

Although we do not formally hypothesize the direct relationship between NET and

[11] In our sample, the top three NAICS4-based Tech-Cumulativeness Industries are Data processing, hosting, and related services; Computer and peripheral equipment manufacturing; and Industrial machinery manufacturing.

R&D investments in the IT industry, it would be informative to observe how firms in the IT industry adjust their R&D investments in response to NET on average. Therefore, we start with a baseline model that estimates the effect of NET on the incumbent firm's R&D investment, using a two-way fixed effects panel data specification below:

$$R\&D\_Intensity_{it} = \eta_t + \lambda_i + \beta \times NET_{it} + \gamma X_{it} + \mu_{it} \tag{1-6}$$

Here, i indexes firms, and t indexes time periods. The variable NET_{it} is constructed from our new text-based measure of new entry threats. X_{it} is a set of firm characteristics that affect a firms' investment decisions. We control for time-invariant unobservable firm characteristics by including firm fixed effects λ_i. We also include year fixed effects η_t to control for economy wide shocks. Standard errors are clustered at the firm-level to control for serial correlation (Wooldridge 2010). μ_{it} represents the idiosyncratic errors.

[Insert Table 1-4 about here]

We report the results from the fixed effects model in Column (1) of Table 1-4. For comparison, we also present a random effects panel data model in column (2). In the random effects models, the unobserved individual heterogeneity λ_i is assumed to be uncorrelated with the included regressors (Greene 2003). We find the coefficient of new entry threat (*NET*) is negative in the fixed effects estimate and significant at 5% level, indicating that greater new entry threats are associated with lower level of R&D investments, all else being equal. The result from a Hausman's test comparing the fixed effects and random effects estimates rejects the orthogonality between the random effects and the regressors ($p<0.01$). Therefore, without the strong assumption that the firm heterogeneity is uncorrelated with the regressors, random effect estimates are likely to be biased. We therefore interpret our results using the fixed effects estimates.

To illustrate the magnitude of the effect of NET on R&D investments, consider a one standard deviation (s.d.) increase in new entry threat (before standardization, NET has a mean of 0.07 and s.d. of 0.05). The coefficient of NET implies a 0.35 percentage point reduction in R&D intensity (recall the sample average R&D intensity is 12.88 percentage points), which translates to a reduction of $6.5 million in R&D investments based on the mean level of total asset in the sample. This finding – firms in the IT industries invest less in R&D as uncertainty increases in the face of new entry – is broadly consistent with the conclusions of papers studying firms' R&D investment decisions in the manufacturing sector facing market uncertainty (Czarnitzki et al. 2011; Czarnitzki et al. 2013), as well as capital investment decisions of firms facing profit uncertainty (Ghosal et al. 2000). As Bloom et al. (2007) note, with irreversibility, higher uncertainty leads to a "cautionary effect" on firms' investment decisions.

While a fixed effects model controls for many unobserved firm heterogeneities, a particular concern here is that the presence of pre-emptive R&D might deter entry or other unobserved industry-wide shocks (such as technological opportunities) may influence entrepreneurial entry, VC funding decisions and incumbent R&D investments, causing our NET measure to be endogenous. As a way to address this issue, we relax the assumption that NET is strictly exogenous and use the generalized method of moments (GMM)-based dynamic panel data models estimator (Arellano et al. 1991; Blundell et al. 1998). Taking advantage of our long panel and large number of firms in our dataset, we construct internal instruments within the data consistent with dynamic panel data models. Specifically, we use the *differences GMM* estimator, employing lag term of our endogenous variables, *NET* and *L.R&D Intensity*, and all difference of other exogenous variables including year dummies as our instrument variables for the differenced equation. We use the second lag and onward of endogenous variables for the difference GMM specifications.[12] We checked the validity of the moment conditions required by the differences GMM estimator using the Hansen test, which does not reject the assumption that our instruments are exogenous (Arellano et al. 1991; Roodman 2009). We also test the validity of the GMM assumptions in our model. The test results are reported at the bottom of Table 1-4, which indicate that our model specification shows no significant serial correlation in

[12] We experimented with different lags and their combinations; results are fully robust to varying lag structures.

the first-differenced disturbances.

We report the results from Arellano-Bond estimator of dynamic panel data models, treating *NET* as exogenous first in Column (3) and then as endogenous in Column (4) of Table 1-4. We observe that the coefficient estimate of *NET* in Column (3) is similar to that of the fixed effects model, consistent with our main finding that new entry threats reduce R&D investments. Moreover, the coefficient of estimate of *NET* in column 4 (-1.337) is significantly higher than that from the fixed effects model. The larger estimate in the dynamic panel data model, accounting for the endogeneity of *NET*, suggests that the presence of endogeneity, if any, likely causes a downward bias in the FE model, while the FE model generates more conservative estimates of the effect of *NET*. Overall, the Arellano-Bond estimates provide further support for the finding that the uncertainty associated with *de novo* entry reduces the inclination of incumbents to invest in R&D. Our results are consistent with existing work showing that firms facing market turbulence are more likely to respond conservatively (Brav et al. 2005; Hoberg et al. 2014).

To further alleviate endogeneity concerns, particularly the reverse causality issues related to R&D investments as an entry barrier, in Secon 1.6.3 Appendix III to Essay 1 we present a 2SLS analysis using an alternative identification strategy involving the use of two instrumental variables for NET that represent industry-level incentives and barriers to potential entry. Here again we find the coefficient estimate of *NET* remains negative and is larger than that from the fixed effects model in Table 1-4, showing that the results reported here are robust to alternative analyses.

1.4.3 Hypotheses Testing

Firm diversification

We examine whether diversified firms respond differently from specialized firms to high NET since, as proposed in H1, a diversified firm may have more flexibility regarding the capacity utilization. We measure diversification using both the firm's product and technology portfolios.

[Insert Table 1-5 – Table 1-7 about here]

In Table 1-5 we report regression results using the firm product diversification measure. In Column (1), we report the estimates from a two-way fixed effects model that incorporates the interaction term of *NET* × *Product Diversity*. The interaction term is positive and statistically significant (p<0.01), showing that more (product) diversified firms tend to invest more in R&D when facing high NET, showing support for Hypothesis H1a. To better understand the quantitative differences between the two groups of firms, we also present split-sample analyses comparing diversified firms to specialized firms (in Columns (2) and (3)), using the sample mean of *Product Diversity* to divide the sample. The results from Column (2) suggest that a one s.d. increase in NET is associated with 0.47 percentage point decrease in R&D intensity (relative to average R&D intensity of 14.06 percentage points for specialized firms), which translates to a reduction of $3.01 million in R&D investment, given the average total assets ($640.94 million) of specialized firms. Interestingly, we find that only specialized firms significantly reduce their R&D investments in response to new entry threats, while diversified firms seem to be less sensitive, thus confirming the insight from the literature that diversified firms are less affected by the irreversibility of capital investment in R&D (Czarnitzki and Toole 2013).

Table 1-6 presents results from analyses examining the role of the boundary condition of technology diversification using a fixed effects panel data model. Because our measure of technology diversification is constructed using patent portfolios of the firms, the sample this analysis is limited to observations over 1997-2006 due to the availability of NBER patent data. As explained earlier, we measure technology diversification by calculating both the Entropy and Blau's Heterogeneity Index using data on the shares of patent applications in different patent subclasses in the previous five years. The estimates from regressions show that the coefficient of the interaction term *NET* × *Technology Diversity* is consistently positive and significant across both measures, showing statistical support for H1b. When viewed together, the empirical evidence from Tables 5a (product diversification) and 5b (technology diversification) confirm that with reduced irreversibility, diversified firms are more likely to invest in R&D when facing higher levels of new entry threats from entrepreneurial new ventures.

Network effects

Recall that H2 postulated that firms in industries where network effects are strong will tend to invest more in R&D when facing high NET, because of costly expandability. We test H2 using the Network Effects (NE) Index measure adopted from Wang et al. (2010) and Srinivasan et al. (2004). The results are reported in Table 1-7. We first use the continuous NE measure and present the FE estimates in Column (1). The coefficient of the interaction term *NET* × *Network Effects* (0.112) is positive and significant ($p<0.10$), lending statistical support to H2.

To understand the economic significance of the boundary condition of network effects, we further employ the binary measure of *strong network effect industries*. This variable is set to 1 for nine 4-digit NAICS industries where their network effects scores are higher than the median.[13] The FE estimates that incorporate this variable are reported in 7, Column (2). We observe that the estimated coefficient of the interaction *NET* × *Strong Network Effects Industries* is positive (0.578) and statistically significant ($p <0.05$), consistent with H2. To better illustrate the quantitative differences between the two groups of firms, we also present split-sample analyses comparing the firms with strong NE with the ones with weak NE (in Columns (3) and (4)), using the binary variable of *Strong Network Effects Industries* to divide the sample. The results from Column (3) suggest that a one s.d. increase in NET is associated with 0.61 percentage point decrease in R&D intensity (relative to the average R&D intensity of 11.35 percentage point of firms in weak NE industries), translating to a reduction of $11.69 million in R&D investment given the $1.91 billion average total assets of firms in these industries. We also find that only firms in weak NE industries significantly reduce their R&D investments in response to NET, while firms operating in high NE industries

[13] Specially, the 9 high network industries are defined with 4 digital NAICS code: 5112, 3341, 5181, 5182, 5173, 5413, 5415, 5416, and 5417, including software publishers, Computer and peripheral equipment, Internet service providers and Web search portals, Data processing, hosting and related services, and Telecommunications resellers, etc.

appear to be insensitive to NET. These results confirm the insight from the literature that firms operating in industries characterized by strong network effects face costly expandability, and are hence more likely to invest in R&D when facing new entry threats (Weeds 2002).

Technological cumulativeness

To test Hypothesis H3 – which proposes the moderating effect of technological cumulativeness on the relationship between NET and R&D investment, we use the rate of backward self-citations of patents as a measure of technological cumulativeness (Oriani et al. 2008). We first employ the continuous, firm-level measure of *technological cumulativeness* and interact this variable with the NET measure. The results from the fixed effects panel data model are presented in Column (1) of Table 1-8. In Column (2), we report the results using the binary, industry-level measure of technological cumulativeness, where the binary variable, *High Tech-Cumulativeness Industries,* which is constructed based on 4-digit NAICS codes as described earlier.

We find that firms that operate in fields with high technological cumulativeness make significantly more R&D investments when facing high level of NET, relative to those that operates in fields with low technological cumulativeness, supporting Hypothesis H3. Furthermore, effect size calculations based on Column (1) suggest that, for firms with technological cumulativeness at the first quartile of the sample (0% patent self-citation), a one standard deviation increase in NET is associated with a decrease of \$15.42 million ($p<0.01$) in R&D investment (based on the mean value of total asset is \$1.85 billion in this subsample). However, the effect size for firms with third quartile level of technological cumulativeness (9.2% patent self-citation) is only a \$0.54 million ($p<0.05$) reduction in R&D investment, indicating that firms experiencing high levels of technological cumulativeness are less likely to reduce their R&D investment when under the threats from entrepreneurs.

The use of the industry-level measure of technological cumulativeness also confirms our finding. In Column (2) of Table 1-8, the coefficient of the interaction *NET* × *High Tech-Cumulativeness Industries* is positive and significant ($p<0.1$), showing that firms in high technology cumulativeness industries make more R&D investments than those operating in low technological cumulativeness industries. Moreover, the estimates in Column (2) show that because of this moderating effect of technological cumulativeness, firms in high technological cumulativeness industry do not appear to reduce their R&D investments when facing high NET; indeed, the effect for this group is statistically insignificant (p=0.638). To compare the differences in the marginal effects of NET between the two groups of firms, the subsample analyses, using the binary variable of *High Tech-Cumulativeness Industries*, are reported in Columns (3) and Column (4). The results show that, for firms in low technological cumulativeness industries (Column (3)), a one s.d. increase in NET is associated with 0.45 percentage point decrease in R&D intensity (relative to the average R&D intensity of 13.74 percentage point for firms in this subsample), translating to a reduction of $15.22 million in R&D investment (based on total assets $3.38 billion for this subsample). By contrast, firms in high technological cumulativeness industries (Column (4)) appear less sensitive and do not significantly reduce their R&D investments in response to new entry threats. Taken together, these results provide clear empirical evidence for the role of technology cumulativeness as a boundary condition that shapes the relationship between NET and R&D spending, consistent with H3.

1.5 Discussion and Conclusion

It is well known that innovation is one of the building blocks of competitive advantage in the IT industry (Giarratana 2004), and R&D investments, as an input of the innovation process, represent particularly important managerial decisions (Schwartz et al. 2000). It is also established that the IT industry tends to be volatile, where creative destruction often emerges from entry by new entrepreneurial ventures backed by venture capital (McAfee et al. 2008). Juxtaposing these two observations begs the question – how do incumbent IT firms adjust their R&D investments in response to increased threats of new entry? This question remains, surprisingly, understudied in extant IS research, due to several reasons. First, there is a lack of established measure of new entry threats, which presents a significant challenge to the empirical studies in this area. Second, firms in the IT industries face varying degrees of the irreversibility and expendabilities of their R&D investments due to conditions specific to their industrial context. As a result, there are significant heterogeneities in their investment strategies in the face of threats from new entries, adding to the complexity of this issue. Finally, new entry threat is conflated with contemporaneous competition or observed entry, both of which are closely linked to but remain distinct from the forward-looking and probabilistic characteristic of this construct.

We examine the relationship between NET and R&D investments by overcoming these challenges. First, we develop a text-based measure of new entry threats by analyzing the product descriptions of both incumbent firms and startups. We conduct a series of validation tests and show that the NET measure indeed captures impending threats from the startup space. Second, adopting the theoretical framework of investments under uncertainty (Dixit et al. 1994), particularly through the lens of real options (Abel et al. 1996) which accounts for the inherent uncertainty of forward-looking perceptions of market threats, we propose several important boundary conditions governing this relationship that are related to firm and industry characteristics particularly salient in the IT industry. Using data on a panel of 2101 firms in the IT industry over the period of 1997-2013, we find that on average, increasing level of new entry threats is associated with a reduction in a IT firm's R&D investments. Our finding is robust to the use of a number of alternative regression specifications addressing the endogeneity of NET. More importantly, consistent with theoretical predictions, we show that responses from IT firms are not uniform. Firms with diversified product or technology portfolios, operating in industries with strong network effects, or facing high levels technological cumulativeness do not reduce their R&D investments as much when facing NET; indeed, in some contexts, they may even choose to invest more in R&D as a result.

We attribute the finding of a negative average association between NET and R&D investments to the "cautionary effects" of uncertainty that have been well-documented in prior literature (Bloom et al. 2007; Bulan 2005). Due to the high irreversibility of R&D investments, most IT firms are likely to take a "wait-and-see" approach to investment decisions in response to the uncertainties associated with new entry threats. From an industry lifecycle standpoint (Klepper 1996), time periods associated with high threats of new entry into the market is often associated with impending technological shifts, wherein a multitude of competing designs and standards emerge and a dominant design is yet to be established (Jovanovic et al. 1994). During these times, delaying R&D investments can be of particular value since they allow the firm to avail of flexibility while avoiding rushed investments that may not pay off in the future. However, we also show exceptions to this observation: IT firms whose investments are subject to lower levels of irreversibility (in diversified firms), or that face costly expandability (when the firm operates in a strong NE industry or has high technological cumulativeness) are less likely to reduce R&D investments.

Our findings reveal several important theoretical implications for understanding firms' investment decisions in the IT industry with its unique fast-paced, dynamic environment. First, although prior literature has investigated firm-level strategic responses to entry (Aghion et al. 2009), empirical studies in this field have placed their emphases on *actual entry* instead of *threat of entry*, partly due to the difficulty of measurement. More to the point, prior work has addressed incumbent responses after entry has occurred but few, if any, have addressed how firms may react before entry materializes (Goolsbee and Syverson (2008) and Seamans (2013) represent rare exceptions). Furthermore, studies of responses to observed entry have addressed strategic responses such as pricing, excessive capacity creation, product market mix, and advertising, among others (e.g., see Geroski 1995, Shankar 1999, Koski and Majumdar 2002) but little work has examined how R&D spending may be implicated as a strategic response. This is noteworthy here, since R&D spending and innovation are particularly critical in the IT industry. Our work here pushes the frontier on both dimensions. Given that ex ante threat of entry from the startup ecosystem forms a vital source of disruption in the IT industry, our work fills a significant gap in prior IS literature on the topic of strategic responses to new entry.

Second, we draw linkages with extant work studying contemporaneous competition and R&D spending, recognizing that some new entry threats will eventually become elements of contemporaneous competition. The relationship between competition and R&D spending is not without ambiguity – in some contexts, firms choose to invest heavily in R&D in order to "escape" competition while in other contexts, empirical evidence shows firms choosing to reduce investments in innovation, since the presence of competition tends to eat away at any ex post benefits (Aghion et al. 2005). Within the IT industry specifically, recent work studying the impact of competition provides results that are complementary to those we present here. Kim et al. (2016) show that when faced with competition, IT firms are likely to invest more in R&D per se, but on the margin are also likely to shift such investments into more *flexible* options like corporate venture capital. Thus, even with competition, the value of flexibility when facing fast-moving technological change is high. We show that when competition has not materialized but appears merely as a threat, firms are more inclined, on average, to wait and see what the future may bring, rather than commit investments prematurely into R&D. Thus, the key benefit of flexibility (captured in the options perspective) is central to how IT firms respond, whether facing contemporaneous competition or the threat of future competition. Certainly, the boundary conditions that firms face as they make these decisions do change, since in the context of contemporaneous competition, the firm's need for preemption is more immediate. However, the common thread of flexibility, and the implications of reversible and expandable options, remains consistent within the IT industry.

Third, we advance the application of real options theory in studying phenomena related to the IT industry (Benaroch et al. 1999; Fichman 2004). Prior empirical studies that adopt the real options lens typically construct measures for uncertainty using historical data, such as those related to profit uncertainty (Ghosal et al. 2000) or market uncertainty (Czarnitzki et al. 2013), making the implicit assumption that historical uncertainty is a good proxy of future uncertainty. While this assumption may be less controversial in slow-changing industries such as manufacturing, it is particularly problematic in the IT industry, given the rapid rate of change. More to the point, forward-looking risk cannot be easily estimated using historical data or backward-looking perspectives. We overcome this issue by constructing a forward-looking measure of uncertainty that captures the changing trend in the technology landscape, and has applicability in the broader high-tech industries as well. Moreover, we use this measure to test hypotheses arising from real options reasoning that pertain to IT-specific factors such as the presence of network effect, technology cumulativeness, and diversification. By incorporating these characteristics into the real options framework, we explore how they interact with uncertainty in complex ways in determining firm investment decisions. Given the increasing research interests in the IT and innovation spaces, we believe there is tremendous potential in further utilizing the real options framework to model decision making; our work here, as well as the NET construct, contribute to this stream of research as well.

In addition to theoretical contributions, we make a methodological contribution by creating and validating a new measurement of new entry threat from the startup ecosystem. Our text-mining approach, in contrast to earlier measurement of market threats based on industry classifications or market shares, not only captures forward-looking threats in a firm's competitive environment, but also changes over time as new ventures are funded and incumbents change their product and service offerings. In this spirit, our NET measure is similar to the TNICs industry classification developed by Hoberg and Phillips (2015). It is our intention to provide these measures to the broader IS community so as to allow the community to further test, verify, and systematically refine these measures in the future. There are several empirical and theoretical contexts where new entry threats faced by incumbents play a central role; the availability of a standard and accepted measure will help by allowing for comparability across models and theories.

Our work here also paves the way for more future work in this area. As mentioned earlier, *new entry threats* as a construct has seen significant theoretical development (Porter 2008), but empirical research has been relatively sparse. We hope that the availability of such a measure will lead to more empirical work addressing the role of NET on various outcomes such as mergers and acquisitions, product pricing strategies, corporate governance, and IT investment choices. Furthermore, innovation-related decisions regarding patent applications, technological alliances, and licensing agreements are all made under varying degrees of new entry threats within the IT industry. We hope that our work here will kickstart further work on understanding and empirically extending the study of new entry threat, distinct from observed entry and competition. We also hope that our work here will encourage the use of the NET measure, as well as the development of similar text-based approaches to study the important topic of competitive dynamics in the IT industry.

1.6 Appendices to Essay 1

1.6.1 Appendix I to Essay 1: IT Industries Used to Define Sample

We present the 24 4-digit NAICS codes that used to define our sample, as well as the text descriptions associated with them in Table 1-A1.

[Insert Table 1-A1 about here]

1.6.2 Appendix II to Essay 1: NET and Turbulent Events - A Qualitative Examination of Year 2009

We select companies with high and low NET values in 2009 to qualitatively examine the industry composition of the firms as well as the turbulent events they experienced in the following five years. There are two reasons that we pick firms in year 2009. First, we try to avoid most recent year in our sample, since we want a 5-year period to observe the subsequent turbulent events. Second, selecting year of 2009 allows us to minimize the influence from dot-com bubble in 2000 and finance crisis in 2007-2008. We summarize the industry sectors (4 digital NACIS) of all companies and present this information in Table 1-A2. As can be seen from Table 1-A2, the majority of low NET companies belong to manufacturing industries, including pharmaceutical and medicine manufacturing, communications equipment manufacturing, and computer and peripheral equipment manufacturing. These industries represent particularly stable ecosystem within the high-tech sector. The probable reasons for this stability include: manufacturing in general has high capital requirements that are natural barriers to entry, markets for manufacturing in the US are relatively mature and highly concentrated, standards and protocols within the manufacturing industry are relatively stable, leading to relatively fewer process and product innovations in 2009. By contrast, the high NET group includes a majority of software publishers, where firms experience high margins, high growth rates, access to skilled human capital, and relatively low entry barriers. These factors make this industry particularly attractive to entrepreneurs, and correspondingly incumbents experience high new entry threat. Table 1-A2 also shows the turbulent events of these companies in the following 5 years (2010 – 2014). We observe that the incident rates of bankruptcies, layoffs, and M&A are much greater for high NET firm.

[Insert Table 1-A2 about here]

1.6.3 Appendix III to Essay 1: Instrumental Variables Regression

Beyond the dynamic panel model to account for the endogeneity of NET, we use an alternative identification strategy that involves instrumental variables approach. We construct instrumental variables for the NET measure that should be ideally correlated with startups' decision to entry a certain industry but not directly affect the firm's R&D investments. As shown by Orr (1974) and Cockburn et al. (2011), new entry in an industry is likely influenced by industry-wide growth opportunities and entry barriers. Therefore, we construct two instrumental variables that represent entry incentive and barrier at the industry level. The first instrumental variable we use is an entry incentive – the lagged value of future profit expectation (Orr 1974), which is measure as the mean of Tobin's q of all companies in the focal industry (Jankowski 1998). The second instrumental variable we construct is an entry barrier – lagged value of market uncertainty (Orr 1974), which is measured as the standard deviation of profit rate of all the companies operating in the industry. We use the text-based industry classification (TNIC) system described in Hoberg et al. (2010) to identify the firms in the relevant industry of the focal firm. The TNIC relaxes the transitivity property typical of SIC / NAICS codes, which allows for a firm-specific influence associated with industry level movement, rather than a general level of influence based on NAICS/SIC codes which lacks within-industry variations.

The results of 2SLS estimation are shown in Table 1-A3. Qualitatively, the results from the second stage estimates (Column(2)) are similar to the FE specification in Table 1-4: the coefficient of NET is negative and statistically significant, providing further evidence for the negative association between new entry threats and incumbent R&D investments. The first-stage F stat has a value (181.32) larger than the rule of thumb value of 10, which is also greater than the 10% max IV size of the Stock-Yogo critical value, which suggests that the instruments are not weak. Furthermore, the Hansen J stat cannot reject the null that the instruments used are valid. We note that the coefficient estimate of *NET* is larger than that from the fixed effects model in Table 1-4, which again suggests that the endogeneity of *NET* due to reverse causality likely biases the coefficient estimate downwards (as suggested by the Arellano-Bond models). The FE model thus generates a more conservative estimate of the effect of NET on innovation.

[Insert Table 1-A3 about here]

Interestingly, the estimation of the first stage provides yet another validation for our text-based measure of new entry threats. The coefficient estimates of the instrumental variables from Column (1) are highly consistent with prior work on entry incentives and entry barriers (Bresnahan et al. 1991; Cockburn et al. 2011; Orr 1974). The coefficient for *Expectation for Future Profit* is positive and significantly ($p<0.01$), suggesting that profit expectation is a strong incentive to enter (Orr 1974; Siegfried 1994). *Industry Uncertainty* is negative and significantly ($p<0.01$), suggesting that startups are risk averse and the uncertainty of profit rate lowers the incentive to enter (Orr 1974). Thus, the results from the first stage equation provide further support for the validity of the NET measure as well.

Essay 2: New Entry Threats and Firm Performance in the IT Industry: The Moderating Role of Board Independence

Abstract

The Information Technology (IT) industry is characterized by rapid technological change and fast-moving dynamics, a significant part of which may be attributed to entrepreneurial ventures that pioneer new innovations. Correspondingly, the rate of new entry in the form of entrepreneurial ventures poses a critical risk factor for incumbent IT firms. While theoretical work points out a negative relationship between new entry threats (NET) and firm performance, empirical findings are scarce due to the inability to measure NET properly. Leveraging a novel NET measure based on text-mining approaches, we show that a higher level of NET indeed leads to a drop in the incumbent's performance. We also show that facing high NET, firms with more independent directors are better able to withstand these threats, possibly due to stronger monitoring and the valuable resources and information provided by the independent directors. Effectively, we circumscribe a set of boundary conditions under which board governance mechanisms may contribute to firm performance. To address the endogeneity issues associated with board independence, we use the enactment of the Sarbanes-Oxley Act and related changes to the NYSE/NASDAQ listing rules as exogenous shocks to create instruments, and our results are robust to the instrumental variable regressions. Further, we show that our findings are generalizable to other high tech industries, and discuss the implications for research and practice.

Keywords: *new entry threats, board independence, board of directors, corporate governance, disruptive technology, text mining*

2.1 Introduction

The threat of new entry is a disruptive force that constantly challenges incumbents within an industry, as highlighted by Porter's five competitive forces model (Porter 1979). The threat of new entry affects the competitive environment in which the incumbents operate and may erode their profits in the future. New entry threat (hereafter, NET) has become particularly salient in recent years where the pace of digital innovations is altering the nature of competition even in traditional industries. New ventures such as Uber are increasingly leveraging social media, business analytics, mobile channels and cloud platforms to disrupt traditional business models by dramatically reducing costs, improving efficiency, creating personalized experiences, and offering great product variety. In addition, recent developments in crowdfunding platforms and alternative funding models have further lowered barriers to entry within the high-tech industry, making it easier for new ventures to jump-start the process of growth and resource acquisition (Aggarwal et al. 2013; Kim et al. 2014) via channels beyond the model of venture-capital funding (Aggarwal et al. 2015; Kim et al. 2016).

The impact of new entry threats is particularly keenly felt within the IT industry, given the fast-moving nature of the industry (McAfee et al. 2008). Incumbents in the IT industry may adjust their strategies in response to NET in different ways, such as reducing price (Goolsbee et al. 2008; Yamawaki 2002), creating product differentiation (Koski et al. 2002; Kuester et al. 1999), or adjusting innovation strategies (Pan et al. 2015). However, firms differ in their abilities to recognize the dynamics in their competitive environment, the speed and effectiveness with which they respond to new entry threats, and therefore the likelihood of surviving disruptions caused by new entries. As is evident from the history of IT firms, not all incumbents are able to withstand the actual entry of new ventures into their markets (Christensen et al. 1998; King et al. 2002). In such contexts, firms need to leverage all the resources and capabilities they can access (King and Tucci 2002). One such significant resource that firms may draw upon to assess their external environment and respond appropriately to NET emerges from the valuable monitoring and advisory capabilities that come with the board of directors, particularly its independent members (Hillman et al. 2000). Compared to internal board members, independent members on the board provide two useful functions: first, they strengthen internal monitoring and oversight functions, acting on behalf of shareholders to resolve agency issues and cut management slacks (Ryan et al. 2004). Second, they provide knowledge and resources that may not be easily available within the organization to aid decision making on strategic issues (Hillman et al. 2000). In this paper, we therefore study how the presence of independent board members helps the firm weather the storm of new entry threats by examining the moderating effect of board independence on the relationship between NET and firm performance.

Empirically establishing a causal effect of board independence on the relationship between NET and performance is challenging for two reasons. First, threats from new entries represent forward-looking estimations of the extent to which the potential future competition may influence firm profit or product market performance, which are yet to be fully materialized at the current moment; thus they are difficult to observe and measure (Hoberg et al. 2014). For example, there are no ready-to-use and accepted industry classifications for startup firms, causing difficulties for the incumbents to identify startups that are competing in their product markets. Second, to the extent that firms make board member appointment decisions partly in response to its competitive environment, board independence may be correlated with a variety of unobserved variables that influence firm performance, therefore causing endogeneity concerns. For instance, Boone et al. (2007) find that board size and board independence increase as firms grow and diversify over time. Other scholars have implicated other factors such as the R&D intensity of the industry as well as institutional forces may be at play, all of which may influence both board structure as well as firm performance (Hermalin et al. 2003). The presence of these confounds makes it hard to disentangle the true effect of board independence on firm performance.

To overcome the first challenge, we adopt a novel, text-based measure of new entry threats introduced by Pan et al. (2015). The unique text-based measure of new entry threats overcomes the limitations of static industry classifications that lack longitudinal variations, and provides the basis for us to empirically examine the specific research questions of interest here. We address the second challenge - the endogeneity of board independence - by leveraging the enactment of Sarbanes-Oxley Act and subsequent changes to the NYSE/NASDAQ listing rules (collectively referred to as SOX hereafter) as a natural experiment that exogenously shifts board independence for US-based public firms. These changes provide an ideal identification strategy, since they create differential shocks to board independence of compliant firms (those with boards that included more than the required ratio of independent directors prior to SOX) and to that of non-compliant firms (those with boards that included less than the required ratio of independent directors prior to SOX), but ensure that such changes are independent of the unobserved firm-specific variables that are correlated with firm performance.

We estimate our models using panel data methods using a sample of public firms in the IT hardware and software industries over the period of 1997-2013; these years are selected based on joint data availability on board characteristics, new entry threats and firm-level data on financial performance. Consistent with theoretical predictions, our results show that higher levels of NET lead to performance deterioration of the incumbent firms. More importantly, we find that board independence mitigates the negative impact of NET, all else being equal, providing evidence for the beneficial effects of independent board members. These findings are robust to the use of instrumental variables estimations and a variety of alternative measures of firm performance. We also show that the findings are generalizable to some other industry segments as well, such as IT service industries and other high-tech sectors.

Our work provides several useful contributions to extant research in information systems and corporate governance. First, we extend the IS literature by drawing attention to an important construct – new entry threats, which is particularly relevant in the IT industries due to fast-changing technological landscapes and the advent of digital innovations during the last decade. Being able to gauge and respond to new entry threats from startup ecosystems effectively has become increasingly vital in the IT sector. Theoretical studies show that disruptions brought by entry threats are likely to apply pressure on the firm's operational performance in a systematic manner (Hill et al. 2003; Porter 1985). However, little empirical research has examined the consequence of NET due to the lack of a proper measure. We fill this gap by empirically studying how new entry threats influence the incumbent firms' operational performance, leveraging a novel text-based measure of NET. Building on this, we also contribute to the small but important literature on quantifying new entry threats and examining their influences on industry dynamics. Utilizing the novel NET measure by Pan et al. (2015), our work provide another piece of validation of the measure of NET by showing that, consistent with prior work, high levels of NET do indeed corrode the incumbent's operating performance (Hill et al. 2003) .

Second, prior research on corporate governance has been unable to establish a direct relationship between board independence and long term firm performance (Bhagat et al. 2001), leading to heated debate over the usefulness of regulatory interventions with regard to board composition. Our finding helps partly address this debate, indicating that board independence does help firms weather the negative performance impacts of new entry threats in the IT industry, and to a broader extent, the high tech industries. Therefore we provide arguments that help establish a set of boundary conditions under which board independence contributes positively to firm performance with the high tech and IT industries.

Finally, our findings have important implications for management practices with regard to corporate governance. Although the selection of board members is a complex process and a multitude of factors should be jointly considered, our analyses show that the influence of independence of board directors cannot be overlooked, especially when the firm operates in a hypercompetitive environment and faces high levels of new entry threats. Compared to internal board members, independent directors are more likely to bring unique perspectives that help firms respond to the threats from highly innovative startups. Our work thus argues for a more contingent perspective on board independence, with special relevance to the IT industry.

2.2 Theoretical Background

2.2.1 New Entry Threats and Firm Performance

The IT industry is characterized by constant technological changes, fast clock-speed, and high risk (Mendelson et al. 1998). Incumbents in these industry sectors face significant turbulence in their product markets, one significant source of turbulence being the continuous waves of entrepreneurial activity. While the rapid rate of entrepreneurial activity may be considered beneficial at the aggregate level of the economy (Samila et al. 2011), this activity has serious implications for incumbent firms in the industry. The literature argues that there are likely to be many positive knowledge spillovers from entrepreneurs to incumbent firms (Audretsch et al. 2005) as well as agglomeration benefits (Delgado et al. 2010). However, in the immediate context, the threats from IT startups are likely to lead to performance deterioration for the incumbents, for a number of reasons. First, by introducing new, innovative products or business models, entrepreneurial ventures possess the ability to disrupt the incumbent's market dramatically in the future (Cockburn et al. 2011). This phenomenon is especially relevant to industry lifecycles in the IT and high-tech industries, where technological platforms and market positions change quickly (McAfee and Brynjolfsson 2008). Prior work on industry lifecycles establishes that a majority of product innovations emerge from the entrepreneurial space (Agarwal et al. 2002; Prusa et al. 1991; Prusa et al. 1994). The new products may be superior to those of the incumbents in terms of performances or production costs, and erode the market shares of the incumbents systematically.

Second, the potential technology changes associated with new entry threats may raise the wages level in the labor market, making it difficult for the incumbents to maintain their human capital. Prior literature shows that technology changes cause higher return to schooling (Acemoglu 1998) and inequality in wages (Hornstein et al. 2005). In addition, emerging technological changes require complementary, skilled labor with high education (Hornstein et al. 2005), heightening the competition for scarce human capital. As a result, the rising labor cost and more frequent job-hopping induced by entry threats lead to significant increases in operating costs (Fallick et al. 2006). Altogether, firms face disruptions in both product market and labor market when they face higher levels of entry threats. These disruptions are likely to apply negative pressure on the firm's operational performance, by influencing the demand side (competition in product markets) as well as the supply side (tightening markets for personnel and resources). Therefore, we expect, as a baseline, that firms experiencing high NET are more likely to experience operational performance degradation, relative to their peers who do not experience high NET.

2.2.2 The Role of Board Independence

The board of directors of incumbent firms plays an increasingly important role in strategic decision making within the firm (Carpenter et al. 2001; Judge et al. 1992). While much effort has been devoted to studying the relationship between board characteristics such as board size and board independence and firm performance, evidence on the role of the board is mixed or inconclusive (Bhagat et al. 2001) for a number of reasons. First, the idiosyncratic characteristics of firms often result in different types of boards, even within the same industry. For example, large firms with complex product/service portfolios may need boards with diverse experiences and background (Dalton et al. 1999), and such firms usually have more outsiders on the board who serve to provide information, expert knowledge and advice to the CEO (Agrawal et al. 1996; Hermalin et al. 1998). By contrast, Coles et al. (2008) find that R&D-intensive firms, for which the firm-specific knowledge of insiders is relatively important, are likely to benefit from greater representation of insiders on the board. Second, the mixed evidence is in part attributable to the endogeneity issues that arise in the selection processes of directors. Corporate governance structures, including board of directors, are endogenous decisions made by firms in response to the environment in which they operate. For example, a growing body of research focuses on optimal board design, including the representation of independent directors on boards (Boone et al. 2007; Raheja 2005). Others suggest that drivers of independent boards may include the private benefits of control and CEO's influence over director appointments (Hermalin et al. 1998). In yet another context, Luoma et al. (1999) argue that board formation is often a result of institutional pressures experienced by the firm in its environment. In effect, there are several reasons to indicate that board formation is endogenous. As a result, the effect of independent board directors on firm performance is often confounded with unobserved heterogeneities.

We argue that the dynamic environment under which the firm operates forms an important boundary condition that circumscribes the relationship between board independence and firm performance. That is, a firm's independent board members are particularly valuable when the firm operates under dynamic and turbulent environments, one instance of which is when it faces considerable new entry threats. In such contexts, firms are in need of systematic rethinking, resource reconfiguration and other strategic changes, and independent board contributes to firm performance through two primary pathways – information/resource provision and effective monitoring and oversight (Hillman et al. 2000). Independent board members represent valuable stores of knowledge, networks, and capabilities that are available to the firm (Kesner 1988). These resources and perspectives provided by independent board members are valuable in that they are not easily replicated within the firm (Hillman et al. 2003). Prior research shows that while internal board members may have greater proximal knowledge about the firm and its workings, the perspective brought in by independent members is particularly influential during times of strategic change and turbulence (Forbes et al. 1999; Rosenstein et al. 1997). Beyond providing new knowledge and perspective, independent board members may help organizations unlearn previous organizational habits that are obsolete or no longer functional (Nystrom et al. 1984). Furthermore, the presence of independent board members can ameliorate the negative effects of "groupthink" visible in embedded group members, thereby questioning taken-for-granted elements of strategy (Forbes et al. 1999). Thus, from a resource dependence perspective (Hillman et al. 2003), firms that face turbulence in their product markets are likely to benefit more from the presence of independent board members than firms in a stable environment.

The second role that board members play pertains to agency, i.e. they are responsible for monitoring the executives of the firm on behalf of the shareholders, and are part of the governance mechanisms instituted within the firm (Hermalin et al. 2003). Prior research show that the role of governance and oversight is more likely with independent board members rather than insiders who are associated with the firm (Hermalin 2005). With internal board members, there is greater likelihood of conflicts of interest as well as issues of collusion between executives such as the CEO (Westphal 1999). Consistent with this reasoning, Boone et al. (2007) and Baker et al. (2003) find that independent boards, i.e. boards in which independent members are in the majority, reduce the bargaining power of the CEO and incentives of empire-building, thereby ensuring that managerial decisions are long-term optimal for the firm. During the periods characterized by turbulent product markets and high levels of new entry threats, this monitoring capability is essential to ensure that the firm's executives take the appropriate strategic reaction to improve the firm's long-term viability, instead of short-term myopic decision making that may provide personal benefits to the manager but will affect the firm negatively in the long run (Guo et al. 2015). The monitoring function also helps the firm to cut management slack and improve efficiency during the period of turbulence, e.g., cutting unnecessary expenses and scaling back highly risky projects. Thus, from an agency perspective (Hillman et al. 2003), the presence of independent board members will alleviate the negative influence of new entry threat on firm performance by reducing overall agency costs and ensuring alignment between the longer-term goals of the firm and executives.

Moreover, prior research show that the level of board involvement in strategic decision making increases with more independent board members (Judge et al. 1992). Inside directors are usually reluctant to voice different opinions during strategic decision making because they are worried about challenging the authority of the CEO (Westphal 1998). Therefore, firms with more inside directors tend to be inertial to strategic changes, making them less adaptable to changing environments. In summary, both theoretical perspectives on the effects of boards – managerial agency and resource dependence – suggest that board independence may play an important role in moderating the relationship between new entry threats and firm's operating performance. We build on these arguments to empirically examine how board independence alters the nature of the relationship between NET and firm operating performance.

2.3 Data and Variables

2.3.1 Sample and Data Sources

The dataset we use to conduct our empirical tests is constructed using multiple sources. We focus on the firms in the IT software, hardware and Telecom industries (Kim et al. 2016) identified by 18 four-digit NAICS industry codes.[14] Financial data and other firm characteristics are obtained from Compustat. To measure board independence, we obtain data on board members of U.S.-based public firms from RiskMetrics (formerly Investor Responsibility Research Center), whose coverage is primarily on the S&P 1500 firms. Our variable of new entry threats is adopted from Pan et al. (2015), who describe such threats as emerging from venture-funded startup firms and measure them using a text-mining approach that compares the product descriptions of the incumbents with those of the new entrepreneurial startups. Our primary sample consists of 583

[14] Our IT sample is defined by 4 digital NAICS code: 2211, 3332, 3333, 3336, 3339, 3341, 3342, 3343, 3344, 3345, 3346, 5112, 5171, 5172, 5173, 5174, 5179 and 5181.

publicly-traded firms over the period of 1997-2013 with 4,175 firm-year observations, representing an unbalanced panel. The sample period includes years when there was considerable turbulence in IT sector (e.g., the Internet boom and bubble burst), the period of the global financial crisis in 2008 and the recovery afterwards, as well as the less volatile years. Together, the dataset provides considerable longitudinal variation in the measure of new entry threats and board independence that allows us to use firm-level fixed effects panel data models to control for many unobserved firm heterogeneities. We describe the key variables in our analyses below. A summary of the variable definitions can be found in Table 2-1.

[Insert Table 2-1 here]

2.3.2 Variables

New Entry Threats (NET). We adopt a novel measure, derived from text mining technique that is recently increasing applied in management studies (Ghose et al. 2012; Li et al. 2014), to capture the threats emerging from startups, introduced by Pan et al. (2015). While the full details on the construction and validation of the NET measure are available in Pan et al. (2015), we briefly discuss the intuition behind this measure here. New entry threats are calculated as the cosine similarity between the product description of an incumbent firm and the aggregated product descriptions from startups that received first-round venture capital funding in a specific year. The product descriptions of established firms are obtained from annual reports (10-Ks) that are timely updated as required by financial market regulations (Hoberg et al. 2016; Tetlock 2011; Tetlock et al. 2008). The product descriptions of startups are obtained from the VentureXpert dataset, commonly used in entrepreneurship research (Aggarwal et al.

2012). The VC-backed entrepreneurial firms have baseline quality and therefore represent credible threats of entry to incumbents (Aggarwal et al. 2015). Conceptually, this measure captures how the text of an established firm's product description is similar to the text of product descriptions from the startup universe. Intuitively, the cosine similarity-based *NET* measure is bounded between 0 and 1, with higher values representing greater threats of new entry.

Board Independence. Following prior work (Knyazeva et al. 2013), we define board independence as the fraction of the board represented by independent (non-gray outsider) directors. We exclude gray directors, who are outside board members with familial or business ties to the firm or its senior management, or have conflicts of interests that can compromise a board's major functions. For an average firm in the sample, the board is comprised of nine directors, of whom 73% are independent and 27% are gray directors or internal officers (including the CEO). We report the average board independence by year in Table 2. The statistics indicate that the average board independence was significant changed over the period of 2002-2007 after SOX and other related regulatory changes, and the general trend is increasing over time.

[Insert Table 2-2 here]

Firm Performance. We start by measuring firm performance using Return on Assets (ROA), defined as operating income before depreciation and amortization (OIBDA) divided by total assets (AT). This measure captures overall operating performance of a firm and is a commonly used firm profitability measure in finance and IS literature (Anderson et al. 2003; Bharadwaj 2000). We also experiment with alternative definition of ROA as net income over total assets, and return on equity (ROE) as alternative measures of operational performance (Allen et al. 2000). Table 2-3 shows the summary statistics of our sample. The firms have a mean ROA of 11.1% (1.9%) using OIBDA (using Net Income), and the average ROE is 11.5%.

Control Variables. Following prior literature (Anderson et al. 2003; Giroud et al. 2011), we control for a vector of firm characteristics that may affect a firm's performance, including firm size, asset tangibility, leverage, capital expenditure, and product market competition. We control for contemporaneous competition by calculating the Herfindahl-Hirschman index based on market shares, where competitors are identified by the increasingly popular Text-based Network Industry Classification (TNIC) scheme created by Hoberg et al. (2016). Unlike the traditional NAICS classification, TNIC classifications are updated every year as firms file 10-K reports, allowing for a more accurate measure of contemporaneous competition. We control for firm size using the natural log of total assets. In addition, following previous studies of corporate board of directors (Triana et al. 2013; Zona et al. 2015), we control for a set of board structure variables that may influence firm performance, including CEO duality, board size, average age of board members, average tenure of board members, and number of board interlocks. In our sample, the CEO also holds the position of the chairman of the board in approximately 65% of the firms. On average, a firm in our sample has a board of 9 directors with an average age of 60 and tenure of 9 years with the focal company, while 5 of them also sit on the board of (therefore create interlocks with) other companies. The summary statistics and correlations are shown in Table 2-3.

[Insert Table 2-3 here]

2.4. Results

We discuss the results of our analysis in stages, starting with firm-level fixed effects models. We then provide additional analyses where we address the endogeneity of board independence, use alternative samples and alternative dependent variables, and show that the results are robust to each of these specifications. Finally, to help better understand the results, we conduct a set of exploratory analyses that investigate the influences of NET and board independence on the different components of operating performance.

2.4.1 Results from Panel Data Models with Fixed Effects

In order to evaluate the impacts of *NET* and *board independence* on corporate operating performance, we estimate a panel data model of the following form:

$$\begin{aligned} Performance_{i,t+1} = \lambda_i + \phi_t + \beta_1 \times BoardIndp_{i,t} + \beta_2 \times NET_{i,t} \\ + \beta_3 \times BoardIndp_{i,t} \times NET_{i,t} + X_{i,t}\theta + \varepsilon_{i,t} \end{aligned} \quad (2\text{-}1)$$

where *i* indexes the firms, and *t* indexes the time periods. In the baseline model we use ROA as the dependent variable. The variable $NET_{i,t}$ is the text-based measure of new entry threats. $BoardIndp_{i,t}$ denotes the fraction of independent, outside directors. X_{it} is a set of firm characteristics that may affect firms' operating performance. We control for time-invariant unobservable firm characteristics by including firm fixed effects λ_i. ϕ_t is a set of year dummies we use to control for economy wide shocks. We estimate the models using OLS regressions with robust standard clustered at the firm level to control for serial correlation (Wooldridge 2010). ε_{it} represents the idiosyncratic error.

Table 2-4 reports the results from our baseline panel data model with firm fixed effects. The dependent variable in Column (1) and Column (2) is ROA, operationalized as OIBDA divided by total assets. Column (1) shows the direct effects of *NET* and *board independence* on firm performance, and Column (2) adds the interaction term between the two in the model. We repeated this pattern for other alternative measures of performance in the table. In the models examining direct effects of NET on performance (columns 1, 3, and 5), we find that the coefficients for *NET* are consistently negative for all the measures of firm performance and statistically significant at the 5% level or less, indicating that greater new entry threats are indeed associated with a decline in firm operational performance. These results provide baseline support for the argument that new entry threats negatively influence the operational performance. To illustrate the magnitude of effect of *NET* on firm performance, calculations based on results using the main ROA variable (column 1) suggest that a one standard deviation (s.d.) increase in new entry threats (before standardization, NET has a mean of 0.06 and s.d. of 0.04) is associated with a 0.55 percentage point decline in ROA, which translates to a reduction of $44.59 million in OIBDA based on the mean level of assets ($8,109 million) in our sample. Interestingly, we find that variations in board independence is, by itself, not directly associated with firm performance, an observation that is consistent with prior studies (e.g., Bhagat et al. 2001).

[Insert Table 2-4 here]

We estimate the moderating effect of *board independence* on the relationship between *NET* and firm performance, and report the results in columns 2, 4, and 6 of Table 2. We find that the interaction terms of *board independence X NET* are significantly positive at the 5% level (or lower) across all performance measures, confirming our conjecture that board independence positively moderates the relationship between new entry treats and firm performance. Effect size calculations based on column (2) suggest that, for firms with low levels of *Board Independence* (0.5 s.d. below mean, approximately 5.9 out of 9 are independent directors), a one s.d. increase in new entry threat is associated with 0.89 percentage point decrease in ROA, equivalent to a reduction of $72.82 million in OIBDA when total assets are evaluated at the mean level. In contrast, at high levels of *Board Independence* (0.5 s.d. above mean, roughly 7.2 out of 9 are independent directors), a one s.d. increase in *NET* results in a 0.105 percentage point reduction in ROA, equivalent to a decline of only $8.51 million in OIBDA on average. The results support our theoretical argument that a higher percentage of independent board directors, who strengthen the monitoring functions while also providing knowledge resources and independent opinions, partially mitigate the negative impact of NET on the incumbent's operational performance.

2.4.2 Addressing Endogeneity of Board Independence

The baseline analyses assume that board independence is strictly exogenous. However, as discussed earlier, endogeneity concerns arise when there are unobserved variables that are correlated with both firm's operating performance and the decision to select board members. For example, powerful CEOs usually have considerable influence on choosing the directors of board (Hermalin et al. 1998) such that she or he could build a board with less independent or more compliant board directors, thereby reducing the extent to which the board restricts agency costs. Powerful CEOs may also be more likely to manage the firm more efficiently and have better operating performance.

These dynamics may lead to a negative correlation between board independence and the firm's operating performance, even though a less independent board per se does not lead to better operating performance.

To address these concerns, we relax the strict erogeneity assumption by using a quasi-experimental setup – we use regulatory changes with regard to board composition to instrument for board independence. During our sample period, an important set of new and tightened corporate governance requirements was introduced with the enactment of Sarbanes-Oxley Act. The main provisions included increased penalties for fraudulent financial activities, independence of audit committees, CEO and CFO certified financial statements, real-time disclosure of equity transactions by corporate insiders, and so on (Chhaochharia et al. 2016). In response to the enactment of SOX, major U.S. stock exchanges required their listed companies to comply with additional corporate governance obligations, such as the requirement for a majority of independent directors on the board, existence or creation of audit, nomination and compensation committees, and board sessions without insiders (Wintoki 2007; Zhang 2007). These regulatory changes form the basis of our identification strategy.

Specifically, we use the enactment of the Sarbanes-Oxley Act and the subsequent changes in the NYSE/NASDAQ listing rules as an exogenous determinant of our endogenous variable – board independence. One of the key requirements of SOX was that a majority of directors on a firm's board should be outsiders, or independent directors who has 'no material relationship' (either directly or as a partner, shareholder or officer of an organization that has a relationship with the company) with the listed company (Banerjee et al. 2015; Chhaochharia et al. 2016). The enactment of SOX was thus associated with a significant, exogenously mandated increase in the number of independent directors for non-compliant firms (i.e., firms with fewer than 50% independent directors prior to SOX), but did not significantly affect the board independence of compliant firms (i.e., firms with greater than 50% independent directors prior to SOX). Therefore, we use the enactment of SOX to construct an instrument for board independence. Figure 2-1 demonstrates the trends of average board independence for compliant firms and non-compliant firms for the years before and after SOX. Compared to the compliant firms, there is a substantial increase in average board independence for non-compliant firms around the year of SOX enactment in 2002. Thus, model-free evidence shows that the enactment of SOX is indeed associated with significant exogenous shocks to board independence, particularly in non-compliant firms.

[Insert Figure 2-1 here]

To construct the instrument, we assign firms in our sample to one of two groups based on their board composition in the year prior to SOX. The first group (compliant group) consists of firms that had already met the regulatory requirements in the year prior to SOX, i.e. they had a majority (more than 50%) of board directors that were independent directors in the year prior to SOX. The second group (non-compliant group) includes the "treated" firms that had not met the requirements with regard to board independence in the year prior to SOX. We create a dummy variable indicating whether a firm belongs to "treated" or control group. We also construct a *post-SOX* timing indicator that equals one if the observation occurs in 2002 or later. Whereas SOX was enacted in mid-2002, we also use an alternative cutoff to construct the timing indicator that equals one if the observation occurs in year 2003 or later as a robustness check (Chhaochharia et al. 2016). The instrumental variable for *Board Independence* is thus defined as the interaction of the *non-compliant group*post-SOX* dummy (Banerjee et al. 2015). For models with interaction *NET* × *Board Independence,* we further interact this instrument with *NET* to address the potential endogeneity of *NET* × *Board Independence* in the full model.

The results from 2SLS regressions are reported in Table 2-5. Panel A represents the results with instrumental variables using 2002 as the cutoff for the *post-SOX* indicator. The first-stage regression results of the IV on *Board Independent* are shown in Column (1).[15] The coefficient estimate of the instrument, *non-compliant firms* post-SOX*, is positive and significant at the 1% level, consistent with the expectation that non-compliant firms were indeed scrambling to add independent board directors after the enactment of SOX. For all IV regressions, we report the F-statistics for the test of weak instrument. For the main effects model (Column 2), the value of the first stage F-statistics (187.30) is larger than the conventional rule of thumb value 10, as suggested by Staiger et al. (1997), showing that the instrument is not weak. It is also greater than the Stock-Yogo critical value at 10% maximal IV size, which is 16.38 (Stock et al. 2005). Column (2) and Column (3) show the second stage of 2SLS regression accounting for the endogeneity of *Board Independence* without and with interaction term of *NET * Board Independence*, respectively. We are primarily interested in the extent to which endogeneity may have biased the effect of *Board Independence* as a

[15] For brevity, the first stage results of IV regression with *NET* × *Board Independence* were not included, which can be obtained upon request.

moderator: the results in the second stage regression after we instrument for the interaction term. The second stage results are qualitatively similar and in the same direction as in our baseline estimates but larger; the larger estimates may reflect the instruments removing measurement error or a local average treatment effect. Therefore, caution is recommended in using point estimates from this analysis for predictions outside the sample. Further, we repeat the empirical practices with instrument variable using 2003 as the cutoff for the time-period indicator and present the results in Panel B. We observe that the results are highly consistent with Panel A.

[Insert Table 2-5 here]

A lingering concern is whether the results in 2SLS regressions are mainly driven by the construction of the panel, which includes more observations long after SOX, when most public firms were already compliant. In order to address this concern, we conduct a robustness test in which we limit the observations to years before 2007, creating a sample with equal number of years prior to SOX (1997-2001) and post SOX (2002 to 2006). We report the results using this sample in Table 2-6 , with both fixed effects models and 2SLS models. We find the results are consistent with those from the full sample. Thus, the IV estimates, taken together, provide strong support for the finding that board independence moderates the relationship between new entry threats and firm operating performance. The results from 2SLS show the same pattern as the baseline regressions, suggesting that the endogeneity of *Board Independence* is unlikely to change the conclusions we draw from the analyses.

[Insert Table 2-6 here]

2.4.3 Analyses with Alternative Samples: HT Firms and IT Service Firms

While the main analyses reported above focus on the IT hardware/software sector, it is of particular interest to check if the findings are generalizable to a more inclusive set of industry sectors. Specifically, we expand the sample to include IT services firms and firms in the high-tech sectors other than IT following the definition by the Bureau of Labor Statistics (Hecker 1999) using 38 four-digit NAICS codes. We caution that the estimates from these extended sample analyses may not apply to IT software and hardware firms directly; however, analyses across industries is always useful since it allows us to probe the robustness of our findings in a more generalizable setting, as well as provides opportunities for falsifiability tests and comparisons between industries.

Table 2-7 shows the results using the IT full sample (which includes IT service firms), with ROA as the dependent variable. We note that the sample here is augmented to 682 firms with 4,855 observations. We find that the direct effect of *NET* on performance is negative and significantly at 10% level, which is consistent with what we find using the set of IT hardware/software firms. Compared to the estimates in IT hardware/software sample, the estimate from IT full sample is slightly smaller in magnitude, showing that new entry threats cause disruptions to a lesser extent to IT services companies, since services firms do not have rigid constraints associated with production lifecycles, R&D costs, and a focus on heavily skilled personnel, and therefore are more flexible to adopt changes and respond to such threats quickly (Kim et al. 2016). With respect to the moderating effect of *Board Independence,* we find that the coefficient of the interaction of *NET* * *Board Independence* is positive and significant 1% level, showing consistency with the results reported earlier using the main sample. Table 2-8 reports the estimates using firms in the high-tech universe with 997 firms and 7,139 observations. The results repeat the same pattern as in the main sample, indicating that our findings may be generalizable to a variety of other high-tech industries.

[Insert Table 2-7 and Table 2-8 here]

2.4.4 Analyses of the Components of Operating Income

The main performance measure of ROA, defined as the ratio of OIBDA to assets, is an aggregate measure that captures the overall operating performance. In this section, we decompose ROA into its components and investigate how *NET* and *board independence* influence firm efficiency following work in the finance literature (Chhaochharia et al. 2016). Specifically, we decompose the ratio of ROA as follows:

$$ROA = \frac{OperatingIncome}{Assets} = \frac{OperatingIncome}{Sales} \times \frac{Sales}{Assets} \tag{2-2}$$

where

$$\begin{aligned} \frac{OperatingIncome}{Sales} &= \frac{Sales - COGS - SGA}{Sales} \\ &= 1 - \frac{COGS}{Sales} - \frac{SGA}{Sales} \end{aligned} \tag{2-3}$$

Here, COGS denotes the *cost of goods sold* and SGA is the *sales, general, and administrative expenses*. Equation (2-2) shows changes in ROA can be broken down into two sources: changes in operating income over sales, and changes in sales over assets. The ratio of operating income over sales, also known as Return On Sales (ROS) or *operating margin*, measures production efficiency; the ratio of sales over assets, known as *asset turnover*, measures how efficiently assets are used to generate sales.

Prior studies use these measures to capture different aspects of the level of efficiency in firms (Ang et al. 2000; Chhaochharia et al. 2016). Equation (2-3) demonstrates that operating income can be further decomposed into total sales, COGS and SGA. Thus, operating income over sales approximately equals to one minus COGS over sales and SGA over sales. The ratio of COGS to sales indicates efficiency in the production of the goods, and the ratio of SGA to sales captures the efficiency of administrative costs.

Table 2-9 reports the results from each decomposed ratios. We present estimates for direct effect of *NET* and interaction effect of *NET* * *board independence* in Column (1) and Column (2), respectively, using ratio of sales to assets as the dependent variable. Here, the coefficient of NET is insignificant (Column (1)), suggesting that the decrease in ROA was not the results of a decrease in *asset turnover*. In contrast, we find that in Column (3), *NET* is negative and significantly associated with the ratio of operating income to sales, thus the deterioration in ROA appears to be caused by a decrease in *operating margins* rather than *asset turnover*. As expected, we observe that the coefficient of the interaction term of *NET* * *board independence* is positive and significant (in Column (4)), showing that a more independent board helps to attenuate the decline in *operating margins*.

To probe further into the drivers behind the deterioration of performance, we break down operating income into sales and two cost components (as in equation (2-3)). Column (5) and Column (6) report the results with COGS to sales ratio as the dependent variables. We find evidence that while *NET* does not cause a rise in the cost of goods significantly for an average firm, there are significant variations among the sample firms: firms with low levels of board independence do see a cost increase (as shown in Column (6)), and an independent board helps reduce management slack and increase cost efficiency. Finally, we present the results of regressions with SGA to sales ratio as the dependent variable in Columns (7) and (8). Column (7) shows that *NET* is associated with a rise in SGA significantly. This is consistent with the notion that firms incur higher administrative and overhead expense in highly dynamic environment where there is heightened competition for human capital. In Column (8), the interaction effect of *NET * board independence* is negative but short of significance at conventional levels, which might be caused by missing observations in SGA that reduce the statistical power of the analysis.

Overall, these ancillary analyses provide a consistent picture of how NET may affect firm performance, and the moderating effects of board independence. We find that the negative impact of *NET* on ROA appears to be attributable to a decrease in *operating margins* rather than in *asset turnover*. Consistent with our main finding, board independence helps alleviate the impact of *NET* on *operating margins*. In addition, we find some suggestive evidence that a high level of *NET* increases the administrative and overhead costs, resulting from uncertainty in the production process as well as the potential loss of important human capital; board independence helps to reduce management slack and boost cost efficiencies, thereby mitigating some of the negative effects of NET.

2.5 Discussion and Conclusion

In this study we examine how threats emerging from entrepreneurial startups impact the incumbents' operational performances in the IT sector, and how this relationship is altered by the appointment of independent board members, all else being equal. Using data on a panel of 583 firms in the IT industries over the period of 1997-2013, we find that increasing level of new entry threats is associated with deterioration in operating performance. In addition, we show that boards represented by a greater number of independent directors, who contribute to stronger monitoring and offer independent opinions in strategic decision making, can mitigate this negative impact. This finding is robustness to the endogeneity of board independence and is generalizable to a number of industries such as IT services and other high-tech sectors.

Our work makes several important contributions to research and managerial practice. First, we extend the IS literature by drawing attention to an important construct that has tremendous implications in the IT sector – new entry threats. Since the IT sector is particularly associated with hyper-competition, fast clock-speed, and rapid technological changes (McAfee and Brynjolfsson 2008), being able to identify and measure new entry threats from the startup ecosystems has become increasingly vital. New entry threat, as a conceptual entity, has existed in the literature since the early days of strategy and industrial organization (Porter 1979). However, because the threat from the individual entrepreneurial startup is difficult to observe, and no existing measure of the threats at aggregated levels has been developed, there is little empirical work that investigates how new entry threats change the competitive dynamics. For example, prior work has focused mostly on competition and turbulence arising from peer incumbents or from actual observed entry of competitors, rather than the threat of new entry from the entrepreneurial ecosystem (Hoberg et al. 2014). In this paper, we attempt to fill this gap by adopting a novel text-based measure that incorporates the behavior of startups and venture capitalists in assessing new entry threats within the IT sector, and by linking this measure to firm performance.

Second, we contribute to the literature on the relationship between firm governance and performance (e.g., Coles et al. 2008; Hillman et al. 2003) by examining how board characteristics, specifically the fraction of independent board members, moderate the relationship between new entry threats and firm performance. Prior literature in finance has provided equivocal guidance on whether there is a definitive relationship between board independence and improvement in firm performance (Bhagat et al. 2001; Coles et al. 2008), often leading to divergent policy advice. While the benefits of independent members is certainly convincing from a theoretical perspective, some empirical evidence of the contingent effects of board independence on performance is still necessary to validate theory. By showing how the nature of this relationship varies in response to the degree of *NET*, we illustrate the role of critical boundary conditions and also provide a possible explanation for the ambiguous findings in the literature. Board independence may not matter if industries are stable and experience limited turbulence; in such contexts, the resources and monitoring that external board members provide may not be as influential as those provided by insiders. It is in turbulent environments that independent members provide value. We empirically identify these effects using a strategy that leverages the exogenous variations in the number of independent directors imposed by Sarbanes-Oxley Act and related changes to the NYSE/NASDAQ listing rules, and therefore are able to rule out some alternative explanations.

In addition, our work also demonstrates the value of adopting machine learning/text-mining techniques in studying questions of relevance to governance and firm strategy. For IS researchers, our study highlights the need to study boards and other corporate governance mechanisms as a source of strategic value within the fast-moving IT industry. Fast clock-speed and hyper-competition are the norm in technology markets, and as markets impose stress and uncertainty on incumbents, it is up to the governance regime within the firm to create effective responses to these imperatives. Governance can strengthen or weaken a firm's ability and effectiveness in its response to turbulent environments such as one that is constantly under the pressure of new entry threats. Boards represent one of such governance mechanisms and inasmuch as the IT industry continues to be characterized by turbulence and hyper-competition, further work is needed within the IS community to fully explicate the role of governance.

Our work here also points the way for future research in this area. First, we recognize that governance is a multi-faceted construct and we only capture one aspect of it through our focus on the board. There are other forms in which firms govern their constituents, such as through alliance contracts, board interlocks, the presence of checks and balances on executives (measured by the G-index, for instance (Gompers et al. 2003), and so on. We see limited research on these constructs within the IT industry, arguably where much more work is needed. Second, we characterize board members broadly as independent or not, but this characterization masks considerable heterogeneity in the skills and experience they bring to the table. Unfortunately, this level of granularity of data is difficult to gather for large samples, but nevertheless represents an interesting extension of our work. Finally, new entry threats emerging from entrepreneurs represent one source of turbulence for incumbents – other sources include threats from foreign technology firms, threats from the open source market (e.g., in the new Big Data ecosystem where most products are open source (Madden 2012), and threats from rapid technological change per se. We believe there is considerable opportunity here for future work that enhances our understanding of how these forces affect the viability, and the performance, of incumbents in the IT industry. We also show how recent advances in machine learning can be leveraged to address these questions of economic interest, thus responding to recent calls for more machine learning in business research (Athey 2015).

Essay 3: The Lesser Evil? The Effect of New Entry Threats on Information Disclosures within the I.T. Industry

Abstract

This paper examines whether the threats of new entry from entrepreneurial firms influence incumbents' information disclosure behavior in the fast-moving information technology (IT) industry, where a significant part of the rapid technological change is attributed to startup ventures that pioneer new innovations. We argue that when facing the new entry threats (NET), incumbents are more likely to withhold proprietary information in order to prevent technological spillovers. Using a novel measure of new entry threats based on text-mining approaches, we show that a higher level of NET is indeed associated with a decrease in the transparency of incumbent's information disclosure, as measured by a disclosure index composed of analyst forecasts as well as confidential treatment orders (CTOs) filed by the firm. Interestingly, we also find the effect is less pronounced in highly concentrated industries, where the relatively high entry barriers due to industry concentration reduces the influence of NET. In addition, we find the effect to be more pronounced in software and IT services sectors relative to hardware sectors, since proprietary information in the former is more vulnerable to misappropriation. We discuss the implications for research and the insights for practitioners.

Keywords: *new entry threats, corporate disclosure, proprietary information, redacted information, disruptive technology, text mining*

3.1 Introduction

In high-tech industries such as information technology, new entry threats (hereafter, NET) have become increasingly salient in recent years where the pace of digital innovations is altering the nature of competition. New ventures such as Uber, Airbnb, and Snapchat are increasingly leveraging social media, business analytics, mobile channels and cloud platforms to disrupt traditional business models by dramatically reducing costs, improving efficiency, creating personalized experiences, or offering great product variety. Furthermore, emerging developments in crowd-funding platforms and startup incubators have further lowered the barriers to entry, making it easier for entrepreneurial startups to acquire resources and grow (Aggarwal et al. 2015; Kim et al. 2016; Kim et al. 2014). Technology startups are constantly introducing new technologies to the market and transforming existing business models, which in turn leads to intensive competition that systematically erodes the product market position of incumbents in the future. As a result, incumbents in the IT industry tend to develop organizational routines that help spot these threats quickly and adjust their strategies accordingly.

One such potential strategy to reduce the possibility of unintentional spillovers of knowledge and personnel to startups pertains to the question of information disclosures, i.e. the guidance on future earnings that public forms provide to the market and the regulatory agencies. The extent to which incumbent firms may choose to strategically manipulate their information disclosure remains understudied in the literature. In this paper, we study how the threat of new entry from the entrepreneurial ecosystem may influence the incumbent firms' information disclosure decisions. Prior work studying disclosure argues that there are countervailing forces at play: on the one hand, the "unraveling" theory suggests that a firm should disclose all private information because withholding such information will be interpreted by the investors as bad news (Grossman 1981). On the other hand, indiscriminate information disclosure can lead to the leakage of valuable proprietary knowledge or reveal firm strategy, placing the firm at a competitive disadvantage (Beyer et al. 2010). Therefore, firms face the tradeoff between the benefits of increased transparency, such as a lower cost of capital, and the proprietary costs of disclosure (Core 2001). Compared to startups, incumbents often have more in-depth knowledge regarding the market potentials, which is subject to spillovers. Further, when facing potential competition from startups, the disclosure of proprietary information related to R&D may lead to imitation by competitors. Hence, the specific research questions we aim to address in this paper are: *In the presence of threats of new entry, how do incumbents respond in terms of their information disclosure practices? Moreover, are there contextual factors that may moderate the effect of NET?*

One critical challenge of examining the influences of NET on firm information disclosure is how to quantify the threats from new ventures. By definition, threats from new entries represent forward-looking expectation of the extent to which the potential for *future* competition may influence firm profit or product market performance, but are not yet to be fully materialized at the current moment; thus they are difficult to observe and measure (Hoberg et al. 2014). To overcome this difficulty, we adopt a novel, text-based measure of new entry threats introduced by Pan et al. (2015), which measures the extent to which there is concordance between the collective corpus of text used by entrepreneurs who receive early-stage venture capital funding in a given year and the text provides by incumbent firms in their 10K filings for that year. This text-based measure of NET is appropriate for empirically examining the specific research questions of interest here for several reasons. First, technology startups backed by VC are more innovative and represent credit source of threats to the incumbents. Second, the product descriptions reflect the most up-to-date product portfolios of the incumbents as well as the new ventures. Finally, such a measure allows the level of new entry threat faced by an incumbent to vary per year, thereby mirroring the ebbs and flows in such threats that occur in the real world. Hence, the NET measures the fast-moving industry dynamics in a timely fashion and provides longitudinal variations that more accurately capture the perception of new entry threats for the specific incumbent firm.

We measure information disclosure using several well-established proxies in the accounting literature, such as the disclosure index and information redaction (Ettredge et al. 2016; Hui et al. 2014). These measures represent the extent to which analysts or industry observers are able to make accurate and reasonable forecasts of the earnings of incumbent firms, based on the information provided by the incumbents to regulators as well as the market. To the extent that such forecasts are accurate, the disclosure provided by the firm is seen to be reliable and unbiased. Furthermore, in some cases, firms may choose to redact certain information given the sensitive and competitive nature of this data – these also indicate the strategic intent to withhold relevant information from the market. Standard measures of information disclosure used in the literature include these elements to construct disclosure indices, which we use in our analysis. We estimate our models using panel data methods on a sample of public firms in the IT hardware, software and services industries over the period of 1997-2013; these years are selected based on joint data availability on firm disclosure, new entry threats and firm-level data on financial performance.

Consistent with the proprietary cost hypothesis (Grossman 1981), our results show that higher levels of NET lead to less information disclosure of the incumbent firms. The negative relation between NET and firm information disclosure is robustness to the use of alternative measures of information disclosure, and the use of instrumental variables approach that addresses the endogeneity of NET. More interestingly, we find that the effect is less pronounced in highly concentrated industry, where the relative high entry barrier due to the industry concentration reduces the influence of NET. In addition, the effect is more pronounced in Software and IT Services sectors, because proprietary information in these sectors is more vulnerable to imitation and spillovers. We show that the findings are applicable to a number of other industries within the high-tech sector as well, in addition to the IT industry.

Our work provides several contributions to the Information Systems (IS) literature as well as the literature on corporate disclosure. First, we help deepen the understanding of IT firms' disclosure decisions when they face fast-changing environments, particularly when these changes emerge from the entrepreneurial space. The United States has moved from an industrial economy to a predominantly knowledge-based economy (Baumol et al. 2010; Eisfeldt et al. 2013), where knowledge assets are not perfectly protected and spillovers may occur through a number of channels. Firms operating in such environments face a trade-off between the benefits of increased transparency, such as presumably lower cost of capital, and the proprietary costs of disclosure, especially if they lead to a weaker competitive positioning in the near future. In these contexts, it is important to understand how new entry threats may impact the firm-level decision to strategically shade information provided to the market. Our work here directly contributes to this gap in the literature. Second, we contribute to the extant accounting literature that addresses the importance of information disclosure as a way to keep markets efficient; indeed, the basis for the efficient markets hypothesis rests on the presumption of reasonable and unbiased information, which then drive rational expectations (Lovell 1986). If, as we argue, firms experiencing volatility in their product markets systematically withhold information, rational investors will need to account for such biases. Of course, it is possible that firms are not intentionally withholding information but that the underlying volatility renders forecasts noisy; if so, it is still important to identify these effects inasmuch as they affect markets. Our work contributes by not only showing the effects of new entry threats on disclosure decisions but also considering the impact of boundary conditions that influence such decisions, thus informing financial analysts as well as accounting professionals on the downstream effects of technological turbulence and the resulting entry threats.

3.2 Theoretical Background and Hypotheses

3.2.1 Information Disclosure by Firms

A firm's decision to voluntarily disclosure proprietary information to the public in order to inform markets and assorted stake-holders represents, at its core, a strategic choice. Based on the assumption that the revelation of information is costless (Verrecchia 1983; Verrecchia 2001), corporate disclosure theory suggests that managers should reveal all private information because the market interprets the withholding of information as bad news (Grossman 1981; Milgrom 1981). However, indiscriminate disclosure can lead to the leakage of valuable proprietary information, such as R&D plans, innovation strategies, or firm strategy, to competitors, thereby hurting the incumbents' competitive position in product markets (Beyer et al. 2010; Verrecchia 2001). Therefore, the disclosure decisions are determined by the tradeoff between the potential benefits of increased transparency, such as lower capital cost, and the proprietary cost of disclosure that may encompass the loss of proprietary information as well as valuable knowledge and resource spillovers that can weaken the incumbent in the future (Core 2001).

Early work in disclosure argued that under competitive pressure from existing rivals, firms are likely to be discouraged from voluntary disclosure. For example, Verrecchia (1983) modeled this relationship and proposed the "proprietary cost hypothesis". He argues that proprietary costs associated with disclosure lead to discretionary disclosure, as long as the capital market cannot tell whether the non-disclosure is due to the withholding of bad news or if the benefits from disclosing good news is not enough to cover the associated costs. In other words, if the capital market cannot isolate the true relationship between the associated costs of disclosure and the actual information disclosed, the firm will prefer to disclose information. He finds support for the "proprietary cost hypothesis" that proprietary costs are positively associated with the disclosure threshold. In other words, as the proprietary costs increase, less information is disclosed.

A number of empirical studies have attempted to further investigate the association between proprietary costs and disclosure (Ali et al. 2014; Li 2010b; Verrecchia et al. 2006). Most of these studies have relied upon measures of industry competition such as industry concentration, or the number of rivals as proxies for the proprietary costs of disclosure, under the rationale that proprietary costs of disclosure are increasing in competitive intensity faced by the firm. For instance, Harris (1998) and Botosan and Stanford (2005) show that firms in more concentrated industries are less likely to provide separate business segment disclosures. Furthemore Bamber and Cheon (1998) report that firms in more concentrated industries provide less specific management forecasts of their earnings. Using a different measure of information disclosure, Verrecchia and Weber (2006) document that firms are more likely to redact information when they are in a competitive industry. Li (2010b) also shows that competition is negatively associated with management forecasts.

Building on the theory of proprietary costs of information disclosure, we argue that incumbents facing a higher level of new entry threats face a greater burden of proprietary costs. Technological competition is related to R&D activities (idea development) and disclosure controls (idea protection). Increasing levels of technological competition from startups make incumbents less willing to disclose proprietary information, especially that related to R&D and other intellectual property (Ettredge et al. 2016). Therefore, facing higher new entry threats, incumbents are likely to be less transparent in terms of their information disclosure.

In addition, firms facing higher NET are likely to face more intense market competition when a proportion of the threats from startups materialize in the future.

The expectation of high levels of competition in the future discourages incumbents' information disclosure, especially for proprietary information related to market potentials. This information will raise the incentives of startups as well as the existing rivals to enter the market based on the expected future payoffs. Hence, taking both technological competition and market competition together into consideration, we propose that:

H1: New entry threat is negatively associated with firm information disclosure.

3.2.2 Boundary conditions

Beyond the direct effect of NET, we consider a number of boundary conditions that regulate the relationship between new entry threats and firm information disclosure. First, new entry in an industry is likely influenced by industry characteristics. For example, prior research suggests that industry concentration is associated with entry barriers, because of the possibility that the established firms may collude to thwart entry (Orr 1974). Bresnahan et al. (1991) propose an empirical framework for measuring the effects of entry in concentrated markets, and provide additional support that industry concentration deters entry. Therefore, incumbents in highly concentrated industries are less threatened by new entry than those operating in a less concentrated industry. As a result, the response to new entry threats in terms of information disclosure is likely to be less pronounced for incumbents in highly concentrated industries. Thus, we propose:

H2: The negative association between new entry threats and firm information disclosure is less pronounced for firms in concentrated industries.

Second, we argue that the negative association between new entry threat and firm information disclosure is more pronounced in industries where appropriation regimes are weak and intellectual properties are more prone to imitation, such as in the software and IT services industries (Cockburn et al. 2011; Huang et al. 2013). Compared to hardware and telecom industries, software and IT services industry are more knowledge-intensive, and the output of the firms is in the form of information and other intangible assets such as computer code or business processes. It is well known that patent protection for software and business processes are significantly weaker and difficult to enforce (Gans et al. 2008; Graham et al. 2009), and intellectual property is more likely to be misappropriated. Given the high level of vulnerability of proprietary information in software and IT services industries, when facing high levels of NET, incumbents in these industries are more likely to withhold proprietary information. Thus, we hypothesize:

H3: The negative association between new entry threats and firm information disclosure is more pronounced for firms in the software and IT services industries.

Third, a firm's geographic proximity to entrepreneurship hubs may affect its disclosure behavior under dynamic environment. Prior research has documented a trend of agglomeration of inventive activities as measured by patents, particularly in the bay area (Forman et al. 2016), which is largely attributed to knowledge spillovers. Literature on agglomeration has studied the benefits of co-location from both the supply side, such as inter-firm knowledge spillover (Almeida et al. 1999) and access to specialized inputs and labor (Bresnahan et al. 2001), and from the demand side, including access to better market information (Porter 2000). With intensive entrepreneurial activities in the hub areas, there is greater risk of information spillovers through labor flows and other channels. Therefore, incumbents located in the entrepreneurial hubs are more likely to protect their competitive advantages by withholding proprietary information. In other words, we expect the negative relationship between new entry threat and firms' information disclosure to be more pronounced among firms that are geographically close to entrepreneurship and innovation hubs. Thus,

H4: The negative association between new entry threats and firm information disclosure is more pronounced for firms located close to innovation hubs.

3.3 Empirical Methodology

3.3.1 Sample and Data Sources

The dataset we use to conduct our empirical tests is constructed using multiple sources. We focus on the firms in the IT software, hardware & Telecom and services industries (Kim et al. 2016) identified by 21 four-digit NAICS industry codes.[16] We use analysts' forecasts of annual earnings per share (retrieved from the IBES database) to construct our main dependent variable - *disclosure index*. Further, firms' redaction information, such as confidential treatment order and technological information redaction information, is obtained from Securities and Exchange Commission (SEC). Our variable of new entry threats is adopted from Pan et al. (2015), who describe such threats as emerging from venture-funded startup firms and measure them using a text-mining approach that compares the product descriptions of the incumbents with those of the new entrepreneurial startups. Industry concentration data are constructed based on Hoberg et al. (2010)'s Text-based Network Industry Classification (TNIC). Finally,

[16] The sample is defined by 21 4-digital NAICS codes: 2211, 3332, 3333, 3336, 3339, 3341, 3342, 3343, 3344, 3345, 3346, 5112, 5161, 5171, 5172, 5173, 5174, 5179, 5181, 5413, and 5417.

we assemble a set of firm-level control variables from Compustat, IBES as well as CRSP. This leads to a sample of 1,721 publicly traded firms and 10,466 firm-year observations over the period 1997-2013, representing an unbalanced panel. The sample period includes years when there was considerable turbulence in IT sector (e.g., the Internet boom and bubble burst), the period of the global financial crisis in 2008 and the recovery afterwards, as well as the less volatile years. We describe the key variables in our analyses below. A summary of the variable definitions can be found in Table 3-1.

[Insert Table 3-1 about here]

3.3.2 Variables

Disclosure Index. Our main measure of information disclosure is based on analysts' forecast of annual earnings. The high accuracy and low dispersion of analyst forecasts, and low variance of analyst forecast revisions are associated with the degree of agreement among analysts' opinions of a firm's financials, which are based on analysts' interpretation of the relevant firm information and therefore reflect the overall disclosure quality (Lang et al. 1996). Following Hui et al. (2014), we use characteristics of analyst forecasts to construct the measure of overall quality of a firm's information disclosure. Specially, *Forecast Error* captures the accuracy of analyst forecasts by calculating the absolute difference between the last consensus forecast of Earning Per Share (EPS) before the release of earning and the actually EPS scaled by the beginning-of-year stock price. *Forecast Dispersion* measures the dispersion of analyst forecasts using the standard deviation of these forecasts prior to the release of earnings, deflated by the absolute value of the last consensus forecast at the end of the year. *Revision Volatility* represents the standard deviation of the monthly revision of the consensus forecast deflated by the beginning-of-year price. We take the median forecast as the consensus number of a particular forecast period. To show the robustness of our results, we also construct the variable by using mean forecast as the consensus number of a particular forecast period. Combining three individual measures, *Disclosure Index* is the sum of the decile rankings of the three, divided by 30. The index is scaled such that a higher value represents higher disclosure quality. The detailed variable definitions are provided in Table 3-1.

Information Redaction. As an alternative measure of firm information disclosure, we also collected data on firm initiated information redaction. Under the Securities Act and the Exchange Act, a firm can request a confidential treatment of information (CTO) when the disclosure of information required by the regulations can adversely affect its business and financial condition. Confidential treatment orders (CTO) allow information in the SEC filing to be kept secret from the public for a certain period of time. Common examples of this kind of information for which firms seek confidential treatment include pricing terms, technical specifications, contracting parties, contracting amounts, and milestone payment.[17] We collect confidential treatment order information from the SEC EDGAR database. The SEC database contains confidential treatment orders issued by firms as a separate file, named *CT ORDER*, from the annual report (10-K) issued since the beginning of 2008.[18] Our information redaction measure is thus based on the number of *CTOs* for each firm. Particularly, the *Number of CTOs* represents the total number of CT ORDERs filed by the focal firm in a specific year. We also constructed a binary measure, *CTO*, which

[17] Appendix I provide an example of confidential treatment order filed by Intuit Inc. in 2012.
[18] https://www.sec.gov/edgar/searchedgar/ctorders.htm

equals 1 if a firm files any Confidential Treatment Order (CTO) in year *t*, and 0 otherwise.

New Entry Threats (NET). We adopt the text-based measure, derived from applied machine learning technique that have been increasingly useful in management studies (Ghose et al. 2012; Li et al. 2014; Li 2010a), to capture the threats emerging from startups. The full details on the construction and validation of the dataset is introduced in essay 1 of this dissertation. Here, we briefly discuss the intuition behind this measure. New entry threats are operationalized as the cosine similarity between the product description of an incumbent firm and the aggregated product descriptions from high-tech startups that received first-round venture capital funding in a specific year. The product descriptions of established firms are obtained from annual reports (10-Ks) that are timely updated as required by financial market regulations (Hoberg et al. 2016; Tetlock 2011; Tetlock et al. 2008). The product descriptions of high tech startups are obtained from the VentureXpert dataset, commonly used in entrepreneurship research (Aggarwal et al. 2015). The VC-backed high-tech entrepreneurial firms represent credible threats of entry to the incumbents (Aggarwal et al. 2015). Conceptually, this measure captures the degree to which the text of an established firm's product description is similar to the text of product descriptions from the VC-backed technology startup universe. Practically, the cosine similarity-based *NET* measure is bounded between 0 and 1, with the higher values representing greater threats of new entry.

Boundary (Moderating) Variables. We calculate *Industry Concentration* as the Herfindahl-Hirschman Index based on the Hoberg et al. (2010)'s Text-based Network

Industry Classification. To capture the industries that have weak appropriation regimes, we created variable *Software & IT Services* as an binary indicator which is set to 1 when the focal firm belongs to one of the following four 4-digit NAICS code industries: 5112 - Software Publishers, 5182 - Data Processing, Hosting, and Related Services, 5415 - Computer Systems Design and Related Services, and 5416 - Management, Scientific, and Technical Consulting Services. Its value is set to 0 otherwise. The binary variable *Innovation Hub* captures the geographic location and equals 1 if the 5-digit postal zip code associated with the location of the firm belongs to one of the three main innovation hubs of the U.S.: the New York Area, the Silicon Valley Area, and the City of Boston. [19]

Control Variables. Following prior literature on firm disclosure (Ettredge et al. 2016; Hui et al. 2014), we control for a vector of firm characteristics that are known to influence a firm's disclosure decision. Specifically, the first set of controls measure the basic financial status of the focal firm, such as firm asset, return on asset (ROA), asset tangibility, leverage, and capital expenditure, R&D intensity, Tobin's Q, number of market segments, loss and number of analysts. In addition, we add a group of variables capturing market uncertainty faced by the focal firm other than NET, such as ROA volatility, stock return volatility and contemporaneous product market competition. We identify competition by the number of rivals in a firm's Text-based Network Industry Classification (TNIC) (Hoberg et al. 2010), which has gained increasing popularity in the literature (Kim et al. 2016).

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[19] New York city comprises 5 boroughs as follows: The Bronx, Brooklyn, Manhattan, Queens, Staten Island; Silicon Valley is consist of the following 15 cities: San Francisco, San Jose, Oakland, Fremont, Santa Rosa, Hayward, Richmond, Sunnyvale, Concord, Santa Clara, Vallejo, Benicia, Berkeley, San Mateo, Fairfield.

[Insert Table3-2 about Here]

Table 3-2 summarizes the descriptive statistics and the pairwise correlation matrix. The *Disclosure Index* (using median forecast as the consensus) has a mean of 5.353 and a standard deviation of 2.136. *A*pproximately 30% of firms belong to *Software and IT Services* Industries and 18% of firms are located in an *Innovation Hub*. We find that about 21.85 percent of our subsample, totally 1,057 firms, after 2008 filed at least one CTO. On average, a firm files 0.23 CTO per year to redact proprietary information, which is consistent with prior findings (Lee 2016).

3.3.3 Regression Models

To examine the relationship between firm information disclosure and new entry threats, we estimate the following panel data model for firm *i* and year *t*:

$$DisclosureIndex_{i,t+1} = \beta \cdot NET_{i,t} + \sum \gamma \cdot Controls_{i,t} + \alpha_i + \eta_t + \varepsilon_{i,t} \qquad (3\text{-}1)$$

where the main dependent variable is Disclosure Index that combines three separate disclosure dimensions. To show the robustness of our results, we also use *number of CTO* and *CTO* as the dependent variable in the additional analyses presented in section 5. NET is the main independent variable capturing the threats from startups. We also include controls for firm and year fixed effects. We cluster standard errors by firm. We use OLS panel data model as the main specification since methods of addressing potential endogeneity issues are well established in OLS panel data models. Meanwhile, we also realize that the *Disclosure Index* is a variable that is truncated to within [0,10]; therefore, as a form of robustness we also report the results from two-sided Tobit model, which provides largely similar results to our main models. These results are shown in Appendix II.

To examine the moderating effects of the boundary variables, we add a set of interactions between NET and the moderating variables, and test the following model:

$$DisclosureIndex_{i,t+1} = \beta \cdot NET_{i,t} + \varphi NET_{i,t} \cdot ModeratingVariable + \sum \gamma \cdot Controls_{i,t} + \alpha_i + \eta_t + \varepsilon_{i,t} \qquad (3\text{-}2)$$

where *ModeratingVariable* represents, respectively, *Industry Concentration*, *Software & IT Services,* and *Innovation hub*.

3.4 Results

3.4.1 Direct Effect of NET on Corporate Disclosure

Table 3-3 presents the regression results of model (1). We use *Disclosure Index* constructed using the median forecast as the consensus and report the results with *Disclosure Index* in year *t+1* and *Disclosure Index* in year *t+2* in Column (1) and Column (2), respectively. Column (3) and Column (4) repeat the same pattern for an alternative measure of *Disclosure Index* constructed with mean forecast as consensus. The coefficient on *NET is* negative and significant at the 0.05 level in Column (1). This finding suggests that new entry threats from startups are negatively related to firms' information disclosure quality. The marginal effect calculations suggest that a one standard deviation increase in *NET* is associated with a 0.10 decrease in the disclosure index.[20] The coefficient of *NET* is also negative and significant at the 0.01 level in Column (2), suggesting that a one standard deviation increase in *NET* is association with a 0.19 reduction in the disclosure index. We observe that the presence of *NET* leads to an even lower information disclosure quality in the year *t+2*, showing that *NET* has a lagged effect as these threats materialize over time. In Column (3) and (4), the coefficients of *NET* are consistently negative and significant at 0.01 level, and the

[20] The standard deviation of *NET* is 1 after standardization.

lagged effect of *NET* is also present. Taken together, these results suggest that firms are less transparent when they face greater threats from startups, presumably due to proprietary cost concerns.

With respect to the control variables, the results are largely consistent with prior literature (Hui et al. 2014). The significantly negative coefficients on *R&D intensity* are consistent with the interpretation that R&D activities generates proprietary information which leads to greater disagreement among analysts. The *Loss* indicator variable captures the lower relevance of accounting earnings associated with firms experienced a loss (Hayn 1995), and its coefficient is negative as expected. The *ROA volatility* variable reflects the uncertainty regarding future income, which is expected to influence firm disclosure negatively. The significant negative coefficients of total asset and number of business segments suggest that large and diversified firms are more complex, generating greater dispersion in earnings forecasts.

Table 3-4 presents the regression results for model (1) using the average level of *NET* over the prior 3-year period as the independent variable. The coefficients of *Average* $(NET_t+NET_{t-1}+NET_{t-2})$ are all negative and significant at 0.01 level, again providing strong support that firms are less likely to disclose when they face higher level of new entry threats. The effective size of the average *NET* is generally larger than *NET* in the prior year: for example, the coefficient in Column (1) of Table 3-4 (0.223) is larger than that in Column (1) of Table3 (0.107), which is consistent with the lagged effect of *NET* that we found in our regression results in Table 3-3. Taken together, the empirical evidence lend strong support to H1 that IT firms are less likely to disclosure information when they face greater new entry threats from startups.

3.4.2 Moderating Effects

H2 predicts that the negative relation between new entry threats and firm information disclosure is less pronounced for firms in concentrated industries. To perform the test of this boundary condition, we use the TNIC HHI in year *t-1* as *Industry Concentration* and include its interaction with *NET* in the baseline model. Results of this estimation, with one-year lagged firm information disclosure as the dependent, are reported in Table 3-5. In the models with the interaction term (Column (2) and Column (4)), we observe that the coefficients of the interaction term are positive and significant at $p < 0.05$. Effect size calculations based on column (2) suggest that, for firms with lower levels of *Industry Concentration* (0.5 s.d. below mean), a one s.d. increase in *NET* is associated with a 0.117 decrease in disclosure index. In contrast, at high levels of *Industry Concentration* (0.5 s.d. above mean), a one s.d. increase in *NET* results in a smaller decrease (0.058) in disclosure index. Consistent with H2, we find that the relationship between new entry threats and firm information disclosure is significantly moderating by industry concentration such that the negative association is less pronounced for firms in more concentrated industries.

H3 predicts that the negative association between new entry threats and firm information disclosure is more pronounced in industries with weak appropriation regimes, such as software and IT service industries. Compared to hardware and telecom industries, software and IT services industries are more knowledge-intensive, and the proprietary information is more vulnerable as intellectual property is more prone to imitation and can be lost due to unintentional spillovers. To test H3, we add the interaction between the indicator variable *Software & IT Services* and *NET* to model

(1). The regression results are reported in Table 3-6. Column (1) and Column (3) present the estimates from model with interaction term of *NET* and *Software & IT Services*. The coefficients of the interaction term in both columns are negative and significant (p<010), lending some support to H3. In addition to the interaction terms, we also performed split-sample analyses by partitioning the sample into the Software and IT Services subsample and the remaining IT sectors (representing Hardware and Telecom broadly). The estimated models allow coefficients to differ across the two subsamples. Results for these subsample analyses are reported in Columns (2 - 3) for Panel A, and Column (5 - 6) for Panel B. Consistent with H3, we find that the negative association between new entry threats and firm information disclosure is significantly more pronounced for *Software and IT Services* firms than for the rest of the IT subsample.

H4 predicts that the negative association between new entry threats and firm information disclosure is more pronounced for firms located within the proximity of an innovation hub. We argued that locating close to an innovation hub makes the proprietary information leakage more likely through knowledge spillovers as well as the possibility for labor movement, a phenomenon that has been studied in some detail in the literature (Tambe et al. 2013). To test H4, we add the interaction between the indicator variable, *Innovation Hub*, and *NET* into the regression model. The results are reported in Table 3-7 and show that the coefficients of the interaction term of *NET* x *Innovation Hub* are statistically insignificant. Thus, we receive no support for the moderating influence of location argued for in H4.

3.5 Robustness Checks and Post-Hoc Analyses

In this section, we provide results of a set of additional robustness analyses in support of the direct relationship between new entry threats and firm information disclosure. Since the observed correlation between NET and information disclosure is the basis for the following moderating tests, we subject this result to several robustness checks. First, we complement the main analysis reported above by using an alternative measure of firms' information disclosure – their information redaction behavior. Second, we adopt an instrumental variable method and estimate the main model with 2SLS to address potential endogeneity of new entry threats. Finally, we test our model in an extended high-tech sample and evaluate the external validity of the findings but in a broader industry context where the same factors that drive information disclosure behavior may be expected to play out, albeit in a more muted manner.

3.5.1 Using Firm Information Redaction

We further strengthen the findings by examining a firm's information redaction records. We collect CTOs filed by the focal firm in SEC EDGAR database after 2008[21]. It is worth noting that in comparison to the disclosure indices used earlier, here the use of CTOs is entirely driven by the incumbent firm. That is, the firm chooses to request a CTO, thereby displaying complete agency and intentionality in terms of redacting relevant information from the market. The sample for firm information redaction analysis includes 4,641 firm-year observations from 1,057 firms during the period 2008 – 2013, since CTOs were made available to firms officially only from 2008 onwards.

[21] SEC database contains confidential treatment order as a separated file CT ORDER from annual report (10-K) issued beginning in 2008. See: https://www.sec.gov/edgar/searchedgar/ctorders.htm

Table 3-8 shows the distribution of total number of CTOs across 4-digit NAICS code industries in our sample.

Table 3-9 reports the results of the analysis with firm's information redaction. The results show that *NET*'s effect on firm's redaction behavior is highly consistent with our main findings. In Column (1), we estimate the results from a logistic regression where the dependent is the binary indicator *CTO*. The coefficient of *NET* is positive and significant (p=0.01), revealing that when facing a high level of new entry threats firms are more likely to file for a CTO and thereby redact proprietary information. Effect size calculations suggest that the likelihood of redacting proprietary information is increased by 1.45 percent when *NET* increases by on standard deviation, all else being equal.[22] This economic effect is large given that the mean of *CTO* in our sample is at 12.3 percent. Further, since the firm can file for several CTOs in a given year, we also use a count model to study the effect of NET on the *Number of CTOs* filed by firms. Since *Number of CTOs* is zero for a large proportion (88%) of the sample, we use Zero-inflated Negative Binomial and Zero-inflated Poisson models and report the results in Column (2) and (3), respectively. The estimates of *NET* are consistently positive and significant, showing that *NET* does indeed positively influence the number of CTOs filed by the incumbent firm. Estimates in Column (2) suggest that the average *Number of CTOs* is about 0.22 when *NET* is at the sample mean level, and the number increases to 0.26 when *NET* is at 1 s.d. above the mean. In other words, holding everything else equal, 1 standard deviation increase in *NET* leads

[22] We use Stata Command margins to calculate the marginal effect for logistic regression. The mean predicted probability of filing CTO is 11.62 percent if *NET* is at mean level (which is 0, after standardization) and increases to 13.07 percent if *NET* is one s.d. above mean, holding everything else equal.

to an additional 0.04 CTO filed, which is significant give the mean value of *number of CTOs* filed by firms in our sample is 0.23. In summary, the analyses from firms' information redaction provide further support for our main finding that firms are more likely to withhold information (reduce disclosure) when facing a high level of *NET*.

3.5.2 Addressing the Endogeneity of New Entry Threats

It is possible that new entry threat is endogenously determined with regard to firm information disclosure behavior. We therefore employ and the instrumental variable (IV) method to further strengthen the causal relationship between new entry threat and firm information disclosure. In theory, valid instrumental variables for the *NET* measure should be correlated with startups' decision to enter a certain industry but not directly associated with the firm's information disclosure decision. As shown by Orr (1974) and Cockburn et al. (2011), new entry in an industry is likely influenced by industry-wide growth opportunities. Thus, we construct an instrumental variable that represents entry incentive at the industry level - *the lagged value of sale growth rate* (Orr 1974). The variable is calculated as the mean of sale growth rate of all companies in the focal industry. We use the text-based industry classification (TNIC) system described in Hoberg et al. (2010) to identify the relevant industry of the focal firm. The TNIC relaxes the transitivity property of SIC / NAICS classification systems, which allows for a firm specific influence associated with industry level movement, rather than a general level of influence based on NAICS/SIC codes which lacks within-industry variations.

The results of the 2SLS estimation are shown in Table 3-10. In general, the results from the second stage estimates (Column (2)) are similar to the FE specification in Table 3-3: the coefficient of *NET* is negative and statistically significant, providing further evidence for the negative association between new entry threats and firm information disclosure. In the first-stage regression, the *lagged value of sale growth rate* is positive and significant correlated with *NET*, which is consistent with our expectation. The Anderson-Rubin test statistics for the second stage regression also reject the null hypothesis that the instrument is weak (Andrews et al. 2005). Overall, Table 3-10 shows that the effects of new entry threats on firm information disclosure are robust to the potential endogeneity of *NET*, supporting a causal inference that new entry threats reduce firms' disclosure of proprietary information.

3.5.3 High-Tech Industries

While the main analyses reported above focus on the IT sectors, it is of particular interest to evaluate if the findings are generalizable to a broader set of industry sectors in which NET is prevalent, though potentially to a lesser degree than the fast-moving IT context. Therefore, we expand the sample to firms in the high-tech sectors following the definition by the Bureau of Labor Statistics (Hecker 1999) using 40 four-digit NAICS codes. Analyses across industries are useful since they allows us to probe the robustness of our findings in a more generalized setting, as well as provides opportunities for falsifiability tests and comparisons between industries.

Tables 3-11 to Table 3-13 show the regression results using the high-tech sample, with *Disclosure Index* as the dependent variable. We note that the sample is augmented to 2,462 firms with 15,444 observations. In Table 3-11, we find that the direct effect of *NET* on firm information disclosure is negative and significant at 0.01 level, which is fully consistent with what we find using the set of IT firms. With respects to the moderating effect of *Industry Concentration,* we find in Table 3-12 that the coefficient of the interaction of *NET * TNIC HHI* is positive and significant 0.05 level, showing consistency with the results reported earlier using the IT sample. With regard to the moderating effect of *Software & IT Services Industries,* we expect that H2 still holds because proprietary information in software and IT services industries is more vulnerable compared to other high-tech industries broadly, such as bio-tech and pharmaceutical industry where intellectual property may be better protected by mechanisms such as patents. In Table 3-13, the coefficient of the interaction of *NET * Software & Services* is negative and strongly significant, which is consistent with our finding using the IT sample. Collectively, the results from the augmented sample indicate that our findings are generalizable to a number of other high-tech industries.

3.6 Conclusions

The United States has become predominantly a knowledge-based economy, where entrepreneurial startups often threaten incumbent firms by introducing disruptive technologies, and potentially erode firms' future profitability. This paper we examine how new entry threats from technology startups affect firms' information disclosure. First, we show that firms facing greater new entry threats from the entrepreneurial space are less likely to disclose information. The effects are less pronounced for firms in high concentrated industries and more pronounced for firms in industries where proprietary information is more vulnerable to imitation. Our results are robust to the use of a number of alternative measures of information disclosure and the instrumental variable approach that addresses endogeneity concerns. We also show that the impact of new entry threats on information disclosure can be extended to some other high-tech sectors as well.

Our paper takes a first step towards understanding the effect of new entry threats on incumbent's disclosure practices and makes several important contributions to the IS literature, and to a broader level, the corporate disclosure literature. First, we help deepen the understanding of IT firms' disclosure decisions when facing fast-changing environments, particularly when these changes emerge from the entrepreneurial space. Second, we advance the literature of corporate disclosure by investigating how the external dynamic environment, such as threats from new entry entrepreneurial startups, influences the firm's disclosure decision. Third, we complement the literature of IT firms' information disclosure at a strategic decision level. Finally, we provide practical implications for investors and stake-holders, and broader concerns for policy-makers interested in well-functioning financial markets.

3.7 Appendices to Essay 3

3.7.1 Appendix I to Essay 3: An Example of Approved "CT Order"

We present an example of approved Confidential Treatment Order of Intuit Inc. filed in 2011.

UNITED STATES
SECURITIES AND EXCHANGE COMMISSION
December 28, 2011

ORDER GRANTING CONFIDENTIAL TREATMENT
UNDER THE SECURITIES EXCHANGE ACT OF 1934

Intuit Inc.

File No. 0-21180 - CF#27368

Intuit Inc. submitted an application under Rule 24b-2 requesting an extension of a previous grant of confidential treatment for information it excluded from the Exhibits to a Form 10-Q filed on May 30, 2008.

Based on representations by Intuit Inc. that this information qualifies as confidential commercial or financial information under the Freedom of Information Act, 5 U.S.C. 552(b)(4), the Division of Corporation Finance has determined not to publicly disclose it. Accordingly, excluded information from the following exhibit will not be released to the public for the time period specified:

Exhibit 10.2 through September 15, 2014

For the Commission, by the Division of Corporation Finance, pursuant to delegated authority:

Sonia Gupta Barros
Special Counsel

3.7.2 Appendix II to Essay 3: Main Results from Two-Sided Tobit Model

We also realize that the Disclosure Index is a variable that is truncated to within [0, 10]; therefore, as a form of robustness we also report the results from two-sided Tobit model here. These results are shown in Table 3-A1, which is largely similar results to our main models.

[Insert Table 3-A1 about here]

3.7.3 Appendix III to Essay 3: Corporate Disclosure Breakdown

While H1 is supported by our empirical analysis, we break down the influence of new entry threats on disclosure index into three individual measures of disclosure. The results are reported in Table 3-A2 to Table 3-A4, with Forecast Error, Forecast Dispersion, and Revision Volatility as dependent variable respectively.

We use Disclosure Index constructed both on median and mean of analyst forecast and report the regression results from NET's effect on firm disclosure in year t+1 as well as NET's lagged effect on firm disclosure in year t+2. Table 3-A2 to Table 3-A4 present the results and are organized following similar fashion as Table 3-3. From Table 3-A2, we observe that the coefficients of NET are consistently negative and significant at 0.01 level cross all columns, which means NET has a strong impact on the difference between last consensus analysts forecast and the true value. Further, the results in Table 3-A3 and Table 3-A4 show similar pattern that NET has a less significant impact on both Forecast Dispersion and Revision Volatility in the year t+1. Taken everything together, NET has a significant influence on the firm's disclosure behavior. In a more granular level, when the NET level is high, market (analysts) forecast is significantly more likely to depart from true value even in the last forecast period before announcing the true value, while the disagreement among analysts and the self-corrected process of analysts are not dramatically affected.

Dissertation Summary and Conclusion

New entry threat has become particularly salient in recent years where the pace of digital innovations is altering the nature of competition in fast-moving IT industry. Equipping with the digit innovation, new ventures are significantly easier for to jump-start the process of growth and resource acquisition, which, on the other side, impose increasingly threats to incumbents. Inasmuch as new entry threats contribute to the uncertainty of an IT firm's future market and profitability, strategic managerial decisions must account for their influences. As a result, there is a call for systematically understanding the strategic response of incumbents under high new entry threats.

R&D investment, operational performance, and information disclosure are three examples of such strategic responses from incumbent for my dissertation. Drawing on theories from information systems and other disciplines, I empirically study how incumbent firms behave when facing high level of new entry threats. In the first essay, incumbent firms on average reduce R&D spending when facing greater new entry threats. More importantly, firms that have a diversified product or technology portfolio, operate in industries with strong network effects, or face high levels of technological cumulativeness invest relatively more in R&D when facing greater new entry threats. In the second essay, I show that a higher level of NET indeed leads to a drop in the incumbent's performance. I also show that facing high NET, firms with more independent directors are better able to withstand these threats. In the third essay, the results show that a higher level of NET indeed leads to a decrease in incumbent's information disclosure. Interestingly, I also find the effect is less pronounced in high concentrated industry and the effect is more pronounced in Software and IT Services sectors.

In addition, findings from the three essays of my dissertation not only are beneficial to senior management of the incumbent firms, but also even have implications for investors and stake-holders, and broader concerns for policy-makers interested in well-functioning financial markets as well as entrepreneurial ecosystems. For example, when senior management team senses the threats from new entries, one potential way for them to mitigate the impact from new entry threats is taking in independent directors to the board. Meanwhile, whenever investors, stake-holders, and market investigators reading the disclosure from public firms who facing high level of new entry threats from entrepreneurial space should take a further thoughts on the potential hidden information from the public disclosure.

Overall, the dissertation contributes to the extant body of literature in several ways. First, I contribute a systematic and validated measure for new entry threats from the startup ecosystem for incumbent firms. My intent is to publish these measures to the broader strategy and entrepreneurship community so that further testing and validation of the measure can be carried out at large. The availability of a standard measure will help by benchmarking across models and theories. My work here will, I hope, encourage a variety of use of this measure to study important topics on impacts of the competitive dynamics from startups. Second, I add to the current literature on entry and in-novation by demonstrating the incumbents actually slow down their innovation investments when facing high levels of NET. Third, by investigating impact of NET on incumbents' operational performance and how they manage the negative influence through board of directors, I make a significant extension to prior research on the value of independent board. Fourth, my study extends information disclosure literature by examining how dynamics from NET causally lead to the changes of incumbent's information dis-closure quality and quantity. Finally, my text-mining approach utilizes standard text documents to capture underlying economic concepts, thereby representing a methodological contribution to the small but increasing literature that applies machine learning techniques to social science research.

FIGURES

Figure 1-1: Number of Unique Words Used in 10-K Product Descriptions

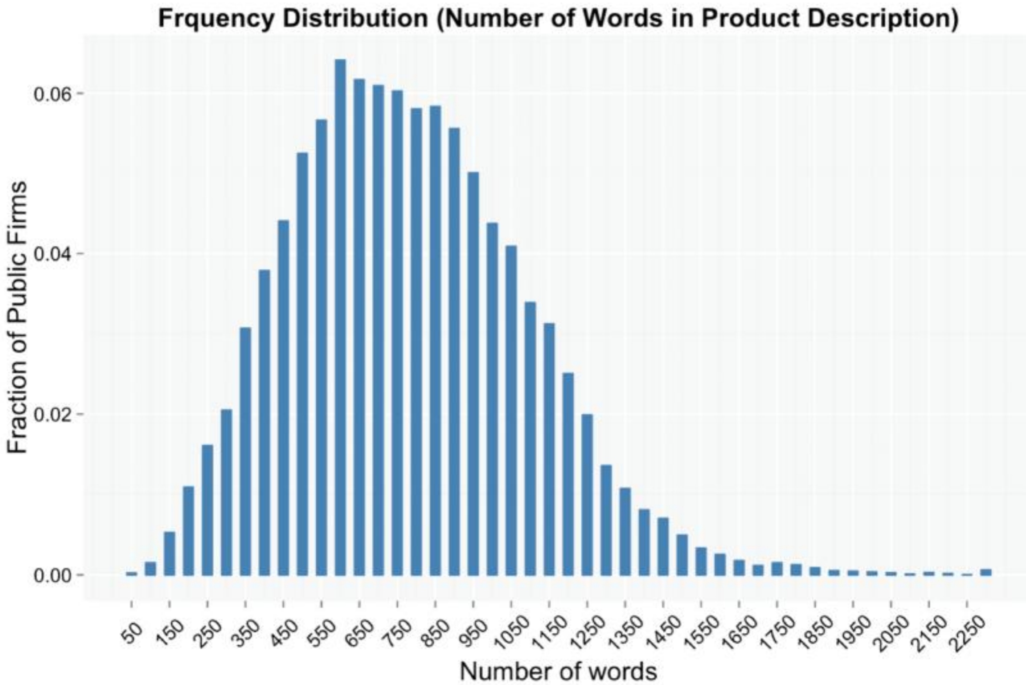


Figure 1-2: Number of Startups That Received First-round Funding, and Number of Unique Words Used in the Collection of Startups' Product Description

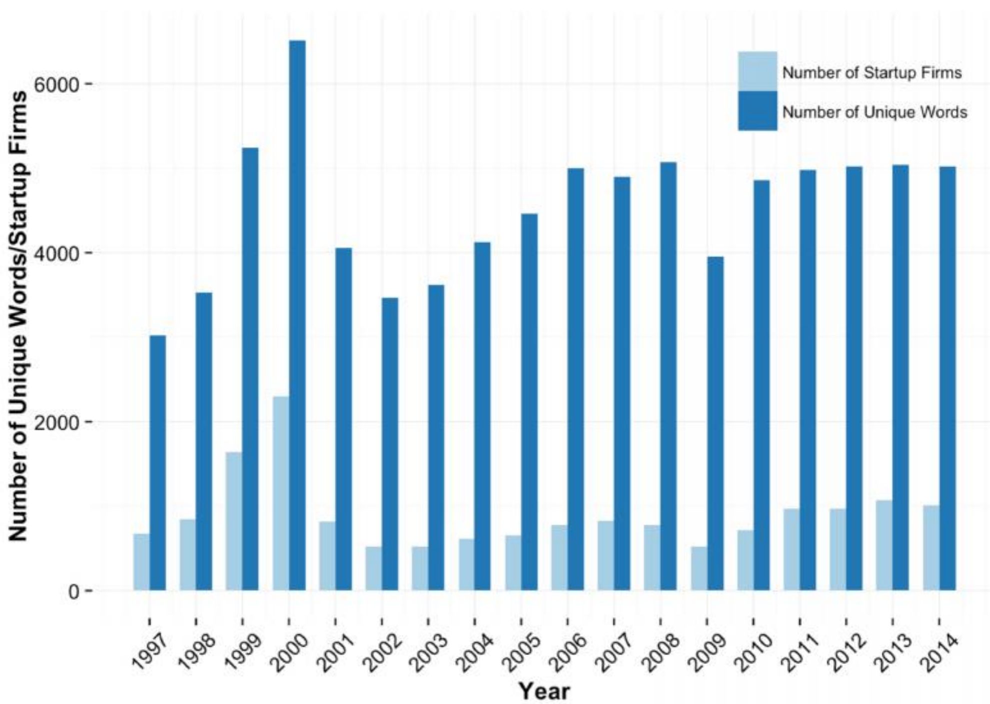


Figure 1-3: New Entry Threats and Ex Post Number of Competitive Rivals for Incumbent (TNIC)

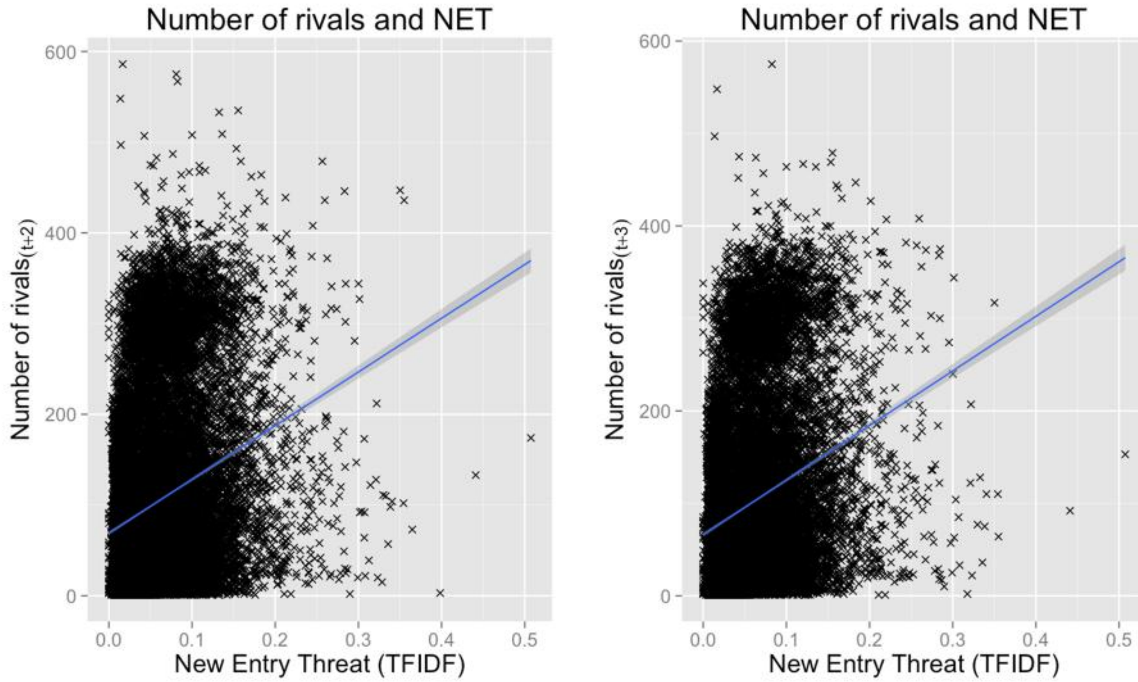


Figure 1-4: New Entry Threats and Ex Post Operating Performance (Return on Asset) for Incumbent

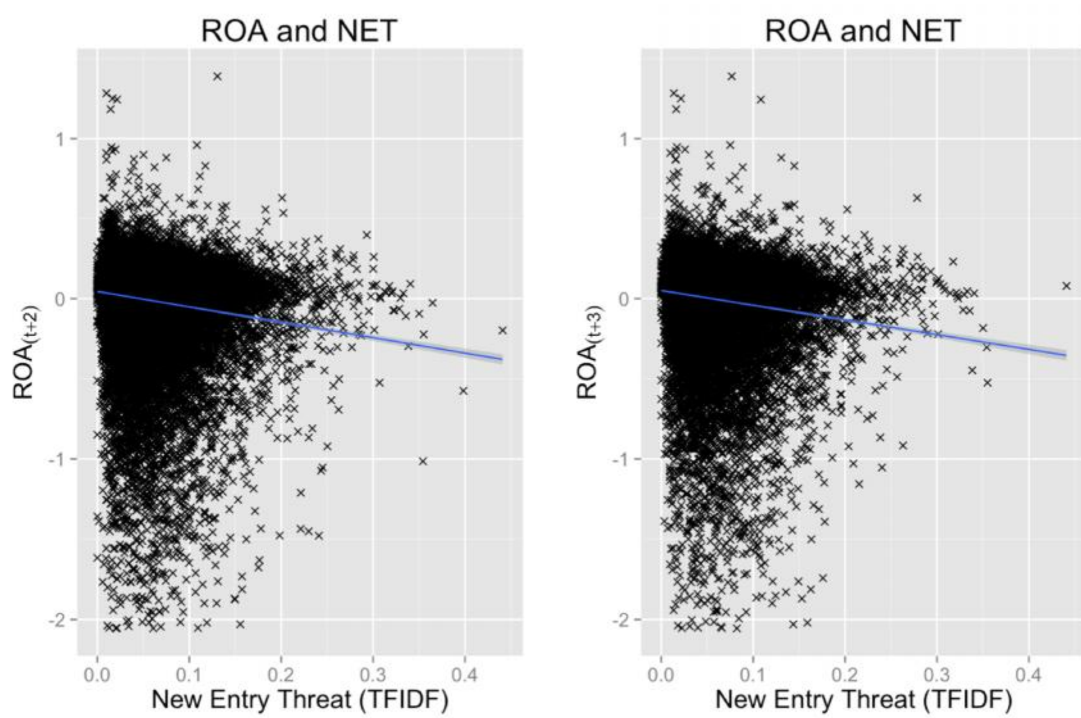
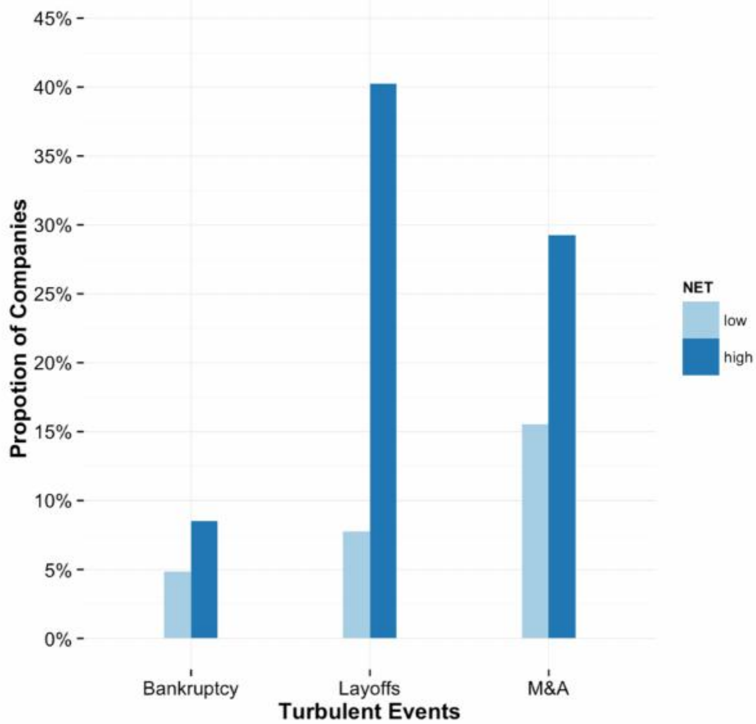


Figure 1-5: Comparing Turbulent Events between 10 Highest-NET Companies and 10 Lowest-NET Companies



Note: Two-sided t-test of group means: Bankruptcy (p=0.329), Layoffs (p=0.000), M&A (p=0.028)

Figure 1-6: Average NET over Time, Military Armored Vehicle Manufacturing

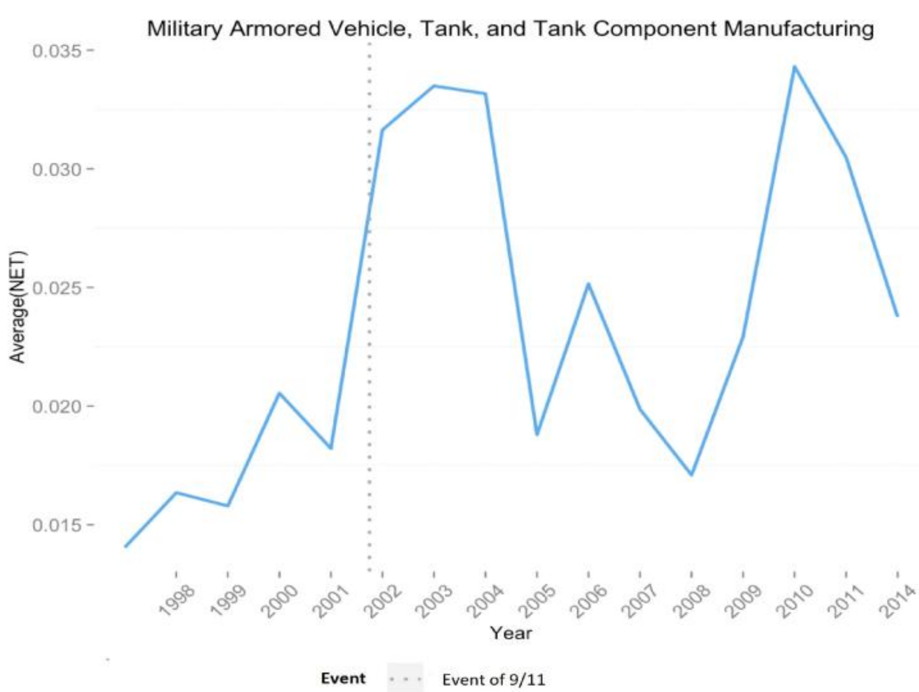


Figure 1-7: Average NET over Time, Internet Related Firms and Software Publishers

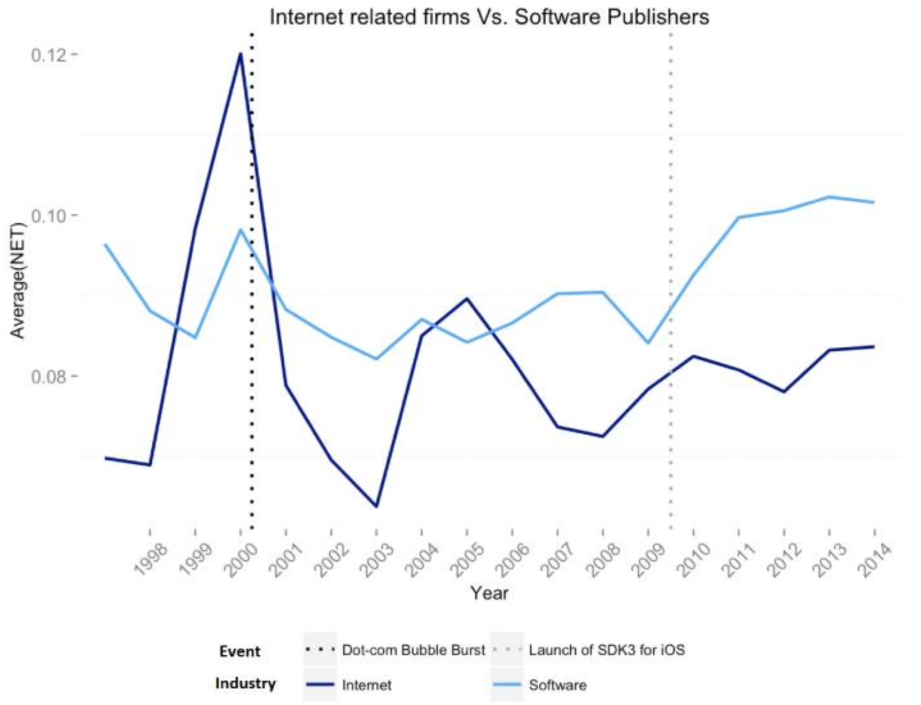


Figure 1-8: Average NET over Time, Biotechnology R&D Services

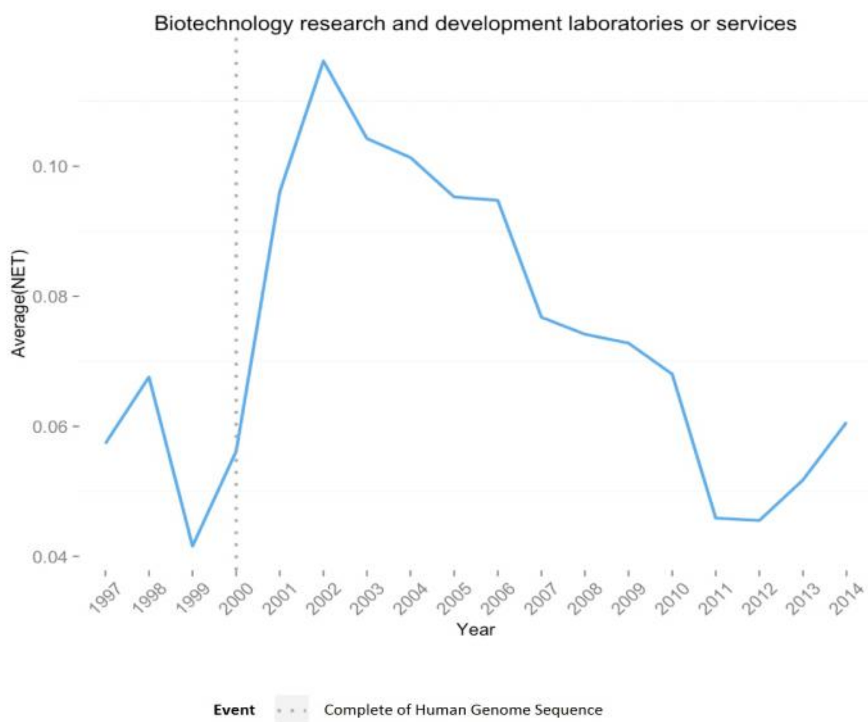


Figure 1-9: Sample Distribution across 4-digit NAICS Industries

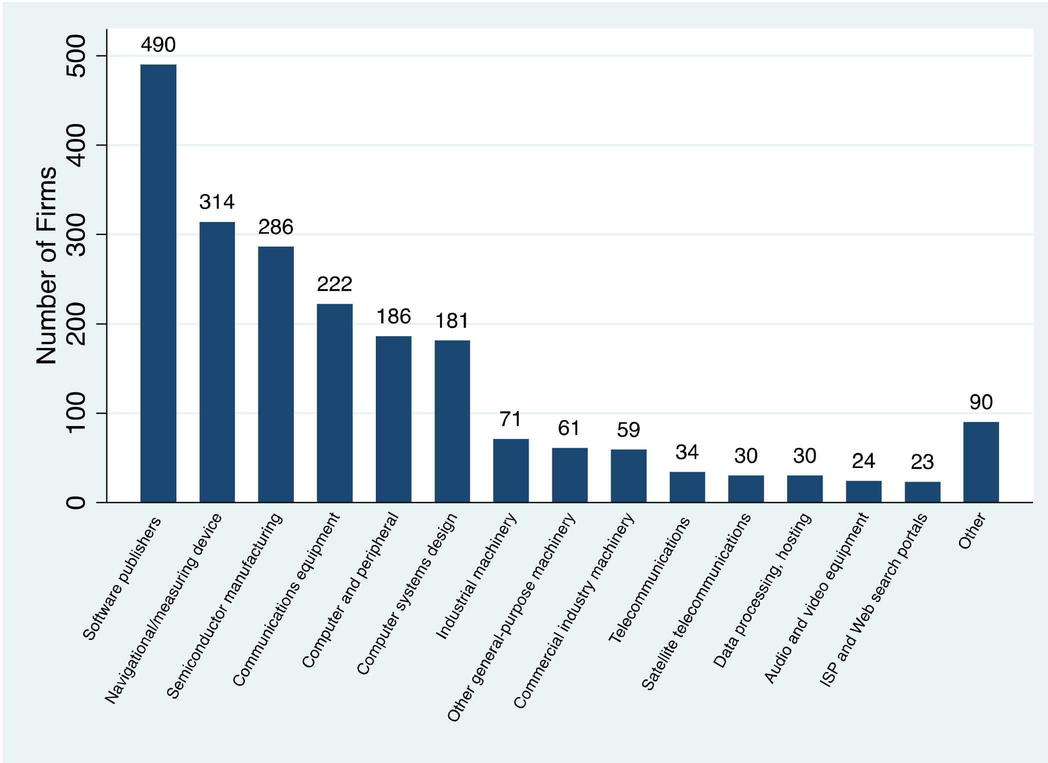
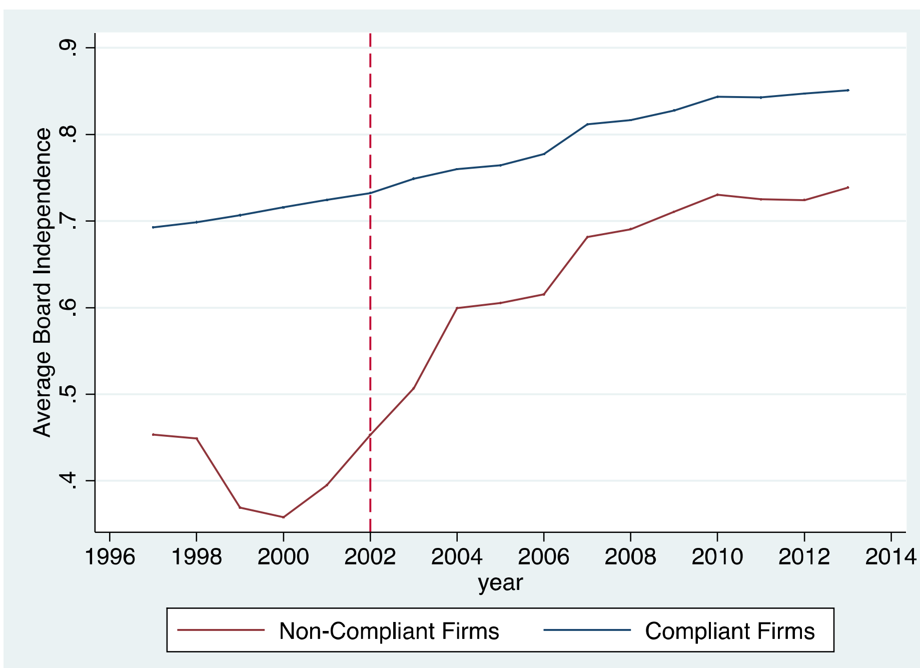


Figure 2-1: Average Board Independence over Years



TABLES

Table 1-1: Top 20 Words with Highest TF-IDF Weights in Entrepreneurial Firms' Documents in the Years 2000, 2003, 2006

Year	Words List
2000	onlin, internet, softwar, wireless, softwareprovid, servicesprovid, solut, web, content, broadband, ecommerc, softwaredevelop, servicesdevelop, platform, media, drug, email, network, enterpris, patient, portal
2003	diseas, patient, drug, therapeut, cancer, softwar, therapi, treatment, protein, wireless, discord, video, molecul, inhibitor, tissu, healthcar, biotechnolog, antibodi, pharmaceut, cell
2006	onlin, diseas, patient, cancer, drug, therapeut, search, publish, media, video, therapi, cloud, blog, antibodi, tissu, treatment, game, softwar, advertis, platform

Note: All documents are stemmed and pre-processed – therefore the words presented here are in their root form.

Table 1-2 Variable Definitions and Data Sources

Innovation Variables (data source: Compustat)	
R&D_intensity$_{it}$	Research and Development expenditure to total assets ratio of firm *i* in year *t*
New Entry Threat Variable (data source: VentureXpert & 10K files)	
NET$_{it}$	A text-based measure of threat from new entry by ***term frequency–inverse document frequency*** weighted cosine similarity between business description of startups and established firms.
Boundary Conditions (data source: Compustat & NBER Patent Database)	
PD$_{i}$	Product diversity measured by over sample within-firm mean of entropy measure of sale shares in different lines of business firm *i* in year *t*.
TD_entropy$_{it}$	Technology diversity measured as Entropy of shares of patent subclass for firm *i* in year *t,* as well as number of patent subclass in previous 5 year.
TD_Blau$_{it}$	Technology diversity measured as Blau heterogeneity Index of shares of patent subclass in previous 5 year.
Network Effects$_{i}$	Network effects index constructed by examining network externality of 45 categories, including computer hardware, computer software, and consumer electronics, etc., from 1950 to 2007 (Srinivasan et al. 2004; Wang et al. 2010).
StongNE_Industry$_{i}$	Equals to 1 if NE is greater than median of NE in 45 categories defined by (Wang et al. 2010), 0 otherwise.
Tech Cumulativeness$_{it}$	The average patent self-citation rate of all the applied patent for firm *i* in year *t.*
HighTC_Industry$_{i}$	Equals to 1 if the 4 digital NAICS industry average patent self-citation rate is at top quartile, 0 otherwise.
Firm Characteristics (data source: Compustat & TNIC)	
Sale$_{it}$	Total Sale of firm *i* in year *t* (in $ Billion)
Age$_{it}$	Number of years since listing of firm *i* in year *t*
ROA$_{it}$	Operating income before depreciation to total assets ratio of firm *i* in year *t*
Asset_tangibility$_{it}$	Net property, plants and equipments to total assets ratio of firm *i* in year *t*
Leverage$_{it}$	Total debt of firm *i* in year *t* divided by its total assets
CapExp/Assets$_{it}$	Capital expenditure to total assets ratio of firm *i* in year *t*
Tobin's Q$_{it}$	Market to book ratio of firm *i* in year *t* as defined in Brown et al. (2006)
KZ Index$_{it}$	Kaplan-Zingales Index (Kaplan et al. 1997) is a relative measurement of reliance on external financing. Companies with higher KZ-Index scores are more likely to experience difficulties when financial conditions tighten since they may have difficulty financing their ongoing operations[23].
TNIC_HHI$_{it}$	Herfindahl-Hirschman Index of firm *i* in year *t* based on Text-based Network Industry Classifications (TNIC) (Hoberg et al. 2014).

[23] Following Chemmanur and Tian (2012), we use the regression coefficients from Kaplan and Zingales (1997) to compute the KZ index as : $-1.002*Cash\ flow - 39.368*Dividends - 1.315*Cash\ flow + 0.28*Q + 3.18*Leverage$

Table 1-3: Summary Statistics and Correlation Coefficients

This table reports the summary statistics for primary variables constructed based on the sample of U.S. public firms in the IT Industries[24] from 1997 to 2013. Please see Table 1-2 for the description of the variables. Pearson Correlation Coefficients are reported for our sample of 14,410 firm year observations.

Variable	Mean	Std. dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. R&D Intensity (%)	12.88	15.53	1.000														
2. NET	0.07	0.05	0.115*	1.000													
3. PD	1.00	0.51	-0.205*	-0.061*	1.000												
4. TD_Entropy	1.25	0.94	-0.106*	0.048*	0.321*	1.000											
5. TD_Blau	0.54	0.31	-0.081*	0.022	0.215*	0.911*	1.000										
6. Network Effects	7.71	1.97	0.078*	0.233*	-0.063*	-0.104*	-0.120*	1.000									
7. Tech Cumulativeness	0.06	0.07	-0.076*	-0.194*	0.125*	0.302*	0.229*	-0.154*	1.000								
8. Sale ($Billion)	1.36	7.03	-0.086*	0.086*	0.307*	0.396*	0.216*	0.030*	0.159*	1.000							
9. Age	15.52	12.37	-0.219*	-0.212*	0.380*	0.414*	0.287*	-0.180*	0.333*	0.285*	1.000						
10. ROA (%)	-1.26	35.99	-0.667*	-0.050*	0.191*	0.162*	0.132*	-0.048*	0.063*	0.086*	0.187*	1.000					
11. Asset Tangibility (%)	13.34	11.91	-0.052*	-0.160*	0.151*	0.143*	0.127*	-0.053*	0.131*	0.038*	0.103*	0.022*	1.000				
12. Leverage (%)	9.34	17.21	-0.084*	-0.069*	0.145*	0.124*	0.105*	-0.041*	0.042*	0.056*	0.109*	0.027*	0.230*	1.000			
13. CapExp/Assets (%)	3.93	4.28	0.063*	-0.004	0.023*	0.033*	0.027*	0.065*	0.045*	0.009	-0.080*	-0.055*	0.613*	0.070*	1.000		
14. Tobin's Q	2.48	2.96	0.194*	0.072*	-0.060*	-0.049*	-0.045*	0.084*	0.043*	-0.017*	-0.140*	-0.207*	-0.049*	-0.045*	0.103*	1.000	
15. KZ Index	0.25	2.69	0.046*	0.016	0.004	0.016	0.013	-0.017*	0.015	-0.008	-0.033*	-0.060*	0.056*	0.232*	0.066*	0.205*	1.000
16. TINC-HHI	0.23	0.21	-0.117*	-0.219*	0.047*	-0.044*	-0.043*	-0.043*	0.059*	-0.030*	0.158*	-0.013	-0.000	0.049*	-0.057*	-0.042*	-0.030*

* $p < .05$

[24] We include all IT Industries, such as hardware, software and IT services industries, which is defined by 4 digital NAICS code: 2211, 3332, 3333, 3336, 3339, 3341, 3342, 3343, 3344, 3345, 3346, 5112, 5161, 5171, 5172, 5173, 5174, 5179, 5112, 5181, 5182, 5413, 5415, 5416 and 5417.

Table 1-4: New Entry Threats and R&D Investments

This table reports the estimates for R&D Intensity as dependent variables. The sample constructed based on the sample of U.S. public firms in the IT Industries from 1997 to 2013.

Dependent Variable: R&D Intensity (%)	Fixed Effect	Random Effect	Dynamic panel model: NET as exogenous	Dynamic panel model: NET as endogenous
	(1)	(2)	(3)	(4)
NET	-0.351**	-0.074	-0.335*	-1.337***
	(0.144)	(0.114)	(0.174)	(0.335)
L.R&D Intensity	-	-	0.119***	0.122***
			(0.040)	(0.039)
Ln (Sales)	0.152	0.011	0.863*	1.011**
	(0.365)	(0.113)	(0.515)	(0.504)
Ln(Age)	1.079*	0.222	1.291*	0.867
	(0.553)	(0.302)	(0.766)	(0.767)
ROA	-26.460***	-27.022***	-28.657***	-28.730***
	(2.422)	(0.294)	(2.957)	(2.953)
PPE / Assets	16.151***	9.525***	14.862***	14.836***
	(2.426)	(1.285)	(3.321)	(3.328)
Leverage	-2.049	-2.901***	-3.052	-2.993
	(1.324)	(0.559)	(1.905)	(1.908)
Capx / Assets	8.180*	8.071***	13.016*	13.105*
	(4.558)	(2.422)	(7.008)	(7.042)
Tobin's Q	0.178**	0.155***	0.194	0.194
	(0.087)	(0.029)	(0.121)	(0.121)
KZ Index	0.096	0.093***	0.005	0.003
	(0.086)	(0.029)	(0.057)	(0.057)
TNIC HHI	0.087	-1.513***	-0.535	-0.786
	(0.530)	(0.474)	(0.555)	(0.564)
Firm Dummies	Yes	-		
Year Dummies	Yes	Yes	Yes	Yes
Observations	14,410	14,410	10,490	10,490
# of Firms	2101	2101	1,557	1,557
Adjusted R^2	0.761		-	-

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
New entry threats are standardized with mean of zero and standard deviation of one.
The dynamic model in column 3 treats *L.R&D Intensity* as endogenous variable. The model in column 4 assumes both *NET* and *L.R&D Intensity* are endogenous variables.
Instruments for differenced equation: GMM-type: *L(2/.).NET, L(2/.).L.R&D Intensity, i.e., all available lags from lag2 onward;* and all difference of exogenous variables, including year dummies.

Arellano-Bond test results for zero autocorrelation in the first differences errors					
Model with NET as exogenous			Model with NET as endogenous		
Order	z	Pr > z	Order	z	Pr > z
1	-3.68	0.000	1	-3.79	0.000
2	-1.85	0.064	2	-1.90	0.058

Table 1-5: Boundary Condition - Product Diversification

This table reports the estimates for *R&D Intensity* as dependent variables. The sample constructed based on the sample of U.S. public firms in the IT Industries from 1997 to 2013.

Dependent Variable: R&D Intensity (%)	Full Sample	Specialized Firms	Diversified Firms
	(1)	(2)	(3)
NET	-0.821***	-0.466**	0.089
	(0.307)	(0.223)	(0.137)
NET × *Product Diversity*$_i$	0.573***	-	-
	(0.221)	-	-
Ln (Sales)	-0.192	0.113	-0.685**
	(0.475)	(0.647)	(0.280)
Ln(Age)	0.946	0.830	0.048
	(0.598)	(0.983)	(0.550)
ROA	-27.380***	-27.994***	-22.534***
	(3.698)	(4.097)	(2.831)
PPE / Assets	14.432***	20.432***	6.135***
	(2.782)	(4.405)	(1.974)
Leverage	-3.353*	-2.746	-3.547***
	(1.951)	(2.928)	(0.854)
Capx / Assets	7.763	4.177	11.691***
	(6.052)	(9.404)	(4.160)
Tobin's Q	0.146	0.091	0.289***
	(0.109)	(0.127)	(0.110)
KZ Index	0.154	0.227	-0.121
	(0.129)	(0.161)	(0.094)
TNIC HHI	-0.141	0.240	-0.782*
	(0.566)	(1.014)	(0.428)
Year & Firm Fixed Effects	Yes	Yes	Yes
Observations	9,571[25]	5,508	4,063
# of Firms	954	594	360
Adjusted R^2	0.736	0.720	0.742

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

[25] 4,829 observations are dropped due to availability of Compustat segment data.

Table 1-6: Boundary Condition - Technology Diversification

This table reports the estimates for *R&D Intensity* as dependent variables. The sample constructed based on the sample of U.S. public firms in the IT Industries from 1997 to 2006. Innovation stock diversity is calculated based on total number of applied patents in previous 6 years.

Dependent Variable: R&D Intensity (%)	Patents Stock Entropy ($TD\_Entropy_{it}$)	Patents Stock Blau Index (TD_Blau_{it})
	(2)	(4)
NET	-1.154***	-1.185***
	(0.330)	(0.411)
Technology Diversity	-0.860***	-1.643**
	(0.311)	(0.699)
NET × *Technology Diversity*	0.391**	0.965*
	(0.152)	(0.542)
Ln (Sales)	0.764	0.730
	(0.533)	(0.529)
Ln(Age)	0.125	-0.003
	(0.991)	(0.994)
ROA	-29.004***	-28.983***
	(2.726)	(2.722)
PPE / Assets	20.542***	20.438***
	(3.152)	(3.150)
Leverage	-10.192***	-10.239***
	(3.572)	(3.579)
Capx / Assets	-3.161	-2.959
	(8.368)	(8.363)
Tobin's Q	0.015	0.016
	(0.081)	(0.081)
KZ Index	0.460***	0.460***
	(0.174)	(0.174)
TNIC HHI	0.615	0.597
	(0.819)	(0.821)
Year & Firm FE	Yes	Yes
Observations	6,418	6,418
# of Firms	1223	1223
Adjusted R^2	0.806	0.805

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 1-7: Boundary Condition - Network Effects

This table reports the estimates for *R&D Intensity* as dependent variables. The sample constructed based on the sample of U.S. public firms in the IT Industries from 1997 to 2013.

Dependent Variable: R&D Intensity (%)	Network Effects[26] Continuous Measure	Network Effects[27] Binary Measure	Weak NE Industries	Strong NE Industries
	(1)	(2)		
NET	-1.186**	-0.649***	-0.606***	-0.011
	(0.499)	(0.160)	(0.177)	(0.232)
NET × *Network Effects*	0.112*	-	-	-
	(0.063)	-	-	-
NET × *Strong NE Industries*	-	0.578**	-	-
	-	(0.274)	-	-
Ln (Sales)	-0.073	0.166	0.678	-0.217
	(0.383)	(0.366)	(0.508)	(0.568)
Ln(Age)	0.883	1.062*	0.431	3.178***
	(0.605)	(0.553)	(0.688)	(0.955)
ROA	-25.684***	-26.462***	-31.332***	-21.848***
	(2.511)	(2.423)	(3.833)	(2.836)
PPE / Assets	18.287***	16.064***	11.323***	30.228***
	(2.757)	(2.427)	(2.138)	(6.945)
Leverage	-2.039	-2.038	-3.227	-0.552
	(1.462)	(1.323)	(2.026)	(1.340)
Capx / Assets	8.879*	8.268*	5.234	12.215*
	(4.972)	(4.559)	(5.511)	(6.777)
Tobin's Q	0.162*	0.180**	0.430***	0.055
	(0.088)	(0.087)	(0.117)	(0.097)
KZ Index	0.103	0.096	0.077	0.108
	(0.092)	(0.086)	(0.082)	(0.149)
TNIC HHI	0.064	0.094	0.571	-0.290
	(0.587)	(0.530)	(0.589)	(1.017)
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	13,228	14,410	8,797	5,613
# of Firms	1942	2101	1135	966
Adjusted R^2	0.753	0.761	0.762	0.764

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: new entry threats are standardized with mean of zero and standard deviation of one.

[26] Continuous measure of network effects are collected from Wang, Q., Chen, Y., and Xie, J. 2010. "Survival in markets with network effects: product compatibility and order-of-entry effects," *Journal of Marketing* (74:4), pp 1-14.).

[27] We identify products with strong network effects following Srinivasan, R., Lilien, G. L., and Rangaswamy, A. 2004. "First in, first out? The effects of network externalities on pioneer survival," ibid. (68:1), pp 41-58, Wang, Q., Chen, Y., and Xie, J. 2010. "Survival in markets with network effects: product compatibility and order-of-entry effects," ibid. (74:4), pp 1-14. as telecommunication devices and personal computer, operating system and software, Internet services provider, personal data assistant services, etc., including 9 4-digital NASIC: 5112,5181,5182,5173,5413,5415,5416, and 5417.

Table 1-8: Boundary Condition - Technological Cumulativeness

Dependent Variable: R&D Intensity (%)	Firm Level Measure	Top quartile in TC by 4-dig-NAICS	Low TC Industries	High TC Industries
	(1)	(2)	(3)	(4)
NET	-0.830***	-0.468***	-0.451***	0.071
	(0.193)	(0.166)	(0.170)	(0.265)
NET * Tech Cumulativeness	5.865***	-	-	-
	(1.972)	-	-	-
NET * High Tech-Cumulativeness Industries	-	0.590*	-	-
	-	(0.303)	-	-
Ln (Sales)	0.547	0.156	0.139	-0.021
	(0.444)	(0.366)	(0.430)	(0.558)
Ln(Age)	0.787	1.107**	1.005	2.092*
	(0.676)	(0.552)	(0.637)	(1.069)
ROA	-30.681***	-26.463***	-27.311***	-22.870***
	(3.226)	(2.423)	(2.908)	(3.014)
PPE / Assets	14.059***	16.259***	14.971***	22.940***
	(2.734)	(2.423)	(2.594)	(6.507)
Leverage	-3.639**	-2.102	-3.487**	2.496
	(1.776)	(1.327)	(1.650)	(1.675)
Capx / Assets	5.640	7.910*	3.648	20.867***
	(5.468)	(4.560)	(5.289)	(7.529)
Tobin's Q	0.165*	0.175**	0.165	0.163
	(0.095)	(0.087)	(0.104)	(0.138)
KZ Index	0.190	0.105	0.143	0.045
	(0.143)	(0.088)	(0.129)	(0.091)
TNIC HHI	-0.267	0.114	0.024	0.843
	(0.599)	(0.530)	(0.571)	(1.138)
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	10,678	14,400	11,075	3,335
# of Firms	1313	2100	1578	523
Adjusted R^2	0.781	0.761	0.763	0.759

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 1-A1: 24 4-digit NAICS ICT Industry Sectors

NAICS code	Industry
2211	Electric power generation, transmission, and distribution
3332	Industrial machinery manufacturing
3333	Commercial and service industry machinery manufacturing
3336	Engine, turbine, and power transmission equipment manufacturing
3339	Other general-purpose machinery manufacturing
3341	Computer and peripheral equipment manufacturing
3342	Communications equipment manufacturing
3343	Audio and video equipment manufacturing
3344	Semiconductor and other electronic component manufacturing
3345	Navigational, measuring, electromedical, and control instruments manufacturing
3346	Manufacturing and reproducing, magnetic and optical media
5112	Software publishers
5161	Internet publishing and broadcasting
5171	Wired telecommunications carriers
5172	Wireless telecommunications carriers (except satellite)
5173	Telecommunications resellers
5174	Satellite telecommunications
5179	Telecommunications
5181	Internet service providers and Web search portals
5182	Data processing, hosting, and related services
5413	Architectural, engineering, and related services
5415	Computer systems design and related services
5416	Management, scientific, and technical consulting services
5417	Scientific research-and-development services

Table 1-A2: Industry Composition and Turbulent Events of High NET vs. Low NET companies, 2009

Company Name	4 Digit NAICS Industry Sector	Events in 2010 - 2014		
Companies with Low NET		***Bankruptcy***	***M&A***	***Layoff***
China Botanic Pharmaceutical Inc.	Pharmaceutical and medicine manufacturing			
FirstEnergy Corp.	Electric power generation, transmission, and distribution			
Intellicheck Mobilisa, Inc.	Computer and peripheral equipment manufacturing			
Intermec, Inc.	Computer and peripheral equipment manufacturing		Yes	
Plantronics, Inc.	Communications equipment manufacturing			
The Singing Machine, Inc.	Audio and video equipment manufacturing			
Strasbaugh, Inc.	Industrial machinery manufacturing			Yes
Wayside Technology Group, Inc.	Professional and commercial equipment and supplies, merchant wholesalers			
World Surveillance Group Inc.	Aerospace product and parts manufacturing			
WorldGate Communications, Inc.	Communications equipment manufacturing	Yes		
Companies with High NET				
Limelight Networks, Inc	Wired telecommunications carriers			
Health Grades, Inc.	Wired telecommunications carriers		Yes	
Salesforce.com Inc.	Software publishers			Yes
Convera Corporation	Software publishers	Yes	Yes	
THQ Inc.	Software publishers	Yes		Yes
Take-Two Interactive Software, Inc.	Software publishers			
Electronic Arts, Inc.	Software publishers			Yes
Vocus Inc.	Software publishers		Yes	Yes
Microsoft Corp.	Software publishers			Yes
Digital River, Inc.	Professional and commercial equipment and supplies, merchant wholesalers			Yes

Table 1-A3: Instrumental Variables Regression

This table reports the 2SLS estimates that treat NET as the endogenous variables. The sample is constructed based on the U.S. public firms in the IT Industries from 1997 to 2013.

	1st Stage	2nd Stage
Dependent Variable:	NET	R&D Intensity (%)
NET	-	-2.868***
	-	(0.770)
L.Ind_ProfitExp (z_1)	0.183***	-
	(0.011)	-
L.Ind_Uncentainty (z_2)	-0.163***	-
	(0.044)	-
Ln (Sales)	0.126***	0.497
	(0.013)	(0.394)
Ln(Age)	-0.366***	-0.292
	(0.040)	(0.644)
ROA	-0.067***	-26.829***
	(0.024)	(2.418)
PPE / Assets	0.029	16.020***
	(0.114)	(2.475)
Leverage	0.065	-2.291*
	(0.045)	(1.362)
Capx / Assets	-0.145	7.535
	(0.325)	(4.858)
Tobin's Q	-0.003	0.202**
	(0.003)	(0.095)
KZ Index	-0.001	0.071
	(0.002)	(0.089)
TNIC HHI	-0.254***	-0.434
	(0.033)	(0.588)
Firm/Industry Dummies	Yes	Yes
Year Dummies	Yes	Yes
First stage F-stat:	181.32	
Stock-Yogo critical value, 10% max IV size	19.93	
Hansen J	1.86 (p>0.1)	
Observations	13,482	
Number of Firms	1,736	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 2-1: Variable Definitions and Data Sources

Main Interest Variables	Definition
ROA_{it}	Operating income before depreciation to total assets ratio of firm *i* in year *t*
ROA_{it} (Alternative)	Net income to total assets ratio of firm *i* in year *t*
ROE_{it}	Net income to common shareholders' equity of firm *i* in year *t*
NET_{it}	New entry threat measured by *term frequency–inverse document frequency* weighted cosine similarity.
$\mathrm{Board\ Independence}_{it}$	Ratio of independent board members over total board members of firm *i* in year *t*
Board Characteristic Controls (Source: Risk Metrics)	
$\mathrm{CEO\_Duality}_{it}$	Firm's CEO also holds the position of the chairman of the board for firm *i* in year *t*
$\mathrm{Board\ Size}_{it}$	Number of board members of firm *i* in year *t*
$\mathrm{Board\ Tenure}_{it}$	The average tenure of board members of firm *i* in year *t*
$\mathrm{Board\ Age}_{it}$	The average age of board members of firm *i* in year *t*
$\mathrm{Interlocks}_{it}$	Number of interlock directors of firm *i* in year *t*
Firm Characteristic Controls (Source: Compustat)	
Assets_{it}	Total assets of firm *i* in year *t* (in $ Billion)
$\mathrm{Asset\_tangibility}_{it}$	Net property, plants and equipments to total assets ratio of firm *i* in year *t*
$\mathrm{Leverage}_{it}$	Total debt of firm *i* in year *t* divided by its total assets
$\mathrm{CapExp/Assets}_{it}$	Capital expenditure to total assets ratio of firm *i* in year *t*
$\mathrm{TNIC\_HHI}_{it}$	Herfindahl-Hirschman Index of firm *i* in year *t* based on Text-based Network Industry Classifications (TNIC) (Hoberg et al. 2014).
$\mathrm{R\&D\ Intensity}_{it}$	R&D expenditure to total assets ratio of firm *i* in year *t*
$\mathrm{Tobin's\ Q}_{it}$	Market to book ratio of firm *i* in year *t* as defined in Brown et al. (2006)

Table 2-2: Sample Composition by Year

This table contains the sample composition by year for the focal variables. Variable definitions are in the Table1. We define Δ Board_Indp = Mean Board_Independence (t) – Mean Board_Independence (t-1).

Year	Obs.	**New Entry Threat (t)**			**Board Independence (t)**			Δ BoardIndp
		Mean	Median	Std dev	Mean	Median	Std dev	
1997	174	0.056	0.043	0.046	0.651	0.680	0.184	
1998	206	0.053	0.040	0.041	0.653	0.667	0.183	0.002
1999	239	0.049	0.035	0.040	0.636	0.667	0.199	-0.017
2000	236	0.073	0.056	0.052	0.643	0.667	0.186	0.007
2001	274	0.078	0.072	0.053	0.655	0.696	0.173	0.012
2002	261	0.071	0.064	0.046	0.682	0.700	0.153	0.027
2003	276	0.074	0.067	0.049	0.704	0.714	0.144	0.022
2004	280	0.074	0.070	0.046	0.721	0.750	0.131	0.017
2005	265	0.067	0.062	0.040	0.732	0.750	0.126	0.011
2006	244	0.060	0.053	0.043	0.746	0.760	0.130	0.014
2007	200	0.058	0.048	0.047	0.785	0.800	0.109	0.039
2008	210	0.057	0.050	0.044	0.785	0.800	0.108	0.000
2009	254	0.056	0.050	0.039	0.795	0.833	0.112	0.010
2010	264	0.058	0.051	0.044	0.808	0.833	0.098	0.013
2011	254	0.055	0.047	0.047	0.807	0.833	0.097	-0.001
2012	264	0.055	0.047	0.046	0.809	0.833	0.094	0.002
2013	270	0.057	0.049	0.046	0.817	0.852	0.090	0.008

Table 2-3: Summary Statistics and Correlation Coefficients

This table reports the summary statistics for primary variables constructed based on the sample of U.S. S&P 1500 firms in the IT Industries[28] from 1997 to 2013. Please see Table 2-1for the description of the variables.

Variable	Mean	Std. dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. ROA (%)	11.129	8.341	1															
2. ROA_alternative (%)	1.945	15.992	0.597*	1														
3. ROE (%)	11.505	205.879	0.013	0.036*	1													
4. New Entry Threats	0.062	0.046	-0.061*	-0.105*	-0.01	1												
5. Board Independence	0.733	0.154	0.027	0.063*	-0.03	-0.119*	1											
6. CEO Duality	0.655	0.475	-0.007	-0.014	0.023	-0.049*	0.005	1										
7. Board Size	8.738	2.343	0.127*	0.081*	0.022	-0.209*	0.187*	0.078*	1									
8. Board Tenure	9.383	3.668	0.111*	0.118*	-0.012	-0.112*	-0.241*	-0.036*	-0.082*	1								
9. Board Age	60.028	4.443	0.054*	0.117*	-0.011	-0.281*	0.214*	-0.049*	0.181*	0.426*	1							
10. Interlocks	4.840	5.054	0.149*	0.055*	0.042*	-0.028	0.148*	0.168*	0.564*	-0.143*	0.092*	1						
11. Assets (Billions)	8.109	21.004	0.094*	0.058*	0.013	0.083*	0.140*	0.081*	0.415*	-0.067*	0.129*	0.409*	1					
12. Asset Tangibility (%)	23.701	21.153	0.019	-0.017	0.031*	-0.432*	0.062*	0.131*	0.431*	-0.039*	0.111*	0.169*	0.218*	1				
13. Leverage (%)	16.071	16.307	-0.045*	-0.084*	0.062*	-0.244*	0.079*	0.107*	0.320*	-0.098*	0.076*	0.166*	0.139*	0.507*	1			
14. Cap Exp/Asset (%)	4.402	3.631	0.156*	-0.019	0.061*	-0.109*	-0.148*	0.095*	0.160*	-0.017	-0.079*	0.149*	0.123*	0.576*	0.209*	1		
15. HHI TNIC	0.167	0.165	0.049*	0.015	-0.011	-0.024	0.002	-0.021	-0.060*	0.028	0.037*	0.050*	-0.098*	-0.275*	-0.078*	-0.131*	1	
16. R&D Intensity	8.160	6.009	-0.186*	-0.241*	0.009	0.320*	-0.158*	-0.097*	-0.329*	-0.062*	-0.206*	-0.173*	-0.176*	-0.273*	-0.293*	-0.029	-0.095*	1
17. Tobin's Q	1.956	1.368	0.366*	0.199*	0.012	0.237*	-0.144*	-0.015	-0.188*	0.000	-0.213*	-0.017	-0.079*	-0.288*	-0.281*	-0.001	0.019	0.161*

[28] We include IT software and hardware Industries, which is defined by 4 digital NAICS code: 2211, 3332, 3333, 3336, 3339, 3341, 3342, 3343, 3344, 3345, 3346, 5112, 5171, 5172, 5173, 5174, 5179 and 5181.

Table 2-4: New Entry Threats, Independent Board and Firm Performance

This table reports the estimates for firm operating performance as dependent variables. All the independent variables are lagged one year. The dataset constructed based on the sample of U.S. S&P 1500 firms in the IT Industries from 1997 to 2013.

	ROA (%) Operationalized as OIBDA / Total Asset		ROA (%) Operationalized as Net Income / Total Asset		ROE (%) Net Income/ Common Shareholders' Equity	
	(1)	(2)	(3)	(4)	(5)	(6)
New Entry Threats	-0.550**	-4.275***	-1.530***	-7.464***	-2.520**	-11.891***
	(0.253)	(0.821)	(0.499)	(2.191)	(1.164)	(4.206)
Board Independence	1.019	0.769	1.776	1.406	2.280	1.939
	(1.196)	(1.178)	(2.158)	(2.110)	(7.126)	(7.087)
*New Entry Threats * Board Independence*		5.148***		8.283***		12.965**
		(1.065)		(2.749)		(5.360)
Board-related controls						
CEO Duality	-0.649**	-0.601**	-1.234*	-1.169*	-2.398	-2.251
	(0.297)	(0.293)	(0.668)	(0.662)	(1.642)	(1.619)
Board Size	0.039	0.028	0.240	0.217	0.708*	0.681
	(0.091)	(0.090)	(0.188)	(0.186)	(0.428)	(0.427)
Board Tenure	-0.045	-0.047	0.034	0.041	0.013	0.031
	(0.066)	(0.066)	(0.124)	(0.125)	(0.327)	(0.327)
Board Age	-0.059	-0.052	-0.089	-0.082	-0.107	-0.104
	(0.068)	(0.067)	(0.123)	(0.123)	(0.325)	(0.325)
Interlocks	0.005	0.000	-0.019	-0.026	-0.293	-0.312
	(0.036)	(0.036)	(0.060)	(0.061)	(0.199)	(0.200)
Firm-related controls						
Log (Assets)	-1.391***	-1.530***	-5.842***	-6.013***	-9.896***	-10.293***
	(0.356)	(0.350)	(1.137)	(1.135)	(3.554)	(3.535)
PPE / Assets	2.552	2.356	-5.151	-5.473	-26.697**	-27.655**
	(1.995)	(2.003)	(5.201)	(5.209)	(12.405)	(12.407)
Leverage	-0.347	-0.325	5.191	5.226	-12.677	-12.424
	(1.438)	(1.436)	(4.050)	(4.042)	(9.099)	(9.080)
Capx / Assets	-3.582	-3.559	-2.899	-2.865	15.824	15.618
	(4.491)	(4.474)	(9.781)	(9.734)	(25.275)	(25.243)
R&D Intensity	-0.052	-0.061*	-0.116	-0.130	-0.293*	-0.318*
	(0.036)	(0.036)	(0.090)	(0.090)	(0.178)	(0.178)
Tobin's Q	1.007***	1.016***	1.216***	1.246***	1.877***	1.926***
	(0.147)	(0.148)	(0.395)	(0.400)	(0.482)	(0.488)
TNIC HHI	-1.538**	-1.701**	-2.627	-2.886*	-10.023**	-10.418**
	(0.757)	(0.752)	(1.718)	(1.713)	(4.580)	(4.583)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Of Firms	583	583	587	587	583	583
Observations	4,175	4,175	4,167	4,167	4,195	4,195
R-squared	0.645	0.649	0.564	0.567	0.468	0.470

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 2-5: 2 SLS Regression with Instruments from Sarbanes-Oxley Act

This table reports the estimates for firm operating performance as dependent variables. All the independent variables are lagged one year.

	SOX implementation year = 2002			SOX implementation year = 2003		
	1st stage without interaction	2nd stage without interaction	2nd stage with interaction	1st Stage without interaction	2nd stage without interaction	2nd stage with interaction
DV: ROA	(1)	(2)	(3)	(4)	(5)	(6)
Non Compliant Firms After SOX (z)	0.137***	-	-	0.125***	-	-
	(0.014)			(0.013)		
New Entry Threats	0.001	-0.519**	-44.287**	0.001	-0.567**	-31.034***
	(0.003)	(0.260)	(17.802)	(0.003)	(0.253)	(10.140)
Board Independence	-	4.697	-22.642*	-	3.738	-20.822**
		(5.467)	(11.998)		(5.420)	(9.775)
*New Entry Threats * Board Independence*	-		60.860**	-		42.153***
			(24.626)			(13.946)
Board-related controls						
CEO Duality	0.019***	-0.731**	0.400	0.017***	-0.704**	0.045
	(0.005)	(0.324)	(0.601)	(0.005)	(0.317)	(0.453)
Board Size	-0.000	0.075	-0.032	0.001	0.041	-0.014
	(0.002)	(0.094)	(0.164)	(0.002)	(0.091)	(0.125)
Board Tenure	-0.011***	0.004	-0.303*	-0.011***	0.007	-0.265*
	(0.001)	(0.093)	(0.175)	(0.001)	(0.089)	(0.144)
Board Age	0.007***	-0.037	0.280*	0.007***	-0.054	0.186
	(0.001)	(0.083)	(0.163)	(0.001)	(0.079)	(0.125)
Interlocks	0.001	-0.014	-0.057	0.001	-0.001	-0.029
	(0.001)	(0.035)	(0.078)	(0.001)	(0.035)	(0.060)
Firm-related controls						
Log (Assets)	0.005	-1.533***	-3.094***	0.003	-1.564***	-2.576***
	(0.005)	(0.375)	(0.833)	(0.005)	(0.367)	(0.557)
PPE / Assets	-0.096***	3.048	-1.642	-0.102***	3.865*	-0.305
	(0.033)	(2.198)	(3.803)	(0.032)	(2.086)	(3.015)
Leverage	-0.024	0.371	0.547	-0.026	0.413	-0.343
	(0.021)	(1.594)	(2.194)	(0.020)	(1.549)	(1.826)
Capx / Assets	-0.223***	-2.165	-6.613	-0.250***	-4.126	-10.113
	(0.077)	(5.135)	(7.972)	(0.078)	(5.022)	(6.830)
R&D Intensity	-0.000	-0.054	-0.177**	0.000	-0.044	-0.128**
	(0.001)	(0.038)	(0.073)	(0.001)	(0.037)	(0.054)
Tobin's Q	-0.001	0.976***	1.089***	-0.001	0.998***	1.058***
	(0.002)	(0.144)	(0.212)	(0.002)	(0.146)	(0.182)
TNIC HHI	-0.017	-2.113***	-4.213***	-0.010	-1.819**	-3.362***
	(0.015)	(0.806)	(1.566)	(0.014)	(0.780)	(1.179)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage F-stat:	-	187.30	14.94	-	155.48	19.33
Stock-Yogo critical value, 10% max IV size	-	16.38	7.03	-	16.38	7.03
No. Of Firms	337	337	337	356	356	356
Observations	3,349	3,349	3,349	3,522	3,522	3,522

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 2-6: Subsample with Balanced Years Before and After Sarbanes-Oxley Act

This table reports the estimates for firm operating performance as dependent variables. All the independent variables are lagged one year. Sample is constructed based on U.S. S&P 1500 firms in the IT Industries from 1997 to 2006.

	Fixed Effect Model		Fixed Effect with IV[29]	
DV: ROA	(1)	(2)	(3)	(4)
New Entry Threats	-0.641*	-3.336***	-0.710*	-20.278***
	(0.363)	(1.131)	(0.363)	(7.581)
Board Independence	3.076*	3.212*	7.478	0.718
	(1.655)	(1.647)	(8.109)	(9.749)
*New Entry Threats * Board Independence*		4.002***		29.055***
		(1.489)		(11.244)
Board-related controls				
CEO Duality	-0.019	-0.007	-0.137	0.096
	(0.455)	(0.453)	(0.477)	(0.538)
Board Size	-0.066	-0.056	-0.024	0.025
	(0.124)	(0.124)	(0.125)	(0.142)
Board Tenure	-0.081	-0.073	0.046	0.027
	(0.110)	(0.111)	(0.126)	(0.149)
Board Age	-0.054	-0.042	-0.114	0.029
	(0.099)	(0.099)	(0.111)	(0.139)
Interlocks	0.030	0.028	0.012	0.008
	(0.051)	(0.052)	(0.051)	(0.063)
Firm-related controls				
Log (Assets)	-3.709***	-3.740***	-3.772***	-3.994***
	(0.604)	(0.600)	(0.597)	(0.640)
PPE / Assets	-5.616*	-5.798**	-4.967*	-5.965*
	(2.892)	(2.908)	(2.849)	(3.321)
Leverage	3.090	3.150	3.272	3.307
	(2.078)	(2.078)	(2.118)	(2.281)
Capx / Assets	-2.465	-2.449	-1.958	-3.185
	(5.383)	(5.385)	(5.698)	(6.404)
R&D Intensity	0.019	0.019	0.005	-0.004
	(0.047)	(0.047)	(0.049)	(0.051)
Tobin's Q	0.826***	0.830***	0.821***	0.845***
	(0.137)	(0.138)	(0.134)	(0.145)
TNIC HHI	-0.802	-0.826	-0.877	-0.937
	(1.116)	(1.111)	(1.127)	(1.265)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
First stage F-stat:	-	-	63.06	15.84
Stock-Yogo critical value, 10% max IV size	-	-	16.38	7.03
No. Of Firms	328	328	328	328
Observations	2,459	2,459	2,149	2,149
R-squared	0.698	0.700	-	-

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: new entry threats are standardized with mean of zero and standard deviation of one.

[29] IV was constructed based on the cutoff timing of SOX in 2002.

Table 2-7: Sample Including IT Services Industries[30]

This table reports the estimates for firm operating performance as dependent variables. All the independent variables are lagged one year. Sample is constructed based on U.S. S&P 1500 firms in the full IT Industries from 1997 to 2013.

	Fixed Effect Model		Fixed Effect with IV[31]	
	(1)	(2)	(3)	(4)
DV: ROA				
New Entry Threats	-0.406*	-3.546***	-0.344	-44.312**
	(0.224)	(0.794)	(0.230)	(20.134)
Board Independence	0.373	0.182	4.807	-12.781
	(1.084)	(1.075)	(4.809)	(10.175)
*New Entry Threats * Board Independence*		4.415***		62.161**
		(1.026)		(28.289)
Board-related controls	Yes	Yes	Yes	Yes
Firm-related controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
First stage F-stat:	-	-	215.59	12.01
Stock-Yogo critical value, 10% max IV size	-	-	16.38	7.03
No. Of Firms	682	682	384	384
Observations	4,855	4,855	3,828	3,828
R-squared	0.661	0.664	-	-

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 2-8: Main Results in the High Tech Sample

This table reports the estimates for firm operating performance as dependent variables. All the independent variables are lagged one year. Sample is constructed based on U.S. S&P 1500 firms in the High-tech Industries from 1997 to 2013.

	Fixed Effect Model		Fixed Effect with IV[6]	
	(1)	(2)	(3)	(4)
DV: ROA				
New Entry Threats	-0.641***	-3.143***	-0.651***	-31.661***
	(0.216)	(0.670)	(0.223)	(11.190)
Board Independence	-1.001	-1.042	-0.776	-4.457
	(0.924)	(0.924)	(4.142)	(6.448)
*New Entry Threats * Board Independence*		3.533***		44.025***
		(0.868)		(15.773)
Board-related controls	Yes	Yes	Yes	Yes
Firm-related controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
First stage F-stat:	-	-	283.06	25.91
Stock-Yogo critical value, 10% max IV size	-	-	16.38	7.03
No. Of Firms	977	977	554	554
Observations	7,139	7,139	5,686	5,686
R-squared	0.662	0.663	-	-

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

[30] We define IT services industries by 4 digital NAICS code: 5182, 5413, 5415, 5416, and 5417.
[31] IV was constructed based on the cutoff timing of SOX in 2002.

Table 2-9: The Effect of NET and Board Independence - Performance and Efficiency

All the independent variables are lagged one year. Sample is constructed based on U.S. S&P 1500 firms in the IT Industries from 1997 to 2013.

	Sales/Assets		Operating Income/Sales		COGS/Sales		SGA/Sales	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New Entry Threats	0.124	-7.012***	-0.727*	-5.398***	-0.002	0.027***	0.007***	0.013*
	(0.535)	(1.698)	(0.383)	(1.584)	(0.003)	(0.008)	(0.002)	(0.007)
Board Independence	5.050*	4.625	0.945	0.680	0.020	0.022*	-0.011	-0.011
	(3.041)	(2.999)	(1.828)	(1.808)	(0.013)	(0.013)	(0.011)	(0.011)
*New Entry Threats * Board Independence*		9.951***		6.434***		-0.040***		-0.008
		(2.243)		(2.004)		(0.011)		(0.010)
Board-related controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-related controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Of Firms	586	586	581	581	583	583	497	497
Observations	4,197	4,197	4,188	4,188	4,191	4,191	3,452	3,452
R-squared	0.842	0.843	0.674	0.676	0.922	0.922	0.914	0.914

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-1: Variable Definitions and Data Sources

Main Interest Variables (Source: IBES)	**Definition**
NET	New entry threat measured by *term frequency–inverse document frequency* weighted cosine similarity;
Disclosure Index (Hui et al. 2014)	The sum of decile ranking each year of analyst forecast error, forecast dispersion, and revision volatility, with the highest decile representing the lowest error, lowest dispersion, and lowest volatility divided by 30;
Forecast Error	The absolute difference between the last consensus forecast of EPS estimate prior to the release of earnings and the actually earnings per share scaled by the beginning-of-year stock price;
Forecast Dispersion	The standard deviation of the analyst forecasts of EPS estimate prior to the release of earnings deflated by the absolute value of the consensus forecast at the end of the year;
Revision Volatility	The standard deviation of the monthly revision of the consensus forecast deflated by the beginning-of-year price;
Moderating Variables (Source: Hoberg and Phillips (2010) & NBER patent)	
TNIC HHI	Industry concentration ratio based on Text-based Network Industry Classifications (TNIC);
Software & IT Services Industry	Software & IT Services Industries is identified by NAICS4 code 5112, 5182, 5415, and 5416;
Alternative Measure of Disclosure (Source: SEC)	
CTO	An indicator variable set equal to one if a firm files Confidential Treatment Order (CTO) in year *t*;
Number of CTO	The number of CTOs in year *t*;
Other Controls (Source: Compustat, CRSP and IBES)	
Log(Asset)	The natural log of the firm's total assets;
ROA	The firm's net incomes scaled by its assets;
Asset Tangibility	Net property, plants and equipments to total assets ratio;
Leverage	Total debt divided by its total assets;
Capital Exp	Capital expenditure to total assets ratio;
R&D Intensity	R&D expenditure to total assets ratio;
Tobin's Q	Market to book ratio as defined in Brown et al. (2006);
Return Volatility	The volatility of daily stock returns in year *t*;
ROA Volatility	The standard deviation of change in annual return on assets for the five-year period immediately prior to the current year;
Loss	1 if the firm recorded a loss in year *t*, and 0 otherwise;
Analyst Coverage	The number of analysts following the firms as of the beginning of year *t*;
Log(Seg)	The natural log of (1 + number of business segments);
Number of Rivals	Total number of rivals in Text-based Network Industry Classifications (TNIC) (Hoberg et al. 2014).

Table 3-2: Summary Statistics and Correlation Coefficients

This table reports the summary statistics for primary variables constructed based on the sample of U.S. firms in the IT Industries[32] from 1997 to 2013. Please see Table 3-1 for the description of the variables.

Variable	Mean	Std. dev.	1	2	3	4	5	6	7	8	9	10	11	12
1. NET	0.069	0.046	1.000											
2. Disclosure Index (median)	5.353	2.136	0.009	1.000										
3. Forecast Error (median)	0.066	1.652	0.007	-0.054*	1.000									
4. Forecast Dispersion (median)	0.108	0.440	0.026*	-0.254*	0.008	1.000								
5. Revision Volatility (median)	0.079	0.183	-0.015	-0.348*	0.056*	0.056*	1.000							
6. Disclosure Index (mean)	5.354	2.149	0.008	0.987*	-0.053*	-0.254*	-0.346*	1.000						
7. Forecast Error (mean)	0.066	1.634	0.007	-0.054*	1.000*	0.008	0.056*	-0.054*	1.000					
8. Forecast Dispersion (mean)	0.110	0.544	0.014	-0.213*	0.009	0.709*	0.079*	-0.220*	0.008	1.000				
9. Revision Volatility (mean)	0.075	0.156	-0.016	-0.383*	0.062*	0.067*	0.975*	-0.385*	0.062*	0.084*	1.000			
10. TNIC HHI	0.205	0.187	-0.093*	-0.024*	0.000	-0.009	0.029*	-0.025*	0.000	0.016	0.033*	1.000		
11. Software & Services	0.299	0.458	0.306*	0.096*	0.012	0.002	-0.048*	0.093*	0.012	0.002	-0.056*	0.085*	1.000	
12. Innovation Hub	0.180	0.384	0.123*	-0.010	0.012	-0.006	-0.007	-0.011	0.012	-0.001	-0.005	-0.150*	-0.064*	1.000
13. CTO	0.123	0.329	0.026	-0.108*	0.036*	0.017	0.064*	-0.108*	0.035*	0.011	0.064*	0.007	-0.017	0.039*
14. Number of CTOs	0.230	0.815	0.021	-0.079*	0.022	0.022	0.046*	-0.084*	0.020	0.015	0.044*	-0.014	-0.044*	0.045*
15. Asset (Billion $)	3.399	14.353	0.019	0.140*	-0.008	-0.036*	-0.022*	0.139*	-0.008	-0.031*	-0.025*	-0.068*	-0.054*	0.003
16. ROA	-0.043	0.329	-0.115*	0.271*	-0.081*	-0.056*	-0.093*	0.270*	-0.082*	-0.051*	-0.107*	0.024*	-0.030*	-0.050*
17. Asset Tangibility	0.173	0.176	-0.308*	-0.018	0.007	-0.011	0.024*	-0.017	0.007	-0.011	0.026*	-0.135*	-0.315*	-0.149*
18. Leverage	0.120	0.179	-0.156*	-0.021*	-0.006	-0.020	0.054*	-0.018	-0.006	-0.011	0.057*	-0.003	-0.173*	-0.122*
19. Capital Exp	0.043	0.043	-0.070*	-0.035*	-0.004	0.004	0.042*	-0.034*	-0.004	0.013	0.044*	-0.076*	-0.139*	-0.050*
20. R&D Intensity	0.095	0.114	0.189*	-0.178*	0.011	0.040*	0.033*	-0.178*	0.011	0.036*	0.040*	-0.126*	0.073*	0.178*
21. Tobin's Q	2.320	2.361	0.129*	0.182*	-0.015	-0.048*	-0.063*	0.182*	-0.015	-0.041*	-0.068*	-0.038*	0.111*	0.093*
22. Return Volatility	0.080	0.147	-0.055*	-0.181*	0.036*	0.074*	0.028*	-0.184*	0.037*	0.063*	0.035*	0.090*	-0.003	-0.060*
23. ROA Volatility	0.090	0.258	0.093*	-0.116*	0.012	0.028*	0.040*	-0.117*	0.012	0.021	0.045*	-0.013	0.032*	0.031*
24. Loss (%)	0.354	0.478	0.153*	-0.451*	0.047*	0.164*	0.149*	-0.453*	0.047*	0.143*	0.169*	-0.020*	0.037*	0.096*
25. Analyst Coverage	9.602	9.020	0.166*	0.278*	-0.031*	-0.089*	-0.041*	0.281*	-0.031*	-0.078*	-0.049*	-0.153*	0.008	0.132*
26. Business Segments	1.489	0.971	-0.111*	0.088*	-0.000	-0.030*	-0.002	0.089*	-0.000	-0.023*	-0.003	0.059*	-0.106*	-0.121*
27. Number of Rivals	92.033	88.201	0.283*	-0.019	0.001	0.026*	-0.029*	-0.018	0.001	0.015	-0.034*	-0.465*	0.136*	0.189*

[32] We include IT software, hardware and services Industries, which is defined by 21 4-digital NAICS code: 2211, 3332, 3333, 3336, 3339, 3341, 3342, 3343, 3344, 3345, 3346, 5112, 5161, 5171, 5172, 5173, 5174, 5179, 5181, 5413, and 5417.

Table 3-2: Summary Statistics and Correlation Coefficients (Cont.)

Variable	13	14	15	16	17	18	19	20	21	22	23	24	25	26
14. Number of CTO	0.752*	1.000												
15. Asset (Billion $)	-0.065*	-0.047*	1.000											
16. ROA	-0.063*	-0.037*	0.064*	1.000										
17. Asset Tangibility	0.025	0.013	0.193*	0.022*	1.000									
18. Leverage	-0.005	0.000	0.123*	-0.021*	0.448*	1.000								
19. Capital Exp	0.084*	0.050*	0.052*	-0.076*	0.568*	0.190*	1.000							
20. R&D Intensity	0.062*	0.054*	-0.131*	-0.479*	-0.234*	-0.241*	-0.034*	1.000						
21. Tobin's Q	0.072*	0.060*	-0.055*	-0.050*	-0.146*	-0.133*	0.052*	0.187*	1.000					
22. Return Volatility	-0.005	-0.001	-0.091*	-0.108*	-0.050*	-0.041*	-0.025*	0.070*	-0.070*	1.000				
23. ROA Volatility	0.084*	0.041*	-0.057*	-0.327*	-0.061*	-0.054*	0.073*	0.248*	0.192*	0.070*	1.000			
24. Loss (%)	0.107*	0.089*	-0.124*	-0.483*	-0.075*	0.010	0.015	0.318*	-0.030*	0.132*	0.185*	1.000		
25. Analyst Coverage	-0.028	-0.012	0.417*	0.148*	0.039*	0.084*	0.035*	-0.117*	0.085*	-0.276*	-0.103*	-0.187*	1.000	
26. Business Segments	-0.080*	-0.047*	0.262*	0.071*	0.224*	0.183*	0.050*	-0.213*	-0.102*	-0.071*	-0.076*	-0.119*	0.112*	1.000
27. Number of Rivals	0.037*	0.050*	-0.017	-0.111*	-0.099*	-0.170*	0.017	0.316*	0.195*	-0.049*	0.092*	0.146*	0.107*	-0.159*

* $p < .05$

Table 3-3: New Entry Threats and Firm information Disclosure

	Consensus Forecast Measured by Median		Consensus Forecast Measured by Mean	
DV: Disclosure Index	*Disclosure Index$_{t+1}$*	*Disclosure Index$_{t+2}$*	*Disclosure Index$_{t+1}$*	*Disclosure Index$_{t+2}$*
	(1)	(2)	(3)	(4)
NET	-0.107**	-0.190***	-0.115***	-0.195***
	(0.043)	(0.046)	(0.043)	(0.046)
Log (Assets)	-0.378***	-0.482***	-0.371***	-0.473***
	(0.056)	(0.059)	(0.056)	(0.059)
ROA	0.002	0.033	0.043	0.080
	(0.101)	(0.106)	(0.102)	(0.105)
Asset Tangibility	-0.466	-0.190	-0.606	-0.353
	(0.379)	(0.400)	(0.381)	(0.404)
Leverage	-0.274	0.008	-0.321*	-0.075
	(0.178)	(0.188)	(0.181)	(0.186)
Capital Exp	-0.943	-0.283	-0.813	-0.231
	(0.669)	(0.720)	(0.675)	(0.729)
R&D Intensity	-1.012**	-1.439***	-0.957**	-1.243***
	(0.466)	(0.466)	(0.471)	(0.472)
Tobin's Q	0.038***	-0.012	0.036***	-0.013
	(0.011)	(0.011)	(0.010)	(0.011)
Return Volatility	0.064	0.280	0.076	0.276
	(0.220)	(0.220)	(0.221)	(0.222)
ROA Volatility	-0.350*	-0.184	-0.396**	-0.274
	(0.191)	(0.264)	(0.196)	(0.275)
Loss	-0.326***	-0.072	-0.336***	-0.088
	(0.054)	(0.056)	(0.054)	(0.057)
Analyst Coverage	-0.004	-0.001	-0.005	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)
Log(Seg)	-0.371***	-0.140	-0.368***	-0.118
	(0.109)	(0.115)	(0.110)	(0.116)
Number of Rivals	-0.001**	-0.001	-0.001**	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	9,690	9,690	8,473	8,473
No. of Firms	1,570	1,570	1,359	1,359
Adjusted R-squared	0.489	0.491	0.492	0.492

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-4: New Entry Threats in Last Three Years and Firm Disclosure

	Consensus Forecast Measured by Median		Consensus Forecast Measured by Mean	
DV: Disclosure Index	*Disclosure Index$_{t+1}$*	*Disclosure Index$_{t+2}$*	*Disclosure Index$_{t+1}$*	*Disclosure Index$_{t+2}$*
	(1)	(2)	(3)	(4)
Average (NET_t+NET_{t-1}+NET_{t-2})	-0.223***	-0.255***	-0.227***	-0.250***
	(0.053)	(0.057)	(0.053)	(0.057)
Log (Assets)	-0.319***	-0.447***	-0.309***	-0.440***
	(0.062)	(0.065)	(0.062)	(0.065)
ROA	-0.007	0.077	0.029	0.132
	(0.106)	(0.105)	(0.106)	(0.103)
Asset Tangibility	-0.321	-0.120	-0.467	-0.289
	(0.414)	(0.436)	(0.413)	(0.438)
Leverage	-0.316*	0.073	-0.346*	-0.020
	(0.188)	(0.200)	(0.191)	(0.197)
Capital Exp	-0.536	-0.967	-0.405	-0.975
	(0.719)	(0.754)	(0.721)	(0.768)
R&D Intensity	-0.968*	-1.687***	-0.954*	-1.484***
	(0.553)	(0.536)	(0.550)	(0.543)
Tobin's Q	0.039***	-0.002	0.038***	-0.005
	(0.011)	(0.011)	(0.011)	(0.011)
Return Volatility	0.304	0.350	0.330	0.336
	(0.240)	(0.235)	(0.240)	(0.235)
ROA Volatility	-0.302	-0.019	-0.346*	-0.103
	(0.191)	(0.252)	(0.195)	(0.267)
Loss	-0.312***	-0.066	-0.324***	-0.085
	(0.057)	(0.059)	(0.057)	(0.059)
Analyst Coverage	-0.002	-0.002	-0.003	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)
Log(Seg)	-0.390***	-0.134	-0.391***	-0.115
	(0.118)	(0.123)	(0.119)	(0.125)
Number of Rivals	-0.001**	-0.000	-0.001**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	8,528	7,469	8,528	7,469
No. of Firms	1,365	1,207	1,365	1,207
Adjusted R-squared	0.497	0.506	0.500	0.508

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-5: New Entry Threats, Firm Disclosure and Industry Concentration

DV: Disclosure Index$_{t+1}$	Consensus Forecast Measured by Median		Consensus Forecast Measured by Mean	
	(1)	(2)	(3)	(4)
NET	-0.092**	-0.152***	-0.102**	-0.166***
	(0.045)	(0.054)	(0.045)	(0.054)
TNIC HHI	-0.028	0.033	0.020	0.085
	(0.147)	(0.149)	(0.149)	(0.152)
NET x *TNIC HHI*		0.314**		0.336**
		(0.143)		(0.145)
Log (Assets)	-0.389***	-0.391***	-0.376***	-0.378***
	(0.060)	(0.060)	(0.061)	(0.061)
ROA	-0.046	-0.046	0.009	0.010
	(0.095)	(0.095)	(0.097)	(0.097)
Asset Tangibility	-0.246	-0.250	-0.379	-0.383
	(0.396)	(0.397)	(0.400)	(0.401)
Leverage	-0.263	-0.276	-0.305	-0.319
	(0.197)	(0.197)	(0.200)	(0.201)
Capital Exp	-0.679	-0.681	-0.532	-0.534
	(0.758)	(0.758)	(0.767)	(0.768)
R&D Intensity	-1.191**	-1.204**	-1.137**	-1.151**
	(0.539)	(0.539)	(0.539)	(0.538)
Tobin's Q	0.048***	0.047***	0.045***	0.044***
	(0.012)	(0.013)	(0.012)	(0.012)
Return Volatility	0.215	0.219	0.215	0.219
	(0.232)	(0.233)	(0.235)	(0.235)
ROA Volatility	-0.167	-0.159	-0.219	-0.211
	(0.266)	(0.265)	(0.276)	(0.275)
Loss	-0.333***	-0.332***	-0.341***	-0.341***
	(0.057)	(0.057)	(0.057)	(0.057)
Analyst Coverage	-0.001	-0.001	-0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)
Log(Seg)	-0.375***	-0.377***	-0.372***	-0.374***
	(0.113)	(0.113)	(0.115)	(0.115)
Number of Rivals	-0.001**	-0.001**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	8,765	8,765	8,765	8,765
No. of Firms	1,396	1,396	1,396	1,396
Adjusted R-squared	0.492	0.492	0.493	0.494

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-6: New Entry Threats, Firm Disclosure and Software & IT Services Industries

DV: Disclosure Index$_{t+1}$	Panel A: Consensus Forecast Measured by Median			Panel B: Consensus Forecast Measured by Mean		
	Full sample	Hardware & Telecom	Software & IT Services	Full sample	Hardware & Telecom	Software & IT Services
	(1)	(2)	(3)	(4)	(5)	(6)
NET	-0.054	-0.099*	-0.167**	-0.059	-0.103*	-0.182**
	(0.052)	(0.055)	(0.071)	(0.053)	(0.055)	(0.071)
NET x *Software & IT Services*	-0.147*	-	-	-0.153*	-	-
	(0.081)	-	-	(0.081)	-	-
Log (Assets)	-0.384***	-0.372***	-0.411***	-0.377***	-0.368***	-0.388***
	(0.056)	(0.066)	(0.107)	(0.056)	(0.066)	(0.108)
ROA	0.004	0.153	-0.171	0.045	0.188	-0.119
	(0.101)	(0.138)	(0.138)	(0.102)	(0.134)	(0.140)
Asset Tangibility	-0.449	-0.333	-0.752	-0.588	-0.410	-1.349
	(0.379)	(0.400)	(1.137)	(0.381)	(0.403)	(1.128)
Leverage	-0.272	-0.322	-0.113	-0.319*	-0.339*	-0.269
	(0.178)	(0.200)	(0.408)	(0.180)	(0.203)	(0.415)
Capital Exp	-0.937	-0.906	-1.614	-0.807	-0.828	-0.911
	(0.669)	(0.719)	(1.871)	(0.675)	(0.724)	(1.877)
R&D Intensity	-0.996**	-0.405	-1.964**	-0.941**	-0.316	-1.938**
	(0.464)	(0.556)	(0.822)	(0.470)	(0.560)	(0.833)
Tobin's Q	0.038***	0.059***	0.016	0.036***	0.054***	0.017
	(0.011)	(0.016)	(0.015)	(0.010)	(0.016)	(0.014)
Return Volatility	0.060	-0.030	0.390	0.073	-0.016	0.414
	(0.220)	(0.256)	(0.431)	(0.221)	(0.257)	(0.435)
ROA Volatility	-0.351*	-0.506***	-0.097	-0.397**	-0.526***	-0.175
	(0.192)	(0.187)	(0.272)	(0.197)	(0.187)	(0.288)
Loss	-0.325***	-0.317***	-0.259**	-0.335***	-0.338***	-0.243**
	(0.054)	(0.064)	(0.102)	(0.054)	(0.064)	(0.103)
Analyst Coverage	-0.004	-0.002	-0.012	-0.004	-0.002	-0.013
	(0.005)	(0.005)	(0.009)	(0.005)	(0.005)	(0.009)
Log(Seg)	-0.370***	-0.421***	-0.108	-0.367***	-0.429***	-0.064
	(0.109)	(0.122)	(0.236)	(0.110)	(0.123)	(0.241)
Number of Rivals	-0.001**	-0.000	-0.001*	-0.001**	-0.000	-0.001
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Year & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,690	6,885	2,805	9,690	6,885	2,805
No. of Firms	1,570	1,041	528	1,570	1,041	528
Adjusted R-squared	0.489	0.482	0.495	0.492	0.486	0.496

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-7: New Entry Threats, Firm Disclosure and Geographic Location

DV: Disclosure Index$_{t+1}$	Panel A: Consensus Forecast Measured by Median		Panel B: Consensus Forecast Measured by Mean	
	(1)	(2)	(3)	(4)
NET	-0.107**	-0.113**	-0.115***	-0.124**
	(0.043)	(0.048)	(0.043)	(0.049)
NET x *Innovation Hub*		0.026		0.043
		(0.087)		(0.087)
Log (Assets)	-0.378***	-0.378***	-0.371***	-0.371***
	(0.056)	(0.056)	(0.056)	(0.056)
ROA	0.002	0.002	0.043	0.044
	(0.101)	(0.101)	(0.102)	(0.102)
Asset Tangibility	-0.466	-0.467	-0.606	-0.608
	(0.379)	(0.379)	(0.381)	(0.381)
Leverage	-0.274	-0.275	-0.321*	-0.322*
	(0.178)	(0.178)	(0.181)	(0.180)
Capital Exp	-0.943	-0.942	-0.813	-0.811
	(0.669)	(0.669)	(0.675)	(0.676)
R&D Intensity	-1.012**	-1.007**	-0.957**	-0.950**
	(0.466)	(0.466)	(0.471)	(0.472)
Tobin's Q	0.038***	0.038***	0.036***	0.036***
	(0.011)	(0.011)	(0.010)	(0.010)
Return Volatility	0.064	0.063	0.076	0.075
	(0.220)	(0.220)	(0.221)	(0.221)
ROA Volatility	-0.350*	-0.350*	-0.396**	-0.397**
	(0.191)	(0.191)	(0.196)	(0.196)
Loss	-0.326***	-0.327***	-0.336***	-0.337***
	(0.054)	(0.054)	(0.054)	(0.054)
Analyst Coverage	-0.004	-0.004	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)
Log(Seg)	-0.371***	-0.371***	-0.368***	-0.367***
	(0.109)	(0.109)	(0.110)	(0.110)
Number of Rivals	-0.001**	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	9,690	9,690	9,690	9,690
No. of Firms	1,570	1,570	1,570	1,570
Adjusted R-squared	0.489	0.489	0.491	0.491

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-8: Industries distribution of Confidential Treatment Order

NAICS code	Industry	# of CTOs
2211	Electric power generation, transmission, and distribution	58
3332	Industrial machinery manufacturing	3
3333	Commercial and service industry machinery manufacturing	14
3336	Engine, turbine, and power transmission equipment manufacturing	6
3339	Other general-purpose machinery manufacturing	3
3341	Computer and peripheral equipment manufacturing	24
3342	Communications equipment manufacturing	74
3343	Audio and video equipment manufacturing	1
3344	Semiconductor and other electronic component manufacturing	138
3345	Navigational, measuring, electromedical, and control instruments manufacturing	135
3346	Manufacturing and reproducing, magnetic and optical media	5
5112	Software publishers	95
5171	Internet publishing and broadcasting	27
5172	Wired telecommunications carriers	19
5174	Wireless telecommunications carriers (except satellite)	30
5179	Telecommunications	37
5182	Data processing, hosting, and related services	43
5415	Computer systems design and related services	36
5416	Management, scientific, and technical consulting services	8

Table 3-9: Confidential Treatment Orders as Alternative Measure of Information Disclosure

DV:	*CTO_{t+1}* Logit	*Number of $CTOs_{t+1}$* Zero-inflated Negative Binomial	*Number of $CTOs_{t+1}$* Zero-inflated Poisson
	(1)	(2)	(3)
NET	0.139***	0.185***	0.174***
	(0.052)	(0.046)	(0.034)
Log (Assets)	0.003	0.038	0.037
	(0.032)	(0.033)	(0.025)
ROA	0.018	0.053	-0.013
	(0.149)	(0.137)	(0.112)
Asset Tangibility	-0.278	0.040	0.120
	(0.416)	(0.370)	(0.294)
Leverage	0.195	0.261	0.230
	(0.255)	(0.262)	(0.198)
Capital Exp	6.995***	2.669**	1.856**
	(1.489)	(1.168)	(0.834)
R&D Intensity	0.298	-0.048	-0.124
	(0.441)	(0.338)	(0.263)
Tobin's Q	0.011	0.017	0.012
	(0.026)	(0.020)	(0.015)
Return Volatility	-1.639***	-0.094	0.253
	(0.393)	(0.320)	(0.272)
ROA Volatility	0.382**	-0.010	-0.082
	(0.177)	(0.112)	(0.107)
Loss	0.471***	0.157	0.103
	(0.115)	(0.105)	(0.082)
Log(Seg)	-0.948***	-0.437**	-0.299*
	(0.193)	(0.198)	(0.166)
Number of Rivals	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Year Dummies	Yes	Yes	Yes
Observations	4,616	4,616	4,616
Chi-squared	-	44.50	52.76
Pseudo R-squared	0.0519	-	-

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-10: Instrumental Variables Regression

This table reports the 2SLS estimates that treat NET as the endogenous variables. The sample is constructed based on the U.S. public firms in the IT Industries from 1997 to 2013.

	1st Stage	2nd Stage
Dependent Variable:	NET	Disclosure Index$_{t+1}$
NET	-	-4.566**
	-	(2.272)
L.Ind_Sale Growth (z_1)	0.069**	-
	(0.032)	-
Log (Assets)	0.085***	0.005
	(0.017)	(0.222)
ROA	-0.056**	-0.303
	(0.025)	(0.188)
Asset Tangibility	-0.108	-0.805
	(0.107)	(0.668)
Leverage	-0.076	-0.593*
	(0.052)	(0.346)
Capital Exp	0.385	1.585
	(0.239)	(1.674)
R&D Intensity	0.212	-0.331
	(0.144)	(0.964)
Tobin's Q	-0.003	0.034
	(0.004)	(0.021)
Return Volatility	-0.002	0.266
	(0.059)	(0.343)
ROA Volatility	0.059	0.172
	(0.046)	(0.384)
Loss	0.040***	-0.153
	(0.015)	(0.122)
Analyst Coverage	-0.002	-0.010
	(0.001)	(0.010)
Log(Seg)	0.139***	0.268
	(0.033)	(0.359)
Number of Rivals	0.001***	0.005
	(0.000)	(0.003)
Firm Dummies	Yes	Yes
Year Dummies	Yes	Yes
First stage F-stat:	7.721	
Stock-Yogo critical value, 10% max IV size	16.38	
Observations	8,151	
Number of Firms	1,097	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-11: New Entry Threats and Firm Disclosure in High Tech Industries

	Consensus Forecast Measured by Median		Consensus Forecast Measured by Mean	
DV: Disclosure Index	*Disclosure Index$_{t+1}$*	*Disclosure Index$_{t+2}$*	*Disclosure Index$_{t+1}$*	*Disclosure Index$_{t+2}$*
	(1)	(2)	(3)	(4)
NET	-0.115***	-0.150***	-0.120***	-0.154***
	(0.038)	(0.039)	(0.038)	(0.039)
Controls	Yes	Yes	Yes	Yes
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	15,444	13,542	15,444	13,542
No. of Firms	2,462	2,132	2,462	2,132
Adjusted R-squared	0.539	0.540	0.541	0.540

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardize

Table 3-12: New Entry Threats, Firm Disclosure and Industry Concentration in High Tech Industries

DV: Disclosure Index$_{t+1}$	Consensus Forecast Measured by Median		Consensus Forecast Measured by Mean	
	(1)	(2)	(3)	(4)
NET	-0.097**	-0.147***	-0.104***	-0.158***
	(0.039)	(0.045)	(0.039)	(0.046)
TNIC HHI	0.035	0.060	0.079	0.105
	(0.122)	(0.122)	(0.123)	(0.123)
NET x *TNIC HHI*		0.271**		0.291**
		(0.119)		(0.119)
Controls	Yes	Yes	Yes	Yes
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	13,983	13,983	13,983	13,983
No. of Firms	2,186	2,186	2,186	2,186
Adjusted R-squared	0.542	0.542	0.543	0.543

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-13: New Entry Threats, Firm Disclosure and Appropriation Regimes in High Tech Industries

DV: Disclosure Index$_{t+1}$	Consensus Forecast Measured by Median		Consensus Forecast Measured by Mean	
	(1)	(2)	(3)	(4)
NET	-0.115***	-0.073	-0.120***	-0.069
	(0.038)	(0.044)	(0.038)	(0.044)
NET x Software & Services		-0.135*		-0.160**
		(0.074)		(0.075)
Controls	Yes	Yes	Yes	Yes
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	15,444	15,444	15,444	15,444
No. of Firms	2,462	2,462	2,462	2,462
Adjusted R-squared	0.539	0.539	0.541	0.541

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-A1: Main Results from Two-sided Tobit Model

	Consensus Forecast Measured by Median		Consensus Forecast Measured by Mean	
DV: Disclosure Index	*Disclosure Index$_{t+1}$*	*Disclosure Index$_{t+2}$*	*Disclosure Index$_{t+1}$*	*Disclosure Index$_{t+2}$*
	(1)	(2)	(3)	(4)
NET	-0.107**	-0.190***	-0.115**	-0.195***
	(0.051)	(0.056)	(0.051)	(0.056)
Log (Assets)	-0.380***	-0.483***	-0.373***	-0.475***
	(0.069)	(0.072)	(0.068)	(0.072)
ROA	0.002	0.034	0.044	0.082
	(0.109)	(0.109)	(0.111)	(0.109)
Asset Tangibility	-0.457	-0.189	-0.593	-0.350
	(0.478)	(0.491)	(0.481)	(0.487)
Leverage	-0.273	0.011	-0.311	-0.075
	(0.195)	(0.244)	(0.196)	(0.243)
Capital Exp	-0.949	-0.261	-0.818	-0.208
	(0.707)	(0.711)	(0.717)	(0.711)
R&D Intensity	-1.019**	-1.429***	-0.960*	-1.234**
	(0.518)	(0.510)	(0.523)	(0.513)
Tobin's Q	0.038***	-0.012	0.036***	-0.014
	(0.012)	(0.012)	(0.012)	(0.012)
Return Volatility	0.074	0.281	0.087	0.277
	(0.244)	(0.237)	(0.244)	(0.234)
ROA Volatility	-0.351	-0.186	-0.396*	-0.274
	(0.223)	(0.307)	(0.225)	(0.309)
Loss	-0.327***	-0.072	-0.337***	-0.087
	(0.055)	(0.056)	(0.057)	(0.056)
Analyst Coverage	-0.004	-0.001	-0.005	-0.003
	(0.006)	(0.006)	(0.006)	(0.006)
Log(Seg)	-0.370***	-0.140	-0.367***	-0.117
	(0.129)	(0.137)	(0.131)	(0.140)
Number of Rivals	-0.001**	-0.001	-0.001*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	9,690	8,473	9,690	8,473
No. of Firms	1,571	1,360	1,571	1,360
Adjusted R-squared	0.196	0.197	0.196	0.197

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-A2: New Entry Threats and Forecast Error

	Consensus Forecast Measured by Median		Consensus Forecast Measured by Mean	
DV: Forecast Error Decile	*Forecast* *Error$_{t+1}$*	*Forecast* *Error$_{t+2}$*	*Forecast* *Error$_{t+1}$*	*Forecast* *Error$_{t+2}$*
	(1)	(2)	(3)	(4)
NET	-0.201***	-0.215***	-0.195***	-0.200***
	(0.058)	(0.064)	(0.058)	(0.063)
Controls	Yes	Yes	Yes	Yes
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	9,584	8,377	9,584	8,377
No. of Firms	1,560	1,348	1,560	1,348
Adjusted R-squared	0.426	0.424	0.434	0.429

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-A3: New Entry Threats and Forecast Dispersion

	Consensus Forecast Measured by Median		Consensus Forecast Measured by Mean	
DV: Forecast Dispersion Decile	*Forecast* *Dispersion$_{+1}$*	*Forecast* *Dispersion$_{+2}$*	*Forecast* *Dispersion$_{+1}$*	*Forecast* *Dispersion$_{+2}$*
	(1)	(2)	(3)	(4)
NET	-0.080	-0.228***	-0.076	-0.228***
	(0.068)	(0.070)	(0.068)	(0.070)
Controls	Yes	Yes	Yes	Yes
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	7,954	6,999	7,954	6,999
No. of Firms	1,307	1,121	1,307	1,121
Adjusted R-squared	0.393	0.398	0.393	0.398

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

Table 3-A4: New Entry Threats and Revision Volatility

	Consensus Forecast Measured by Median		Consensus Forecast Measured by Mean	
DV: Revision Volatility Decile	*Revision* *Volatility$_{t+1}$*	*Revision* *Volatility$_{t+2}$*	*Revision* *Volatility$_{t+1}$*	*Revision* *Volatility$_{t+2}$*
	(1)	(2)	(3)	(4)
NET	-0.060	-0.112*	-0.086	-0.141**
	(0.065)	(0.067)	(0.065)	(0.067)
Controls	Yes	Yes	Yes	Yes
Year & Firm FE	Yes	Yes	Yes	Yes
Observations	9,530	8,330	9,530	8,330
No. of Firms	1,556	1,347	1,556	1,347
Adjusted R-squared	0.397	0.395	0.403	0.399

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: new entry threats are standardized with mean of zero and standard deviation of one.

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