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INNOVATION AND EXPERT EVALUATIONS: THE INFLUENCE OF A FIRM'S APPROACH TO INNOVATION ON ASSESSMENTS IN FINANCIAL MARKETS

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For Yolanda, Nolan and Kenan.

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INNOVATION AND EXPERT EVALUATIONS: THE INFLUENCE OF A FIRM'S APPROACH TO INNOVATION ON ASSESSMENTS IN FINANCIAL MARKETS

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Prior research shows that when a firm uses an approach to innovation based on diverse, distant, and distinctive knowledge it can enhance its ability to develop innovations. However, less is known about how such an approach to innovation affects evaluations in financial markets by securities analysts and investors. In this dissertation I examine how a firm's approach to innovation influences its ability to attract coverage and favorable recommendations from securities analysts. After considering the influence of innovation on analysts' evaluations, I examine how analysts' recommendations, in turn, influence a firm's ability to attract investment. I argue that when a firm uses an approach to innovation based on diverse, distant, and distinctive knowledge it may complicate securities analysts' efforts to evaluate its strategy, which may make them less willing to provide the firm with coverage and favorable recommendations. I also explore how disagreement among securities analysts' recommendations may create opportunities for investors, which can ultimately help a firm to attract investment. This dissertation contributes to strategy research by highlighting an important trade-off related to a firm's approach to innovation. Whereas prior research has shown that using diverse, distant, and distinctive knowledge helps a firm to develop knowledge-based resources, this research, in contrast, shows that such an approach to innovation may hinder efforts to capture value from these resources in financial markets. This research also contributes to the literature on financial intermediaries. It shows that financial markets are not fully intermediated by analysts' recommendations and that uncertainty reflected in disagreement among analysts' recommendations can signal valuable opportunities for investors that will make them more likely to buy shares in a firm. Furthermore, it also shows that characteristics of investors and aspects of a firm's innovation strategy, which enhance investors' ability to identify and profit from opportunities that arise under uncertainty, will make investors even more likely to buy shares when analysts disagree about their recommendations.

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Chapter 1: Introduction

THEORETICAL MOTIVATION

A firm's resources can provide the basis for its competitive advantage (Barney, 1991; Grant, 1991) and by acquiring and aggregating knowledge, a company can produce valuable knowledge-based resources (Grant, 1996). Innovations are an important type of knowledge-based resource, which may contribute to a company's success (Rumelt, 1984). However, developing innovations typically involves uncertainty as it requires a firm to make choices among several apparently feasible alternatives (Dosi, 1982). Uncertainty, in turn, enables a firm to develop resources that are different from those of its rivals, which can contribute to the persistence of resource heterogeneity across firms (Nelson, 1991). In this way, uncertainty may help a company to develop the unique and potentially valuable resources that can provide the basis for its competitive advantage (Barney, 1986; Peteraf, 1993).

The link between innovation and a firm's success has led to numerous strategic management studies which emphasize the potential benefits associated with a company's approach to innovation. Studies show, for example, that the manner in which a company acquires and combines knowledge can determine how successful it is at developing innovations (e.g., Rosenkopf & Nerkar, 2001; Katila & Ahuja, 2002; Ahuja & Katila, 2004). However, after a firm has developed resources, its ability to capture value from them ultimately depends on evaluations made outside of the firm's boundaries

(Thompson, 1967; Barney, 2001). These external evaluations not only influence the firm's ability to commercialize its current innovations (Nelson & Winter, 1982), but may also influence its ability to attract critical inputs from outside parties, such as the talent needed to develop future innovations (Henderson and Cockburn 1994; Cockburn and Henderson, 1998).

The same uncertainty that makes it possible for a firm to develop valuable innovations can make it difficult for outside parties to understand them (Rindova & Petkova, 2007; Kaplan & Tripsas, 2008). This, in turn, increases outsiders' reliance on expert evaluations as a basis for providing or withholding inputs to firms (Rao, 1994; Pollock & Gulati, 2007). One particularly important and consequential type of expert evaluation is provided by securities analysts (Useem, 1996). Such analysts serve as expert intermediaries in financial markets by mitigating uncertainty that investors face when evaluating a firm's strategy (Rao & Sivakumar, 1999; Beunza & Garud, 2007). Moreover, securities analysts have discretion over the set of firms which they cover (Rao, Greve & Davis, 2001) and over the specific recommendations they provide on those firms (Mikhail, Walther & Willis, 1997). Research shows that both securities analysts' coverage decisions and their recommendations can influence the firm's ability to attract critical inputs and external support (Womack, 1996; Zuckerman, 1999; Pollock & Gulati, 2007).

Studies suggest that securities analysts and investors consider a firm's innovation activities when developing their assessments (Levitas & McFadyen, 2009; Benner, 2010). However, the fact that uncertainty can simultaneously help resource creation (Barney, 1986; Peteraf, 1993) and hinder external evaluation (Thompson, 1967), suggests the possibility that a firm may face a tension between how its approach to innovation, which helps it create resources, may subsequently hinder efforts to elicit favorable evaluations from outside parties. With the goal of exploring this possible tension, the present research seeks to examine the potential influence of a firm's approach to innovation on expert evaluations in financial markets. Since different types of evaluations occur in financial markets, this study is divided into distinct sections that correspond to the different coverage, evaluation and investment decisions made by analysts and investors.

OVERVIEW OF THEORY DEVELOPMENT

When attempting to understand how a company's approach to innovation influences experts' evaluations, a natural starting point involves the key features of internal innovation that have been examined by prior studies. Developing innovations requires a firm to create new combinations of knowledge components that are available from a variety of sources (Kogut & Zander, 1992; Fleming, 2001). By using knowledge components from different technological areas a firm can increase the diversity of its knowledge. After making decisions about the diversity of the knowledge that it uses, a firm also make choices about how it will obtain that knowledge. Specifically, a firm may

decide to use more proximate knowledge from its internal stock of knowledge components or to explore externally for more distant knowledge. In addition to having discretion over the diversity and distance of its knowledge, a firm also has some discretion over how similar or distinct its knowledge is from that of its competitors.

Studies have examined how these features of a firm's approach to developing knowledge influence its ability to innovate. Prior research shows how a firm's ability to develop innovations is enhanced by (1) combining diverse types of knowledge (Ahuja & Katila, 2004; Leiponen & Helfat, 2010), (2) drawing on distant sources of knowledge (Rosenkopf & Nerkar, 2001; Katila & Ahuja, 2002), and (3) developing knowledge that is different from industry rivals (Ahuja & Lampert, 2001; Katila & Chen, 2008). Accordingly, when examining the influence of a firm's approach to innovation on expert evaluations, I focus on these key features that have been deemed important by prior researchers.

Analyst coverage is a logical starting point to examine how a firm's approach to innovation affects financial market evaluations because a firm needs to be covered by an analyst before it is able to compete for evaluations (Jensen, 2004). Accordingly, I begin by examining how an approach to innovation based on the use of diverse, distant, and distinctive knowledge affects the firm's efforts to attract analyst coverage. To do so, I build on prior research about the potential challenges that such an approach to innovation may create for outsiders who are attempting to understand a firm's strategy (e.g.,

Plumlee, 2003; Gu & Wang, 2005). In spite of the various benefits associated with the use of diverse, distant, and distinctive knowledge in innovation, such an approach may make it difficult for analysts to evaluate the firm. This might be due to the inherent complexity associated with diverse knowledge and the unfamiliarity associated with distant and distinctive knowledge. Moreover, it appears likely that the potential difficulties that analysts face evaluating a firm may be relevant to their decision of whether to provide coverage for the firm.

After exploring how different features of the firm's approach to innovation influence its ability to attract analyst coverage, the question remains as to how these same features will influence the recommendations that the firm subsequently receives from analysts. Therefore, I next examine how a firm's approach to innovation based on the use of distant and distinctive knowledge will influence the favorability of the recommendations that it receives from securities analysts, controlling for the analysts' decision to cover the firm. After the initial coverage decision has been made, analysts' concerns likely shift to the more immediate task of accurately evaluating the firms they are covering (Stickel, 1992; Hong, Kubik & Solomon, 2000). Whereas the use of distant knowledge might create challenges related to the increased risk associated with exploration (March, 1991; Benner, 2010), the use of distinctive knowledge may enhance the firm's ability to gain favorable recommendations because of the greater value associated with possessing unique resources (Barney, 1991; Peteraf, 1993). Finally, after

considering how a firm's approach to innovation influences coverage and recommendations, I then focus on how analysts' recommendations influence the firm's ability to attract outside investment.

The relationship between favorable recommendations and investment is fairly well established (e.g., Womak, 1996). Although favorable recommendations can help firms attract investment by mitigating the uncertainty that investors face (Beunza & Garud, 2007), securities analysts do not always agree about their recommendations (Fanelli, Misangyi & Tosi, 2009). The residual uncertainty that is implied by disagreement among analysts may be relevant to investors' efforts to identify opportunities in financial markets. Specifically, just as a firm's ability to develop valuable resources is enhanced when uncertainty reduces competition for such resources (Barney, 1986; Peteraf, 1993; Denrell, Fang & Winter, 2003), investors' ability to identify lucrative investment opportunities may also be enhanced when uncertainty among securities analysts reduces competition for potentially lucrative investments. Accordingly, after considering the favorability of securities analysts' recommendations, investors may also take into account the level of disagreement among analysts as a means of identifying opportunities.

To test the propositions relating to these different stages of financial market evaluations, I focus empirically on firms in the medical devices (e.g., Mitchell, 1989; Chatterji, 2009), computer hardware (e.g., Baysinger, Kosnik & Turk, 1991; Henderson

& Stern, 2004) and computer software industries (e.g., Lavie, 2007). The medical devices industry is appropriate because firms and their investors face substantial uncertainty when developing and evaluating innovations (Garud and Rappa, 1994; Rasheed, Datta & Chinta, 1997) and because firms often depend on financial support from equity markets to pay for innovation (Zinner, 2000). Similarly, the computer hardware and software industries are also innovation-driven contexts (e.g., Eisenhardt & Tabrizi, 1995; Henderson & Stern, 2004; Lavie, 2007), where securities analysts are relevant to the evaluation of firms' strategies (Jensen, 2004).

POTENTIAL THEORETICAL CONTRIBUTIONS

This current research attempts to contribute to the strategic management literature by drawing attention to a potential trade-off that a company may face when attempting to develop competitive advantage based on innovation. Somewhat paradoxically, it suggests that an approach to innovation based on the use of diverse, distant, and distinctive knowledge that is beneficial to a firm's efforts to develop internal resources may actually hinder its efforts to win the favorable evaluations needed to attract critical inputs from outside parties.

An additional contribution of this research may be to highlight the process through which different types of expert evaluations influence a firm's ability to attract critical inputs from outside parties. By following the entire chain of evaluations in financial markets from coverage to investment, this study may illuminate potential trade-

offs associated with a firm's approach to innovation that it may encounter at different stages of evaluations. Furthermore, this research may also offer insights about when expert evaluations are more or less important to a company's efforts to attract inputs from outside parties.

Finally, this research also attempts to advance understanding about how expert evaluations influence a firm's efforts to attract outside resources. By considering the potential role of uncertainty to outside parties' efforts to identify opportunities, the current research suggests that it may be necessary to distinguish between the favorability of expert evaluations and the level of agreement among them. Even though research from different theoretical perspectives suggests that developing an external consensus may contribute to a firm's success (e.g., Thompson, 1967; Dosi, 1982; Suchman, 1995), this current research draws attention to a potential downside associated with the use of consensus to attract inputs from outside parties. Namely, too much consensus among experts may sometimes limit outside parties' ability to identify opportunities. In doing so, it may make these outside parties less willing to provide the critical inputs that a firm requires for its survival and growth.

Chapter 2: Core Concepts and Literatures

INNOVATION

Resources are important to a firm's competitive success (Barney, 1991; Grant, 1991). The investments that a company makes over time can produce valuable resources from which it may derive competitive advantage (Dierickx & Cool, 1989). Innovations, which embody the cumulative investments a firm makes in knowledge, are an important type of resource that can contribute to competitive success (Rumelt, 1984; Grant, 1996). However, creating innovations often entails considerable uncertainty, since it requires a firm to choose among several potentially viable alternatives (Dosi, 1982; Nelson & Winter, 1982). Although uncertainty prevents a company from knowing in advance precisely which alternative will prove to be the most valuable, that same uncertainty creates opportunities for a company to pursue alternatives that are different from those of its competitors (Barney, 1986; McGrath & McMillian, 2000). When combined with path dependence that prevents firms from easily switching among alternatives, uncertainty may contribute to the persistence of resource heterogeneity across firms (Nelson, 1991). Without uncertainty, consensus among firms about the value of developing a resource would increase competition for that resource to the point where any potential value would eventually be eroded (Rumelt, 1987). Therefore, uncertainty allows firms to develop a competitive advantage from resources, like innovations, by making it possible to create valuable resources and by helping to limit competition that would otherwise eat away at the value that a firm creates (Nelson, 1991; Peteraf, 1993).

To develop innovations, firms create new combinations from existing knowledge located in the firm or in its environment (Kogut & Zander, 1992; Fleming, 2001). In order to access the knowledge required to innovate, companies must also overcome internal inertia that favors the use of existing knowledge (Nelson & Winter, 1982; Helfat, 1994). When accessing and combining knowledge to create innovations, prior research suggests that firms make decisions about (1) the diversity of knowledge that they will combine, (2) the distance that they will search to find the knowledge and, (3) the distinctiveness of the knowledge relative to that of their rivals (Nelson & Winter, 1982; Henderson & Clark, 1990; Fleming, 2001). Strategic management research suggests that innovating based on the use of diverse, distant, and distinctive knowledge can help a firm to develop valuable resources.

Increasing the diversity of knowledge helps the firm to create innovations based on new knowledge combinations (Schumpeter, 1934; Fleming, 2001). Moreover, studies indicate that the diversity of knowledge that a firm uses enhances its ability to create innovations (Ahuja & Katila, 2004), and that combining diverse types of scientific knowledge increases the usefulness of the firm's innovations (Fleming & Sorenson, 2004). In addition, research also finds that the number of knowledge sources from which a company draws increases its innovative output and contributes to the commercial success of its innovations (Leiponen & Helfat, 2010). Taken together, these studies indicate that an approach to innovation that emphasizes knowledge diversity— based on

the use of multiple types of knowledge— increases the firm's innovation output and contributes to the success of its innovations.

Utilizing knowledge that is distant relative to the firm's existing knowledge may also benefit a company by increasing the amount of knowledge available to develop innovations (Cohen & Levinthal, 1990; March, 1991). Note that knowledge distance is not the same as knowledge diversity. This is because a company can increase the use of distant knowledge without increasing knowledge diversity if it simply combines more of a similar type of knowledge obtained from outside of the firm. Studies show that a firm that innovates using distant sources of knowledge has a greater impact on the technological development of its industry (Rosenkopf & Nerkar, 2001; Phene, Fladmoe-Lindquist & Marsh, 2006). The use of distant knowledge also improves a company's ability to develop new products (Katila & Ahuja, 2002). Accordingly, using distant knowledge can benefit the firm's efforts to innovate.

In addition to having discretion about the diversity of knowledge used and the distance searched to find this knowledge, a firm may also decide how distinctive the knowledge that it uses is from that of its industry rivals (e.g., McEvily & Chakravarthy, 2002). By developing knowledge that is distinct from industry rivals, a firm is more likely to develop breakthrough innovations (Ahuja & Lampert, 2001). Moreover, a company that searches for knowledge in ways that are different from its rivals is likely to have greater innovation output and to develop more innovative products (Katila & Chen,

2008). Again, this literature shows that developing knowledge that is distinct from rivals can help the firm to innovate.

EXPERT EVALUATIONS

After a firm has developed resources, such as innovations, its ability to profit from them depends on value assessments that occur outside its boundaries (Barney, 2001; Priem & Butler, 2001). Evolutionary theory scholars suggest that value assessments about a company's innovations are made in what is referred to as the selection environment (Thompson, 1967; Nelson & Winter, 1982). The selection environment, which encompasses different groups of outside parties, influences the success of the firm's innovations by determining "the manner in which customer and regulatory preferences and rules influence what is profitable" (Nelson & Winter, 1982: 266). It may include outside parties with a direct interest in the success of a firm's innovations, like customers and investors, as well as other parties, such as regulators and experts, who influence the success of a firm's innovations through their assessments (Nelson & Winter, 1977).

It is important to note that research has examined the role that evaluations made in the selection environment play in determining the success of a firm's innovations. Not surprisingly, such studies typically show how a firm's customers influence the success of its innovations through their purchase decisions (Abernathy & Clark, 1985; Christensen & Bower, 1996; Martin & Mitchell, 1998). However, because of uncertainty surrounding

the assessment of innovations, customers' decisions to adopt or reject an innovation may themselves be influenced by evaluations of still other outside parties, such as regulators and standards setting bodies (Nelson & Winter, 1982; Tushman & Rosenkopf, 1992).

A variety of studies corroborate the importance of these other outside parties to the success of a firm's innovations. For example, Wade (1995) has shown that gaining support of communities comprised of individuals and organizations that use and develop related innovations was critical to the success of microprocessor firms. Podolny & Stuart (1995) demonstrate, in the context of the semiconductor industry, that the impact of a firm's innovations depends not only on technological characteristics of the innovations, but also on the size of the firm's technological niche and on other outside parties associated with the innovations. Similarly, Garud, Jain and Kumaraswanmy (2002) found that the success of Sun Microsystems' efforts to promote Java standardization depended on its ability to develop an external coalition of support, which included users and influential outside parties. Also, Rosenkopf and Tushman (1998) examined how community networks that encompass manufacturers, suppliers, professional societies and regulatory bodies emerged to help mitigate uncertainty related to the evaluation of flight simulation technologies. The above studies strongly suggest that a firm's ability to attract critical inputs from outside parties depends not only on the evaluations of customers, but also on expert evaluations made by a variety of outside parties. Given the relevance of

outside evaluations to the success of a firm's innovations, it is important to more closely examine how experts evaluate firms.

The evaluations of outside parties can help to mitigate uncertainty that may complicate a firm's efforts to attract critical resources from outside parties (Thompson, 1967). For example, uncertainty due to asymmetric information between buyers and sellers about the quality of a good or service can cause markets to fail as those parties become unwilling to exchange resources (Akerlof, 1970). Similarly, uncertainty about the attributes and evolution of technologies can complicate outside parties' ability to understand resulting innovations (Rindova & Petkova, 2007; Kaplan & Tripsas, 2008). Both economists and organizational scholars agree on the significance of experts' evaluations as a way to reduce uncertainty that can prevent the exchange of resources. The economics literature suggests that experts' evaluations facilitate exchanges by reducing search costs and information asymmetries that can limit parties' ability to objectively determine the value associated with an exchange (e.g., Biglaiser, 1993; Lizzeri, 1999). In contrast, the organizations literature draws attention to the role that the evaluations of experts plays in influencing parties' subjective perceptions about the value and legitimacy of an exchange (e.g., Pollock & Rindova, 2003; Graffin & Ward, 2010). Both because of their role as information providers and as assessors of value, experts' evaluations can influence a company's ability to attract the critical inputs it requires.

Numerous studies have shown how the evaluations of experts can help a firm attract critical resources. For example, Rao (1994) showed that auto companies that won reliability and performance certifications were more likely to survive than rivals that performed poorly on such evaluations. Similarly, Rindova and colleagues (2005) found that winning favorable rankings from media experts enhanced business schools' ability to attract inputs by charging a premium for MBA tuition. Zuckerman and Kim (2003) also found that feature films attracted more customers when they received reviews from critics that specialized in major releases. It is evident from these studies that the evaluations of outside experts can be important determinants of a company's success.

While experts' evaluations have been shown to have a wide-spread influence, they are particularly important in financial markets, where uncertainty makes it difficult for investors to understand and evaluate a firm's strategy (Zuckerman, 1999). For example, securities analysts' recommendations help to mitigate uncertainty (Beunza & Garud, 2007) and research shows that getting favorable recommendations can help a firm attract investment (Womack, 1996). Moreover, securities analysts may be especially influential in innovation-intensive contexts, where investors may face greater difficulty than normal understanding the firm's strategy due to the high level of uncertainty associated with technological change (Barth, Kasznik & McNichols, 2001; Benner, 2007).

Securities analysts make choices about which firms they cover (Rao, Greve & Davis, 2001) and about the specific 'buy' or 'sell' recommendations that they provide for those firms (Mikhail, Walther & Willis, 1997). Both their decisions about coverage and their decisions about recommendations are consequential to firms. For example, gaining analysts' coverage is an important external endorsement that helps the firm attract critical inputs and support (Zuckerman, 1999; Jensen, 2004; Pollock & Gulati, 2007). Even after the firm has convinced analysts to cover it, winning favorable evaluations from them is an additional way in which it can compete to attract inputs from investors (Womack, 1996). Empirical evidence shows that, when evaluating a firm, securities analysts and investors routinely consider the company's approach to innovation. For example, Levitas and McFadyen (2009) found that patents serve as an important external signal that helps a firm attract financial resources by lowering its need to hold liquid assets. Similarly, Benner (2010) also found that securities analysts consider a company's approach to innovation when developing buy/sell recommendations.

In spite of the importance of experts' evaluations, prior literature shows that experts do not always agree in their evaluations (Fanelli, Misangyi & Tosi, 2009). Such disagreement implies that some level of uncertainty remains (Barney, 1986). Studies across a range of theoretical perspectives have indirectly touched upon the role that consensus may play in a firm's efforts to attract critical inputs and support from the environment (e.g., Thompson, 1967). These studies suggest that achieving external

agreement on a variety of issues may be important to a firm's success. For example, research shows that consensus among external parties underlies the legitimacy that an organization depends on for its successful interaction with outsiders (e.g., Suchman, 1995; Cattani, Ferriani, Negro & Perretti, 2008). Other research in the context of technology suggests that consensus among outside evaluators about the performance and attributes of innovations contributes to the success of a firm's innovations (e.g., Dosi, 1982; Nelson & Winter, 1982).

In conclusion, the literature reviewed above suggests that aspects of a firm's approach to innovation that are beneficial to its efforts to develop resources may also be relevant to the external evaluations that a firm depends on to attract critical inputs from outside parties. Only very recently have scholars begun to examine how a firm's innovative activities influence external assessments in financial markets (Benner, 2010). Accordingly, relatively little is known about how different aspects of a firm's approach to innovation may relate to the external evaluations that the firm relies on to attract critical inputs from outside parties. Furthermore, prior research has not systematically examined how a firm's approach to innovation influences the different stages of financial market evaluations that may ultimately culminate in investment.

The literature reviewed above also suggests that uncertainty may be a double-edged sword that can help the firm to develop resources, while simultaneously complicating efforts to capture value from resources or attract inputs from outside parties.

While prior studies highlight the importance of experts' evaluations as a way to mitigate uncertainty that can prevent outside parties from providing critical inputs to a firm, they have not considered the potential role that disagreement and uncertainty may play in outside parties' own efforts to identify valuable opportunities. Furthermore, prior literature has also not considered the possibility that the favorability of external evaluations and the level of consensus among evaluations may exert distinct influences on a firm's ability to attract critical inputs.

In subsequent chapters I build on the literature reviewed above to explore these issues. In chapter three, I develop theory about how a firm's approach to innovation based on the use of diverse, distant, and distinctive knowledge influences securities analysts' decision to cover that firm. Next, in chapter four, I explore how a firm's approach to innovation influences the favorability of the recommendations it receives. After considering these influences, I focus in chapter five on how the level of disagreement among securities analysts' recommendations influences the firm's ability to attract investment. After developing the theory in chapters three and four about coverage and recommendations the theory is tested using data from the medical devices, computer hardware and computer software industries. Finally, the theory developed in chapter five, which requires detailed innovation data from the food and drug administration that is not available for these other two industries is tested using the medical devices industry only.

Chapter 3: The Approach to Innovation and Analyst's Coverage

A firm's resources can provide the basis for its competitive advantage (Barney, 1991; Grant, 1991). Innovations embody the knowledge that a firm internally accumulates over time (Grant, 1996) and are an important type of knowledge-based resource that can contribute to a company's success (Rumelt, 1984). However, developing innovations entails uncertainty since a firm must select among a number of viable alternatives (Dosi, 1982). Although uncertainty makes it possible for the firm to develop valuable resources (Barney, 1986; Peteraf, 1993), it can also make it difficult for the firm to attract inputs from outside parties (Akerlof, 1970).

Research shows that securities analysts are an influential type of outside party whose recommendations can mitigate the uncertainty that outside investors face (Beunza & Garud, 2007). Such analysts make decisions about which firms they cover and about the specific recommendations and forecasts that they make for these firms (Jensen, 2004). Before a company is able to compete for favorable 'buy' recommendations from securities analysts, it must first convince analysts to cover it (Rao, Greve & Davis, 2001). Some research suggests that analysts' coverage is itself an important endorsement that can help a firm to attract outside resources and support (Zuckerman, 1999; Pollock & Gulati, 2007). Both the value of coverage as an endorsement in its own right and its importance as a stepping stone to subsequent competition for favorable assessments make gaining analysts' coverage a consequential event for a firm, one that may contribute to

the development of competitive advantage. Because innovations may both serve as a source of uncertainty to investors and a source of value to firms, it is natural that securities analysts will evaluate them. Studies show that securities analysts evaluating a firm do indeed consider its approach to innovation (Benner, 2010). Consequently, it may be relevant to explore how a firm's approach to innovation influences the coverage that it receives from analysts.

To understand how a firm's approach to innovation influences its ability to attract analyst coverage, I consider factors that have been deemed important by prior research. That research has emphasized the innovative benefits that a firm may derive when its approach to innovation emphasizes the use of: (1) diverse types of knowledge (Ahuja & Katila, 2004; Leiponen & Helfat, 2010), (2) distant sources of knowledge (Rosenkopf & Nerkar, 2001; Katila & Ahuja, 2002), and (3) knowledge that is different from industry rivals (Ahuja & Lampert, 2001; Katila & Chen, 2008). The relevance of these features of a firm's approach to innovation highlighted by prior research suggests that they may be a natural starting point for examining how a firm's approach to innovation affects analysts' coverage.

In this first study, I explore how a company's approach to innovation influences its ability to attract coverage by a securities analyst. Central to the arguments developed in this section is the idea that securities analysts may experience professional consequences if they fail to select firms that they can successfully evaluate and

understand (Hong, Kubik & Solomon, 2000). Specifically, analysts' ability to accurately evaluate a firm may contribute to their career progression, professional longevity and compensation (Stickel, 1992; Hong, Kubik & Solomon, 2000). Therefore, their decision to provide coverage for a given firm is likely based on a consideration of the likelihood that they can successfully evaluate the firm. Arguably, factors that make it difficult for securities analysts to develop accurate recommendations should make them less likely to provide coverage for that firm. Conversely, factors that make it easier for analysts to develop accurate recommendations should make them more likely to provide coverage for that firm.

Given the above, the propositions that I develop below build on this assumption that securities analysts anticipate their ability to accurately evaluate a particular firm when deciding whether to cover it. Based on this assumption, I argue that different aspects of a firm's approach to innovation that improve or diminish analysts' ability to understand and evaluate a firm may make them more or less inclined to provide coverage. Since an approach to innovation based on the use of diverse, distant and distinctive knowledge may make it more difficult for analysts to accurately evaluate a firm, I argue below that the use of these features may complicate the firm's ability to attract coverage. Somewhat paradoxically, this study may suggest that an approach to innovation that is beneficial to the firm's efforts to develop resources may be detrimental to its efforts to attract coverage from securities analysts.

KNOWLEDGE DIVERSITY

As mentioned earlier, the use of diverse knowledge can help a firm to develop innovations (e.g., Ahuja & Katila, 2004). But, in spite of the innovative benefits associated with the use of diverse knowledge, it may increase the difficulty that securities analysts have understanding the firm's strategy. In the same way that securities analysts, who typically specialize in one or a few industries, prefer firms that are less diversified from a product market perspective, since such firms are easier to understand (Zuckerman, 2000) and less costly to evaluate (Bhushan, 1989), they may also prefer firms that are less diversified with respect to their knowledge. When a firm uses diverse knowledge it makes its knowledge more complex by increasing the number of interdependent elements (Simon, 1962). Simply stated, complex knowledge is more difficult to understand (Zander & Kogut, 1995; Rivkin, 2000). Just as the complexity of a firm's knowledge can hinder rivals' efforts to imitate it by making it more difficult for them to understand causal linkages that contribute to competitive advantage (e.g., Reed & DeFillippi, 1990; McEvily & Chakavarthy, 2002), the use of diverse knowledge may also complicate outside evaluators' ability to evaluate the firm's more complex approach to innovation.

Studies show that securities analysts are less likely to incorporate complex information in their forecast revisions (Plumlee, 2003) and their forecast errors are higher for companies that are more technologically diverse (Gu & Wang, 2005). Accordingly, companies with greater knowledge diversity may require more time and effort for

analysts to evaluate and place those same analysts at greater risk of developing inaccurate assessments. Because of the career incentives that securities analysts have to successfully evaluate a firm (Hong, Kubik & Solomon, 2000), they will avoid firms with greater knowledge diversity due to the increased difficulty that they will have in understanding and evaluating these inherently more complex firms. Thus:

> *Proposition 1 (P1): The greater the firm's knowledge diversity, the lower the likelihood that a securities analyst will cover the firm.*

KNOWLEDGE DISTANCE

In addition to making decisions about how many different types of knowledge it will use, a firm can also make choices about how it will obtain that knowledge. In spite of inertial pressures that tend to favor the use of existing knowledge (Nelson & Winter, 1982; Helfat, 1994), extant literature shows that it is possible for a firm to overcome these pressures by exploring for distant knowledge outside of its boundaries (e.g., Rosenkopf & Nerkar, 2001; Katila, 2002). Securities analysts face constraints on their time and attention that influence their ability to evaluate firms (Baldwin & Rice, 1997; Clement, 1999). When faced with cognitive limitations, boundedly rational decision makers routinely rely on shortcuts and heuristics to guide and simplify their decision making (March & Simon, 1958; Cyert & March, 1963). Scholars have shown that securities analysts often base their recommendations on heuristics that are unrelated to their formal forecast models (Bradshaw, 2004; Barniv, Hope, Myring & Thomas, 2009).

The degree to which new information is consistent with that with which decision makers are already familiar can increase their expectations about the likelihood of future events (Tversky & Kahneman, 1973, 1974). This, in turn, may contribute to analysts' confidence in being able to develop accurate evaluations when the company builds on familiar knowledge. Furthermore, by making extensive use of the same knowledge it will be easier to understand due to increased repetition (Winter & Szulanski, 2001), which may help to simplify evaluations. In contrast, a company that explores extensively is more likely to build on distant knowledge with which analysts are unfamiliar. By exploring more distant knowledge, the connections between the firm's past and current knowledge may also be less clear, which may make it more difficult for analysts to evaluate its strategy. Because of the lack of familiarity with this more distant knowledge and analysts' diminished ability to evaluate the firm, analysts may have difficulty accurately evaluating companies that build more extensively on distant knowledge.

It is important to note that studies in the finance and accounting literature lend support for the above assertions. For example, a longitudinal examination of more than 700 firms across multiple industries found that securities analysts' forecast errors were higher for firms that built on new and original knowledge than for firms that build on more familiar knowledge (Gu & Wang, 2005). Because of the career incentives analysts have to provide coverage for companies that they can successfully evaluate (Hong, Kubik & Solomon, 2000), this lack of familiarity with a firm's distant knowledge will increase

the amount of time and effort that analysts will need to expend evaluating it. Further, to the extent that analysts can anticipate the higher forecast errors associated with evaluating a firm that uses more distant knowledge with which they are less familiar (Gu & Wang, 2005), they may also have a lower expectation that they will be able to successfully evaluate the firm. Since covering a firm that explores more distant knowledge will entail greater effort, while also putting analysts at greater risk of developing inaccurate evaluations, analysts will be less likely to cover such firms. Hence:

> *Proposition 2 (P2): The more extensively the firm explores distant knowledge, the lower the likelihood that a securities analyst will cover the firm.*

KNOWLEDGE DISTINCTIVENESS

In addition to having discretion over how many types of knowledge it uses and from where it obtains that knowledge, a firm also has discretion over how similar or different its knowledge is from that of its competitors. One way to understand how distinctive a firm's knowledge is from other firms is by looking at the degree of knowledge overlap among firms (Mowery, Oxley, & Silverman, 1996). Greater knowledge overlap with competitors implies greater similarity in knowledge, which may suggest that a company's knowledge is not distinctive relative to that of its competitors. Conversely, less knowledge overlap with rivals suggests that a firm's knowledge is more different and distinctive relative to that of its rivals.

In addition to the influence that diverse knowledge and distant knowledge exert on the analysts' decision to cover a firm, the degree to which the firm's knowledge is

distinctive from that of its rivals may also influence analysts' decision to provide or withhold coverage. In a similar fashion to how distant knowledge may create challenges related to unfamiliarity, distinctive knowledge may also create similar challenges.

Studies show that technological norms that develop in an industry can influence how outside parties evaluate innovations (Garud & Rappa, 1994) and contribute to the evolution of technology (Anderson & Tushman, 1990). In a similar fashion to the way that categorical conformity may facilitate investors' understanding of the firm (Zuckerman, 1999), the extent to which a firm's knowledge conforms with the knowledge of other firms in its industry may also make it easier for analysts to understand the firm's knowledge. The increased familiarity associated with knowledge that conforms to industry norms will increase the likelihood that an analyst will cover the firm, since the firm's knowledge is more comprehensible and consistent with that of other firms. This, in turn, will increase the analyst's ability to successfully understand and evaluate the firm's internal innovation, making her more likely to cover the firm. Hence:

> *Proposition 3 (P3): The greater the knowledge overlap between the firm and its industry rivals, the greater the likelihood that a securities analyst will cover the firm.*

To help increase confidence in the drivers of the propositions discussed above, in the next section I examine contingencies about the knowledge overlap between the firm and the securities analyst and the innovation intensity of the focal firm's industry. These

contingencies may help to shed additional light on the causal mechanisms invoked for propositions two and three.

CONTINGENT EFFECTS

In developing proposition two, I argue that securities analysts are less likely to cover a firm that explores distant knowledge because they will tend to be less familiar with its knowledge. If lack of familiarity contributes to the difficulties that analysts have in evaluating these firms, then it should be the case that the relationship between exploration of distant knowledge and coverage will vary depending on analysts' level of familiarity with the types of knowledge upon which a firm is building. Just as knowledge overlap among organizational subunits may enhance a firm's efforts to transfer its knowledge internally by making parties more familiar with its knowledge and better able to understand it (Cohen & Levinthal, 1990; Grant, 1996), greater overlap between the knowledge of analysts and the knowledge of the firm may also facilitate analysts' understanding of the firm's more distant knowledge.

The increased familiarity that results from greater knowledge overlap between the securities analyst and the firm will make it easier for analysts to understand how the firm's more distant knowledge relates to its existing knowledge and how it will contribute to future performance. In this way, greater knowledge overlap between the firm and the analyst should increase the likelihood that analysts will be familiar with the more distant knowledge that the firm is drawing upon. Their increased familiarity with

the firm's knowledge may make them more confident that they will be able to successfully understand and evaluate the firm. Consequently, the enhanced ability of analysts with greater knowledge overlap to comprehend and assess the firm's knowledge will diminish the negative influence that exploring distant knowledge has on a firm's ability to gain analysts' coverage. Therefore:

> *Proposition 4 (P4): The greater the knowledge overlap between the analyst and the firm, the less negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm.*

Whereas proposition 4 deals with the contingent effect of knowledge overlap between the analyst and the firm, propositions 5 and 6 explore the contingent effect of the innovation intensity of the firm's industry. Innovation-intensive industries are typically characterized by high levels of technological change and uncertainty (Nelson, 1991; McGrath, 1997). This technological change and uncertainty will compound the difficulties that securities analysts face in attempting to understand the distant knowledge that a firm develops through exploration. In innovation-intensive contexts, analysts must not only overcome difficulties understanding the firm's distant knowledge in relation to the firm's prior innovative efforts, but they must also overcome challenges understanding the firm's knowledge against the backdrop of a changing technological landscape. Accordingly, the increased uncertainty associated with innovation-intensive contexts may make analysts even more likely to provide coverage to a firm that builds more consistently on existing knowledge, since such firms can be more easily evaluated. In

contrast, a company that builds on more distant, unfamiliar knowledge will be even less likely to receive analysts' coverage, since technological uncertainty will make it even more difficult for analysts to accurately assess the firm's innovative efforts. Hence:

> *Proposition 5 (P5): The greater the innovation intensity of the firm's industry, the more negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm.*

At the same time that innovation intensity may increase analysts' preference for internal knowledge as a way to understand and evaluate the firm it may also decrease analysts' ability to successfully evaluate the firm based on external industry norms. Prior literature suggests that increased rate of change and variation associated with innovation-intensive industries may affect the stability of industry norms (Anderson & Tushman, 1990; Kaplan & Tripsas, 2008). Since industry norms are less stable in innovation-intensive contexts, they may be less useful to securities analysts as a basis for understanding a firm's innovative activities. The possibility that an industry's technological norms may be relatively weaker and provide less guidance may decrease analysts' expectation about being able to successfully evaluate a firm with knowledge overlap in an innovation-intensive industry. Therefore:

> *Proposition 6 (P6): The greater the innovation intensity of the firm's industry, the less positive the effect of knowledge overlap between the firm and its industry rivals on the likelihood an analyst will cover the firm.*

This study examined the influence that a company's approach to innovation exerts on a securities analyst's decision to cover that firm. Figure 1 illustrates the theoretical model for study one that was developed in this chapter of the dissertation.

In the next study, I continue to explore the influence that a firm's innovative activities exert on external assessments in financial markets. Specifically, I focus on how the distance and distinctiveness of the firm's knowledge, examined above in relation to analysts' coverage, will also influence its ability to gain more favorable recommendations from a securities analyst who is already covering the firm. In the next study I argue that the cognitive challenges that influenced the initial coverage decision will be less relevant, since analysts have had to overcome these challenges when providing coverage to the firm. Given the career incentives that analysts have to accurately evaluate a firm (e.g., Stickel, 1992), securities analysts' concerns will likely shift to more pragmatic and immediate ones about accurately identifying how a firm's strategy relates to its future performance.

Chapter 4: The Approach to Innovation and Recommendations

After exploring the link between a firm's approach to innovation and its ability to attract coverage from securities analysts, the question remains whether these same aspects of the firm's innovative activities will influence the evaluations of analysts who are already covering the firm. This present study explores the influence that a firm's approach to innovation has on the favorability of the recommendations it receives from analysts, controlling for the initial decision to provide coverage that was examined in the previous study. With the initial coverage decision behind them, I argue that securities analysts' concerns shift from cognitive challenges influencing whether or not they expect to be able to successfully evaluate a prospective firm, to more immediate concerns about accurately evaluating the performance of the firms that they are already covering (e.g., Stickel, 1992).

By following the chain of analysts' evaluations from the initial coverage decision all the way to the point where analysts provide specific buy/sell recommendations for firms, this research may draw attention to a potential secondary trade-off that the firm may face between conformity and differentiation (e.g., Deephouse, 1999; Zuckerman, 1999) in the context of financial market evaluations. Whereas a company's approach to innovation based on the use of distinctive knowledge may hinder efforts to attract analysts' coverage by making its knowledge more difficult to understand, I argue in this second study that the use of distinctive knowledge may subsequently help it to win more

favorable recommendations by increasing the uniqueness of its knowledge. In the next section, I develop propositions relating knowledge distance and knowledge distinctiveness to the favorability of the recommendations that a firm receives from analysts that are already covering it. After developing these main propositions, I also explore two contingencies that may help shed additional light on the mechanisms underlying the link between knowledge distance and the favorability of recommendations.

KNOWLEDGE DISTANCE

In the previous study I argued that a firm's use of distant knowledge will make securities analysts less familiar with its knowledge and will, therefore, make them less able to evaluate the firm. In this current study, I focus on the influence that a firm's use of distant knowledge has on the favorability of the recommendations that it receives from analysts, controlling for analysts' decision to cover the firm. Analysts' decision to cover a firm suggests that they have likely already had to overcome some of the cognitive challenges discussed previously. Therefore, I argue that their concerns shift to accurately evaluating the firms that they are covering. Since analysts make decisions under uncertainty, their recommendations and forecasts are likely developed based on an assessment of the expected value associated with different events (Beunza & Garud, 2007; Whitwell, Lukas & Hill, 2007). Expected value assessments enable decision

makers to compare the value of alternatives that have different levels of risk and return, such as the alternatives analysts compare to develop recommendations.

The nature of the career incentives in the investment firms that employ analysts may influence securities analysts' risk preferences by making them more risk-averse. Although there is evidence that more accurate analysts can expect to gain upside opportunities in the form of higher compensation (Stickel, 1992), there is also evidence showing that less accurate analysts may face significant risk of termination (Hong, Kubik & Solomon, 2000). The consequential nature of the risk of termination may contribute to making securities analysts risk averse when they develop their recommendations.

When developing their buy/sell recommendations, analysts consider a firm's approach to innovation (Benner, 2010). In doing so, they may need to make comparisons among firms that make different risk/return trade-offs with regard to their innovation decisions. Prior literature suggests that a firm with an approach to innovation based on exploration of more distant knowledge may be riskier than a firm whose approach is based on exploitation of existing knowledge (March, 1991). When determining the favorability of a company's recommendations, analysts may encounter situations where the expected value associated with exploratory and exploitative approaches to innovation are very similar, even though the risk/return trade-offs are quite different. However, given the tendency toward risk aversion discussed above, analysts may place relatively less weight on the extreme positive outcomes associated with exploration and more

weight on extreme negative outcomes associated with it. In this way, the risk aversion of securities analysts may cause them to assign more value to the greater certainty associated with an approach to innovation based on exploitation. This may occur even when the expected value associated with such an approach is actually comparable to one based on exploration of distant knowledge.

In light of analysts' tendency toward risk aversion and the fact that exploring knowledge outside of the firm entails greater risk (March, 1991), securities analysts should be less likely to provide a favorable recommendation when a firm explores more distant knowledge from outside its boundaries. It is important to note that this conjecture is fully consistent with Benner's (2010) finding that incumbent firms that pursued strategies that preserve existing technologies were more likely to receive favorable evaluations from securities analysts. Therefore, for the reasons mentioned above:

> *Proposition 7 (P7): Exploring distant knowledge will have a negative impact on the favorability of the analyst's recommendation for the firm.*

KNOWLEDGE DISTINCTIVENESS

In the previous study I argued that knowledge overlap between the firm and its industry rivals increases the degree to which the firm's knowledge is comprehensible to analysts, which helps the firm to attract coverage of a securities analyst. However, I argue here that after controlling for analysts' decision to cover the firm, greater knowledge overlap may have an opposite effect on the favorability of the analyst's recommendations. Analysts' decision about whether to cover a company is likely based

on a general consideration of how successful they will be evaluating that company given cognitive limitations and the ease with which it can be compared to rivals. However, analysts' decision about providing a more favorable recommendation hinges on their expectations about the firm's future performance (Lys & Soo, 1995; Mikhail, Walther & Willis, 1997). Prior literature has established the importance of the uniqueness of a firm's knowledge to its ability to compete with rivals to create value (Barney, 1991; Peteraf, 1993; Polidoro & Toh, 2011). Therefore, when emphasizing a firm's performance versus rivals, the increased value associated with possessing knowledge that is different from that of its industry rivals will outweigh the increased difficulty that analysts face evaluating a firm that does not conform to industry norms. Conversely, when a firm's knowledge overlaps more with its rivals, it will be less unique, which will reduce the value associated with this knowledge. The reduced value associated with knowledge that overlaps with a firm's industry will lower the likelihood that securities analysts will provide a firm with a more favorable recommendation. Hence:

> *Proposition 8 (P8): Greater knowledge overlap between the firm and its rivals will have a negative impact on the favorability of the analyst's recommendation for the firm.*

To increase confidence in the proposed mechanisms behind proposition seven, in the next section I develop two contingencies related to analysts' job security and their experience covering firms that explore distant knowledge.

CONTINGENT EFFECTS

I argued above in proposition seven that analysts will tend to be risk-averse as a result of the incentive structure within the investment firms where they work. Prior research shows that analysts' risk tolerance may vary depending on their level of job security. Since more experienced securities analysts are less likely to be terminated as a result of making inaccurate evaluations, they can afford to take greater risks than less experienced analysts. For example, Hong, Kubik and Solomon (2000) found that more experienced securities analysts were less likely to be terminated when their evaluations were inaccurate. If it is true that increased risk associated with the exploration of distant knowledge reduces the likelihood that securities analysts will provide a more favorable recommendation, then it should be the case that analysts with greater experience, who have a greater tolerance for risk due to their lower chances of being terminated for inaccurate evaluations, will be more willing to provide a more favorable recommendation to an exploratory firm than more risk-averse analysts with lower experience. Hence:

> *Proposition 9 (P9): The greater the analyst's experience, the less negative the effect that exploration of distant knowledge will have on the favorability of the recommendation.*

In this next proposition I explore how analysts' previous experience covering firms that explore distant knowledge will moderate the relationship between a firm's exploration of distant knowledge and the favorability of the recommendations it gets from a securities analyst. Extant research shows that prior experience taking risks can

influence future risk-taking behavior (e.g., March & Shapira, 1987; Thaler & Johnson, 1990) and that decision makers that took risks in the past are more likely to take them in the future (Lant & Montgomery, 1987). Similarly, managers' prior experience influences whether their firms will engage in exploration and exploitation (Hambrick, Geletkanycz & Fredrickson, 1993; Beckman & Burton, 2008). Accordingly, analysts who have prior experience evaluating riskier firms that explore more distant knowledge may be more receptive to evaluating riskier firms, which may increase their willingness to provide such firms with positive evaluations.

Analysts with prior experience evaluating these types of firms may also be better at understanding the causal relationships between exploration and future performance. Securities analysts' experience influences the way in which they evaluate firms and prior research shows that forecast accuracy improves based on experience (Mikhail, Walther & Willis, 1997). The improved performance of more experienced analysts is likely related to their increased ability to understand causal relationships (Huber, 1991). Consequently, analysts who have greater experience evaluating firms that build more extensively on new knowledge may be better able to understand the causal linkages between exploring knowledge and a firm's performance. The combination of being more receptive to more exploratory firms and analysts' increased ability to understand and evaluate the relationship between exploration and performance may diminish the negative effect that

building on distant knowledge has on the likelihood that the analysts will increase the favorability of the firm's recommendation. Hence:

> *Proposition 10 (P10): The more extensively other firms covered by the analyst explore external knowledge, the less negative the effect that exploration of distant knowledge will have on the favorability of the recommendation.*

This study examined the influence that a company's approach to innovation exerts on the firm's ability to gain more favorable recommendations from a securities analyst who is already covering that company. Figure 2 illustrates the theoretical model for study two that was developed in this chapter of the dissertation.

In the next and final study, I complete the circle by examining how securities analysts' recommendations influence the firm's ability to attract investment. Specifically, I consider how disagreement among securities analysts' recommendations influences the firm's ability to attract resources from investors.

Chapter 5: Analysts' Recommendations and Investment

Having examined the influence of a firm's approach to innovation on analysts' coverage and recommendation decisions in the previous two studies, this current study completes the loop by exploring the final stage in the evaluation process, where assessments ultimately influence investment decisions. Innovations are an important knowledge-based resource from which a firm can derive competitive advantage (Rumelt, 1984; Barney, 1991; Grant, 1996). Developing innovations depends on a company's ability to access resources in the environment (Nelson & Winter, 1982; Henderson & Cockburn, 1994) and investors are an important source of financial resources (Useem, 1996; Benner, 2007). Profiting from resources, such as innovations, depends on uncertainty that limits competition that would otherwise erode the value of such resources (Rumelt, 1987; Peteraf, 1993). Although uncertainty helps a firm create valuable resources, it also creates difficulties for investors to understand and evaluate firms' strategies (Haunschild, 1994; Sanders & Bovie, 2004).

Securities analysts' recommendations help to mitigate uncertainty and research shows that getting favorable recommendations helps firms attract investment (Womack, 1996; Zuckerman, 1999). Therefore, the importance of winning favorable assessments from securities analysts has spurred interest in understanding how a firm's strategies influence the favorability of analysts' recommendations (e.g., Westphal & Clement, 2008; Westphal & Graebner, 2010; Benner, 2010). By emphasizing favorable

recommendations as a means of reducing uncertainty to attract investment, studies have overlooked the potential importance of uncertainty to investors' own efforts to create value. Analysts do not always agree about their recommendations (Fanelli, Misangyi & Tosi, 2009) and disagreement among evaluations implies that some uncertainty remains (Barney, 1986), even after evaluations have been made. Just as a firm's ability to compete for valuable resources is enhanced when uncertainty creates opportunities by clouding the valuation of resources (Barney, 1986; Peteraf, 1993; Denrell, Fang & Winter, 2003), investors' ability to compete for profitable opportunities may also be enhanced when uncertainty obscures the valuation of investments.

This final study builds on insights from prior literature about the role of uncertainty as an antecedent of opportunity and value creation (Knight, 1921; Rumelt, 1987; McGrath & MacMillian, 2000) and focuses on the impact of the level of consensus among analysts about a firm's prospects. Whereas perfect consensus among experts suggests that opportunities for value creation may be narrowly based on a given trajectory whose value can be easily anticipated, lack of consensus suggests opportunities for unforeseen value creation based on multiple potential trajectories. Accordingly, in this study I propose that uncertainty related to disagreement among securities analysts' recommendations will improve a company's ability to attract shareholders by creating opportunities for investors to identify profitable investment opportunities.

By demonstrating how the interplay between securities analysts and investors affects the ability of a firm engaged in innovation to attract investors, this study may make contributions to strategy research. Furthering understanding of factors that influence the extent to which investors buy shares of a firm in innovation-driven contexts is relevant because financial markets constitute crucial elements in the broader selection environment that ultimately assesses the prospects of the firm's innovation-based strategies. Prior research has envisaged securities analysts as expert intermediaries that help mitigate the uncertainty that prospective investors face. Accordingly, researchers have examined how a firm can elicit favorable recommendations from securities analysts.

This present study investigates whether those recommendations, in turn, shape the firm's ability to attract investors. In this study I argue that financial markets are not fully intermediated by securities analysts' recommendations and suggest that a firm's approach to innovation may be important to its efforts to create value from this residual uncertainty by attracting investors. Contrary to received wisdom about the benefits that accrue to a firm that is consistently viewed favorably by securities analysts, this study argues that consensus among securities analysts can cause some investors to discount opportunities to buy the firm's shares, making it more difficult for the firm to attract the investment required for its growth and survival.

SECURITIES ANALYSTS' RECOMMENDATIONS

The ability to profit from an investment requires *ex ante* uncertainty that enables buyers to make investments at a cost below the *ex post* value (Rumelt, 1987). In competitive contexts, uncertainty can serve as an *ex ante* limit to competition among investors for valuable strategic investments and can increase the relevance of idiosyncratic information needed to identify opportunities (Peteraf, 1993; Denrell, Fang & Winter, 2003). Differences in expectations reflect uncertainty in competitive environments (Barney, 1986). At the same time that agreement about a firm's prospects implies lower levels of uncertainty, it also causes valuations to converge around the shared expectations, which results in asset prices getting bid up to the point of the agreed upon expected value (Barney, 1991; Peteraf, 1993).

The recommendations that securities analysts make for the different firms that they cover reflect some mix of idiosyncratic and common expectations about the link between firms' strategies and future financial performance (Bradshaw, 2004; Barniv, Hope, Myring & Thomas, 2009). While perfect consensus among securities analysts' recommendations suggests that opportunities for value creation may be narrowly defined around a trajectory whose value can be easily anticipated by all of the analysts evaluating the firm, lack of consensus suggests opportunities for unforeseen value creation based on multiple idiosyncratic interpretations. In this way, greater consensus about the prospects of a firm can diminish opportunities for investors to acquire it at favorable terms. In

contrast, the existence of diverse views and interpretations about the link between a firm's current strategic position and future performance suggests, not one, but rather multiple potential trajectories to which many different values may be assigned. Accordingly, the uncertainty associated with lack of consensus about the firm's prospects may present buyers with opportunities to capture unrecognized value (Knight, 1921; Rumelt, 1987; McGrath & MacMillan, 2000), which may increase the firm's ability to attract investment.

In addition to the greater buying opportunities that lower levels of analyst consensus may entail for investors, investors may also discount firms with high levels of consensus among securities analysts' recommendations due to a concern that this consensus may be a signal of consequential 'herding' behavior on the part of analysts (e.g., Welch, 2000). For example, prior literature has found that consensus sometimes suggests the type of 'herding' behavior that can lead to overvaluation (Hong, Kubik & Solomon, 2000; Rao, Greve & Davis, 2001). Since lower levels of consensus among securities analysts' recommendations suggest both an increased potential for identifying unforeseen opportunities and a reduced risk of overpaying for unwarranted exuberance, after controlling for the favorability of securities analysts' recommendations, it follows that:

> *Proposition 11 (P11): The lower the level of consensus among securities analysts' recommendations about the firm, the greater the likelihood that the investor will buy shares in the firm.*

To further probe the argument that lower levels of consensus among securities analysts will enhance a firm's ability to attract investors, I now turn to contingencies about the investor's industry experience, investor's time horizon and aspects of the firm's innovation strategy that should exacerbate this influence.

CONTINGENT EFFECTS

If a lack of consensus among analysts' recommendations presents investors with increased opportunities to buy firms at favorable terms, then it follows that more experienced investors who have more knowledge and greater access to unique information should be more capable than less experienced investors at recognizing these opportunities. Investors sometimes trade based on idiosyncratic or private information (Ke & Petroni, 2004; Bushee & Goodman, 2007). Further, their prior experience influences their investment decisions (Kaustia & Knupfer, 2008) and their performance can improve based on experience (Seru, Shumway & Stoffman, 2010). Just as the prior experience of entrepreneurs helps them to recognize opportunities more effectively than less experienced peers (Shane, 2000), so too will more experienced investors be better able to identify the opportunities that arise due to analyst disagreement. Other evidence of the importance of experience to investment decision making comes from strategy research showing that more experienced foreign investors were more willing to undertake entry into the US market using higher risk acquisitions rather than safer equity joint

ventures (Hennart & Reddy, 1997) and that firms' investment experience enhances foreign direct investment survival prospects (Shaver, Mitchell & Yeung, 1997).

Experienced investors may also be better than less experienced peers at identifying situations where investments are potentially overpriced due to excess exuberance (e.g., Rao, Greve & Davis, 2001). For example, research shows that more experienced 'serial acquirers' are less likely to overpay when making acquisitions (McNamara, Haleblian & Dykes, 2008) and that experienced investors are less likely to induce stock market bubbles (Greenwood & Nagel, 2009). Taken together, this research suggests that investors' experience may both be beneficial to their efforts to identify opportunities related to analyst disagreement, while also promoting a greater awareness of the potential risks associated with unwarranted optimism and herding. For both of these reasons:

> *Proposition 12 (P12): The greater the investor's industry experience, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.*

Having explored the contingent effect of industry experience in the previous proposition, I turn next to the contingent effect of the investor's time horizon. Prior research has shown that investors differ with respect to their time horizon (e.g., Bushee, 1998). Since investors with a longer time horizon should be especially interested in investments that create long-term value, they may be more sensitive to concerns about the potential for herding-related overvaluation that is suggested by greater consensus among analysts' recommendations than short-term investors who are more likely to sell their

shares before overvaluation is recognized. Additionally, the longer time horizon of these investors may increase their incentives to more closely and independently scrutinize firms for opportunities that analysts may have overlooked. For both of these reasons:

> *Proposition 13 (P13): The longer the investor's time horizon, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.*

In addition to the influence that characteristics of the focal investor exert on investment decisions based on disagreement among securities analysts' recommendations, characteristics of the firm itself may also be relevant to whether investors decide to increase their ownership amidst analyst uncertainty. Prior research shows that costly and visible signals help decision makers to distinguish between higher and lower quality in the absence of clear assessments (Spence, 1973). Studies also show that visible aspects of a firm's innovation strategy can serve as an important signal of its innovative potential that can enhance the firm's ability to secure external resources (e.g., Baum & Silverman, 2004; Levitas & McFadyen, 2009). Accordingly, the next two contingencies examine the influence that characteristics of the firm's approach to innovation exert on the investor's decision. Proposition fourteen deals with the contingent effect of the scope of a firm's innovation portfolio and proposition fifteen explores the contingent effect of a firm's ability to commercialize innovations.

Differences in expectations reflect uncertainty (Barney, 1986). Prior research has shown that the scope of the firm's technological portfolio can create technological options, which can become even more valuable when uncertainty increases (McGrath,

1997; McGrath & Nerkar, 2003). Furthermore, other studies show that the scope of firms' technological knowledge can also help them deal with fluctuating rates of technological change and with unpredictable interdependencies among products (Brusoni, Prencipe & Pavitt, 2001).

In light of these different benefits related to greater technological scope amidst uncertainty, it follows that investors faced with disagreement among analysts may be even more likely to invest when the firm's innovation scope is greater. This is because greater innovation scope makes the firm even better able to capitalize on the unforeseen opportunities inherent under uncertainty. Because of the increased flexibility and greater opportunities for future growth associated with possessing a broader portfolio of technologies that can be either developed or abandoned depending on how technology evolves, investors who are faced with the increased opportunity related to disagreement will be even more likely to invest in a company with broader technological scope, since the firm is even better positioned to capitalize on this uncertainty. Therefore:

> *Proposition 14 (P14): The greater the scope of the firm's innovation portfolio, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.*

Whereas the scope of the firm's innovation portfolio discussed above in proposition fourteen benefits the firm by increasing its technological options, the firm's ability to capitalize on the multiple possibilities that exist amidst uncertainty also depends on its ability to transform different types of technological knowledge into innovations that can be monetized in product markets. The capability to bring new innovations into

the marketplace often depends on the possession of domain-specific manufacturing and product market experience (Nerkar & Roberts, 2004) and a firm that possesses 'complementary assets' such as specialized manufacturing and sales networks is better positioned to profit from its innovative efforts when faced with technological change (Teece, 1986). When technological uncertainty renders the value of some types of knowledge obsolete, a firm that possesses the specialized complementary assets and capabilities required to bring new products into the marketplace may have additional time to build knowledge in emerging technological domains (Tripsas, 1997). Furthermore, being able to successfully bring new products to market is suggested to be especially important in dynamic contexts characterized by high levels of uncertainty (Eisenhardt & Martin, 2000). Taken together, this research suggests that the ability to commercialize innovations may be especially valuable in uncertain contexts where technological change is most likely to create new opportunities and render innovations based on existing knowledge obsolete.

Even if none of the firm's technological options turn out to be compatible with the technologies that dominate, the increased speed and responsiveness related to knowing how to successfully commercialize innovations may both allow the firm additional time to develop the dominant types of knowledge and enable it to exploit new technological opportunities more effectively than rivals. Accordingly, investors faced with increased opportunities associated with the multiple technological possibilities that disagreement

among securities analysts suggests will be even more likely to increase their investment when a firm has demonstrated the capability to successfully develop new products. This is because the firm will have a greater chance of being able to successfully deploy an innovation in whatever technological area ultimately prevails. Hence:

> *Proposition 15 (P15): The greater the firm's ability to commercialize innovations, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.*

Figure 3 illustrates the theoretical model for study 3 that was developed in this chapter of the dissertation.

Chapter 6: Data and Methods

SETTING

This research focuses on the interplay between a firm's approach to innovation and experts' evaluations in financial markets. Consequently, it is important to test this theory in an innovation-driven context where securities analysts' coverage and evaluations help a firm to attract critical inputs in equity markets. Also, since some of the theory developed in this research considers the focal firm in relation to its industry (i.e., innovation intensity of the industry, knowledge overlap with industry rivals), it is also important to consider firms across different types of knowledge-intensive industries. Accordingly, I use data from the medical devices (e.g., Mitchell, 1989; Chaterji, 2009), computer hardware (e.g., Baysinger, Kosnik & Turk, 1991) and computer software industries (e.g., Lavie, 2007).

The medical devices industry is appropriate because medical device companies and their investors face substantial uncertainty when developing and evaluating innovations (Garud & Rappa, 1994; Rasheed, Datta & Chinta, 1997). Such firms often depend on financial support from equity markets to pay for innovation (Zinner, 2000) and the high financial stakes associated with developing and commercializing medical technology make the evaluation of expert intermediaries important to investors' decision making (Topol & Blumenthal, 2005; Bukh & Nielsen, 2011).

Similarly, the computer hardware and software industries are also innovation-driven contexts (e.g., Eisenhardt & Tabrizi, 1995; Henderson & Stern, 2004; Lavie, 2006), where securities analysts are relevant to the evaluation of firms' strategies (Jensen, 2004). Studies one and two of the dissertation draw on all three of these industries and study three focuses in greater detail on the medical devices industry only, since the detailed data from the Food and Drug Administration used to assess innovation in study three are not available for the other two industries.

SAMPLE

Studies one and two examine securities analysts' decisions about providing coverage and favorable recommendations to firms in the medical devices, computer hardware and computer software industries. Accordingly, these studies require data on both securities analysts and on the firms that these analysts consider when making their coverage and recommendation decisions. When constructing the sample I needed to include: (1) all analysts that might cover a given firm in the respective industry and (2) all firms in that industry that these analysts might consider when making decisions about coverage and recommendations. Consequently, I required a sampling approach that provides a representative group of the analysts who evaluate the firms across the three industries of interest and the firms that these analysts consider in making their evaluations. I describe below the rationale behind the procedure that I employed to identify the analysts and firms that were included in the sample for studies one and two.

Before elaborating on the procedure that I used to select the group of securities analysts for the sample it is important to acknowledge trade-offs associated with some of the different sampling alternatives that I considered. At the extremes one could develop a sample that includes all of the securities analysts who are active during the period of analysis or one could only include those analysts who are currently covering a firm in one of the three industries. Although basing the sample on the entire population of securities analysts would help to minimize selection bias, the inclusion of a large number of securities analysts who may never realistically consider evaluating a firm in one of the three focal industries could inflate the number of zero observations in the dataset. Having an excess number of zeros in the sample could bias estimates (King & Zeng, 1999), while also increasing the computational difficulty of the analysis. Therefore, any potential benefits of reduced selection bias gained by including the entire population of securities analysts may be more than offset by these potential analytical and computational costs.

At the other extreme one could develop a sample based exclusively on those securities analysts who are already providing coverage and recommendations to a firm in one of the three focal industries. This alternative sampling procedure would help to eliminate many of the non-active securities analysts who would be present when including the entire population of analysts. However, since securities analysts sometimes evaluate firms that reside outside of the industry in which they specialize (Zuckerman,

1999), failing to consider securities analysts who do not specialize in a given industry may engender selection bias.

Given the potential issues associated with these two extreme approaches, I have instead chosen a sampling approach for selecting securities analysts that falls somewhere in between taking the whole population of analysts and only those analysts who specialize in a given industry. Specifically, I only consider securities analysts employed by firms that have previously provided recommendations on firms in one of the three focal industries. To the extent that brokerage firms may specialize in certain industries this sampling procedure should help to minimize selection bias by ensuring that I am including the majority of the securities analyst who could potentially evaluate firms in these industries, without artificially inflating the number of zero observations in the sample. To develop the set of analysts I first identified all securities analysts whose employer had previously provided recommendations for a firm in each of the three industries (i.e., medical devices, computer hardware, computer software) between 1993 and 2006. Using this approach I identified roughly 2,500 securities analysts for the medical devices and computer hardware industries and approximately 3,000 analysts for the computer software industry from the *Institutional Brokers Estimation System (I/B/E/S) Database*. In comparison, the entire population of analysts during this period exceeded 10,000 securities analysts.

After identifying the securities analysts to include in the sample, the next step was to determine the set of firms that these analysts might consider evaluating across the three industries. Given that securities analysts typically provide forecasts and recommendations on publically traded firms (Useem, 1996), a logical starting point to develop the sample of firms was to consider the set of publically traded firms for which data are reported in *COMPUSTAT*. Since *COMPUSTAT* contains data on firms across multiple industries, I used four digit standard industry classifications (SIC) to identify firms in the medical devices, computer hardware and computer software industries. Consistent with prior literature, I consider medical devices firms in the 3841 and the 3842 SIC codes (e.g., Short et al., 2007), computer hardware firms in the 3570 though 3579 SIC codes (e,g., Iyengar & Zampelli, 2009) and computer software firms in the 7372 SIC code (e.g., Matusik, 2002) . The groups of firms indentified in *COMPUSTAT* were then matched with patent data from the *National Bureau of Economic Research Patent Database* (Hall, Jaffe & Trajtenberg, 2001). The resulting sample of firms, which increases over the period of analysis, includes between 38 to 50 firms from the medical devices industry, between 36 and 71 firms from the computer hardware industry and between 36 and 151 firms from the computer software industry. After constructing the sample for studies one and two, the next step was to develop a sampling frame for study three.

Study three examines a focal investor's decision to increase her ownership stake in a given medical devices firm in response to disagreement among securities analysts'

recommendations. This study requires data on investors and medical devices firms. Since the study examines equity investment decisions made by individual investors the first step in developing the sample involves the identification of investors. Since it is important to be able to account for sources of unobserved heterogeneity across investors that may influence the extent to which these investors will increase their ownership in response to analyst disagreement, it is critical to develop a sample that provides detailed information on individual investor characteristics. Thus, for the purpose of this study using an aggregate firm-level construct, such as the firm's average stock price, was not appropriate as it would not have provided the requisite investor-level granularity to test the theory.

While one would ideally develop a sample comprised of all equity investors who could potentially trade in medical devices firms, comprehensive data of this sort on investment patterns are not readily available for all investors. Consequently, I follow the approach used in other strategy studies of developing a sample comprised of large, institutional investors (Dharwadka et al., 2008). Institutional investors, such as pension funds, banks and investment funds hold approximately 60% of U.S. equity (Hoskisson et al., 2002). These institutional investors, with more than $100 million dollars of invested capital, are required to report their investments to the Securities and Exchange Commission (SEC) on a quarterly basis. Therefore, I use the *Thomson-Reuters Institutional Holdings (13F) Database* to develop a sample based on all of the

approximately two thousand institutional investors in the database. Since basing the sample on data on institutional investors may influence the generalizability of the findings, I will consider potential limitations associated with this approach in the discussion section at the end of the dissertation.

After identifying the set of investors to include in the sample, I next needed to identify the medical devices firms in which these investors could potentially buy equity in response to securities analysts' recommendations. Because of my interest in analysts' recommendations, I only considered publically traded firms that were covered by at least one securities analyst between 1993 and 2006. I identified medical devices firms in SIC 3841 and SIC 3842 using *COMPUSTAT* for which analysts' recommendations were also available in the *Institutional Brokers Estimation System (I/B/E/S) Database*. By integrating these different datasets I was able to identify more than 25,000 distinct investments that institutional investors made between 1993 and 2006 in roughly 50 medical devices firms.

DATA SOURCES

As mentioned previously, this research integrates data from multiple archival sources to examine the interplay between a firm's approach to innovation and evaluations in financial markets. The primary source of financial data for R&D expenditures, revenue, net income, stock prices, etc. is *COMPUSTAT*. *The Institutional Brokers Estimation System (I/B/E/S) from Thomson Reuters* is used as a primary source of data

about securities analysts' coverage and recommendations. The patent data required to assess firms' approach to innovation is taken from the *National Bureau of Economic Research Patent Database* (Hall, Jaffe & Trajtenberg, 2001). The detailed investment data required for study three of the dissertation comes from the *Thomson-Reuters Institutional Holdings (13F) Database*. This database is used to collect data on the investment patterns of more than two thousand large, institutional investors. For study three, data from the US Food & Drug Administration (FDA) are used to develop contingency variables and controls related to firms' approach to innovation.

UNIT OF ANALYSIS

Studies one and two of the dissertation use yearly data at the level of the firm-analyst dyad. In study one I examine the likelihood that a firm in the medical devices, computer hardware or computer software industry will receive coverage by a given securities analyst. In study two, I assess the likelihood that a focal firm in the medical devices, computer hardware or computer software industry will receive more favorable coverage from a focal securities analyst that is already covering the focal firm, controlling for the likelihood that securities analysts will provide coverage for the focal firm. Finally, in study three, I use yearly data at the level of the firm-investor dyad to assess the likelihood that the focal firm in the medical devices industry will attract increased investment by a focal investor.

MEASURES

Approach to Innovation and Analysts' Coverage – Study 1

Dependent Variable - Likelihood the firm will gain analyst coverage. The propositions in study one relate the influence that a firm's approach to innovation exerts on a focal securities analyst's decision to cover the focal firm. Consistent with the approach used in other studies that have examined analyst coverage (e.g., Rao, Greve, & Davis, 2001; Jensen, 2004), for each firm-analyst observation I created a dichotomous variable set to "1" if the focal securities analyst decided to cover the focal firm in the observation year. Alternatively, if the focal securities analyst did not decide to cover the focal firm, this variable is set to "0". The determination of whether the firm was covered by a securities analyst was based on whether the focal securities analyst had issued a recommendation for the focal firm as reported in the *Institutional Brokers Estimation System (I/B/E/S) Database.*

*Independent Variables***.** In line with prior strategy studies that have examined the influences of a firm's approach to innovation on different organizational outcomes (e.g., Sorenson & Stuart, 2000; Rosenkopf & Nerkar, 2001; Benner & Tushman, 2002; Song, Almeida & Wu, 2003), I use patent data to measure different aspects of the firm's approach to innovation.

Firm's knowledge diversity (P1). Knowledge diversity is measured using the number of distinct technological classes in which the focal firm has filed patents during the previous five years (Ahuja & Katila, 2004).

Extent to which the firm explores distant knowledge (P2). Knowledge distance is assessed using the focal firm's citations to existing (previously cited within firm) patents divided by its total citations made during the previous five years (Benner & Tushman, 2002; Katila & Ahuja, 2002). To check for robustness to alternative measures of this key variable, I also assess knowledge distance based on the focal firm's self-citations divided by its total citations made during the previous five years (Sorenson & Stuart, 2000; Rosenkopf & Nerkar, 2001).

Knowledge overlap between the firm and its industry rivals (P3). Knowledge overlap between the firm and industry rivals is measured using the common citation rate between firm and industry rivals during the previous 5 years. This measure is appropriate because it has been used previously to gauge the similarity between firms' knowledge in the alliance literature (e.g., Mowery, Oxley & Silverman, 1996; Mowery, Oxley & Silverman, 1998). For each firm in the sample I calculated the percentage of that firm's outward patent citations that had also been cited by another firm in the firm's industry.

Knowledge overlap between the analyst and the firm (P4). The degree of knowledge overlap between the analyst and the firm is measured as the percentage of the focal firm's

primary patent classes in which the focal analyst has had experience based on the set of firms that she has covered over her career.

Innovation intensity of firm's industry (P5 & P6). Consistent with prior research, innovation intensity is measured using the average R&D expense / revenue for the firm's 4-digit SIC (Sarkar, Echambadi, Agarwal & Sen, 2006; Ang, 2008),

Control Variables. To capture potential sources of unobserved heterogeneity I include controls to account for various influences related to the focal firm, the focal securities analyst and the focal investor that may affect both a firm's approach to innovation and analyst coverage. Larger firms may be more likely to attract analyst coverage due to the increased visibility associated with their size (Bhushan, 1989). Such firms may also be better able to adopt a particular approach to innovation. I control for firm size based on the number of employees. Firm performance may also affect the degree to which the firm is covered by securities analysts (Bhushan, 1989; McNichols & O'Brien, 1997), while also influencing the firm's ability to conduct an approach to innovation based on diverse, distant and distinctive knowledge. To capture this potential influence I control for firm performance based on net income.

Prior research shows that securities analysts sometimes engage in herding behavior by following one others' coverage decisions (Rao, Greve & Davis, 2000). Since the extent to which analysts cover an industry may also vary with the approach to innovation used by firms in the industry, it is important to account for the potential

influence that the prior level of industry coverage by securities analysts may have on the firm's approach to innovation and the decision of a focal securities analyst to cover that firm. I capture this potential influence by controlling for the number of analysts covering the firm's industry.

Additionally, since a firm's innovative output, technological capabilities and geographic scope may influence both its approach to innovation and the likelihood that it will gain the coverage of a securities analyst, I control for the firm's number of patents, the citations that the firm receives from other firms and the number of geographic locations in which the firm conducts R&D. Also, prior literature suggests that the level of analyst coverage may be greater when firms engage more heavily in R&D and in the development of intangible assets (Barth, Kasznik & McNichols, 2001). Given that the degree to which firms draw upon diverse, distant and distinctive knowledge may also be influenced by the innovation intensity of the firm's industry, I control for this potential influence by including a control for the research and development expense as a percentage of sales in the firm's four digit SIC. Furthermore, to help account for heterogeneity across analysts that may relate to coverage and the firm's approach to innovation, I also control for the degree of knowledge overlap between the analyst and the focal firm.

There have been important changes in the information environment that may influence securities analysts' decisions to cover and evaluate firms. One particularly

important change to the information environment in the United States occurred on October 23rd, 2000 with the enactment of Regulation Fair Disclosure (RegFD) by the Securities and Exchange Commission (Bailey, Li, Mao & Zhong, 2003). This regulation made it illegal for companies to selectively or privately disclose information to securities analysts or investors. By providing more equal access to information across analysts, the enactment of RegFD influenced the pattern of analyst coverage across firms (Mohanram & Sunder, 2006). Accordingly, I include a dummy variable to capture any potential influence that the passage of RegFD had on a firm's coverage and its approach to innovation. In addition to all of these other controls, I also include year dummies to capture influences related to specific years that may influence the firm's approach to innovation and coverage.

Approach to Innovation and Analysts' Recommendations – Study 2

Dependent Variable **-** *Likelihood securities analyst will increase favorability of the firm's recommendation.* The propositions in this study relate the influence that a firm's approach to innovation exerts on a focal securities analyst's decision to increase the favorability of her recommendation for the focal firm. For each firm-analyst observation I created a dichotomous dependent variable to assess when the favorability of the recommendations that the firm receives from a securities analyst improves. I used the analyst detail file from the *Institutional Brokers Estimation System (I/B/E/S) Database.* Securities analysts recommendations typically range from favorable, 'strong buy'

recommendations to unfavorable, 'sell' recommendations (i.e., 1=Strong Buy, 2=Buy, 3=Hold, 4=Underperform, 5=Sell). Accordingly, this measure is set to "1" if the focal firm's recommendation from the focal analyst becomes more favorable versus the previous year, "0" otherwise (Hayward & Boeker, 1998; Westphal & Clement, 2008; Westphal & Graebner, 2010).

Independent Variables. In line with prior strategy studies that have examined the influences of a firm's approach to innovation on different organizational outcomes (e.g., Sorenson & Stuart, 2000; Rosenkopf & Nerkar, 2001; Benner & Tushman, 2002; Song, Almeida & Wu, 2003), I use patent data to measure different aspects of the firm's approach to innovation.

Extent to which the firm explores distant knowledge (P7). Please refer to description above for proposition 2.

Knowledge overlap between the firm and its industry rivals (P8). Please refer to description above for proposition 3.

Analyst's experience (P9). I measure an analyst's experience based on the number of years that the analyst has provided recommendations (Hong, Kubik & Solomon, 2000).

Degree to which other firms covered by the securities analyst explore new knowledge (P10). This construct is assessed by taking the average across the firms covered by the analyst of citations to existing (previously cited within firm) patents divided by the total citations these firms made during the previous 5 years (Katila & Ahuja, 2002).

Control Variables. When examining the analyst's likelihood of increasing the favorability of the focal firm's recommendation in study two, it is important to account for other influences that may affect the firm's approach to innovation and the likelihood that the analyst will increase the favorability of the recommendation. Since larger and more profitable firms may be more able to pursue a particular approach to innovation, while also being more likely to garner favorable recommendations, I control for firm size based on number of employees (Westphal & Graebner, 2010) and for firm performance based on net income (Fanelli, Misangyi & Tosi, 2009).

The average recommendation that the focal firm receives from all analysts covering the firm may also influence the likelihood that the focal firm will be given a more favorable recommendation (Hayward & Boeker, 1998; Westphal & Clement, 2008). As the firm's approach to innovation may also be influenced by the prior evaluation of securities analysts, I include a control for the average recommendation that the firm received from all analysts covering that firm. Moreover, since other aspects of the firm's innovation strategy may influence the degree to which it explores distant knowledge and builds on the knowledge of rivals and also affect the likelihood that the securities analyst will increase the favorability of her recommendation it is important to account for these other attributes of innovation. Consequently, I also control for the firm's number of patents, the citations that it receives from other firms and the number of

geographic locations in which it conducts R&D, to account for the influence of innovative output, technological capabilities and geographic scope.

In addition to accounting for heterogeneity across firms, it is also important to account for heterogeneity across securities analysts that may correlate with the firm's approach to innovation and the likelihood that the firm will garner a more favorable recommendation. Since an analyst's general experience evaluating firms and her specific experience covering firms that explore distant knowledge may both affect the likelihood that she will increase the favorability of the recommendation given to a firm and since these types of experience may relate to the firm's approach to innovation, I control for the number of years of experience that the analyst has and the average percentage of new knowledge used by the firms that the analyst has previously covered. I also control for the analyst's accuracy in developing earnings per share forecasts, which may relate to the favorability of recommendations and the firm's approach to innovation.

There is also evidence that the passage of Fair Disclosure Regulation (RegFD) in 2000 contributed to a reduction in forecast accuracy (Mohanram & Sunder, 2006) and increased the dispersion in securities analysts' forecasts (Bailey, Li, Mao & Zhong, 2003). Given that this change may have influenced a firm's approach to innovation, I include a dummy variable to capture any potential influence associated with this regulatory change.

Analysts' Recommendations and Investment – Study 3

Dependent Variable - Likelihood that investor will buy shares in the firm. The propositions in this third study relate the influence that consensus among securities analysts' recommendations about the focal firm exerts on a focal investor's decision to increase her ownership in the focal firm. For each firm-investor observation I created a dichotomous variable that is set to "1" if the focal investor buys or increases her ownership of the firm's shares, "0" otherwise (e.g., Baum & Silverman, 2004).

Independent Variables. The measures used for the independent and contingency variables are described below.

Consensus among analysts' recommendations (P11). To examine the degree of consensus among securities analysts' recommendations I follow the approach used in prior literature of measuring the standard deviation of the average recommendations across all of the securities analysts covering the focal firm in the year preceding the observation year (Fanelli, Misangyi and Tosi, 2009).

Investor's industry experience (P12). To examine the contingent effect of the focal investor's industry experience on her hazard of increasing investment in the focal firm, I created a variable using the count of the total number of medical devices firms held by the focal investor in the year preceding the observation year (Sorenson and Stuart, 2001).

Investor's time horizon (P13). The investor's time horizon is measured based on the annual percentage of shares that she holds rather than selling (e.g., Bushee, 1998;

Dharwadka et al. 2008). Investors who turn over their portfolio more frequently likely have a shorter time horizon than those who turn over their portfolios less frequently.

Scope of the firm's innovation portfolio (P14). The scope of the investor's innovation portfolio is measured based on the number of distinct FDA product codes in which the focal firm has introduced innovations.

Firm's ability to commercialize innovations (P15). The firm's ability to commercialize innovations is measured based on the firm's yearly number of FDA approved products in the year preceding the observation year (Hitt et al., 1996; Katila & Ahuja, 2002; Zahra and Nielsen, 2002).

Control Variables. Since prior literature shows that the favorability of securities analysts' recommendations enhances firms' ability to attract investors (Womack, 1996) and since the favorability of recommendations may contribute to the level of consensus, I control for the average favorability of all of the buy/sell recommendations made by all of the analysts covering the focal firm. Accordingly, this control captures the average opinion about whether to buy or sell the firm's shares held by all analysts covering the firm. The number of securities analysts covering the firm can influence the level of agreement among analysts (Hong, Kubik & Solomon, 2000; Rao, Greve & Davis, 2001) while also influencing the likelihood that investors will buy the firm's shares (Jensen, 2004). Accordingly, I include a control that captures the count of the number of securities analysts who provide coverage for the focal firm.

Prior studies suggest that firm size may influence the level of consensus among analysts (Barron, Byard, Kile & Riedl, 2002) while also affecting investors' efforts to profit from analysts' recommendations (Barber, Lehavy, McNicols & Trueman, 2001). I control for firm size based on the number of employees. Given that studies have shown that firm performance can influence the uniformity of the recommendations that analysts make (Fanelli, Misangyi & Tosi, 2009) and that firm performance also influences the firm's ability to attract investors, I account for this potential influence by including a control for the firm's profitability based on net income. It is also possible that the firm's share price or dividends may influence both the level of consensus of analysts' recommendations and its ability to attract investment. To capture these potential influences I include controls for the firm's average share price and its annual dividend. Prior literature shows that the level of consensus can be influenced by the extent to which firms produce intangible assets, such as R&D and innovations (e.g., Barron, Byard, Kile & Riedl, 2002). Due to the possibility that innovation-intensive firms may also differ in their ability to attract investors, I control for several characteristics of the firm's innovation strategy, including the average age of its products, its ability to commercialize innovations, the amount of competition it faces from rivals' innovations and its share of innovations in its product categories.

It is also important to control for potential unobserved heterogeneity related to investors. I, therefore, include controls for the investor's experience, portfolio size,

portfolio turnover and for the type of investor (dummies for pension and investor fund). Note that the inclusion of these dummies for pension and investor fund may also help capture potential differences in risk preferences across types of investors. Finally, the potential exists that general economic conditions may contribute to uncertainty among securities analysts while also influencing the willingness of investors to buy shares in medical innovation companies. To help mitigate this potential concern I control for macroeconomic factors such as inflation, U.S. Government T-bill rates and the index value of U.S. equities.

MODEL SPECIFICATION

This research examines discrete choices involving dichotomous outcomes which violate the OLS assumption of linearity (Kennedy, 2003). Because the use of linear models to examine discrete outcomes can yield spurious results, I instead use logit models based on the logistic distribution to assess the likelihood of increased coverage, favorability and investment (Greene, 2003). I use discrete-time logistic method with robust standard errors to analyze the hazards across the three sections of this study. This approach deals with right-censored observations while also accommodating time-varying covariates. In the logit model, $\log [\pi_{ijt}/(1-\pi_{it})] = X_{ijt-1}\beta + \varepsilon_{ijt}$, where X_{itj-1} is a time-varying vector of lagged covariates, β is a vector of estimated coefficients, and ε_{ijt} is a vector of normally distributed error terms.

In study one (chapter 3), where I examine the influence of a firm's approach to innovation on the likelihood that an analyst will provide coverage for the firm (Figure 1), the dependent variable – Analyst's coverage$_{ijt}$ – denotes whether a given securities analyst (subscript *i*) decided to cover a specific firm (subscript *j*) in a given year (subscript *t*). The logit specification models the logarithm of the odds that the securities analyst will cover a specific firm in the observation year, that is, log $[\pi_{ijt}/(1-\pi_{ijt})]$, where π_{ijt} = Pr (Analyst covering the firm$_{ijt}$ = 1) and $(1-\pi_{ijt})$ = Pr (Analyst covering the firm$_{ijt}$ = 0).

Similarly, in study two (chapter 4), where I examine the influence of a firm's approach to innovation on the likelihood that an analyst will increase the favorability of the recommendation for a given firm (Figure 2), the dependent variable – Analyst's increased favorablity$_{ijt}$ – denotes whether a given securities analyst (subscript *i*) decided to increase the favorability of the recommendation given to a specific firm (subscript *j*) in a given year (subscript *t*). The logit specification models the logarithm of the odds that the securities analyst will increase the favorability of the recommendation in the observation year, that is, log $[\pi_{ijt}/(1-\pi_{ijt})]$, where π_{ijt} = Pr (Analyst increasing favorability of recommendation given to the firm$_{ijt}$ = 1) and $(1-\pi_{ijt})$ = Pr (Analyst increasing favorability of recommendation given to the firm$_{ijt}$= 0).

For studies one and two that examine three distinct industries, I had the option of either pooling the sample and analyzing the three industries together with industry

dummies or of analyzing each industry separately. Since the pooled sample approach does not allow the coefficients to vary across the three industries, it would result in a less conservative test of the theory. Consequently, I opted to use the more stringent test of running separate models for each of the three industries across the first two studies of the dissertation. This approach results in a more conservative test, since it allows the coefficients to vary across the different industries, which should increase the hurdle required to find empirical support.

Finally in study three (chapter 5), where I examine the influence of a disagreement among securities analysts' recommendations on the likelihood that an investor will buy additional shares of a given firm's stock (Figure 3), the dependent variable – Investor's decision to increase investment$_{ijt}$ – denotes whether a given investor (subscript *i*) decided to buy additional shares of a specific firm's stock (subscript *j*) in a given year (subscript *t*). The logit specification models the logarithm of the odds that the investor will increase the ownership in the firm's shares during the observation year, that is, log $[\pi_{ijt}/(1-\pi_{ijt})]$, where π_{ijt} = Pr (Investor increasing ownership in the firm$_{ijt}$ = 1) and $(1-\pi_{ijt})$ = Pr (Investor increasing ownership in the firm$_{ijt}$= 0).

Prior studies highlight the importance of accounting for endogeneity in strategy research (e.g., Hamilton & Nickerson, 2003; Bascle, 2008). Failing to account for endogeneity can bias estimates which can lead to erroneous results (Shaver, 1998). In light of the possibility that analysts' decisions to provide coverage for a particular firm

may itself influence their subsequent decisions about providing favorable recommendations in the second study, it is important to take steps to address potential endogeneity concerns. Consequently, I use a two-stage estimate procedure (Hamilton & Nickerson, 2003), following the approach introduced by Heckman (1974; 1979) and Lee (1978).

In the first stage I use the variables from study one and two new variables to estimate the likelihood that a securities analyst will cover a given firm. I then include the inverse mills ratio derived from these new variables and the other variables as regressors when estimating the influence that a firm's approach to innovation exerts on the favorability of the recommendation that it receives from an analyst. The first new variable that I have selected measures the number of firms in the same two-digit SIC code that are listed on the stock exchange (e.g., NYSE, NASDAQ) where the firm is listed. I expect that having a greater number of firms with the same two-digit SIC code listed on the stock exchange may have a negative effect on the likelihood that it will be covered by an analyst. However, the number of firms with the same two-digit SIC code listed on the stock exchange may not as directly affect the favorability of the recommendations that the firm receives.

The second new variable that I have selected measures whether the focal firm is headquartered in the state of New York. Due to the concentration of investment banks located in New York, firms that are headquartered there may find it easier to attract

analyst coverage. However, being located in New York may not directly influence the favorability of the recommendations that analysts provide for firms. This two-stage approach helps ensure that the influence of a firm's approach to innovation on the favorability of coverage it receives is conditional on, or net of, the analyst's decision to cover that firm. Note that since the inclusion of the inverse mills ratio may cause the standard errors to be understated which can erroneously inflate the statistical significance of the coefficients (Hamilton & Nickerson, 2003), I use bootstrapping to correct for this potential issue.

A number of the propositions involve contingency effects. However, because logit models are non-linear, I am not able to test these contingencies using the standard approach of multiplicative interaction terms (Penner-Hahn & Shaver, 2005; Hoetker, 2007; Wiersema & Bowen, 2009). Furthermore, the marginal effects of logit models depend on levels of other variables. Accordingly, to test the contingencies, I use a combination of graphical analysis and split sample econometric tests where I conduct a t-test to compare differences in the marginal effect at different levels of the contingency variables.

Chapter 7: Results

The results section is divided into three sections that correspond to the three main theory chapters of the dissertation. The first two sections are further broken down into sub-sections corresponding to the medical devices, computer hardware and computer software industries.

APPROACH TO INNOVATION AND ANALYSTS' COVERAGE – STUDY 1

Table 1 summarizes the results for propositions 1 through 6 across the medical devices, computer hardware and computer software industries. This summary table shows the propositions that received support across the three industries. Specifically, this table shows that four out of the six propositions from study one received empirical support across at least two of the three industries.

The subsections below, corresponding to each of the three industries, explain how the empirical tests were conducted to analyze the results for propositions 1 through 6. I begin below by exploring the results for medical device firms in study one.

Results for Medical Devices Industry

Table 2 shows descriptive statistics and correlations for the medical devices industry. I ran variance inflation factors to examine collinearity. Since all of the variance inflation factors were well below the critical threshold of 10 (Kennedy, 2003), I found no evidence that multi-collinearity is affecting the results (mean 2.2; max 5.6.).

Table 3 shows the logit estimates for the independent variables and controls. Proposition 1 predicted that the likelihood that a securities analyst will provide coverage to a given firm will be lower when the firm's knowledge diversity increases. Model 4 from Table 3 offers support for this proposition for the medical devices industry ($\beta = -0.04$, $p < .001$). These findings support proposition 1.

Proposition 2 predicted that the likelihood that a securities analyst will provide coverage to a given firm will be lower when the firm explores more distant knowledge. Model 4 from Table 3 offers support for this proposition for the medical devices industry ($\beta = -1.83$, $p < .001$). These findings support proposition 2.

Proposition 3 predicted that the likelihood that a securities analyst will provide coverage to a given firm will be greater when the firm's knowledge overlaps more with industry rivals. Model 4 from Table 3 offers support for this proposition for the medical devices industry ($\beta = 2.95$, $p < .001$). These findings offer support for proposition 3.

Propositions 4 through 6 involve contingency effects. Proposition 4 predicts that the greater the knowledge overlap between the analyst and the firm, the less negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm. Proposition 5 predicts that the greater the innovation intensity of the firm's industry, the more negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm. Finally, proposition 6 predicts that the greater the innovation intensity of the firm's industry, the less positive the effect of

knowledge overlap between the firm and its industry rivals on the likelihood an analyst will cover the firm. Due to the non-linearity of logit models and the fact that values of the main variable can vary at different levels of the contingency variables, the approach of testing contingency effects through multiplicative interaction terms is not appropriate (Hoetker, 2007; Wiersema & Bowen, 2009). Consequently, I tested the contingency effects using a combination of graphical analysis and split sample econometric tests (Penner-Hahn & Shaver, 2005). I split the sample into high and low groups of observations based on the mean of the contingency variables (knowledge overlap between the analyst and firm in proposition 4, and innovation intensity of the firm's industry in proposition 5 and 6), while holding all other variables at their respective means. The high group contains values above the mean of the contingency variable, while the low group contains values below the mean of the contingency variable. These groups were then used as a basis for the graphical analysis and econometric tests.

Figures 4-6 show the graphical analysis of these contingencies based on the high and low values. Since the figures suggest that the slopes of the lines for high and low values of the moderating variables may be different, I also performed a split sample econometric test to formally examine whether the contingent effects in propositions 4, 5 and 6 were supported for medical devices firms. Comparing coefficients between models in a split-sample analysis can be misleading because of the fact that these models are non-linear and due to the possibility that observations can fall systematically in different

parts of the curve across models (Penner-Hahn & Shaver, 2005; Wiersema & Bowen, 2009). Therefore, I instead compare the marginal effects. Thus, to determine whether the contingency effects are supported for propositions 4 through 6, I conducted t-tests to establish whether the marginal effects for high and low levels of the contingency variables are statistically significant in the hypothesized direction. Specifically, I calculated for each group of observations the marginal effects of the main variable, while holding the other variables constant at their respective mean values. I then performed t-tests to compare differences in marginal effects of the main variable at different levels of the contingency variable. Tables 4 and 5 report the results of the split-sample analyses.

Proposition 4 predicts that the greater the knowledge overlap between the analyst and the firm, the less negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm. To find support for this proposition I would need to establish that the marginal effect of knowledge distance on coverage is significantly less negative (i.e., more likely to provide coverage) for high levels of knowledge overlap between the firm and analyst than it is for low levels of knowledge overlap between the firm and the analyst. However, contrary to this prediction, results of models 1 and 2 in Table 4 show that high levels of knowledge overlap between the firm and analyst actually had the opposite effect by making the analyst even less likely to cover a firm that explores distant knowledge ($t = 4{,}500$; $p < .001$). Therefore, the split sample econometric test does not support proposition 4 for the medical devices industry.

Proposition 5 predicts that the greater the innovation intensity of the firm's industry, the more negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm. Finding support for this proposition requires that the split sample econometric test shows that the marginal effect of knowledge distance on coverage is significantly more negative (i.e., less likely to provide coverage) for high levels of innovation intensity than it is for low levels of innovation intensity. Again, contrary to this prediction, results of models 1 and 2 in Table 5 show that high levels of innovation intensity actually had the opposite effect by making the analyst more likely to cover a firm that explores distant knowledge ($t = 200$; $p < .001$). Therefore, the split sample econometric test does not support proposition 5 for the medical devices industry.

Proposition 6 predicts that the greater the innovation intensity of the firm's industry, the less positive the effect of knowledge overlap between the firm and its industry rivals on the likelihood an analyst will cover the firm. Finding support for this proposition requires that the split sample econometric test shows that the marginal effect of knowledge overlap on coverage is significantly less positive (i.e., less likely to provide coverage) for high levels of innovation intensity than it is for low levels of innovation intensity. In support of this prediction, results of models 1 and 2 in Table 5 show that high levels of innovation intensity made the analyst less likely to cover a firm when the

firm's knowledge overlaps with rivals (t = 320; p < .001). Therefore, the split sample econometric test strongly supports proposition 6 for the medical devices industry.

Many of the control variables had a significant effect on the securities analyst's decision to provide coverage for the focal medical devices firm. In the medical devices industry, firm size, firm performance, the firm's innovative output, the level of knowledge overlap between the focal firm and the analyst and the Fair Disclosure Regulation (RegFD) controls all exerted a positive influence on the likelihood that the securities analyst would provide coverage for the focal firm.

I turn next to the results for the computer hardware industry for study one.

Results for Computer Hardware Industry

Table 6 shows descriptive statistics and correlations for the computer hardware industry. I ran variance inflation factors to examine collinearity (Kennedy, 2003) and found no evidence that multi-collinearity is affecting the results (mean 3.0; max 5.5.).

Table 7 shows the logit estimates of analysts' hazard of covering the focal firm in the computer hardware industry. Proposition 1 predicted that the likelihood that a securities analyst will provide coverage to a given firm will be lower when the firm's knowledge diversity increases. Contrary to the prediction in proposition 1, Model 4 from Table 7 shows that greater knowledge diversity increased the likelihood that the analyst would cover the focal firm in the computer hardware industry ($\beta = 0.01$, $p < .01$). Therefore, proposition 1 is not supported in the computer hardware industry.

Proposition 2 predicted that the likelihood that a securities analyst will provide coverage to a given firm will be lower when the firm explores more distant knowledge. Model 4 from Table 7 offers support for this proposition for the computer hardware industry ($\beta = -1.44$, $p < .001$). These findings support proposition 2.

Proposition 3 predicted that the likelihood that a securities analyst will provide coverage to a given firm will be greater when the firm's knowledge overlaps more with industry rivals. Model 4 from Table 7 offers support for this proposition for the computer hardware industry ($\beta = 1.38$, $p < .01$). These findings offer support for proposition 3.

Propositions 4 through 6 involve contingency effects. Following the approach described above, I used a combination of graphical analysis and split sample econometric tests to test these propositions. Figures 7 through 9 show the graphical analysis of these contingencies based on the high and low values.

Since these figures suggest that the slopes of the lines for high and low values of the moderating variables may be different, I also performed a split sample econometric test to formally examine whether the contingent effects in propositions 4, 5 and 6 were supported for computer hardware firms. Tables 8 and 9 show the split sample econometric test used in conjunction with the graphs to examine the contingency effects.

Proposition 4 predicts that the greater the knowledge overlap between the analyst and the firm, the less negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm. To find support for this proposition I would need to establish that the marginal effect of knowledge distance on coverage is

significantly less negative (i.e., more likely to provide coverage) for high levels of knowledge overlap between the firm and the analyst than it is for low levels of knowledge overlap between the firm and the analyst. Contrary to this prediction, results of models 1 and 2 in Table 8 show that high levels of knowledge overlap between the firm and the analyst actually had the opposite effect by making the analyst even less likely to cover a firm that explores distant knowledge (t = 3,100; $p < .001$). Therefore, the split sample econometric test does not support proposition 4 for the computer hardware industry.

Proposition 5 predicts that the greater the innovation intensity of the firm's industry, the more negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm. Finding support for this proposition requires that the split sample econometric test shows that the marginal effect of knowledge distance on coverage is significantly more negative (i.e., less likely to provide coverage) for high levels of innovation intensity than it is for low levels of innovation intensity. Again, contrary to this prediction, results of models 1 and 2 in Table 9 show that high levels of innovation intensity actually had the opposite effect by making the analyst more likely to cover a firm that explores distant knowledge (t = 2,500; $p < .001$). Therefore, the split sample econometric test does not support proposition 5 for the computer hardware industry.

Proposition 6 predicts that the greater the innovation intensity of the firm's industry, the less positive the effect of knowledge overlap between the firm and its industry rivals on the likelihood an analyst will cover the firm. Finding support for this proposition requires that the split sample econometric test shows that the marginal effect of knowledge overlap on coverage is significantly less positive (i.e., less likely to provide coverage) for high levels of innovation intensity than it is for low levels of innovation intensity. In support of this prediction, results of models 1 and 2 in Table 9 show that high levels of innovation intensity made the analyst less likely to cover a firm when the firm's knowledge overlaps with rivals (t = 3,200; $p < .001$). Therefore, the split sample econometric test strongly supports proposition 6 for the computer hardware industry.

Many of the control variables had a significant effect on the securities analyst's decision to provide coverage for the focal computer hardware firm. In the computer hardware industry, firm size, the number of analysts covering the firm, the firm's technological quality and the level of knowledge overlap between the focal firm and the analyst exerted a positive influence on the likelihood that the securities analyst would provide coverage for the focal firm. Conversely, the firm's geographic scope, the innovation intensity of the firm's industry and the dummy variable for the Fair Disclosure Regulation change (RegFD) exerted a negative influence on the likelihood that a securities analyst would provide coverage for a firm in the computer hardware industry.

Now that I have reported the results of study one for the medical devices and computer hardware industries, I consider below the results for study one for computer software firms.

Results for Computer Software Industry

I ran variance inflation factors to examine collinearity (Kennedy, 2003) and found no evidence that multi-collinearity is affecting the results (mean 1.8; max 2.6). Table 10 shows descriptive statistics and correlation matrix.

Table 11 shows the logit estimates of the analyst's hazard of covering a firm in the computer software industry.

Proposition 1 predicted that the likelihood that a securities analyst will provide coverage to a given firm will be lower when the firm's knowledge diversity increases. Model 4 from Table 11 offers support for this proposition for the computer software industry ($\beta = -0.05$, $p < .001$). These findings support proposition 1.

Proposition 2 predicted that the likelihood that a securities analyst will provide coverage to a given firm will be lower when the firm explores more distant knowledge. Model 4 from Table 11 offers support for this proposition for the computer software industry ($\beta = -0.36$, $p < .05$). These findings support proposition 2.

Proposition 3 predicted that the likelihood that a securities analyst will provide coverage to a given firm will be greater when the firm's knowledge overlaps more with

industry rivals. Model 4 from Table 11 does not offer support for this proposition for the computer software industry.

Propositions 4 through 6 involve contingency effects. Following the approach described above I used a combination of graphical analysis and split sample econometric tests to test these propositions.

Figures 10 through 12 show the graphical analysis of these contingencies based on the high and low values of the contingency variables.

Since these graphs suggest that the slopes may be different for high and low levels of the contingency variables, I have also conducted split sample econometric analyses to formally test these propositions. Tables 12 and 13 show the split sample econometric test used in conjunction with the graphs to examine the contingency effects.

Proposition 4 predicts that the greater the knowledge overlap between the analyst and the firm, the less negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm. To find support for this proposition I would need to establish that the marginal effect of knowledge distance on coverage is significantly less negative (i.e., more likely to provide coverage) for high levels of knowledge overlap between the firm and the analyst than it is for low levels of knowledge overlap between the firm and the analyst. Contrary to this prediction, results of models 1 and 2 in Table 12 show that high levels of knowledge overlap between the firm and the analyst actually had the opposite effect by making the analyst even less

likely to cover a firm that explores distant knowledge (t = 2,600; p < .001). Therefore, the split sample econometric test does not support proposition 4 for the computer software industry.

Proposition 5 predicts that the greater the innovation intensity of the firm's industry, the more negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm. Finding support for this proposition requires that the split sample econometric test shows that the marginal effect of knowledge distance on coverage is significantly more negative (i.e., less likely to provide coverage) for high levels of innovation intensity than it is for low levels of innovation intensity. Again, contrary to this prediction, results of models 1 and 2 in Table 13 show that high levels of innovation intensity actually had the opposite effect by making the analyst more likely to cover a firm that explores distant knowledge (t = 110; p < .001). Therefore, the split sample econometric test does not support proposition 5 for the computer software industry.

Proposition 6 predicts that the greater the innovation intensity of the firm's industry, the less positive the effect of knowledge overlap between the firm and its industry rivals on the likelihood an analyst will cover the firm. Since the main effect of knowledge overlap between the firm and its rivals (proposition 3) was not supported for the computer software industry, this related contingency is also not supported.

Many of the control variables had a significant effect on the securities analyst's decision to provide coverage for the focal computer software firm. In the computer software industry, firm size, the number of analysts covering the firm, the firm's technological quality, the firm's innovative output and the level of knowledge overlap between the focal firm and the analyst exerted a positive influence on the likelihood that the securities analyst would provide coverage for the focal firm. Conversely, the firm's geographic scope, the innovation intensity of the firm's industry and the dummy variable for the Fair Disclosure Regulation change (RegFD) exerted a negative influence on the likelihood that a securities analyst would provide coverage for a firm in the computer software industry.

Having explored the results for propositions 1 through 6 for all three industries considered in study one, I next focus on the results for propositions 7 through 10 from study two across these same three industries.

APPROACH TO INNOVATION AND RECOMMENDATIONS – STUDY 2

Table 14 summarizes the empirical findings for propositions 7 through 10 across the medical devices, computer hardware and computer software industries. This table shows that none of the four propositions from this study received support across more than one industry and only one proposition received support in a single industry (i.e., proposition 8 for the computer software industry).

I begin below with the results from the medical devices industry for study two

Results for Medical Devices Industry

Table 15 shows descriptive statistics and correlations for the medical devices industry. I computed variance inflation factors to examine multicollinearity (Kennedy, 2003). With the exception of the variance inflation factor of 15.4 for the control variable for firm size, all of the other variance inflation factors (mean: 4.3, max: 15.4) were well below the threshold of 10. Since dropping the firm size variable from models altogether and including a different measure of firm size based on revenues yielded results consistent to the ones reported below, it does not, however, appear that multicollinearity is affecting the results.

Table 16 shows the first stage model that was used to predict the likelihood that a securities analyst would provide coverage for the focal firm. As discussed previously, this first stage model is similar to the model from study one with addition of two new variables that were expected to influence coverage, but not the favorability of recommendations. Model 1 from Table 16 shows that the variable for the number of firms in the firm's industry listed on the same stock exchange exerts a positive and statistically significant effect on the likelihood that the analyst will cover the firm in the first stage model ($\beta = 0.01$, $p < .001$). This suggests that one of these new, first stage selection variables contributed to the analyst's coverage decision.

Table 17 shows the second stage model that includes the inverse mills ratio derived based on the first stage logit model reported above in Table 16. The inclusion of

the inverse mills ratio can cause the standard errors to be understated which can erroneously inflate the statistical significance of the coefficients and bootstrapping is one method to correct for this potential issue (Hamilton & Nickerson, 2003). Models 1 through 3 in Table 17 report the logit results without the bootstrap correction and Model 4 reports the full model with the bootstrap corrected standard errors.

Proposition 7 predicted that when a firm explores more distant knowledge it will have a negative impact on the favorability of the analyst's recommendation for the firm. Model 4 from Table 17 does not offer support for this proposition for the medical devices industry ($\beta = 0.03$, not significant). These findings do not support proposition 7 for the medical devices industry.

Proposition 8 predicted that when a firm's approach to innovation emphasizes greater knowledge overlap between the firm and its rivals it will have a negative impact on the favorability of the analyst's recommendation for the firm. Contrary to this prediction, Model 4 from Table 17 shows a positive, yet non-significant, coefficient for knowledge overlap ($\beta = -2.26$, not significant). These findings do not support proposition 8 for the medical devices industry.

Proposition 9 and 10 predict contingency effects that attenuate the relationship between the exploration of distant knowledge and the likelihood that the focal analyst will increase the favorability of the recommendation for the firm. Proposition 9 predicts that the greater the analyst's experience, the less negative the effect that exploration of

distant knowledge will have on the favorability of the recommendation. Proposition 10 predicts that the more extensively other firms covered by the analyst explore external knowledge, the less negative the effect that exploration of distant knowledge will have on the favorability of the recommendation Since neither the main effect of exploration of distant knowledge nor the contingency variables themselves had a statistically significant effect on the likelihood that the analyst will increase the favorability of the recommendation, the proposed contingencies are also not supported. Hence, I do not find any support for propositions 9 and 10 for the medical devices industry.

Some of the control variables had a significant effect on the securities analyst's decision to increase the favorability of the recommendation for the focal medical devices firm. In the medical devices industry, the average favorability of the recommendation that the firm received from securities analysts in the prior period had a positive influence on the likelihood that the firm would receive a more favorable recommendation from the focal analyst.

I turn next to the results from the computer hardware industry for study two.

Results for Computer Hardware Industry

Table 18 shows descriptive statistics and correlations for the computer hardware industry. I computed variance inflation factors to examine multicollinearity and found that all of the variance inflation factors (mean: 3.3, max: 7.2) were well below the threshold of 10.

Table 19 shows the first stage model that was used to predict the likelihood that a securities analyst would provide coverage for the focal firm. Model 1 from Table 19 shows that both the new variable for the number of firms in the firm's industry listed on the same stock exchange ($\beta = 0.01$, $p < .001$) and the new variable measuring whether the firm is headquartered in New York ($\beta = 1.45$, $p < .001$) had a positive and statistically significant effect on the likelihood that the analyst will cover the firm in the first stage model. This suggests that these new, first stage selection variables contributed to the analyst's coverage decision.

Table 20 shows the second stage models. The inclusion of the inverse mills ratio can cause the standard errors to be understated which can erroneously inflate the statistical significance of the coefficients and bootstrapping is one method to correct for this potential issue (Hamilton & Nickerson, 2003). Models 1 through 3 in Table 20 report the logit results without the bootstrap correction and Model 4 reports the full model with the bootstrap corrected standard errors.

Proposition 7 predicted that when a firm explores more distant knowledge it will have a negative impact on the favorability of the analyst's recommendation for the firm. Model 4 from Table 20 does not offer support for this proposition for the computer hardware industry ($\beta = -0.77$, not significant). These findings do not support proposition 7 for the computer hardware industry.

Proposition 8 predicted that when a firm's approach to innovation emphasizes greater knowledge overlap between the firm and its rivals it will have a negative impact on the favorability of the analyst's recommendation for the firm. Contrary to this prediction, Model 4 from Table 20 shows a positive, yet non-significant, coefficient for knowledge overlap ($\beta = 0.39$, not significant). These findings do not offer support for proposition 8 for the computer hardware industry.

Proposition 9 and 10 predict contingency effects that attenuate the relationship between the exploration of distant knowledge and the likelihood that the focal analyst will increase the favorability of the recommendation for the firm. Proposition 9 predicts that the greater the analyst's experience, the less negative the effect that exploration of distant knowledge will have on the favorability of the recommendation. Proposition 10 predicts that the more extensively other firms covered by the analyst explore external knowledge, the less negative the effect that exploration of distant knowledge will have on the favorability of the recommendation. Since neither the main effect of distant knowledge nor the effects of the contingency variables themselves were statistically significant, the proposed contingencies are also not supported. Therefore, I also do not find any support for propositions 9 and 10 for the computer hardware industry.

Some of the control variables had a significant effect on the securities analyst's decision to increase the favorability of the recommendation for the focal computer hardware firm. In the computer hardware industry, the firm's performance and the

average favorability of the recommendation that the firm received from securities analysts in the prior period had a positive influence on the likelihood that the firm would receive a more favorable recommendation from the focal analyst.

Finally, I proceed, in the next section, to report the results from the computer software industry for study two.

Results for Computer Software Industry

Table 21 shows descriptive statistics and correlations for the computer software industry. I computed variance inflation factors to examine multicollinearity and found that all of the variance inflation factors (mean: 3.6, max: 7.1) were well below the threshold of 10 (Kennedy, 2003).

Table 22 shows the first stage logit model predicting the likelihood that the analyst will cover the firm. Model 1 from Table 22 shows that both the new variable for the number of firms in the firm's industry listed on the same stock exchange ($\beta = 0.0017$, $p < .001$) and the new variable measuring whether the firm is headquartered in New York ($\beta = -3.41$, $p < .001$) had a statistically significant effect on the likelihood that the analyst will cover the firm in the first stage model. This suggests that these new, first stage selection variables contributed to the analyst's coverage decision.

Table 23 shows the second stage model. The inclusion of the inverse mills ratio may cause the standard errors to be understated which can erroneously inflate the statistical significance of the coefficients and bootstrapping is one method to correct for

this potential issue (Hamilton & Nickerson, 2003). Models 1 through 3 in Table 23 report the logit results without the bootstrap correction and Model 4 reports the full model with the bootstrap corrected standard errors.

Proposition 7 predicted that when a firm explores more distant knowledge it will have a negative impact on the favorability of the analyst's recommendation for the firm. Model 4 from Table 23 does not offer support for this proposition for the computer software industry ($\beta = 0.23$, not significant). These findings do not support proposition 7 for the computer software industry.

Proposition 8 predicted that when a firm's approach to innovation emphasizes greater knowledge overlap between the firm and its rivals it will have a negative impact on the favorability of the analyst's recommendation for the firm. Contrary to this prediction, Model 4 from Table 23 shows a negative, non-significant, coefficient for knowledge overlap ($\beta = -0.52$, not significant). These results do not support proposition 8 for the computer software industry.

Proposition 9 and 10 predict contingency effects that attenuate the relationship between the exploration of distant knowledge and the likelihood that the focal analyst will increase the favorability of the recommendation for the firm. Proposition 9 predicts that the greater the analyst's experience, the less negative the effect that exploration of distant knowledge will have on the favorability of the recommendation. Proposition 10 predicts that the more extensively other firms covered by the analyst explore external

knowledge, the less negative the effect that exploration of distant knowledge will have on the favorability of the recommendation. Since the main effect of exploration of distant knowledge did not exert a statistically significant effect on the likelihood that the analyst will increase the favorability of the recommendation, these related contingencies are also not supported. Therefore, I also do not find any support for propositions 9 and 10 for the computer software industry.

One of the control variables had a significant effect on the securities analyst's decision to increase the favorability of the recommendation for the focal firm in the computer software industry. The average favorability of the recommendation that the firm received from securities analysts in the prior period had a positive influence on the likelihood that the firm would receive a more favorable recommendation from the focal analyst.

In the final section of this chapter, I report the results for propositions 11 through 15, which correspond to study three of the dissertation. As discussed earlier, this study relates to medical device firms only.

ANALYSTS' RECOMMENDATIONS AND INVESTMENT – STUDY 3

Table 24 summarizes the empirical findings for propositions 11 through 15. This table shows that all five propositions from this study received empirical support. The results in this section correspond to the medical devices industry.

Table 25 reports descriptive statistics and correlations between the variables. I computed variance inflation factors to examine multicollinearity and found that all of the variance inflation factors (mean: 2.4, max: 5.4) were well below the threshold of 10.

Table 26 reports the logistic estimates of influences on the investor's hazard of increasing the investment in the focal firm. Proposition 11 predicted that the hazard that the investor will increase ownership in the focal firm increases the greater the disagreement among securities analysts' recommendations about the focal firm. Even after controlling for the favorability of securities analysts' recommendations, I find that the coefficient on 'Standard deviation of securities analysts' recommendations' is positive and statistically significant ($\beta = 0.26$, $p < .001$), showing that the greater the disagreement among securities analysts' recommendations (i.e., the lower the level of consensus), the greater the hazard that the focal investor will increase ownership in the focal firm. These findings strongly support proposition 11.

Propositions 12 through 15 involve moderating variables that exacerbate the main relationship between lack of consensus and increased investment. Propositions 13 and 14 deal with contingencies related to the focal investor. Propositions 14 and 15 deal with contingencies related to the focal firm's innovation strategy. In support of these propositions, the four graphs in Figures 13 through 16 suggest differences in the slope for high investor's industry experience, time horizon, firm's innovation scope and firm's ability to commercialize innovations, lending support for these contingent effects.

For each of the four contingencies, I also conducted a split sample econometric test. Proposition 12 predicts that the focal investor's industry experience will exacerbate the positive influence of disagreement among securities analysts' recommendations on the likelihood that the focal investor will increase ownership in the focal firm. To find support for this proposition requires that the split sample econometric test shows that the marginal effect of analyst disagreement on investment is significantly more positive for high levels of investor industry experience than it is for low levels of investor industry experience. Results of models 1 and 2 in Table 27 show that high levels of investor's industry experience made investors more likely to buy shares in the firm when analysts disagreed (t = 4,700; $p < .001$). Accordingly, the split sample econometric test offers support for proposition 12.

Proposition 13 predicts that the focal investor's time horizon will exacerbate the positive influence of disagreement among securities analysts' recommendations on the likelihood that the focal investor will increase ownership in the focal firm. To find support for this proposition requires that the split sample econometric test shows that the marginal effect of analyst disagreement on investment is significantly more positive for high levels of investor time horizon than it is for low levels of investor time horizon. Results of models 1 and 2 in Table 28 show that high levels of investor's time horizon made investors more likely to buy shares in the firm when analysts disagreed (t = 1,000; $p < .001$). This test supports proposition 13.

Proposition 14 predicts that the scope of the firm's innovation portfolio will increase the positive effect of disagreement among securities analysts' recommendations on the likelihood that the focal investor will increase ownership in the focal firm. To find support for this proposition requires that the split sample econometric test shows that the marginal effect of analyst disagreement on investment is significantly more positive when the focal firm's innovation scope is high than when the focal firm's innovation scope is low. Results of models 1 and 2 in Table 29 show that high levels of innovation scope increased the likelihood that investors would buy shares in the firm when analysts disagreed (t = 3,200; $p < .001$). This test offers support for proposition 14.

Finally, proposition 15 predicts that the firm's ability to commercialize innovations will exacerbate the positive influence of disagreement among securities analysts' recommendations on the likelihood that the focal investor will increase ownership in the focal firm. To find support for this proposition requires that the split sample econometric test shows that the marginal effect of analyst disagreement on investment is significantly more positive when the focal firm's ability to commercialize innovations is high than when this ability is low. Consistent with this predictions, results of models 1 and 2 in Table 30 show that high ability to commercialize innovations increased the likelihood that investors would buy shares in the firm when analysts disagreed (t = 3,400; $p < .001$). Therefore, proposition 15 is also supported.

Therefore, the results of the graphical analysis for study 3 are fully corroborated by the split sample econometric tests shown in Tables 27 through 30.

Many of the control variables had a significant effect on the focal investor's decision to increase her stake in the focal firm. Consistent with prior studies (e.g., Womack, 1996), the average favorability of securities analysts' recommendations for the focal firm increased the likelihood that the focal investor bought additional shares in the focal firm. Firm size, average share price, the firm's share of products in its product categories, its average product age, R&D spending and ability to commercialize innovations all positively contributed to the likelihood that the focal investor increased ownership in the firm. Additionally, investor-specific controls related to the focal investor's experience, size of portfolio, level of diversification and prior investment in the focal firm also positively influenced the decision to increase ownership in the focal firm. All three of the macroeconomic controls were also significant, with inflation and the risk-free rate increasing the hazard of increased investment and the index level of US-based equities decreasing the hazard of increased investment. Finally, the focal firm's annual dividend was also negatively related with the hazard of increased investment.

Chapter 8: Sensitivity Analyses and Robustness Checks

I have conducted various sensitivity analyses to explore the robustness of the empirical findings for the main hypothesized effects across each of the three studies. In the subsections below, corresponding to the three studies of the dissertation, I describe the supplemental analyses that I have conducted to increase confidence in the initial findings for studies one and three and to probe the non-findings for study two.

APPROACH TO INNOVATION AND ANALYSTS' COVERAGE – STUDY 1

Robustness to Alternative Sampling Frames

A potential concern may be that the results discussed above for study one are specific to the selection of analysts and firms included in the sampling frame. By including any analyst employed by a brokerage house that has previously provided coverage for any firm in the three industries it is possible that the sampling procedure is including analysts who are dedicated to other industries and who, therefore, may never realistically even consider covering a firm in the medical devices or computer industries. The inclusion of these analysts who are not active in the focal industries may be problematic as it may inflate the number of zeros in the sample, which can bias estimates. To help account for this possibility, I ran additional models on a reduced sample of analysts who had themselves previously covered one the three industries under consideration. This alternative sampling procedure reduced the number of analysts from more than 2,500 to less than 100 across each of the three industries (computer hardware,

computer software and medical devices). Model 1 in Table 31 shows consistent results for propositions 1 through 3 for the medical devices industry. Model 2 in Table 31 shows support for propositions 2 and 3 for the computer hardware industry, but not for proposition 1. Finally, for the computer software industry, model 3 from Table 31 only supports proposition 1. Overall, these models based on the alternative sampling frame for analysts support the majority of the main propositions for study one.

As mentioned above, another potential issue with the sampling approach employed in the dissertation relates to the choice of firms included in the three industries. While the computer software industry is mostly comprised of firms in the 7372 SIC code (e.g., Lavie, 2007), the computer hardware and medical devices industries span multiple SIC codes and have been constructed using a variety of different groups of SIC codes in prior studies (e.g., Henderson, Miller & Hambrick, 2006; Iyengar & Zampelli, 2009). To help account for the possibility that the results may be influenced by the specific set of SIC codes that I have selected to include, I have constructed alternate industry groupings for the medical devices and computer hardware industries.

For the medical devices industry, I expanded the industry scope from the 3841 and 3842 SIC codes that were included in the main analysis to also include firms in the 3443, 3844 and 3845 SIC codes (Kor, 2003; 2006). This alternative sampling procedure roughly doubled the number of medical devices firms from about 50 to more than 100.

Model 1 in Table 32 shows robust results when using this more expansive industry definition of the medical devices industry.

For the computer hardware industry, I reduced the number of SIC codes from 3570 through 3579 to consider a more narrow industry scope, based on SIC 3570 through 3572 (Henderson, Miller & Hambrick 2006). This alternative sampling procedure reduced the number of computer hardware firms from about 70 to about 20. Model 2 in Table 32 shows consistent results when considering this narrower definition of the computer hardware industry.

Robustness to Alternative Measures

In addition to the efforts taken to examine whether the results in study one are robust to different sampling approaches, it is also important to understand whether these results are robust to an alternative measure of the key independent variable for knowledge distance. As mentioned previously, prior studies have used different measures of exploration of distant knowledge (e.g., Sorenson & Stuart, 2000; Rosenkopf & Nerkar, 2001; Benner & Tushman, 2002; Katila & Ahuja, 2002). In conjunction with the reported measure based on repeat citations as a percentage of total citations, I also report below a logit model that uses a different measure based on the firm's citation of internal knowledge (i.e., cites to the focal firm's own patents) divided by total citations. Models 1, 2 and 3 in Table 33 show the full logit model for the medical devices, computer hardware and computer software industries using this alternative measure of

knowledge distance. Although model 2 in Table 33 shows robust results to this alternative measure of knowledge distance for the computer hardware industry ($\beta = -2.43$, $P < .001$), the results shown in models 1 and 3 for the medical devices and computer software industry are not robust to this different measure of knowledge distance.

Robustness to Alternative Model Specifications

There is also the possibility that the results for study one are somehow influenced by the model specification that I have selected. Consequently, it is important to explore whether alternative model specifications will produce consistent findings. Toward this end, Tables 34, 35 and 36 report three additional model specifications for each of the medical devices, computer hardware and computer software industries. Given the low frequency with which analysts cover firms in the sample (i.e., less than 1%), it is appropriate to test robustness to model specifications for rare or low frequency events. With this goal in mind, I have run models identical to the ones reported above based on complementary log-log (Allison, 1995; Long, 1997) and rare events logistic regression (King & Zeng, 1999).

It is also a possibility that unobserved differences across analysts may somehow relate in a systematic fashion to the firm's approach to innovation and the analysts decision to provide or withhold coverage to the focal firm. To help mitigate this concern, I also report robustness to a logit model with analyst fixed effects, which captures time invariant heterogeneity across analysts. In Tables 34, 35 and 36 below, model 1 is

complementary log-log (cloglog), model 2 is rare events logit (relogit) and model 3 is fixed effects logit.

Table 34 reports complementary log-log, rare events logit and analyst fixed effects models for the medical devices industry. For the medical devices industry these alternative model specifications produced fully consistent results in support of propositions 1, 2 and 3.

Table 35 reports these same models for the computer hardware industry. For the computer hardware industry these alternative model specifications produced consistent results in support of propositions 2 and 3.

Finally, Table 36 reports these models for the computer software industry. In comparison to the main logit model reported above, the cloglog model (model 1) and the relogit models (model 2) generated comparable results in support of propositions 1 and 2. The fixed effects model (model 3) only offered support for proposition 1. On balance, the robustness tests to alternative model specifications produced results that were consistent with the main logit models for the computer software industry.

Now that I have discussed the robustness tests for study one, I turn next to consider the results for study two.

APPROACH TO INNOVATION AND RECOMMENDATIONS – STUDY 2

In the previous section I conducted sensitivity analyses to assess the robustness of the empirical findings reported for study one. In contrast, this current section uses

sensitivity analyses to probe the lack of empirical findings for study two. Specifically, I examine whether the failure to find empirical support for propositions 7 though 10 may somehow be influenced by the sample, measures or model specification that I used in the main analysis reported in the results section above. Since the bootstrap corrections in the report models were not significantly different from the uncorrected models, I did not bootstrap correct the standard errors in the robustness tests reported below.

Robustness to Alternative Sampling Frames

As a first step, I consider whether the manner in which I constructed the industry groupings for the medical devices and computer hardware industries contributed to the absence of results. Table 37 shows logit models based on different industry definitions for the medical devices (model 1) and the computer hardware industries (model 2). Analogous to the approach described above for study one, I have expanded the number of medical devices firms to included SIC 3841 through 3845 and have reduced the number of computer hardware firms to only include SIC 3570 through 3572. As models 1 and 2 in Table 37 show, the coefficients for knowledge distance and knowledge overlap continue to be statistically insignificant when using these alternative industry definitions.

Robustness to Alternative Measures

It is also important to consider whether the lack of empirical support for study two may be related to the measures that were selected. Consequently, I have run a robustness test using a different measure of exploration based on the focal firm's self-citations

divided by its total citations made during the previous 5 years (Sorenson & Stuart, 2000; Rosenkopf & Nerkar, 2001).

Table 38 reports the full models for each of the three industries based on this alternative measure. Models 2 and 3, corresponding to the computer software and the computer hardware industries, continue to show non-significant coefficients for knowledge distance and knowledge overlap when using the alternate measure of distance. Similarly, Model 1 from Table 38, which shows a logit model for the medical devices industry with an alternate measure of knowledge distance, also continues to find no support for knowledge distance (proposition 7), while showing significant results for knowledge overlap in proposition 8 ($\beta = -2.15$, $P < .05$). Overall, the continued lack of support for the main propositions in study two when employing this alternative measure of knowledge distance suggests that the lack of empirical support for study two is not merely due to the measures that I have chosen.

Robustness to Alternative Model Specifications

It may also be the case that the estimation procedure or the choice of a dichotomous dependent variable may contribute to the lack of findings in study two. To help rule out these possibilities I have run an alternative regression model with a continuous version of the dependent variable based on the average recommendation that the focal firm received from the securities analyst. Analysts' recommendations are reported on a scale from "1 – Stong Buy" to "5 – Sell". Therefore, higher values of this

alternative dependent variable reflect less favorable recommendations. Model 1 from Tables 39, 40 and 41 shows the results of this regression model for the medical devices, computer hardware and computer software industries respectively.

In these same tables I also report robustness to a firm fixed-effects logit model based on the dichotomous version of the dependent variable. Including fixed effects at the level of the firm should help to reduce the potential concern that I am not finding results due to a failure to control for time invariant heterogeneity across firms. Model 2 from Tables 39, 40 and 41 shows the results of this fixed effects logit for the medical devices, computer hardware and computer software industries respectively.

Model 1 from Tables 39, which reports a regression model based on a continuous version of dependent variable, shows results consistent with the ones reported above. The fact that coefficients on knowledge distance and knowledge overlap continue to be non-significant using this alternative specification helps to further increase confidence in the insignificance of the reported results. The firm fixed-effects logit models, which help capture potential time invariant heterogeneity across firms, also points to a lack of significance in the coefficients for knowledge distance and knowledge overlap. Hence, model 2 from Tables 39 shows consistently non-significant findings for the medical devices industry.

Model 1 from Tables 40, which reports a regression model based on a continuous version of dependent variable for the computer hardware industry, continues to show

insignificant results for this industry. The firm fixed-effects logit model reported in model 2 from Table 40, however, does offer support for proposition 7 ($\beta = -3.97$, $P < .01$), while still failing to offer support for proposition 8.

Turning to the results of the computer software industry, model 1 from Table 41 reports a regression model based on a continuous version of dependent variable. While the coefficient for knowledge distance in proposition 7 remains insignificant, the coefficient for knowledge overlap in proposition 8 ($\beta = 0.52$, $P < .05$) becomes significant in the hypothesized direction in this regression model. I also ran a firm fixed-effects logit model to help capture potential time invariant heterogeneity across firms that may affect the results. The lack of significance in the coefficients for knowledge distance and knowledge overlap in model 2 from Table 41 corroborates the lack of findings of the main logit models reported above.

In conjunction with the other robustness tests that I discuss above, I also explored the possibility that the failure to find empirical support may somehow result from a misspecification of the original theoretical model. For all three industries, the models reported in Tables 17, 20, and 23 show that the control variable for the average analyst recommendation had a significant influence on the likelihood that the focal analyst would increase the favorability of the recommendation for the focal firm. Since it is possible that the inclusion of this highly significant control variable could be masking the influence of knowledge distance and knowledge overlap on the likelihood that the analyst

will increase the favorability of the firm's recommendations, I ran models excluding the control for the average favorability of analysts' recommendations. The main effects of knowledge distance and knowledge overlap, however, continued to be insignificant even when dropping this control variable from the models. This additional step reduces the possibility that the failure to find empirical support is being driven by the model specification. Overall, the results of the multiple robustness and sensitivity tests conducted in this section corroborate the lack of findings for propositions 7 through 10. In the next section I explore the robustness of the results reported in study three.

ANALYSTS' RECOMMENDATIONS AND INVESTMENT – STUDY 3

Robustness to Alternative Model Specifications

In addition to the logit model upon which the results of study three were based, I have also run sensitivity analyses to alternative model specifications. Table 42 robusts robustness to complementary log-log (model 1), rare events logit (model 2) and firm fixed effects logit models (model 3). This table shows that the predicted relationship between analyst disagreement and investment is fully robust across these different model specifications.

Robustness to Alternative Dependent Variables

Study three examines the influence of analyst disagreement on the likelihood that an investor will either buy shares in the firm for the first time or will increase the number of shares that she already holds in the focal firm. While the shares that investors purchase

may in some cases coincide with new equity issued by the focal firm, in other cases investors may simply purchase shares that are sold by other investors. Thus, a potential concern is that disagreement may predict both sales and purchases of the focal firm's shares by investors.

I have taken various steps to address this potential concern. I ran models with other variations of the dependent variable. For example, I considered whether analyst disagreement would increase the likelihood that a firm could attract new investors that did not already own shares in the firm. I also considered whether analyst disagreement would increase the likelihood that a firm could attract new investment from existing investors who already held shares in the firm. Models 1 and 2 in Table 43 show that the positive relationship between analyst disagreement and the firm's ability to attract investment remained robust to these alternative measures of the dependent variable based respectively on new and existing investors.

I also ran an identical model to the ones reported predicting the likelihood that the focal investor will sell her shares in the focal firm in response to securities analyst disagreement. See model 1 in Table 44. Not only did analyst disagreement not significantly predict the likelihood that an investor would sell shares in the focal firm, but the sign of the coefficient in this model changed from positive to negative. The results of this supplementary analysis helps to mitigate the potential concern identified above by

providing some evidence that sales and purchases do not respond identically to disagreement among securities analysts' recommendations.

Taken together, these robustness tests help to assuage potential concerns that the reported findings for study three are merely an artifact of the model specification or the dependent variable that I selected for the analysis. Having discussed the different sensitivity analyses and tests to examine the robustness of the findings across three studies of the dissertation, I now turn to the final chapter of the dissertation where I consider some of the potential implications of the results.

Chapter 9: Discussion and Conclusions

Strategy research highlights the innovative benefits that can accrue to firms that rely on an approach to innovation based on the use of diverse, distant, and distinctive knowledge. However, after firms have created innovations their ability to capture value from them often depends on the evaluations of outside parties. This dissertation explores the influence that an approach to innovation based on diverse, distant, and distinctive knowledge has on evaluations in financial markets. It also examines how disagreement among evaluations subsequently influences firms' ability to attract resources in financial markets. Table 45 summarizes the empirical findings across the three studies in the dissertation. Overall, this table shows that nine of the fifteen propositions across the three studies were supported.

Before considering the potential theoretical contributions that the dissertation offers to the literature on innovation and expert evaluations, it is important to briefly discuss the empirical findings. It is especially important to consider some possible reasons why some of the propositions in studies one and two were not supported.

DISCUSSION

Even though nine of the fifteen propositions were empirically supported, it is still important to consider potential reasons why I did not find support for six propositions across the first two studies of the dissertation. As mentioned above, four of the six propositions for study one were empirically supported. Furthermore, most of these

propositions that received support were robust when considering alternative sampling approaches for analysts and firms and when employing different model specifications. It is nonetheless worthwhile to consider some possible reasons why the contingent effects in propositions 4 and 5 were not supported and why the coefficients had a significant effect in the opposite direction.

Proposition 4 predicted that when there is more knowledge overlap between the analyst and the firm, exploration of distant knowledge will have a less negative influence on the likelihood that a securities analyst will cover the firm because analysts are more familiar with the distant knowledge upon which the firm is building. However, contrary to this prediction, I found that greater knowledge overlap between the firm and the analyst had the opposite effect by making the analyst even less likely to provide coverage for firms that engage in exploration.

One possible explanation for this finding may be that exploration diminishes the value of analysts' own knowledge base more when there is greater knowledge overlap between the analyst and the firm. It is possible that covering firms that engage in exploration of distant knowledge may simultaneously prevent securities analysts from fully utilizing their knowledge overlap with the firm, while also requiring them to invest additional time and resources developing an understanding of the more distant knowledge upon which the firm is building. For both of these reasons, analysts may be less willing to cover firms that engage in exploration when their knowledge overlaps with that of the

firm since it requires greater effort on their part while simultaneously making them less able to utilize the knowledge that they already possess.

Another possible explanation for these findings is that greater knowledge overlap may increase securities analysts' awareness of the potential risks that exploration entails (March, 1991). This might also help explain why analysts with greater knowledge overlap with the focal firm are less likely to provide coverage for the firm when it engages in exploration.

Proposition 5 predicted that the greater the innovation intensity of the firm's industry, the more that exploration of distant knowledge will decrease the likelihood that a securities analyst will cover the firm. In opposition to this prediction, the results suggest that greater innovation intensity made securities analysts even more likely to provide coverage to a firm that engaged in exploration. An explanation for this finding may relate to the fact that the desirability and value associated with exploration can depend on characteristics of the environment in which firms operate. Since exploration can be especially valuable in dynamic, innovation-intensive contexts (Uotila et al., 2009), analysts may be more inclined to provide coverage to firms that engage in exploration when these firms operate in a high innovation-intensity environment where exploration is most likely to pay off. Therefore, under these circumstances, the benefits associated with being an analyst who is covering a more profitable firm could offset the risks associated with not being as able to accurately evaluate the firm engaged in exploration. If this

conjecture is correct, this would help to explain why an analyst is more likely to provide coverage to a firm engaged in exploration when the innovation-intensity of the industry is high.

I shift next to discussing the lack of results for study two. As discussed previously, all four of the propositions relating a firm's approach to innovation and the favorability of securities analysts' recommendations were not supported in the medical devices, computer hardware and software industries. Furthermore, these findings remained non-significant even when considering a different sampling frame, a different measure of one of the key independent variables and when using several alternative model specifications. Although the lack of results may not be very informative when viewed in isolation, some potential lessons may emerge when these findings are viewed in combination with the results of study one.

In particular, the fact that securities analysts responded to the firm's approach to innovation when making coverage decisions, but not when making recommendations may help us to better understand how analysts evaluate innovation. One possible reason that securities analysts may attend to these aspects of a firm's approach to innovation when making coverage decisions, but not when making recommendations, may be due to the fact that analysts have better access to information about firms that they are already covering. Prior literature suggests that securities analysts sometimes obtain the information that they use for evaluations directly from firms' managers (Baldwin & Rice,

1997). Perhaps, the personal relationships that securities analysts covering a firm develop with managers enable them to obtain richer internal information that reduces the need to interpret external signals related to the firm's approach to innovation. If this conjecture is correct, it may help to explain why securities analysts respond to external information about the firm's approach to innovation prior to covering a firm, but not after they are already covering the firm.

Another possibility is that the type of external information that securities analysts pay attention to and use to make recommendations may change after they begin covering a firm. For example, it is possible that analysts may pay attention to a firm's knowledge distance and knowledge overlap when they are trying to generally determine how successful they will be evaluating a firm if they decide to cover it. However, once analysts are already covering a firm, they may require finer-grained information about the firm's approach to innovation in order to develop accurate buy/sell recommendations. Thus, rather than broadly considering exploration or knowledge overlap when developing their recommendations, analysts already covering a firm may, for example, consider ways in which the firm balances exploration and exploitation (Benner & Choi, 2011) or other aspects of R&D that more fully comprehend the different costs and benefits trade-offs associated with innovation. In this section I have considered some possible reasons for the lack of empirical support for propositions across studies one and two. In the final sections, I discuss the theoretical contributions, potential limitations and conclusion.

THEORETICAL CONTRIBUTIONS

Innovation and Strategic Management

The dissertation makes contributions to the strategic management literature by drawing attention to a trade-off that a company may face when attempting to develop competitive advantage based on innovation. Somewhat paradoxically, it suggests that an approach to innovation based on the use of diverse, distant, and distinctive knowledge that is beneficial to a firm's efforts to develop knowledge-based resources may actually hinder its efforts to win the favorable evaluations needed to attract critical inputs from outside parties.

An additional contribution of this research is to further understanding of the role that financial intermediaries may play in the evolution of technology. Prior literature suggests that firms often favor the use of existing knowledge because of the inertia that results from the persistence of internal routines (Nelson & Winter, 1982; Helfat, 1994). In addition to these internal pressures related to firms' own routines, other studies show that firms may also face external pressures to avoid developing knowledge in new technological areas that emanate from their customers (Christensen & Bower, 1996). This current study adds to an emerging stream of literature about the influence of financial intermediaries on innovation (e.g., Benner, 2010; Benner & Ranganathan, 2012). By showing that securities analysts are less likely to provide coverage for firms that build on more diverse, distant or distinctive knowledge, this study may help to advance

understanding of the role that financial markets can play as a selection environment for a firm's innovations.

Finally, the theory about how analysts' assessments influence firms' ability to attract investors developed in study three also has potential implications for the strategy literature. Importantly, I highlight the role that investor and firm heterogeneity exert on the influence of securities analysts' recommendations and show that the firm's innovation strategy is an important factor that can be used in conjunction with securities analysts' recommendations to attract investors. In particular, this study draws attention to the relevance of internal innovation to external value assessments in selection environments. Recently, scholars have called for additional studies to understand how firms can influence the amount of value that is assigned to their resources (e.g., Lepak, Smith & Taylor, 2007; Sirmon, Hitt & Ireland, 2007). This current research suggests that firms' innovation strategy may be one tool that firms can use to influence how much value outside parties assign to their resources.

Expert Evaluations and Financial Intermediaries

The dissertation also attempts to contribute to the management literature on financial intermediaries. Extant management literature is largely divided between studies that examine the consequences of being covered by securities analysts (Zuckerman, 1999; Pollock & Gulati, 2007) and other studies that explore the different strategies that firms can use to garner favorable evaluations from securities analysts who

are already providing coverage to the firm (e.g., Westphal & Clement, 2008). By focusing on these consequences of analyst coverage, these prior studies have largely overlooked the role that firm strategy plays in the decision of securities analysts to provide coverage in the first place. Consequently, an important contribution of this current study is to illuminate how a firm's innovation strategy can influence its ability to attract analyst coverage.

The dissertation also offers insights regarding the role of uncertainty in competitive contexts. Prior research has primarily emphasized the challenges that uncertainty creates for firms (e.g., Podolny, 1994; Beckman, Haunschild & Phillips, 2004) and suggests the important role that intermediaries play in mitigating uncertainty (e.g., Rao, 1994; Rindova et al., 2005). This current research shows that markets are not fully intermediated and that residual uncertainty among experts in financial markets may sometimes be beneficial to firms' efforts to attract critical external resources. Moreover, it also highlights potential trade-offs associated with using consensus to interact with outside parties. By broadening the focus of research from firms' competition with rivals for favorable evaluations to also consider external competition in selection environments among investors, the dissertation illuminates a potential downside of using consensus to attract external resources.

Finally, this research may also extend the literature on financial intermediaries by showing that the expert advice of intermediaries may be subject to greater scrutiny than

previously assumed. Prior literature has found that securities analysts' evaluations can lead investors to discount the value of firms' shares (e.g., Zuckerman, 1999; Benner, 2007), whereas this dissertation suggests that too much consensus among analysts' recommendations may sometimes also cause investors to discount the expert advice of securities analysts.

LIMITATIONS

It is important to acknowledge some potential limitations associated with this research. The first three limitations discussed below are especially relevant to studies one and two. These first two studies examine how securities analysts respond to medical devices and computer firms' approach to innovation. Since the medical devices and computer hardware and software industries are highly innovation-driven contexts that are subject to technological change, it is possible that these results may not fully generalize to less innovative industry contexts where firms are less subject to technological change and uncertainty. Consequently, it is possible that theory developed in this study is most applicable to other innovation-intensive industries (e.g., semiconductor, chemicals, robotics, pharmaceuticals, etc.), that are similar to the ones examined.

Second, because the dissertation focuses on the effect of a firm's approach to innovation on analysts' evaluations and the fact that securities analysts typically only provide coverage and recommendations for publically-traded firms, the theory is tested based on publically traded companies for which data are available in *COMPUSTAT*.

Since it is possible that smaller firms or privately held firms may differ from the ones that I have studied, caution should be exercised when generalizing this theory to different types of companies.

Finally, the fact that the dissertation assesses a firm's approach to innovation using patent data means that this current research shares the same limitations as all of the other studies that assess innovation via the patent records (e.g., Rosenkopf & Nerkar, 2001; Ahuja & Katila, 2004). For example, it is possible that a firm's approach to innovation may not be fully reflected in its patenting activities. In spite of the potential limitations associated with the use of patents, prior researchers have argued that patents can provide a valid measure of firms' innovative activity (e.g., Podolny & Stuart, 1995; Benner & Tushman, 2002). Although it cannot entirely be ruled out that the firm's approach to innovation may not be reflected in its patenting activity, the fact that firms in the medical devices and computer industries frequently file patents to protect their innovations (Levin et al., 1987) should help to partially assuage this concern since these firms have strong incentives to file patents.

It is also important to consider potential limitations associated with study three. As mentioned previously, this section of the dissertation uses data on large, institutional investors to assess the likelihood that an investor will buy additional shares in response to disagreement among securities analysts. Since professional institutional investors control portfolios valued in the hundreds of millions of dollars, they are likely to be more

knowledgeable and have greater resources to analyze investments than investors with smaller portfolios. Hence, it is possible that the theory developed in study 3 may not fully generalize across all classes of investors. In spite of this potential limitation, the fact that institutional investors hold the majority of U.S. equity (Hoskisson et al., 2002) and that significant heterogeneity exists across different types of institutional investors (Bushee, 1998) suggests that this theory may generalize to many different types of U.S. equity investors.

Another potential limitation of study 3 pertains to the use of the medical devices industry as the empirical context. Since medical devices firms are subject to governmental regulation from the Food and Drug Administration (FDA) (Birbaum, 1985), it is possible that FDA regulators may help to reduce the uncertainty that securities analysts and investors face when evaluating firms. Since the level of disagreement among securities analysts and the extent to which investors depend on securities analysts' evaluations may be influenced by the regulated nature of this industry context, it is important to entertain the possibility that the theory developed in study three may not fully generalize across industry contexts, especially to industries that are not subject to external oversight or governmental regulation.

In the final section, I provide a brief conclusion to the dissertation.

CONCLUSION

This dissertation illuminates important trade-offs that firms may face when attempting to develop competitive advantage based on innovation. Contrary to the benefits that prior studies associate with the use of diverse, distant, and distinctive knowledge to firms' efforts to create valuable resources (e.g., Rosenkopf & Nerkar, 2001; Ahuja & Katila, 2004), this dissertation shows that these aspects of firms' approach to innovation may entail costs related to greater difficulty gaining analyst coverage.

Furthermore, this dissertation also shows that too much consensus among analysts' recommendations may sometimes make it more difficult for firms to attract financial resources from investors. In doing so, this research challenges prevailing views on how firms interact with financial intermediaries. While many prior management studies suggest that the evaluations of financial intermediaries help to mitigate the uncertainty that outside parties face (e.g., Rao & Sivakumar, 1999; Beunza & Garud, 2007), this dissertation shows that these intermediaries may sometimes avoid evaluating the firms that are pursuing an approach to innovation that is most likely to create value for investors. Moreover, this research suggests that financial markets are not always fully intermediated by securities analysts. This lack of intermediation results both from securities analysts not providing coverage to all firms and from the disagreement that can exist across the recommendations that different securities analysts make for the firms that they do cover. This research shows that opportunities for investors may arise precisely

when financial markets are not perfectly intermediated. Specifically, the dissertation suggests that the uncertainty implied by disagreement among analysts may be an important signal of opportunities that investors consider in addition to the favorability of securities analysts' recommendations.

Overall, this dissertation highlights the importance of innovation to firms' efforts to attract evaluations and financial resources from outside parties by showing that innovation may not only be relevant to firms' efforts to attract the coverage of securities analysts, but that it may also be an important factor that shareholders use in conjunction with analysts' recommendations to make investment decisions. I hope that this research contributes to a more complete understanding of the role that expert evaluations play in firms' efforts to achieve competitive advantage from innovation.

Figures and Tables

Figure 1- Approach to Innovation and Analysts' Coverage

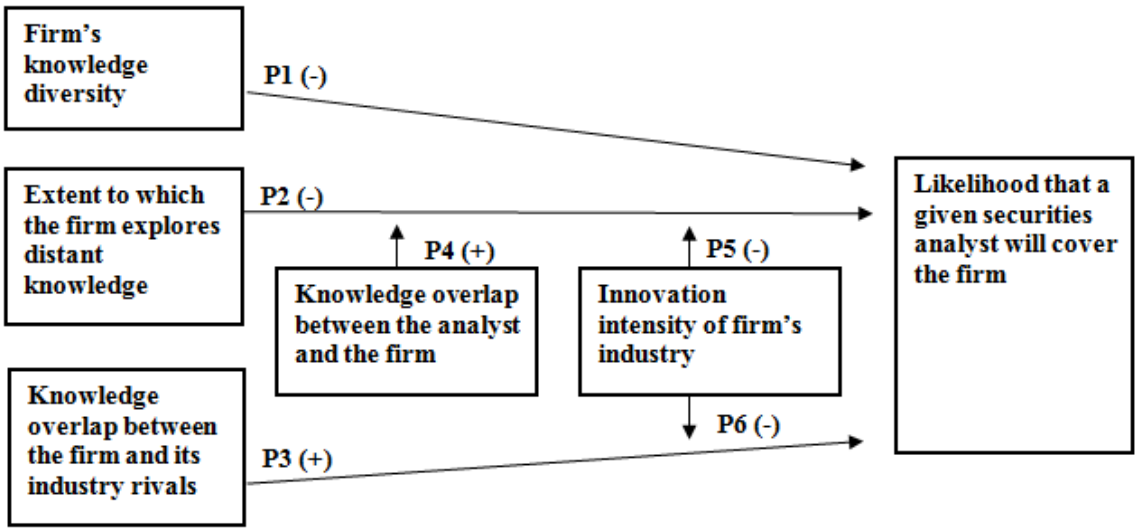

Figure 2 – Approach to Innovation and Analysts' Recommendations

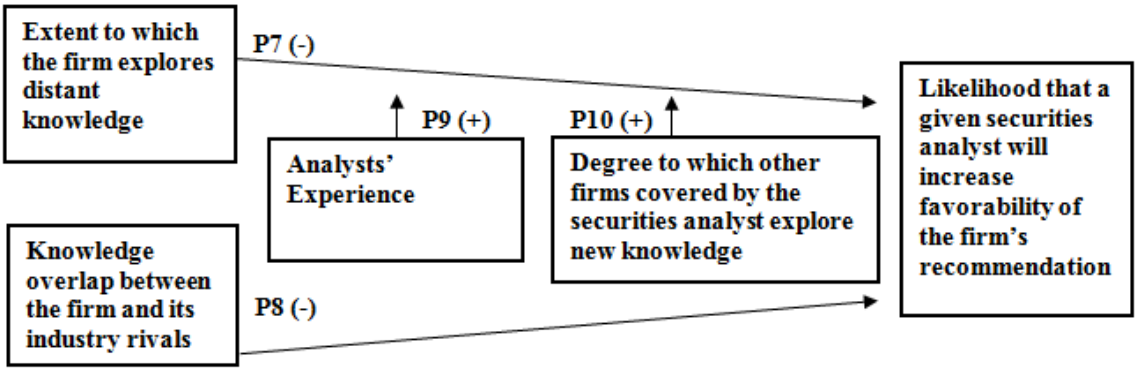

Figure 3 – Analysts' Recommendations and Investment

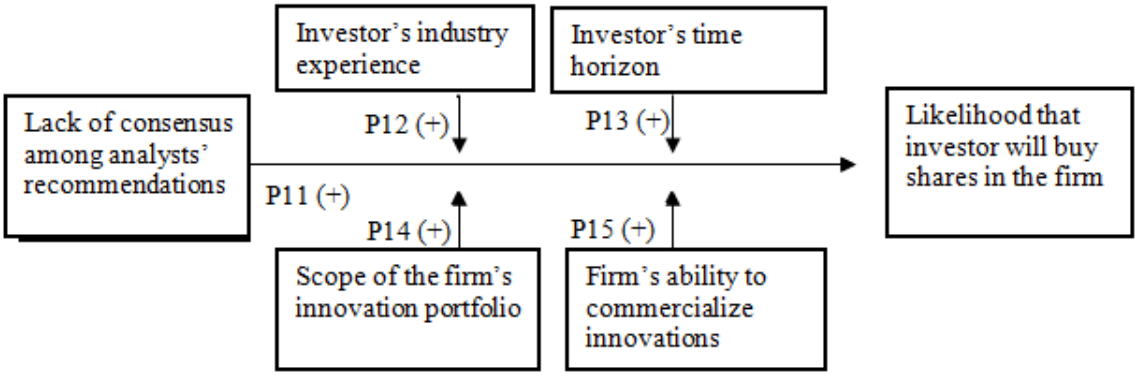

Figure 4: Contingent effect of knowledge overlap between the analyst and the firm on the relationship between exploration of distant knowledge and the firm's ability to attract analyst coverage (P4 - medical devices).

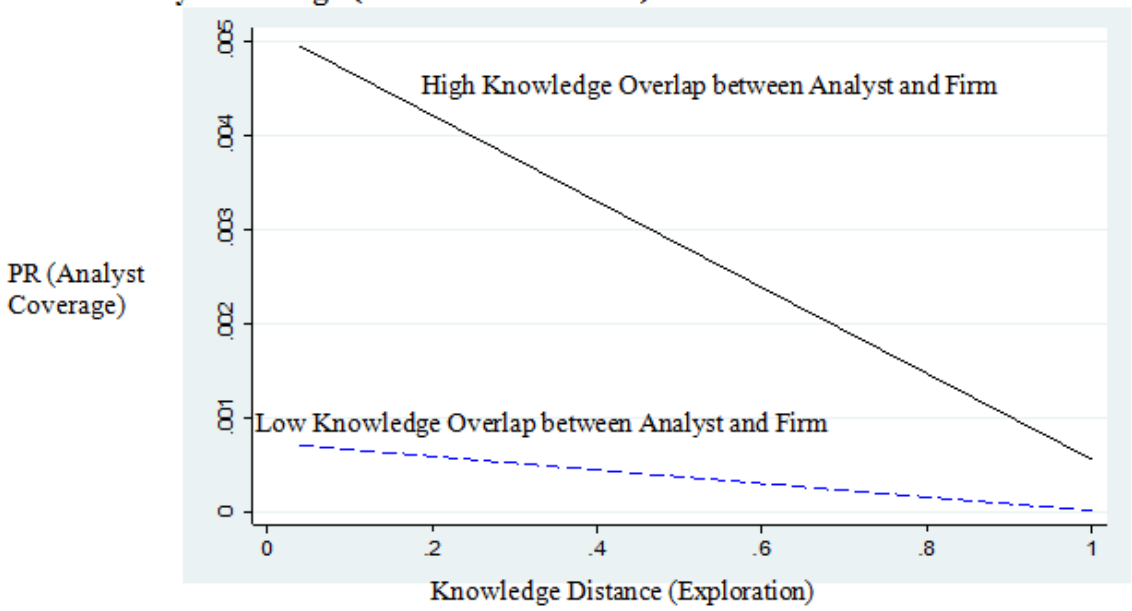

Figure 5: Contingent effect of industry innovation intensity on the relationship between exploration of distant knowledge and the firm's ability to attract analyst coverage (P5 - medical devices).

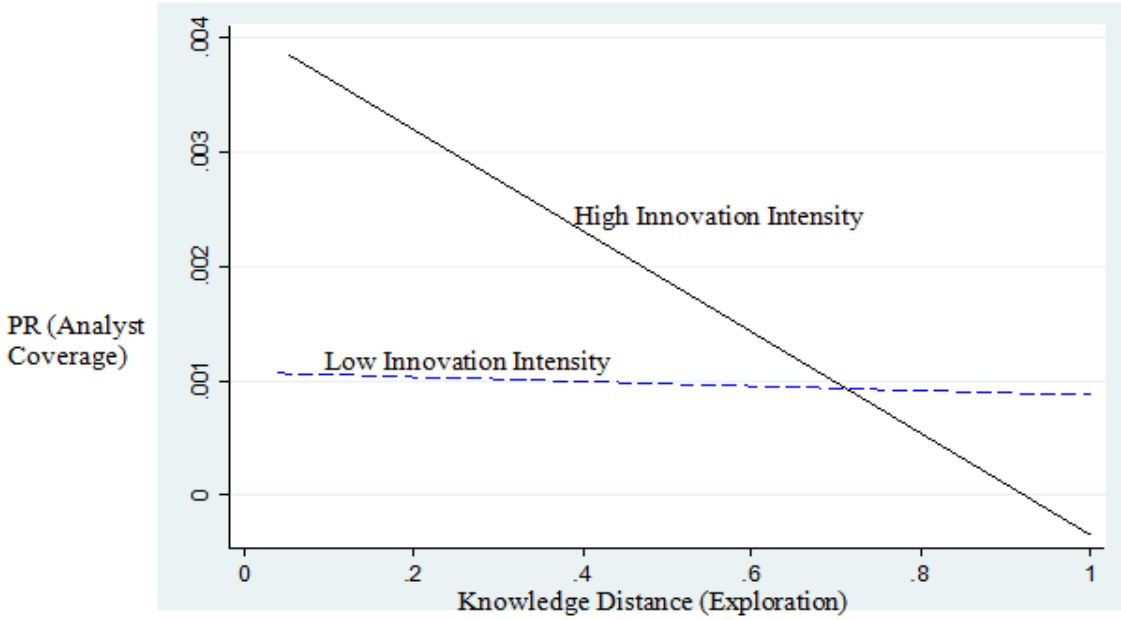

Figure 6: Contingent effect of industry innovation intensity on the relationship between firms' knowledge overlap with industry rivals and the firm's ability to attract analyst coverage (P6 - medical devices).

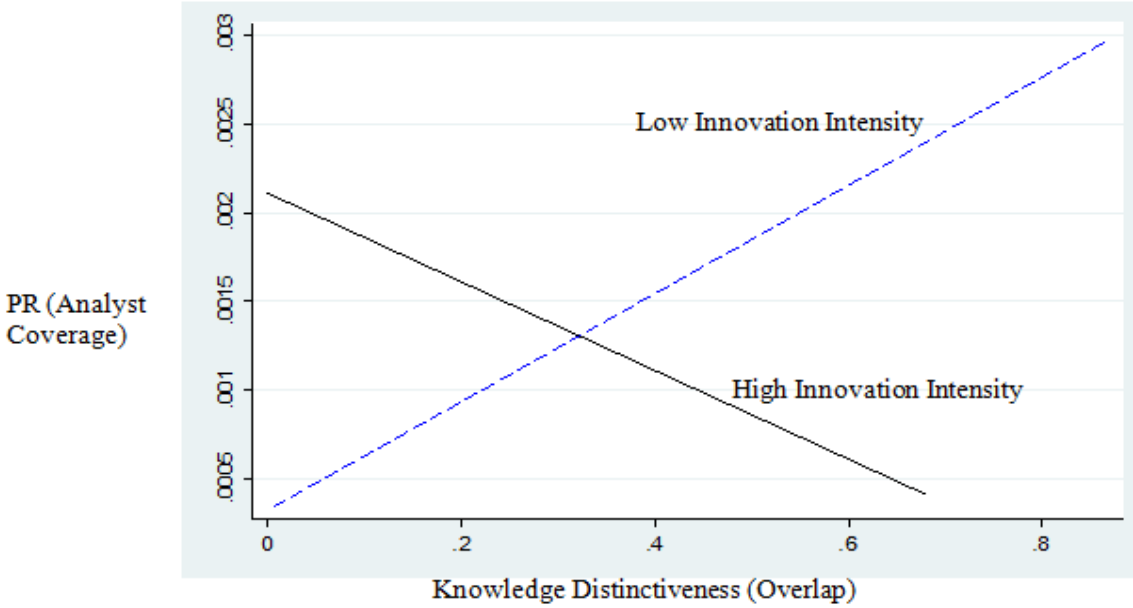

Figure 7: Contingent effect of knowledge overlap between the analyst and the firm on the relationship between exploration of distant knowledge and the firm's ability to attract analyst coverage (P4 - computer hardware).

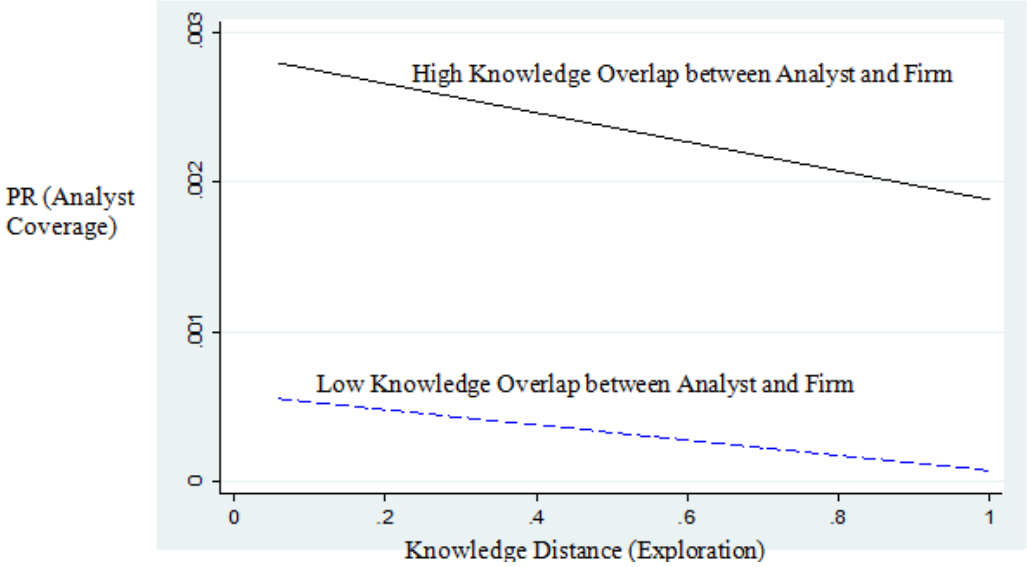

Figure 8: Contingent effect of industry innovation intensity on the relationship between exploration of distant knowledge and the firm's ability to attract analyst coverage (P5 - computer hardware).

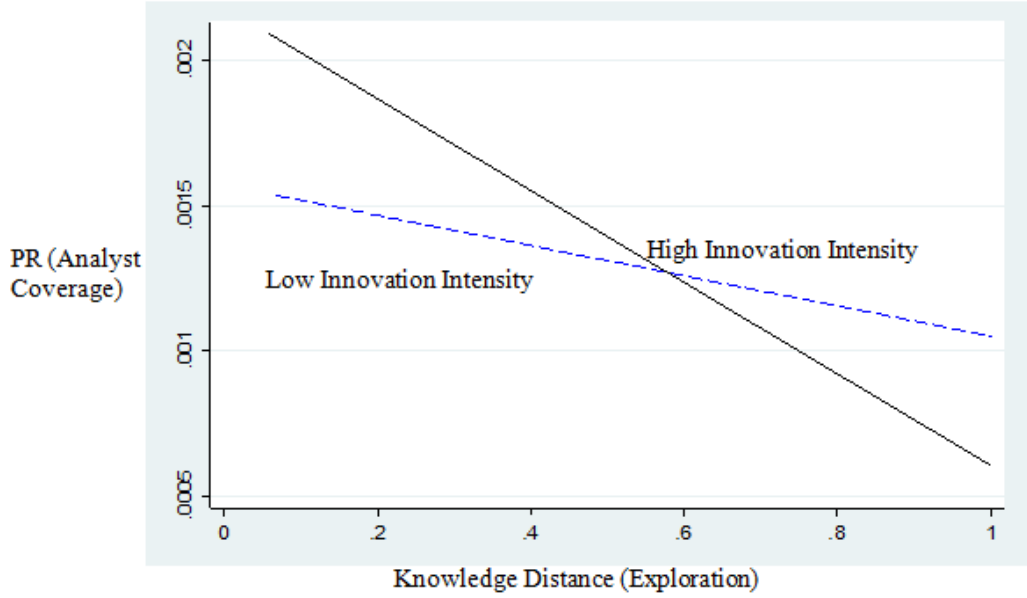

Figure 9: Contingent effect of industry innovation intensity on the relationship between firms' knowledge overlap with industry rivals and the firm's ability to attract analyst coverage (P6 - computer hardware).

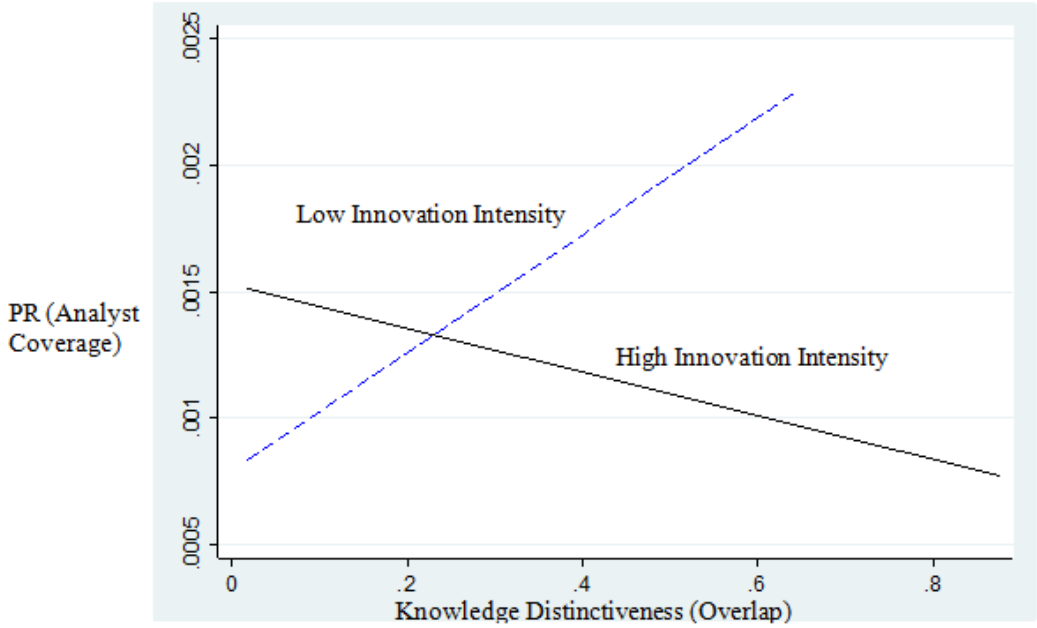

Figure 10: Contingent effect of knowledge overlap between the analyst and the firm on the relationship between exploration of distant knowledge and the firm's ability to attract analyst coverage (P4 - computer software).

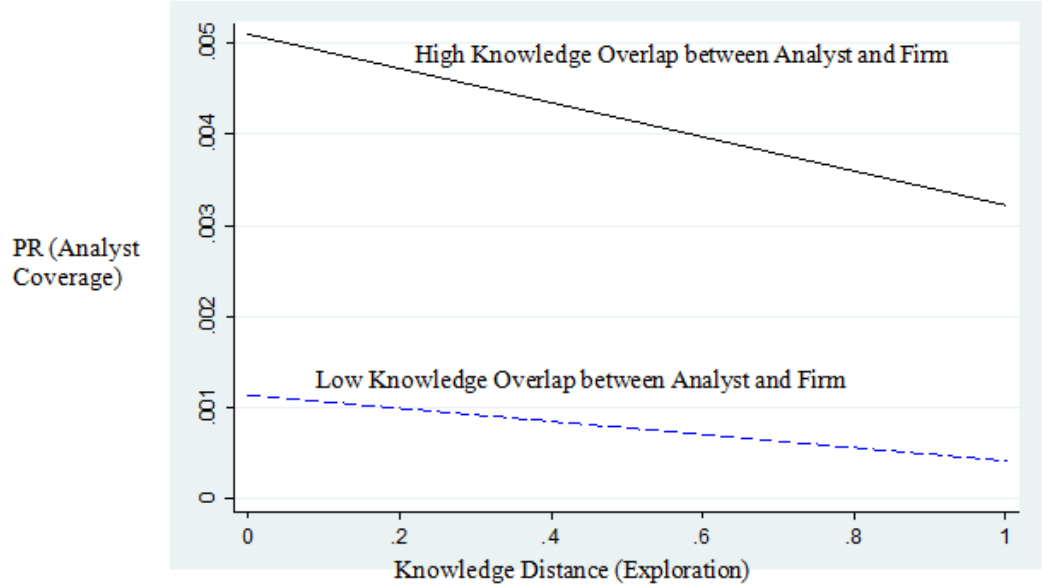

Figure 11: Contingent effect of industry innovation intensity on the relationship between exploration of distant knowledge and the firm's ability to attract analyst coverage (P5 - computer software).

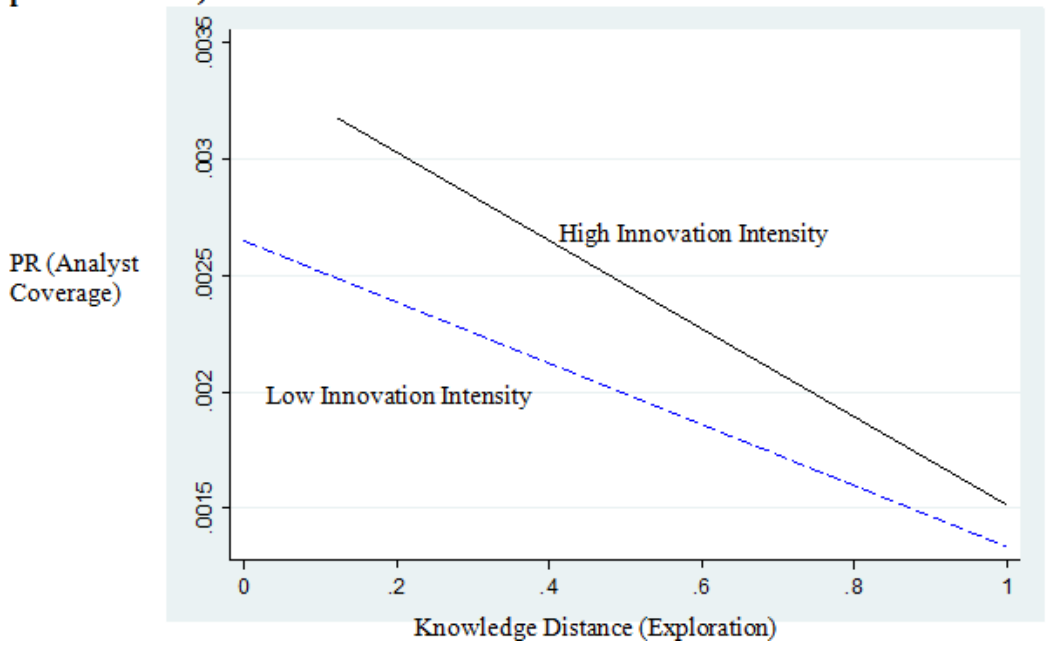

Figure 12: Contingent effect of industry innovation intensity on the relationship between firms' knowledge overlap with industry rivals and the firm's ability to attract analyst coverage (P6 - computer software).

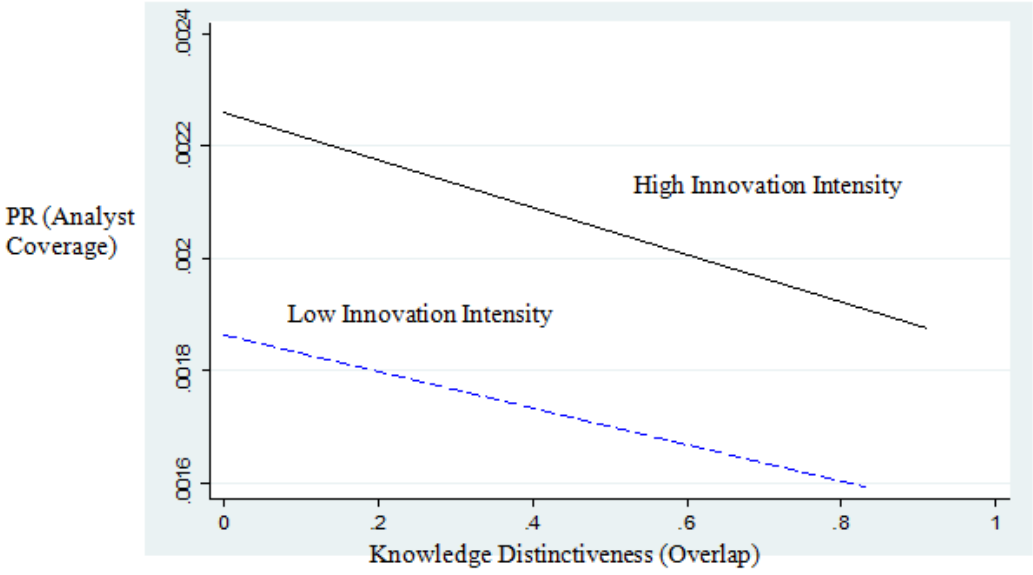

Figure 13: Contingent Effect of Investor's Industry Experience on the Relationship between Securities Analysts' Consensus and the Hazard that the Focal Investor will Increase Investment in the Focal Firm (P12).

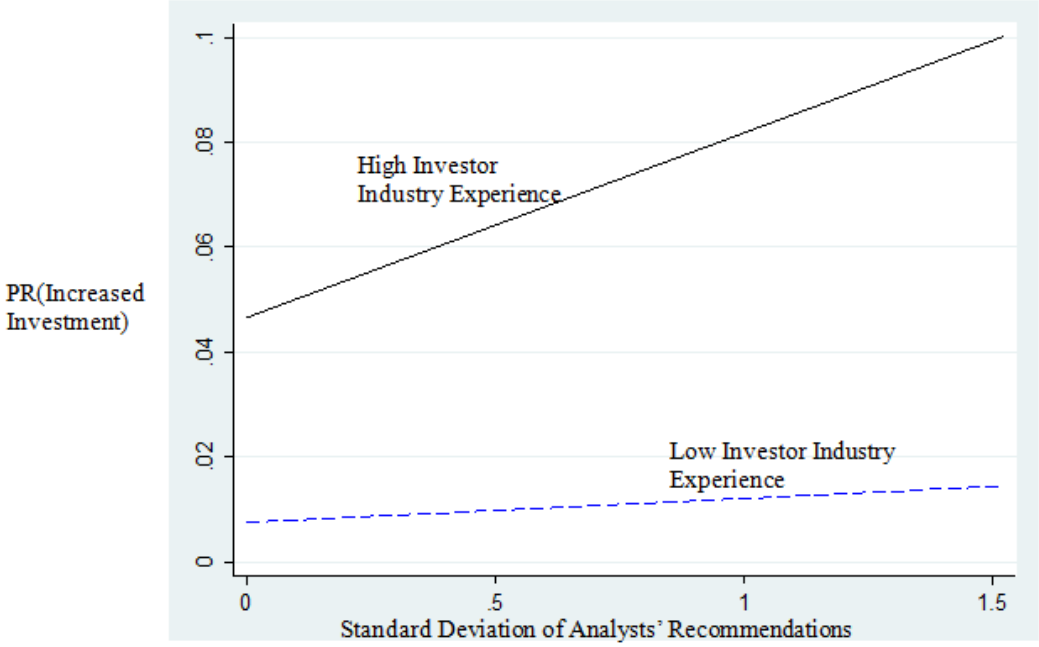

Figure 14: Contingent Effect of Investor's Time Horizon on the Relationship between Securities Analysts' Consensus and the Hazard that the Focal Investor will Increase Investment in the Focal Firm (P13).

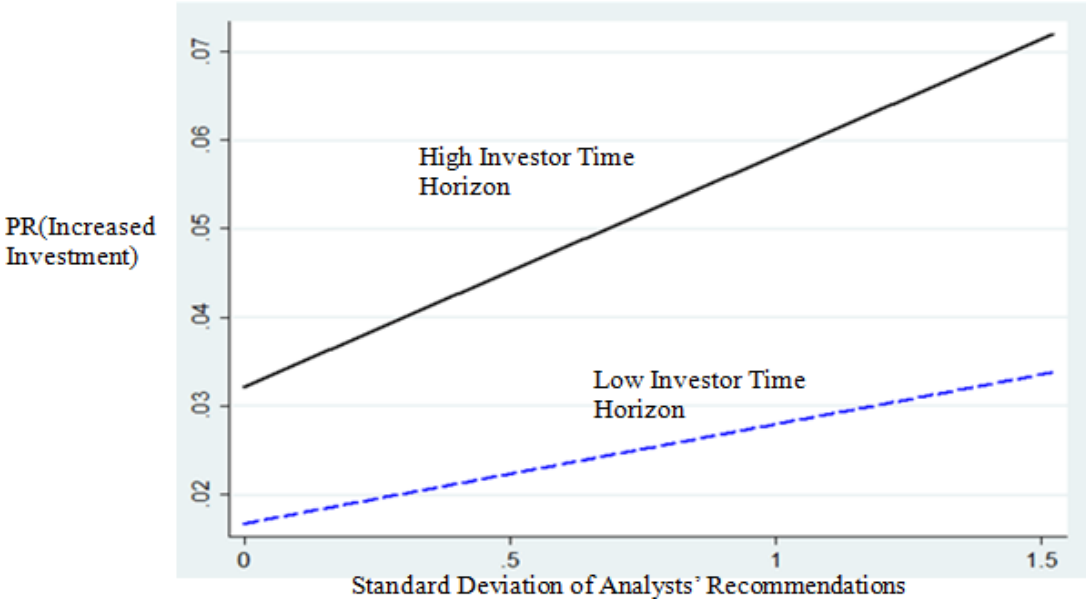

Figure 15: Contingent Effect of Innovation Scope on the Relationship between Securities Analysts' Consensus and the Hazard that the Focal Investor will Increase Investment in the Focal Firm (P14).

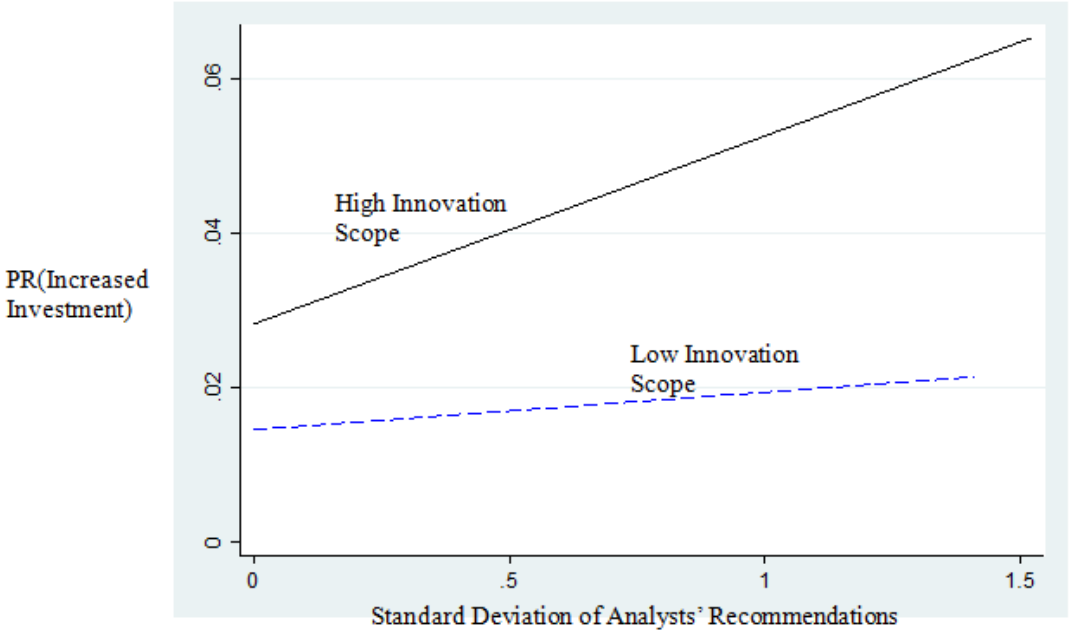

Figure 16: Contingent Effect of Firm's Ability to Commercialize Innovations on the Relationship between Securities Analysts' Consensus and the Hazard that the Focal Investor will Increase Investment in the Focal Firm (P15).

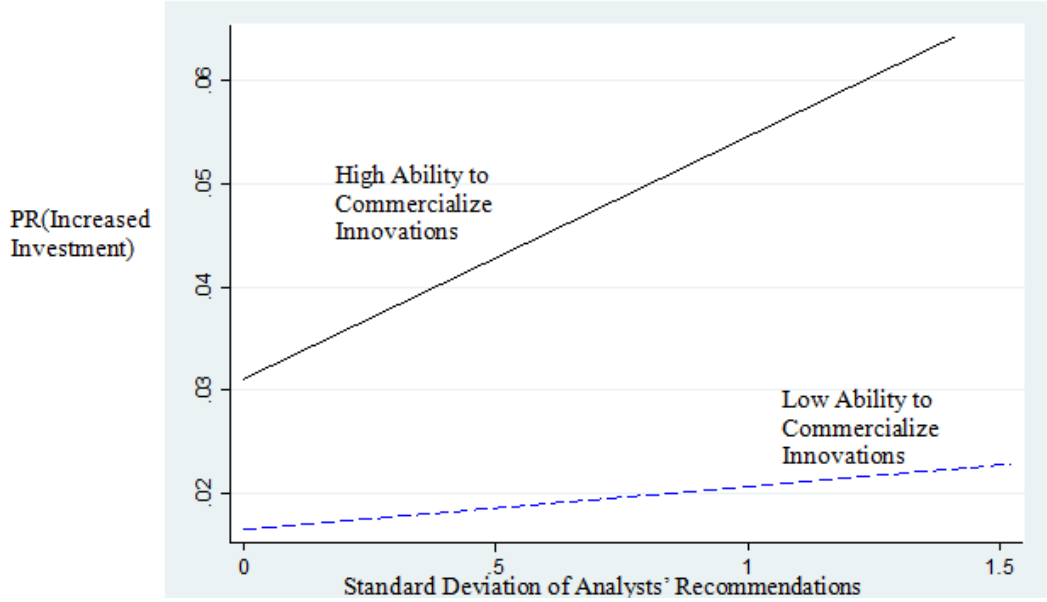

Table 1
Summary of Empirical Findings - Study 1
Propositions 1 -6

	Medical Devices	Computer Hardware	Computer Software	
Proposition 1 (P1): The greater the firm's knowledge diversity, the lower the likelihood that a securities analyst will cover the firm.	Yes	No	Yes	**Partially Supported**
Proposition 2 (P2): The more extensively the firm explores distant knowledge, the lower the likelihood that a securities analyst will cover the firm.	Yes	Yes	Yes	**Supported**
Proposition 3 (P3): The greater the knowledge overlap between the firm and its industry rivals, the greater the likelihood that a securities analyst will cover the firm.	Yes	Yes	No	**Partially Supported**
Proposition 4 (P4): The greater the knowledge overlap between the analyst and the firm, the less negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm.	No	No	No	**Not Supported**
Proposition 5 (P5): The greater the innovation intensity of the firm's industry, the more negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm.	No	No	No	**Not Supported**
Proposition 6 (P6): The greater the innovation intensity of the firm's industry, the less positive the effect of knowledge overlap between the firm and its industry rivals on the likelihood an analyst will cover the firm.	Yes	Yes	No	**Partially Supported**

Table 2
Descriptive Statistics For Medical Devices - Study 1
Medical Devices Industry (SIC 3841-3842)

Descriptive Statistics and Correlation Matrix

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1 Analysts Coverage	0.001	0.03												
2 Knowledge Diversity	5.06	6.97	0.00											
3 Knowledge Distance	0.55	0.22	0.00	-0.19										
4 Knowledge Overlap	0.25	0.19	0.01	-0.31	0.44									
5 Firm Performance	57.01	141.76	0.02	0.49	-0.01	0.06								
6 Firm Size	0.93	0.93	0.01	0.72	-0.05	-0.18	0.68							
7 Number of Analysts Covering the Industry	62.80	12.23	0.00	-0.02	0.04	0.11	0.05	-0.02						
8 Firm's Yearly Number of Patents	5.97	15.53	0.01	0.59	-0.20	-0.20	0.31	0.55	-0.24					
9 Firm's Technological Quality	5.06	2.33	0.01	0.57	-0.37	-0.26	0.47	0.69	-0.01	0.48				
10 Firm's Geographic Scope	1.71	1.47	0.00	0.69	-0.13	-0.27	0.53	0.82	-0.01	0.48	0.63			
11 Innovation intensity of firm’s industry	0.07	0.02	0.00	0.00	-0.11	0.10	-0.01	0.04	-0.10	0.04	0.10	0.00		
12 Knowledge overlap between the analyst and the firm	0.17	0.31	0.06	-0.01	-0.01	-0.02	0.00	-0.01	-0.05	-0.01	0.00	0.00	0.03	
13 Regulation FD (dummy)	0.57	0.50	0.01	0.00	0.08	0.18	0.18	0.05	0.55	-0.25	0.04	-0.01	-0.07	-0.05

Table 3
Logit Estimates on Coverage For Medical Devices - Study 1
Estimates of Analyst's Hazard of Covering the Focal Firm

	Medical Devices Industry (SIC 3841 & 3842)							
	Logit Model 1		Logit Model 2		Logit Model 3		Logit Model 4	
Knowledge Diversity (H1 < 0)			-0.05	***	-0.06	***	-0.04	***
			(0.01)		(0.01)		(0.01)	
Knowledge Distance (H2 < 0)					-1.00	***	-1.83	***
					(0.30)		(0.36)	
Knowledge Overlap (H3 > 0)							2.95	***
							(0.49)	
Control Variables								
Firm Performance	0.00	***	0.00	***	0.00	***	0.00	**
	(0.00)		(0.00)		(0.00)		(0.00)	
Firm Size	0.63	***	0.62	***	0.79	***	0.60	***
	(0.13)		(0.12)		(0.14)		(0.13)	
Number of Analysts Covering the Industry	0.01		0.01		0.01		0.01	
	(0.01)		(0.01)		(0.01)		(0.01)	
Firm's Yearly Number of Patents	0.01	**	0.01	***	0.01	***	0.01	***
	(0.00)		(0.00)		(0.00)		(0.00)	
Firm's Technological Quality	-0.01		0.01		-0.06		-0.02	
	(0.05)		(0.05)		(0.06)		(0.06)	
Firm's Geographic Scope	-0.30	***	-0.16	**	-0.17	**	-0.09	
	(0.06)		(0.06)		(0.06)		(0.06)	
Innovation intensity of firm's industry	2.31		-2.86		-3.24		-7.66	
	(5.45)		(5.79)		(5.81)		(5.90)	
Knowledge overlap between the analyst and the firm	5.96	***	5.87	***	5.86	***	5.80	***
	(0.26)		(0.26)		(0.26)		(0.25)	
Regulation FD (dummy)	0.53		0.46		0.39		0.49	***
	(0.28)		(0.28)		(0.30)		(0.29)	
Year Dummies	Included		Included		Included		Included	
Constant	-12.084	***	-11.773	***	-10.919	***	-11.089	***
Number of Observations	773,684		773,684		773,684		773,684	
Model log likelihood	-4,795.89		-4,770.56		-4,758.80		-4,722.56	
Wald X 2	1171.23	***	1315.22	***	1307.26	***	1329.67	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 4
Econometric Test #1 For Medical Devices - Study 1
Split-Sample Logit Estimates of Influences on Firm's Ability to Attract Analyst Coverage

	Medical Devices Industry (3841 & 3842) Knowledge overlap between the analyst and the firm			
	Model 1		Model 2	
	Firm-Analyst Overlap < Mean		Firm-Analyst Overlap > Mean	
Knowledge Distance	-1.16		-2.17	***
	(0.72)		(0.36)	
[Marginal effects]	[-.0000972]		[-.0042226]	
		t = 4,500		
p-value of *t* -test of difference in marginal effects		***		
Knowledge Overlap	1.70		3.65	***
	(0.91)		(0.85)	
[Marginal effects]	[.0001429]		[.0071186]	
Control Variables				
Knowledge Diversity	-0.05		-0.05	***
	(0.02)		(0.01)	
Firm Performance	0.00	***	0.00	***
	(0.00)		(0.00)	
Firm Size	-0.29		0.59	***
	(0.25)		(0.12)	
Number of Analysts Covering the Industry	0.07	*	-0.04	
	(0.04)		(0.05)	
Firm's Yearly Number of Patents	0.02	***	0.01	***
	(0.01)		(0.00)	
Firm's Technological Quality	0.05		-0.04	
	(0.09)		(0.05)	
Firm's Geographic Scope	0.04		-0.11	*
	(0.08)		(0.06)	
Innovation intensity of firm's industry	16.45		-5.00	
	(12.22)		(6.10)	
Regulation FD (dummy)	-3.49	***	0.89	
	(0.96)		(0.27)	
Year Dummies	Included		Included	
Constant	-13.670	***	-6.013	***
Number of Observations	552,208		221,476	
Model loglikelihood	-1,102.98		-4,007.45	
Wald X 2	330.91	***	286.84	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for all variables; Marginal effects in brackets

Table 5
Econometric Test #2 For Medical Devices - Study 1
Split-Sample Logit Estimates of Influences on Firm's Ability to Attract Analyst Coverage

	Medical Devices Industry (3841 & 3842) Innovation Intensity of the Industry			
	Model 1		Model 2	
	Innov. Intensity < Mean		Innov. Intensity > Mean	
Knowledge Distance	-1.84	***	-1.18	*
	(0.38)		(0.51)	
[Marginal effects]	[-.00015]		[-.00013]	
		t = 200		
p-value of *t* -test of difference in marginal effects		***		
Knowledge Overlap	3.58	*	2.13	*
	(0.48)		(0.85)	
[Marginal effects]	[.0002916]		[.00024]	
		t = 320		
p-value of *t* -test of difference in marginal effects		***		
Control Variables				
Knowledge Diversity	-0.12	***	-0.02	
	(0.01)		(0.01)	
Firm Performance	0.00	***	0.00	**
	(0.00)		(0.00)	
Firm Size	0.83	***	0.51	**
	(0.15)		(0.19)	
Number of Analysts Covering the Industry	0.00		-0.03	
	(0.01)		(0.04)	
Firm's Yearly Number of Patents	0.01	***	0.01	*
	(0.00)		(0.00)	
Firm's Technological Quality	0.06		-0.02	
	(0.05)		(0.08)	
Firm's Geographic Scope	-0.26	***	0.02	
	(0.07)		(0.11)	
Knowledge overlap betw. analyst and the firm	5.76	***	5.76	***
	(0.36)		(0.35)	
Regulation FD (dummy)	0.38		1.14	
	(0.38)		(0.95)	
Year Dummies	Included		Included	
Constant	-11.341	***	-10.187	***
Number of Observations	421,641		352,043	
Model loglikelihood	-2,212.45		-2,336.01	
Wald X 2	951.71	***	675.16	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for all variables; Marginal effects in brackets

Table 6
Descriptive Statistics For Computer Hardware - Study 1
Computer Hardware Industry (SIC 3570-3579)

Descriptive Statistics and Correlation Matrix

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1 Analysts Coverage	0.001	0.03												
2 Knowledge Diversity	13.57	19.82	0.01											
3 Knowledge Distance	0.56	0.22	-0.01	-0.18										
4 Knowledge Overlap	0.31	0.22	0.00	-0.22	0.65									
5 Firm Performance	173.44	702.14	0.02	0.42	-0.12	-0.13								
6 Firm Size	1.18	1.26	0.02	0.75	-0.13	-0.15	0.55							
7 Number of Analysts Covering the Industry	38.81	30.50	0.01	-0.25	0.11	0.25	-0.10	-0.45						
8 Firm's Yearly Number of Patents	36.96	162.08	0.00	0.68	-0.11	-0.16	0.29	0.53	-0.26					
9 Firm's Technological Quality	4.50	3.23	0.01	0.70	-0.49	-0.42	0.42	0.77	-0.26	0.45				
10 Firm's Geographic Scope	1.50	1.17	0.00	0.73	-0.19	-0.29	0.44	0.72	-0.36	0.67	0.68			
11 Innovation intensity of firm's industry	0.09	0.06	0.00	-0.13	0.14	0.23	-0.05	-0.32	0.81	-0.05	-0.20	-0.18		
12 Knowledge overlap between the analyst and the firm	0.19	0.33	0.07	-0.06	0.02	0.03	0.00	-0.05	0.01	-0.04	-0.05	-0.04	0.00	
13 Regulation FD (dummy)	0.50	0.50	0.00	-0.06	0.00	0.08	0.00	-0.13	0.35	-0.16	-0.05	-0.10	0.14	0.01

Table 7
Logit Estimates on Coverage For Computer Hardware - Study 1
Estimates of Analyst's Hazard of Covering the Focal Firm

	Computer Hardware Industry (SIC 3570-3579)							
	Logit Model 1		Logit Model 2		Logit Model 3		Logit Model 4	
Knowledge Diversity (H1 < 0)			0.01	***	0.01	*	0.01	**
			(0.00)		(0.00)		(0.00)	
Knowledge Distance (H2 < 0)					-0.82	**	-1.44	***
					(0.27)		(0.30)	
Knowledge Overlap (H3 > 0)							1.38	**
							(0.44)	
Control Variables								
Firm Performance	0.00		0.00		0.00	*	0.00	
	(0.00)		(0.00)		(0.00)		(0.00)	
Firm Size	0.63	***	0.59	***	0.66	***	0.62	***
	(0.06)		(0.06)		(0.06)		(0.06)	
Number of Analysts Covering the Industry	0.03	***	0.03	**	0.03	***	0.03	***
	(0.00)		(0.00)		(0.00)		(0.00)	
Firm's Yearly Number of Patents	0.00		0.00		0.00		0.00	
	(0.00)		(0.00)		(0.00)		(0.00)	
Firm's Technological Quality	0.17	***	0.16	***	0.09	*	0.10	*
	(0.04)		(0.04)		(0.05)		(0.05)	
Firm's Geographic Scope	-0.34	***	-0.36	***	-0.35	***	-0.32	***
	(0.06)		(0.06)		(0.06)		(0.06)	
Innovation intensity of firm's industry	-9.48	***	-9.27	***	-9.21	***	-8.84	***
	(1.81)		(1.77)		(1.79)		(1.76)	
Knowledge overlap between the analyst and the firm	6.06	***	6.08	***	6.08	***	6.06	***
	(0.21)		(0.21)		(0.21)		(0.21)	
Regulation FD (dummy)	-1.84	***	-1.82	***	-1.86	***	-1.97	***
	(0.22)		(0.22)		(0.22)		(0.23)	
Year Dummies	Included		Included		Included		Included	
Constant	-10.821	***	-10.711	***	-9.871	***	-9.844	***
Number of Observations	1,062,971		1,062,971		1,062,971		1,062,971	
Model log likelihood	-7,846.30		-7,842.78		-7,833.60		-7,825.98	
Wald X 2	2035.83	***	2044.15	***	2139.47	***	2138.01	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 8
Econometric Test #1 For Computer Hardware - Study 1
Split-Sample Logit Estimates of Influences on Firm's Ability to Attract Analyst Coverage

	Computer Hardware Industry (3570-3579) Knowledge overlap between the analyst and the firm			
	Model 1		Model 2	
	Firm-Analyst Overlap < Mean		Firm-Analyst Overlap > Mean	
Knowledge Distance	-2.61	***	-1.28	***
	(0.77)		(0.32)	
[Marginal effects]	[-.0003213]	t = 3,100	[-.0033076]	
p-value of *t* -test of difference in marginal effects		***		
Knowledge Overlap	1.42		1.84	***
	(0.84)		(0.45)	
[Marginal effects]	[.0001755]		[.004772]	
Control Variables				
Knowledge Diversity	-0.01		0.01	
	(0.01)		(0.01)	
Firm Performance	0.00		0.00	
	(0.00)		(0.00)	
Firm Size	0.79	***	0.55	***
	(0.11)		(0.06)	
Number of Analysts Covering the Industry	0.02	***	0.04	***
	(0.01)		(0.00)	
Firm's Yearly Number of Patents	0.00		0.00	
	(0.00)		(0.00)	
Firm's Technological Quality	0.01		0.06	
	(0.09)		(0.05)	
Firm's Geographic Scope	-0.32		-0.11	*
	(0.09)		(0.06)	
Innovation intensity of firm's industry	-7.54	*	-10.35	***
	(3.35)		(2.00)	
Regulation FD (dummy)	-3.26	***	-1.90	***
	(0.59)		(0.26)	
Year Dummies	Included		Included	
Constant	-6.839	***	-5.346	***
Number of Observations	763,631		299,340	
Model loglikelihood	-1,913.40		-7,027.33	
Wald X 2	446.28	***	589.72	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for all variables; Marginal effects in brackets

Table 9
Econometric Test #2 For Computer Hardware - Study 1
Split-Sample Logit Estimates of Influences on Firm's Ability to Attract Analyst Coverage

	Computer Hardware Industry (3570-3579) Innovation Intensity of the Industry			
	Model 1		Model 2	
	Innov. Intensity < Mean		Innov. Intensity > Mean	
Knowledge Distance	-2.41	***	0.26	
	(0.43)		(0.47)	
[Marginal effects]	[-.00022]	t = 2,500	[.000035]	
p-value of *t* -test of difference in marginal effects		***		
Knowledge Overlap	1.62	*	-2.59	***
	(0.66)		(0.76)	
[Marginal effects]	[.00015]	t = 3,200	[-.00035]	
p-value of *t* -test of difference in marginal effects		***		
Control Variables				
Knowledge Diversity	0.00		0.02	**
	(0.00)		(0.01)	
Firm Performance	0.00	*	0.00	*
	(0.00)		(0.00)	
Firm Size	0.76	***	0.72	***
	(0.08)		(0.09)	
Number of Analysts Covering the Industry	0.03	***	0.00	
	(0.01)		(0.01)	
Firm's Yearly Number of Patents	0.00		0.00	
	(0.00)		(0.00)	
Firm's Technological Quality	0.20	*	0.02	
	(0.06)		(0.05)	
Firm's Geographic Scope	-0.36	***	-1.18	***
	(0.06)		(0.18)	
Knowledge overlap between the analyst and the firm	6.24	***	5.61	***
	(0.27)		(0.29)	
Regulation FD (dummy)	-2.30	***	-1.32	**
	(0.30)		(0.48)	
Year Dummies	Included		Included	
Constant	-10.151	***	-8.605	***
Number of Observations	677,746		380,387	
Model loglikelihood	-4,679.70		-3,020.05	
Wald X 2	1397.38	***	1045.3	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for all variables; Marginal effects in brackets

Table 10
Descriptive Statistics For Computer Software - Study 1
Computer Software Industry (SIC 7372)

Descriptive Statistics and Correlation Matrix

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1 Analysts Coverage	0.002	0.04												
2 Knowledge Diversity	5.29	7.20	0.01											
3 Knowledge Distance	0.68	0.24	-0.01	-0.47										
4 Knowledge Overlap	0.35	0.20	0.00	-0.35	0.48									
5 Firm Performance	257.02	1,266.04	0.02	0.60	-0.20	-0.17								
6 Firm Size	1.04	0.88	0.02	0.50	-0.19	-0.01	0.59							
7 Number of Analysts Covering the Industry	345.94	72.90	0.01	0.18	-0.06	0.14	-0.01	0.00						
8 Firm's Yearly Number of Patents	17.66	83.89	0.02	0.60	-0.24	-0.21	0.79	0.48	0.00					
9 Firm's Technological Quality	5.14	1.88	0.02	0.62	-0.49	-0.33	0.46	0.53	0.21	0.44				
10 Firm's Geographic Scope	1.28	0.56	0.00	0.41	-0.20	-0.27	0.27	0.25	0.00	0.24	0.35			
11 Innovation intensity of firm’s industry	0.17	0.01	0.00	0.03	0.03	0.06	-0.02	-0.02	0.28	-0.03	0.02	0.00		
12 Knowledge overlap between the analyst and the firm	0.22	0.34	0.07	-0.04	0.01	0.03	-0.01	0.00	-0.06	-0.02	-0.04	-0.02	0.02	
13 Regulation FD (dummy)	0.71	0.45	0.00	0.07	-0.01	0.18	-0.02	-0.01	0.52	-0.11	0.07	-0.03	0.37	0.01

Table 11
Estimates on Coverage For Computer Software - Study 1
Estimates of Analyst's Hazard of Covering the Focal Firm

	Computer Software Industry (SIC 7372)							
	Logit Model 1		Logit Model 2		Logit Model 3		Logit Model 4	
Knowledge Diversity (H1 < 0)			-0.05	***	-0.05	***	-0.05	***
			(0.01)		(0.01)		(0.01)	
Knowledge Distance (H2 < 0)					-0.46	**	-0.36	*
					(0.17)		(0.18)	
Knowledge Overlap (H3 > 0)							-0.33	
							(0.22)	
Control Variables								
Firm Performance	0.00		0.00		0.00		0.00	
	(0.00)		(0.00)		(0.00)		(0.00)	
Firm Size	0.39	***	0.43	***	0.44	***	0.46	***
	(0.04)		(0.04)		(0.04)		(0.05)	
Number of Analysts Covering the Industry	0.01		0.01	**	0.01	***	0.01	***
	(0.00)		(0.00)		(0.00)		(0.00)	
Firm's Yearly Number of Patents	0.00	**	0.00	***	0.00	***	0.00	***
	(0.00)		(0.00)		(0.00)		(0.00)	
Firm's Technological Quality	0.17	***	0.22	***	0.20	***	0.19	***
	(0.02)		(0.02)		(0.02)		(0.02)	
Firm's Geographic Scope	-0.45	***	-0.33	***	-0.34	***	-0.36	***
	(0.08)		(0.08)		(0.08)		(0.08)	
Innovation intensity of firm's industry	-9.36	*	-11.53	**	-12.19	**	-12.48	**
	(4.19)		(4.24)		(4.26)		(4.28)	
Knowledge overlap between the analyst and the firm	4.51	***	4.50	***	4.50	***	4.50	***
	(0.10)		(0.10)		(0.10)		(0.10)	
Regulation FD (dummy)	-3.13	***	-4.10	***	4.43	***	-4.46	***
	(0.91)		(0.94)		(0.95)		(0.95)	
Year Dummies	Included		Included		Included		Included	
Constant	-7.912	***	-7.906	***	-7.506	***	-7.558	***
Number of Observations	1,025,863		1,025,863		1,025,863		1,025,863	
Model log likelihood	-11,979.18		-11,943.95		-11,936.55		-11,934.74	
Wald X 2	2901.56	***	2956.82	***	2973.86	***	2970.43	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 12
Econometric Test #1 For Computer Software - Study 1
Split-Sample Logit Estimates of Influences on Firm's Ability to Attract Analyst Coverage

	Computer Software Industry (7372) Knowledge overlap between the analyst and the firm			
	Model 1		Model 2	
	Firm-Analyst Overlap < Mean		Firm-Analyst Overlap > Mean	
Knowledge Distance	-0.54		-0.62	**
	(0.29)		(0.20)	
[Marginal effects]	[-.0001038]		[-.0025538]	
p-value of *t* -test of difference in marginal effects		*t* = 2,600 ***		
Knowledge Overlap	-0.34		0.20	
	(0.33)		(0.27)	
[Marginal effects]	[-.0000655]		[.0008084]	
Control Variables				
Knowledge Diversity	-0.06	***	-0.05	***
	(0.01)		(0.01)	
Firm Performance	0.00	***	0.00	
	(0.00)		(0.00)	
Firm Size	0.59	***	0.39	***
	(0.07)		(0.05)	
Number of Analysts Covering the Industry	0.02		0.01	**
	(0.03)		(0.00)	
Firm's Yearly Number of Patents	0.00		0.00	***
	(0.00)		(0.00)	
Firm's Technological Quality	0.11	*	0.17	***
	(0.05)		(0.02)	
Firm's Geographic Scope	-0.46	**	-0.38	***
	(0.15)		(0.09)	
Innovation intensity of firm's industry	-18.39		-10.94	*
	(33.52)		(4.30)	
Regulation FD (dummy)	-6.51		-4.17	
	(6.35)		(0.96)	
Year Dummies	Included		Included	
Constant	-6.303	***	-4.005	***
Number of Observations	713,949		311,914	
Model loglikelihood	-3,200.28		-9,490.38	
Wald X 2	673.02	***	428.74	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for all variables; Marginal effects in brackets

Table 13
Econometric Test #2 For Computer Software - Study 1
Split-Sample Logit Estimates of Influences on Firm's Ability to Attract Analyst Coverage

	Computer Software Industry (7372) Innovation Intensity of the Industry			
	Model 1		Model 2	
	Innov. Intensity < Mean		Innov. Intensity > Mean	
Knowledge Distance	-0.63	**	-0.53	*
	(0.20)		(0.23)	
[Marginal effects]	[-.0009457]	t = 110	[-.000874]	
p-value of *t* -test of difference in marginal effects		***		
Knowledge Overlap	0.00		0.21	
	(0.28)		(0.28)	
[Marginal effects]	[0.00000124]		[.00035]	
Control Variables				
Knowledge Diversity	-0.06	***	-0.05	***
	(0.01)		(0.01)	
Firm Performance	0.00	*	0.00	*
	(0.00)		(0.00)	
Firm Size	0.42	***	0.47	***
	(0.05)		(0.06)	
Number of Analysts Covering the Industry	0.01	***	0.00	**
	(0.00)		(0.00)	
Firm's Yearly Number of Patents	0.00		0.00	
	(0.00)		(0.00)	
Firm's Technological Quality	0.10	***	0.20	***
	(0.02)		(0.03)	
Firm's Geographic Scope	-0.35	***	-0.51	***
	(0.09)		(0.10)	
Knowledge overlap between the analyst and the firm	omited		omited	
Regulation FD (dummy)	-4.29		-0.02	
	(0.94)		(0.29)	
Year Dummies	Included		Included	
Constant	-6.685	***	-7.858	***
Number of Observations	569,800		456,063	
Model loglikelihood	-7,381.28		-6,608.92	
Wald X 2	336.37	***	403.90	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for all variables; Marginal effects in brackets

Table 14
Summary of Empirical Findings - Study 2
Propositions 7 -10

	Medical Devices	Computer Hardware	Computer Software	
Proposition 7 (P7): Exploring distant knowledge will have a negative impact on the favorability of the analyst's recommendation for the firm.	No	No	No	**Not Supported**
Proposition 8 (P8): Greater knowledge overlap between the firm and its rivals will have a negative impact on the favorability of the analyst's recommendation for the firm.	No	No	No	**Not Supported**
Proposition 9 (P9): The greater the analyst's experience, the less negative the effect that exploration of distant knowledge will have on the favorability of the recommendation.	No	No	No	**Not Supported**
Proposition 10 (P10): The more extensively other firms covered by the analyst explore external knowledge, the less negative the effect that exploration of distant knowledge will have on the favorability of the recommendation.	No	No	No	**Not Supported**

Table 15

Descriptive Statistics For Medical Devices - Study 2

Medical Devices Industry (SIC 3841-3842)

Descriptive Statistics and Correlation Matrix

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Increased Favorability of Recommendation	0.14	0.35													
2 Knowledge Distance	0.54	0.23	-0.03												
3 Knowledge Overlap	0.28	0.17	0.03	0.68											
4 Firm Size	1.54	1.05	-0.02	0.17	-0.03										
5 Firm Performance	168.55	214.29	0.03	0.28	0.25	0.71									
6 Average Analysts Recomendation	2.29	0.47	0.02	0.15	0.07	0.32	0.29								
7 Firm's Yearly Number of Patents	15.63	33.03	0.01	-0.24	-0.40	0.52	0.18	-0.07							
8 Firm's Technological Quality	6.52	1.89	0.00	-0.40	-0.45	0.53	0.17	0.18	0.52						
9 Knowledge Diversity	6.56	7.95	-0.04	-0.25	-0.48	0.65	0.41	0.15	0.59	0.53					
10 Firm's Geographic Scope	2.19	1.37	-0.08	-0.12	-0.36	0.81	0.44	0.30	0.48	0.64	0.73				
11 Degree to which analysts' firms explore new knowledge	0.50	0.11	-0.02	0.43	0.23	0.01	0.05	0.15	-0.26	-0.23	-0.09	-0.03			
12 Analyst Experience	6.18	5.35	0.02	0.10	0.03	0.14	0.11	0.11	0.10	0.02	0.10	0.06	0.04		
13 Analyst Accuracy	0.44	1.31	0.05	0.13	0.14	0.09	0.11	0.03	-0.03	-0.01	-0.05	0.01	0.00	0.04	
14 Regulation FD (dummy)	0.65	0.48	0.04	0.25	0.36	0.06	0.29	0.25	-0.44	-0.17	-0.07	-0.02	0.40	-0.01	0.07

Table 16
First Stage Logit Model For Medical Devices - Study 2
Logit Esitmates on Analysts' Decision to Provide Coverage

	Logit Model 1	
Knowledge Diversity	-0.03	***
	(0.01)	
Knowledge Distance	-0.97	***
	(0.22)	
Knowledge Overlap	2.17	***
	(0.31)	
Control Variables		
Firm Performance	0.00	*
	(0.00)	
Firm Size	0.99	***
	(0.11)	
Number of Analysts Covering the Industry	0.00	
	(0.00)	
Firm's Yearly Number of Patents	0.01	***
	(0.00)	
Firm's Technological Quality	-0.06	
	(0.06)	
Firm's Geographic Scope	-0.03	
	(0.05)	
Innovation intensity of firm's industry	-0.33	
	(1.81)	
Knowledge overlap between the analyst and the firm	5.13	***
	(0.14)	
Regulation FD (dummy)	0.67	***
	(0.16)	
Number of Industry Firms in Stock Exchange	0.01	***
	(0.00)	
Firm HQ in NY	-0.30	
	(0.23)	
Year Dummies	Included	
Constant	-12.250	***
Number of Observations	773,684	
Model log likelihood	-4,568.54	
Wald X 2	1427.14	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 17

Second Stage Logit Model For Medical Devices - Study 2

Logistic Regression Estimates of Analyst's Increasing Favorability of Recommendation

	Medical Devices Industry (SIC 3841 & 3842)							
	Logit Model 1		Logit Model 2		Logit Model 3		Bootstrap Corr.Logit Model 4	
Knowledge Distance (P7 < 0)			-1.02		0.03		0.03	
			(0.63)		(0.81)		(0.76)	
Knowledge Overlap (P8 < 0)					-2.26		-2.26	
					(1.28)		(1.61)	
Control Variables								
Inverse Mills Ratio	-1.08	***	-0.99	***	-1.35	***	-1.35	**
	(0.29)		(0.31)		(0.39)		(0.48)	
Firm Size	-0.69	*	-0.43		-0.66		-0.66	
	(0.32)		(0.37)		(0.41)		(0.43)	
Firm Performance	0.00		0.00		0.00		0.00	
	(0.00)		(0.00)		(0.00)		(0.00)	
Average Analysts Recomendation	0.37		0.37		0.38		0.38	*
	(0.25)		(0.25)		(0.25)		(0.18)	
Firm's Yearly Number of Patents	0.00		0.00		0.00		0.00	
	(0.01)		(0.01)		(0.01)		(0.01)	
Firm's Technological Quality	0.12		0.07		0.06		0.06	
	(0.08)		(0.08)		(0.08)		(0.08)	
Firm's Knowledge Diversity	0.04		0.03		0.03		0.03	
	(0.02)		(0.02)		(0.02)		(0.02)	
Firm's Geographic Scope	-0.38		-0.46	*	-0.37		-0.37	
	(0.21)		(0.22)		(0.20)		(0.22)	
Degree to which analysts' firms explore new knowledge	-0.15		0.34		0.19		0.19	
	(1.05)		(1.06)		(1.04)		(0.98)	
Analyst Experience	0.00		0.01		0.01		0.01	
	(0.01)		(0.02)		(0.02)		(0.02)	
Analyst Accuracy	0.05		0.06		0.05		0.05	
	(0.07)		(0.07)		(0.07)		(0.12)	
Regulation FD (dummy)	0.06		0.09		0.07		0.07	
	(0.30)		(0.30)		(0.30)		(0.31)	
Constant	2.662		2.677		4.697	*	4.697	*
Number of Observations	758		758		758		758	
Model log likelihood	-288.96		-289.50		-286.95		-286.95	
Wald X 2	27.76	**	28.8	**	32.66	**	32.66	**

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 18

Descriptive Statistics For Computer Hardware - Study 2

Computer Hardware Industry (SIC 3570-3579)

Descriptive Statistics and Correlation Matrix

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Increased Favorability of Recommendation	0.17	0.38													
2 Knowledge Distance	0.52	0.18	-0.04												
3 Knowledge Overlap	0.25	0.13	-0.02	0.78											
4 Firm Size	2.32	1.30	0.04	-0.19	-0.14										
5 Firm Performance	686.57	1,340.20	0.05	-0.19	-0.21	0.52									
6 Average Analysts Recomendation	2.32	0.41	0.11	0.01	0.04	0.03	-0.13								
7 Firm's Yearly Number of Patents	89.31	156.36	-0.01	-0.23	-0.33	0.51	-0.02	-0.03							
8 Firm's Technological Quality	7.90	2.13	0.05	-0.50	-0.42	0.77	0.40	0.03	0.46						
9 Knowledge Diversity	22.74	18.83	0.02	-0.23	-0.27	0.74	0.34	-0.05	0.74	0.69					
10 Firm's Geographic Scope	1.90	1.33	0.01	-0.26	-0.39	0.56	0.12	-0.09	0.67	0.60	0.63				
11 Degree to which analysts' firms explore new knowledge	0.55	0.11	-0.02	0.47	0.32	-0.14	0.02	0.04	-0.16	-0.28	-0.15	-0.19			
12 Analyst Experience	6.34	5.80	0.04	-0.02	0.02	0.11	0.05	0.01	0.04	0.10	0.08	0.06	-0.05		
13 Analyst Accuracy	0.80	3.62	0.00	0.00	0.00	0.00	0.05	-0.01	0.00	0.00	0.03	-0.03	0.02	0.19	
14 Regulation FD (dummy)	0.64	0.48	0.02	-0.15	0.01	-0.16	0.18	0.12	-0.38	-0.07	-0.16	-0.19	0.08	-0.01	0.00

Table 19

First Stage Logit Model For Computer Hardware - Study 2

Logit Esitmates on Analysts' Decision to Provide Coverage

	Logit Model 1	
Knowledge Diversity	0.01	**
	(0.00)	
Knowledge Distance	-1.93	***
	(0.28)	
Knowledge Overlap	2.30	***
	(0.46)	
Control Variables		
Firm Performance	0.00	***
	(0.00)	
Firm Size	0.72	***
	(0.05)	
Number of Analysts Covering the Industry	0.02	***
	(0.00)	
Firm's Yearly Number of Patents	0.00	
	(0.00)	
Firm's Technological Quality	0.11	
	(0.04)	
Firm's Geographic Scope	-0.32	***
	(0.06)	
Innovation intensity of firm's industry	-6.27	***
	(1.64)	
Knowledge overlap between the analyst and the firm	6.04	***
	(0.20)	
Regulation FD (dummy)	-1.89	***
	(0.22)	
Number of Industry Firms in Stock Exchange	0.01	***
	(0.00)	
Firm HQ in NY	1.45	***
	(0.42)	
Year Dummies	Included	
Constant	-10.816	***
Number of Observations	1,062,971	
Model log likelihood	-7,760.26	
Wald X 2	2376.22	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 20

Second Stage Logit Model For Computer Hardware - Study 2

Logistic Regression Estimates of Analyst's Increasing Favorability of Recommendation

	Computer Hardware Industry (SIC 3570-3579)							
	Logit Model 1		Logit Model 2		Logit Model 3		Bootstrap Corr. Logit Model 4	
Knowledge Distance (P7 < 0)			-0.57		-0.77		-0.77	
			(0.53)		(0.75)		(0.74)	
Knowledge Overlap (P8 < 0)					0.39		0.39	
					(1.10)		(1.20)	
Control Variables								
Inverse Mills Ratio	-0.37	*	-0.36	*	-0.35	*	-0.35	*
	(0.15)		(0.15)		(0.15)		(0.15)	
Firm Size	-0.24	*	-0.20		-0.21		-0.21	
	(0.12)		(0.13)		(0.13)		(0.12)	
Firm Performance	0.00	*	0.00		0.00	*	0.00	*
	(0.00)		(0.00)		(0.00)		(0.00)	
Average Analysts Recomendation	0.75	***	0.76	***	0.77	***	0.77	***
	(0.18)		(0.18)		(0.18)		(0.19)	
Firm's Yearly Number of Patents	0.00		0.00		0.00		0.00	
	(0.00)		(0.00)		(0.00)		(0.00)	
Firm's Technological Quality	-0.03		-0.06		-0.06		-0.06	
	(0.06)		(0.07)		(0.07)		(0.07)	
Firm's Knowledge Diversity	0.00		0.00		0.00		0.00	
	(0.01)		(0.01)		(0.01)		(0.01)	
Firm's Geographic Scope	0.19	*	0.19	*	0.20		0.20	
	(0.10)		(0.09)		(0.10)		(0.11)	
Degree to which analysts' firms explore new knowledge	-0.55		-0.23		-0.20		-0.20	
	(0.62)		(0.67)		(0.67)		(0.62)	
Analyst Experience	0.01		0.01		0.01		0.01	
	(0.01)		(0.01)		(0.01)		(0.01)	
Analyst Accuracy	-0.01		-0.01		-0.01		-0.01	
	(0.02)		(0.02)		(0.02)		(0.03)	
Regulation FD (dummy)	0.02		-0.03		-0.05		-0.05	
	(0.18)		(0.18)		(0.19)		(0.21)	
Constant	-1.334		-1.079		-1.187		-1.187	
Number of Observations	1,412		1,412		1,412		1,412	
Model log likelihood	-633.62		-633.14		-633.09		-633.09	
Wald X 2	41.26	***	42.6	***	42.27	***	42.27	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 21

Descriptive Statistics For Computer Software - Study 2

Computer Software Industry (SIC 7372)

Descriptive Statistics and Correlation Matrix

	Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Increased Favorability of Recommendation	0.17	0.38													
2	Knowledge Distance	0.64	0.24	0.01												
3	Knowledge Overlap	0.34	0.18	0.00	0.62											
4	Firm Size	1.52	1.09	-0.03	-0.41	-0.34										
5	Firm Performance	830.09	2,110.98	-0.01	-0.36	-0.37	0.74									
6	Average Analysts Recomendation	2.28	0.39	0.09	0.07	0.25	-0.15	-0.24								
7	Firm's Yearly Number of Patents	52.08	152.63	0.01	-0.36	-0.40	0.59	0.80	-0.23							
8	Firm's Technological Quality	5.91	1.99	0.00	-0.64	-0.50	0.72	0.70	-0.09	0.60						
9	Knowledge Diversity	6.66	8.71	-0.03	-0.47	-0.43	0.64	0.84	-0.18	0.72	0.77					
10	Firm's Geographic Scope	1.24	0.44	-0.01	-0.44	-0.39	0.60	0.59	-0.18	0.52	0.71	0.66				
11	Degree to which analysts' firms explore new knowledge	0.63	0.13	0.01	0.57	0.39	-0.26	-0.25	0.03	-0.29	-0.41	-0.33	-0.30			
12	Analyst Experience	4.85	4.72	-0.03	-0.07	-0.05	0.06	0.06	-0.01	0.04	0.07	0.05	0.07	-0.06		
13	Analyst Accuracy	0.74	4.73	0.00	0.05	0.04	-0.01	-0.02	-0.01	0.00	-0.04	-0.03	-0.01	0.00	0.16	
14	Regulation FD (dummy)	0.74	0.44	0.02	0.06	0.30	-0.12	-0.11	0.42	-0.31	0.02	-0.03	-0.13	0.09	0.00	-0.07

Table 22

First Stage Logit Model For Computer Software - Study 2

Logit Esitmates on Analysts' Decision to Provide Coverage

	Logit Model 1	
Knowledge Diversity	-0.04	***
	(0.01)	
Knowledge Distance	-0.07	
	(0.19)	
Knowledge Overlap	-0.40	
	(0.21)	
Control Variables		
Firm Performance	0.00	
	(0.00)	
Firm Size	0.60	***
	(0.05)	
Number of Analysts Covering the Industry	0.01	*
	(0.00)	
Firm's Yearly Number of Patents	0.00	***
	(0.00)	
Firm's Technological Quality	0.16	
	(0.03)	
Firm's Geographic Scope	-0.38	
	(0.10)	
Innovation intensity of firm's industry	-11.17	**
	(4.30)	
Knowledge overlap between the analyst and the firm	4.50	***
	(0.10)	
Regulation FD (dummy)	-4.23	***
	(0.95)	
Number of Industry Firms in Stock Exchange	0.00	***
	(0.00)	
Firm HQ in NY	-3.41	***
	(0.54)	
Year Dummies	Included	
Constant	-7.805	***
Number of Observations	1,025,863	
Model log likelihood	-11,765.85	
Wald X 2	3151.3	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 23

Second Stage Logit Model For Computer Software - Study 2

Logistic Regression Estimates of Analyst's Increasing Favorability of Recommendation

	Computer Software Industry (SIC 7372)							
	Logit Model 1		Logit Model 2		Logit Model 3		Bootstrap Corr. Logit Model 4	
Knowledge Distance (P7 < 0)			0.07		0.23		0.23	
			(0.45)		(0.42)		(0.41)	
Knowledge Overlap (P8 < 0)					-0.52		-0.52	
					(0.50)		(0.49)	
Control Variables								
Inverse Mills Ratio	-0.13		-0.13		-0.08		-0.08	
	(0.16)		(0.16)		(0.16)		(0.18)	
Firm Size	-0.01		-0.02		0.02		0.02	
	(0.14)		(0.14)		(0.15)		(0.16)	
Firm Performance	0.00		0.00		0.00		0.00	
	(0.00)		(0.00)		(0.00)		(0.00)	
Average Analysts Recomendation	0.68	**	0.67	**	0.69	**	0.69	***
	(0.22)		(0.22)		(0.22)		(0.19)	
Firm's Yearly Number of Patents	0.00		0.00		0.00		0.00	
	(0.00)		(0.00)		(0.00)		(0.00)	
Firm's Technological Quality	0.00		0.00		0.00		0.00	
	(0.10)		(0.10)		(0.10)		(0.07)	
Firm's Knowledge Diversity	-0.04		-0.04		-0.04		-0.04	
	(0.02)		(0.02)		(0.02)		(0.02)	
Firm's Geographic Scope	0.20		0.20		0.18		0.18	
	(0.28)		(0.28)		(0.28)		(0.21)	
Degree to which analysts' firms explore new knowledge	0.18		0.13		0.15		0.15	
	(0.64)		(0.70)		(0.72)		(0.47)	
Analyst Experience	-0.02		-0.02		-0.02		-0.02	
	(0.01)		(0.01)		(0.01)		(0.01)	
Analyst Accuracy	0.00		0.00		0.00		0.00	
	(0.01)		(0.01)		(0.01)		(0.01)	
Regulation FD (dummy)	0.08		0.08		0.13		0.13	
	(0.22)		(0.22)		(0.22)		(0.19)	
Constant	-2.752	*	-2.769	*	-3.015	*	-3.015	*
Number of Observations	1,916		1,916		1,916		1,916	
Model log likelihood	-857.84		-857.82		-857.31		-857.31	
Wald X 2	72.12	***	85.57	***	91.94	***	91.94	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 24
Summary of Empirical Findings - Study 3
Propositions 11-15

	Medical Devices	Computer Hardware	Computer Software	
Proposition 11 (P11): The lower the level of consensus among securities analysts' recommendations about the firm, the greater the likelihood that the investor will buy shares in the firm.	Yes			**Supported**
Proposition 12 (P12): The greater the investor's industry experience, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.	Yes			**Supported**
Proposition 13 (P13): The longer the investor's time horizon, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.	Yes			**Supported**
Proposition 14 (P14): The greater the scope of the firm's innovation portfolio, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.	Yes			**Supported**
Proposition 15 (P15): The greater the firm's ability to commercialize innovations, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.	Yes			**Supported**

Table 25
Descriptive Statistics For Medical Devices - Study 3

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1 Hazard of Increased Investment (dummy)	0.03	0.17										
2 Standard Deviation of Securities Analysts' Recommendations	0.68	0.40	0.04									
3 Investor's Industry Experience	2.87	5.76	0.30	0.03								
4 Firm's Scope of Innovation Portfolio	72.51	121.15	0.09	0.11	-0.02							
5 Firm's Ability to Commercialize Innovations	6.48	9.12	0.13	0.13	-0.01	0.71						
6 Securities Analysts' Favorability of Firm's Recommendation	-2.16	0.58	-0.02	-0.22	-0.01	-0.21	-0.15					
7 Number of Securities Analysts Covering Focal Firm	5.46	4.99	0.14	0.34	0.02	0.32	0.53	-0.19				
8 Firm's Products' Average Age	8.31	4.49	0.04	0.10	-0.01	0.48	0.16	-0.13	-0.05			
9 Firm's Products % of Total Products in its Categories	0.02	0.03	0.01	-0.01	0.01	0.07	0.09	0.03	0.05	-0.12		
10 Firm's Number of Competing Products in its Product Categories	1,084.94	1,184.82	0.10	0.14	0.00	0.74	0.72	-0.25	0.49	0.16	-0.04	
11 Firm's Innovative Inputs	2.77	1.67	0.12	0.24	0.03	0.64	0.63	-0.22	0.69	0.15	0.02	0.70
12 Firm Performance	73.41	287.38	0.06	0.05	0.01	0.35	0.30	-0.12	0.18	0.23	0.00	0.34
13 Firm Size	1.02	0.96	0.11	0.23	-0.01	0.73	0.63	-0.34	0.55	0.36	-0.03	0.74
14 Firm's Share Price	26.83	17.90	0.09	0.24	0.02	0.52	0.43	-0.25	0.37	0.33	-0.04	0.58
15 Firm's Annual Dividend	0.13	0.43	0.01	0.05	-0.02	0.40	0.25	-0.11	-0.01	0.22	-0.02	0.38
16 Investor's Portfolio Value	18.51	5.46	0.10	0.01	0.22	-0.02	-0.02	-0.01	0.00	-0.01	0.01	-0.01
17 Investor's Annual Number of Firms' Held % Total in Portfolio	0.56	0.28	0.07	0.00	0.14	-0.02	-0.01	-0.01	0.00	-0.02	0.01	-0.01
18 Investor's Number of Distinct Industries	25.58	9.44	0.16	-0.03	0.44	-0.04	-0.02	0.02	-0.02	-0.05	0.01	-0.02
19 Investor's Prior Number of Shares in the Focal Firm	0.49	2.28	0.41	0.05	0.43	0.13	0.17	-0.05	0.21	0.06	0.01	0.15
20 Annual Inflation (CPI)	100.51	6.53	0.05	0.05	0.03	0.06	0.08	0.06	0.18	0.11	-0.12	0.00
21 U.S. Government T-Bill Rate	5.06	0.86	-0.02	-0.26	-0.09	-0.09	-0.04	0.16	-0.20	-0.17	0.00	-0.06
22 Annual US Equities Index	87.37	26.14	-0.03	0.22	0.06	0.09	-0.02	-0.09	0.07	0.18	0.05	0.05

Variable	11	12	13	14	15	16	17	18	19	20	21	22
12 Firm Performance	0.22											
13 Firm Size	0.67	0.31										
14 Firm's Share Price	0.55	0.43	0.71									
15 Firm's Annual Dividend	0.15	0.19	0.45	0.36								
16 Investor's Portfolio Value	0.01	-0.01	-0.03	0.00	-0.02							
17 Investor's Annual Number of Firms' Held % Total in Portfolio	-0.01	0.00	-0.03	-0.01	-0.02	0.59						
18 Investor's Number of Distinct Industries	-0.03	-0.01	-0.05	-0.04	-0.03	0.30	0.20					
19 Investor's Prior Number of Shares in the Focal Firm	0.17	0.09	0.17	0.12	0.02	0.14	0.11	0.19				
20 Annual Inflation (CPI)	0.11	0.07	0.10	0.08	0.06	-0.03	-0.04	-0.08	0.06			
21 U.S. Government T-Bill Rate	-0.23	-0.11	-0.14	-0.27	0.00	-0.01	0.01	0.10	-0.04	-0.48		
22 Annual US Equities Index	0.22	0.04	0.12	0.26	0.04	0.04	-0.04	-0.11	-0.03	0.17	-0.60	

Table 26

Logit Estimates on Investment For Medical Devices - Study 3

Estimates of Investor's Hazard of Increasing Investment in the Focal Firm

	Logit Model 1		Logit Model 2	
Standard Deviation of Analysts' Recommendations (Higher Value = Less Consensus)			0.26	***
			(0.03)	
Contingency Variables				
Investor's Industry Experience	0.05	***	0.05	***
	(0.00)		(0.00)	
Investor's Time Horizon	0.02		0.02	
	(0.05)		(0.05)	
Firm's Scope of Innovation Portfolio	0.00	***	0.00	***
	(0.00)		(0.00)	
Firm's Ability To Commercialize Innovations	0.02	***	0.02	***
Other Control Variables	(0.00)		(0.00)	
Firm's Innovative Inputs	0.11	***	0.12	***
	(0.01)		(0.01)	
Securities Analysts' Favorability of Focal Firm's Recommendation	0.09	***	0.12	***
	(0.02)		(0.02)	
Number of Securities Analysts Covering Focal Firm	0.01	*	0.00	
	(0.00)		(0.00)	
Firm's Products' Average Age	0.04	***	0.04	***
	(0.00)		(0.00)	
Firm's Products % of Total Products in its Categories	2.78	***	2.91	***
	(0.38)		(0.39)	
Firm's Number of Competing Products in its Product Categories	0.00		0.00	
	(0.00)		(0.00)	
Firm Performance	0.00		0.00	
	(0.00)		(0.00)	
Firm Size	0.28	***	0.29	***
	(0.03)		(0.03)	
Firm's Share Price	0.01	***	0.01	***
	(0.00)		(0.00)	
Firm's Annual Dividend	-0.71	***	-0.72	***
	(0.09)		(0.09)	
Investor's Portfolio Value	0.08	***	0.08	***
	(0.00)		(0.00)	
Investor's Number of Distinct Industries	0.11	***	0.10	***
	(0.00)		(0.00)	
Investor's Prior Number of Shares in the Focal Firm	0.15	***	0.15	***
	(0.00)		(0.00)	
Annual Inflation (CPI)	0.05	***	0.05	***
	(0.00)		(0.00)	
U.S. Government T-Bill Rate	0.05	**	0.06	***
	(0.02)		(0.02)	
Annual US Equities Index	-0.02	***	-0.02	***
	(0.00)		(0.00)	
Constant	-13.579	***	-13.979	***
Number of Observations	566,472		566,472	
Model log likelihood	-52,319.53		-52,281.50	
Wald X 2	30908.38	***	30919.02	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for all variables. Includes dummies for pension & investment fund ownership

Table 27

Econometric Test #1 For Medical Devices - Study 3

Split-Sample Logit Estimates on Contingent Effect of Investor's Industry Experience on the Relationship between Analysts' Consensus and the Hazard that the Focal Investor will Increase Investment in the Focal Firm (test of proposition 12).

	Model 1		Model 2	
	Investor's Experience < Mean		Investor's Experience > Mean	
Standard Deviation of Securities Analysts' Recommendations	0.15		0.27	***
	(0.08)		(0.03)	
	[.0002965]		[.0078692]	
		t = 4,700		
p-value of *t* -test of difference in marginal effects		***		
Contingency Variables				
Investor's Time Horizon	-0.42	***	0.11	
	(0.10)		(0.06)	
Firm's Scope of Innovation Portfolio	0.00	***	0.03	***
	(0.00)		(0.00)	
Firm's Ability To Commercialize Innovations	0.02	***	0.02	***
	(0.00)		(0.00)	
Other Control Variables				
Firm's Innovative Inputs	0.25	***	0.10	***
	(0.04)		(0.02)	
Securities Analysts' Favorability of Focal Firm's Recommendation	0.26	***	0.09	***
	(0.06)		(0.02)	
Number of Securities Analysts Covering Focal Firm	0.02	**	-0.01	*
	(0.01)		(0.00)	
Firm's Products' Average Age	0.11	***	0.03	***
	(0.01)		(0.00)	
Firm's Products % of Total Products in its Categories	7.53	***	2.52	***
	(1.29)		(0.39)	
Firm's Number of Competing Products in its Product Categories	0.00	*	0.00	
	(0.00)		(0.00)	
Firm Performance	0.00		0.00	
	(0.00)		(0.00)	
Firm Size	0.53	***	0.25	***
	(0.07)		(0.03)	
Firm's Share Price	0.01	***	0.02	***
	(0.00)		(0.00)	
Firm's Annual Dividend	-0.59	***	-0.70	***
	(0.17)		(0.10)	
Investor's Portfolio Value	0.07	***	0.08	***
	(0.01)		(0.00)	
Investor's Number of Distinct Industries	0.08	***	0.06	***
	(0.00)		(0.00)	
Investor's Prior Number of Shares in the Focal Firm	0.07	***	0.14	***
	(0.01)		(0.00)	
Annual Inflation (CPI)	0.04	***	0.05	***
	(0.00)		(0.00)	
U.S. Government T-Bill Rate	0.05		0.10	***
	(0.04)		(0.02)	
Annual US Equities Index	-0.02	***	-0.02	***
	(0.00)		(0.00)	
Constant	-13.612	***	-12.645	***
Number of Observations	334,369		232,103	
Model log likelihood	-10,601.80		-40,799.59	
Wald X 2	6382.13	***	20374.26	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for all variables. Includes investor dummies for pension and investment fund ownership

Table 28

Econometric Test #2 For Medical Devices - Study 3

Split-Sample Logit Estimates on Contingent Effect of Investor's Time Horizon on the Relationship between Securities Analysts' Consensus and the Hazard that the Focal Investor will Increase Investment in the Focal Firm (test of proposition 13).

	Model 1		Model 2	
	Investor's Time Horizon < Mean		Investor's Time Horizon > Mean	
Standard Deviation of Securities Analysts' Recommendations	0.26	***	0.26	***
	(0.05)		(0.04)	
Marginal Effect	[.00177]		[.00277]	
		t = 1,000		
p-value of *t* -test of difference in marginal effects		***		
Contingency Variables				
Investor's Industry Experience	0.07	***	0.04	***
	(0.00)		(0.00)	
Firm's Scope of Innovation Portfolio	0.00	***	0.00	***
	(0.00)		(0.00)	
Firm's Ability To Commercialize Innovations	0.02	***	0.02	***
	(0.00)		(0.00)	
Other Control Variables				
Firm's Innovative Inputs	0.14	***	0.10	***
	(0.02)		(0.02)	
Securities Analysts' Favorability of Focal Firm's Recommendation	0.14	***	0.11	***
	(0.03)		(0.03)	
Number of Securities Analysts Covering Focal Firm	0.01		0.00	*
	(0.00)		(0.00)	
Firm's Products' Average Age	0.04	***	0.04	***
	(0.00)		(0.00)	
Firm's Products % of Total Products in its Categories	4.07	***	2.00	***
	(0.57)		(0.51)	
Firm's Number of Competing Products in its Product Categories	0.00		0.00	
	(0.00)		(0.00)	
Firm Performance	0.00		0.00	
	(0.00)		(0.00)	
Firm Size	0.32	***	0.26	***
	(0.04)		(0.04)	
Firm's Share Price	0.01	***	0.02	***
	(0.00)		(0.00)	
Firm's Annual Dividend	-0.58	***	-0.79	***
	(0.12)		(0.13)	
Investor's Portfolio Value	0.09	***	0.04	***
	(0.00)		(0.01)	
Investor's Number of Distinct Industries	0.09	***	0.11	***
	(0.00)		(0.00)	
Investor's Prior Number of Shares in the Focal Firm	0.12	***	0.17	***
	(0.00)		(0.00)	
Annual Inflation (CPI)	0.04	***	0.05	***
	(0.00)		(0.00)	
U.S. Government T-Bill Rate	0.07		0.08	***
	(0.03)		(0.02)	
Annual US Equities Index	-0.02	***	-0.02	***
	(0.00)		(0.00)	
Constant	-13.443	***	-13.933	***
Number of Observations	295,117		271,355	
Model log likelihood	-22,982.57		-29,136.26	
Wald X 2	13872.7	***	19254.2	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for all variables. Includes investor dummies for pension and investment fund ownership

Table 29

Econometric Test #3 For Medical Devices - Study 3

Split-Sample Logit Estimates on Contingent Effect of Innovation Scope on the Relationship between Securities Analysts' Consensus and the Hazard that the Focal Investor will Increase Investment in the Focal Firm (test of proposition 14).

	Model 1		Model 2	
	Scope of Innovation Portfolio < Mean		Scope of Innovation Portfolio > Mean	
Standard Deviation of Securities Analysts' Recommendations	0.13	*	0.34	***
	(0.06)		(0.04)	
Marginal Effect	[.00053]		[.00368]	
		t = 3,200		
p-value of *t* -test of difference in marginal effects		*******		
Contingency Variables				
Investor's Industry Experience	0.06	***	0.04	***
	(0.00)		(0.00)	
Investor's Time Horizon	-0.81	***	0.17	**
	(0.12)		(0.06)	
Firm's Ability To Commercialize Innovations	-0.10	***	0.02	***
	(0.02)		(0.00)	
Other Control Variables				
Firm's Innovative Inputs	0.31	***	0.09	***
	(0.04)		(0.02)	
Securities Analysts' Favorability of Focal Firm's Recommendation	0.07		0.10	***
	(0.05)		(0.02)	
Number of Securities Analysts Covering Focal Firm	-0.04	***	0.01	*
	(0.01)		(0.00)	
Firm's Products' Average Age	-0.01		0.04	***
	(0.01)		(0.00)	
Firm's Products % of Total Products in its Categories	2.22	***	-3.37	*
	(0.46)		(1.33)	
Firm's Number of Competing Products in its Product Categories	0.00		0.00	
	(0.00)		(0.00)	
Firm Performance	0.00	***	0.00	
	(0.00)		(0.00)	
Firm Size	0.19	***	0.23	***
	(0.10)		(0.04)	
Firm's Share Price	0.01	***	0.01	***
	(0.00)		(0.00)	
Firm's Annual Dividend	1.13	**	-0.91	***
	(0.44)		(0.10)	
Investor's Portfolio Value	0.15	***	0.07	***
	(0.02)		(0.00)	
Investor's Number of Distinct Industries	0.09	***	0.11	***
	(0.01)		(0.00)	
Investor's Prior Number of Shares in the Focal Firm	0.17	***	0.15	***
	(0.01)		(0.00)	
Annual Inflation (CPI)	0.05	***	0.05	***
	(0.00)		(0.00)	
U.S. Government T-Bill Rate	-0.01		0.09	***
	(0.05)		(0.02)	
Annual US Equities Index	-0.02	***	-0.02	***
	(0.00)		(0.00)	
Constant	-13.646	***	-13.920	***
Number of Observations	179,744		386,728	
Model log likelihood	-9,663.51		-42,283.66	
Wald X 2	8137.97	***	25608.03	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for all variables. Includes investor dummies for pension and investment fund ownership

Table 30

Econometric Test #4 For Medical Devices - Study 3

Split-Sample Logit Estimates on Contingent Effect of Firm's Ability to Commercialize Innovations on the Relationship between Securities Analysts' Consensus and the Hazard that the Focal Investor will Increase Investment in the Focal Firm (test of proposition 15).

	Model 1		Model 2	
	Ability to Commercialize < Mean		Ability to Commercialize > Mean	
Standard Deviation of Securities Analysts' Recommendations	0.22	*	0.38	***
	(0.05)		(0.04)	
Marginal Effect	[.00085]		[.00449]	
		t = 3,400		
p-value of *t* -test of difference in marginal effects		***		
Contingency Variables				
Investor's Industry Experience	0.06	***	0.03	***
	(0.00)		(0.00)	
Investor's Time Horizon	-0.93	***	0.25	**
	(0.10)		(0.06)	
Firm's Scope of Innovation Portfolio	0.00		0.00	
	(0.00)		(0.00)	
Other Control Variables				
Firm's Innovative Inputs	0.20	***	0.12	***
	(0.03)		(0.02)	
Securities Analysts' Favorability of Focal Firm's Recommendation	0.17	***	0.06	*
	(0.03)		(0.03)	
Number of Securities Analysts Covering Focal Firm	-0.04	***	0.01	**
	(0.01)		(0.00)	
Firm's Products' Average Age	-0.01		0.05	***
	(0.01)		(0.00)	
Firm's Products % of Total Products in its Categories	2.77	***	3.06	***
	(0.46)		(0.71)	
Firm's Number of Competing Products in its Product Categories	0.00		0.00	***
	(0.00)		(0.00)	
Firm Performance	0.00	***	0.00	
	(0.00)		(0.00)	
Firm Size	0.51	***	0.21	***
	(0.08)		(0.00)	
Firm's Share Price	0.02	***	0.01	***
	(0.00)		(0.00)	
Firm's Annual Dividend	0.29		-0.92	***
	(0.27)		(0.10)	
Investor's Portfolio Value	0.14	***	0.06	***
	(0.01)		(0.00)	
Investor's Number of Distinct Industries	0.10	***	0.10	***
	(0.01)		(0.00)	
Investor's Prior Number of Shares in the Focal Firm	0.17	***	0.15	***
	(0.01)		(0.00)	
Annual Inflation (CPI)	0.05	***	0.05	***
	(0.00)		(0.00)	
U.S. Government T-Bill Rate	0.07		0.08	***
	(0.04)		(0.02)	
Annual US Equities Index	-0.02	***	-0.02	***
	(0.00)		(0.00)	
Constant	14.960	***	-14.331	***
Number of Observations	227,191		339,281	
Model log likelihood	-12,724.68		-39,257.79	
Wald X 2	9549.59	***	23934.16	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for all variables. Includes investor dummies for pension and investment fund ownership

Table 31
Robustness to Analysts Covering Industries - Study 1
Logistic Regression Estimates of Analyst's Hazard of Covering the Focal Firm

	Medical Devices (SIC 3841 & 3842) Logit Model 1		Computer Hardware (SIC 3570-3579) Logit Model 2		Computer Software (SIC 7372) Logit Model 3	
Knowledge Diversity (H1 < 0)	-0.04	***	0.00		-0.02	**
	(0.01)		(0.01)		(0.01)	
Knowledge Distance (H2 < 0)	-1.49	***	-1.67	***	-0.12	
	(0.37)		(0.35)		(0.18)	
Knowledge Overlap (H3 > 0)	2.36	***	1.57	**	-0.27	
	(0.54)		(0.54)		(0.26)	
Control Variables						
Firm Performance	0.00	*	0.00		0.00	*
	(0.00)		(0.00)		(0.00)	
Firm Size	0.79	***	0.70	***	0.39	***
	(0.14)		(0.07)		(0.05)	
Number of Analysts Covering the Industry	0.00		0.00		0.00	***
	(0.01)		(0.00)		(0.00)	
Firm's Yearly Number of Patents	0.01	**	0.00		0.00	***
	(0.00)		(0.00)		(0.00)	
Firm's Technological Quality	-0.02		0.09		0.17	***
	(0.05)		(0.05)		(0.02)	
Firm's Geographic Scope	-0.10		-0.29	***	-0.49	***
	(0.07)		(0.06)		(0.09)	
Innovation intensity of firm's industry	-19.53	**	-0.50		14.37	***
	(6.48)		(2.05)		(2.70)	
Knowledge overlap between the analyst and the firm	5.50	***	7.81	***	1.96	***
	(0.65)		(0.89)		(0.08)	
Regulation FD (dummy)	0.81	*	-1.42	***	-0.15	*
	(0.33)		(0.36)		(0.07)	
Year Dummies	Included		Included		Not Included	
Constant	-8.155	***	-9.593	***	-9.584	***
Number of Observations	19,152		22,605		162,891	
Model log likelihood	-2,278.55		-3,224.55		-9,246.98	
Wald X 2	421.72	***	674.99	***	1290.38	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 32
Robustness to Different Industry Groupings - Study 1
Logistic Regression Estimates of Analyst's Hazard of Covering the Focal Firm

	Medical Devices Industry (SIC 3841-3845) Logit Model 1		Computer Hardware Industry (SIC 3570-3572) Logit Model 2	
Knowledge Diversity (H1 < 0)	-0.02	**	0.01	
	(0.01)		(0.01)	
Knowledge Distance (H2 < 0)	-0.95	***	-1.48	**
	(0.22)		(0.58)	
Knowledge Overlap (H3 > 0)	2.23	***	6.96	***
	(0.32)		(1.34)	
Control Variables				
Firm Performance	0.00	*	0.00	***
	(0.00)		(0.00)	
Firm Size	0.56	***	-0.17	
	(0.08)		(0.12)	
Number of Analysts Covering the Industry	0.00		0.07	***
	(0.00)		(0.01)	
Firm's Yearly Number of Patents	0.01	***	0.00	***
	(0.00)		(0.00)	
Firm's Technological Quality	0.02		0.62	***
	(0.04)		(0.10)	
Firm's Geographic Scope	-0.07		-1.24	***
	(0.05)		(0.19)	
Innovation intensity of firm's industry	0.95		-26.27	***
	(1.77)		(4.25)	
Knowledge overlap between the analyst and the firm	5.17	***	6.38	***
	(0.15)		(0.34)	
Regulation FD (dummy)	0.94	***	-4.10	***
	(0.16)		(0.46)	
Year Dummies	Included		Included	
Constant	-11.165	***	-12.259	***
Number of Observations	1,444,159		387,317	
Model log likelihood	-8,861.26		-3,047.91	
Wald X 2	2263.00	***	1815.92	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 33
Robustness to Alternative Measures - Study 1
Logistic Regression Estimates of Analyst's Hazard of Covering the Focal Firm

	Medical Devices (SIC 3841 & 3842) Logit Model 1		Computer Hardware (SIC 3570-3579) Logit Model 2		Computer Software (SIC 7372) Logit Model 3	
Knowledge Diversity (H1 < 0)	-0.03	***	0.01	*	-0.05	***
	(0.01)		(0.00)		(0.01)	
Knowledge Distance (H2 < 0)	0.22		-2.43	***	5.01	***
	(1.10)		(0.60)		(0.89)	
Knowledge Overlap (H3 > 0)	1.77	***	0.48		-0.47	*
	(0.39)		(0.40)		(0.22)	
Control Variables						
Firm Performance	0.00	**	0.00		0.00	
	(0.00)		(0.00)		(0.00)	
Firm Size	0.42	***	0.61	***	0.44	***
	(0.13)		(0.06)		(0.05)	
Number of Analysts Covering the Industry	0.00		0.02	***	0.01	**
	(0.01)		(0.00)		(0.00)	
Firm's Yearly Number of Patents	0.01	***	0.00		0.00	***
	(0.00)		(0.00)		(0.00)	
Firm's Technological Quality	0.09		0.14	**	0.28	***
	(0.05)		(0.05)		(0.03)	
Firm's Geographic Scope	-0.11		-0.49	***	-0.35	***
	(0.06)		(0.06)		(0.08)	
Innovation intensity of firm's industry	-6.43		-7.84	***	-12.92	**
	(5.85)		(1.79)		(4.30)	
Knowledge overlap between the analyst and th	5.81	***	6.08	***	4.51	***
	(0.26)		(0.21)		(0.10)	
Regulation FD (dummy)	0.77	***	-1.79	***	-4.17	***
	(0.25)		(0.22)		(0.94)	
Year Dummies	Included		Included		Included	
Constant	-11.903	***	-8.372		-12.876	***
Number of Observations	773,684		1,062,971		1,025,863	
Model log likelihood	-4,606.35		-7,831.08		-11,904.66	
Wald X 2	1356.47	***	2122.88	***	2996.69	***

* p < .05; ** p < .01; *** p < .001
Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 34
Robustness to Different Models For Medical Devices - Study 1
Logistic Regression Estimates of Analyst's Hazard of Covering the Focal Firm

	Cloglog Model 1		RELOGIT Model 2		Analyst FE Logit Model 3	
Knowledge Diversity (H1 < 0)	-0.04	***	-0.04	***	-0.04	***
	(0.01)		(0.01)		(0.01)	
Knowledge Distance (H2 < 0)	-1.56	***	-1.56	***	-1.28	***
	(0.34)		(0.34)		(0.25)	
Knowledge Overlap (H3 > 0)	2.80	***	2.81	***	1.91	***
	(0.49)		(0.49)		(0.38)	
Control Variables						
Firm Performance	0.00	**	0.00	**	0.00	***
	(0.00)		(0.00)		(0.00)	
Firm Size	0.56	***	0.56	***	0.70	***
	(0.13)		(0.13)		(0.10)	
Number of Analysts Covering the Industry	0.01		0.00		0.01	***
	(0.01)		(0.01)		(0.00)	
Firm's Yearly Number of Patents	0.01	***	0.01	***	0.01	
	(0.00)		(0.00)		(0.03)	
Firm's Technological Quality	-0.02		0.01		0.01	
	(0.06)		(0.05)		(0.03)	
Firm's Geographic Scope	-0.09		-0.10		-0.11	*
	(0.06)		(0.06)		(0.05)	
Innovation intensity of firm's industry	-7.86		-7.75		-7.32	
	(5.82)		(5.84)		(4.42)	
Knowledge overlap between the analyst and the firm	5.76	***	5.76	***	4.16	***
	(0.25)		(0.25)		(0.23)	
Regulation FD (dummy)	0.76	**	0.75	***	-0.08	
	(0.25)		(0.25)		(0.29)	
Year Dummies	Included		Included		Included	
Constant	-10.665	***	10.650	***		
Number of Observations	773,684		773,684		31,883	
Model log likelihood	-4,584.20				-2,565.51	
Wald X 2	1355.35	***			953.25	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 35
Robustness to Different Models For Computer Hardware - Study 1
Logistic Regression Estimates of Analyst's Hazard of Covering the Focal Firm

	Cloglog Model 1		RELOGIT Model 2		Analyst FE Logit Model 3	
Knowledge Diversity (H1 < 0)	0.01	**	0.01	**	0.01	***
	(0.00)		(0.00)		(0.00)	
Knowledge Distance (H2 < 0)	-1.44	***	-1.44	***	-1.51	***
	(0.30)		(0.30)		(0.26)	
Knowledge Overlap (H3 > 0)	1.39	**	1.39	***	1.19	***
	(0.43)		(0.44)		(0.37)	
Control Variables						
Firm Performance	0.00		0.00		0.00	
	(0.00)		(0.00)		(0.00)	
Firm Size	0.61	***	0.62	***	0.65	***
	(0.06)		(0.06)		(0.05)	
Number of Analysts Covering the Industry	0.03	***	0.03	***	0.03	***
	(0.00)		(0.00)		(0.00)	
Firm's Yearly Number of Patents	0.00		0.00		0.00	
	(0.00)		(0.00)		(0.00)	
Firm's Technological Quality	0.10	*	0.10	*	0.10	***
	(0.05)		(0.05)		(0.03)	
Firm's Geographic Scope	-0.32	***	-0.32	***	-0.31	***
	(0.06)		(0.06)		(0.04)	
Innovation intensity of firm's industry	-8.86	***	-8.78	***	-9.17	***
	(1.76)		(1.76)		(1.23)	
Knowledge overlap between the analyst and the firm	6.06	***	6.06	***	4.89	***
	(0.21)		(0.21)		(0.18)	
Regulation FD (dummy)	-1.96	***	-1.97	***	-3.89	***
	(0.23)		(0.23)		(0.27)	
Year Dummies	Included		Included		Included	
Constant	-9.854	***	-9.824	***		
Number of Observations	1,062,971		1,062,971		78,893	
Model log likelihood	-7,822.22				-4,860.55	
Wald X 2	2189.3	***			2022.14	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 36
Robustness to Different Models For Computer Software - Study 1
Logistic Regression Estimates of Analyst's Hazard of Covering the Focal Firm

	Cloglog Model 1		RELOGIT Model 2		Analyst FE Logit Model 3	
Knowledge Diversity (H1 < 0)	-0.05	***	-0.06	***	-0.04	***
	(0.01)		(0.01)		(0.01)	
Knowledge Distance (H2 < 0)	-0.36	*	-0.39	*	-0.04	
	(0.18)		(0.18)		(0.14)	
Knowledge Overlap (H3 > 0)	-0.33		-0.38		-1.17	***
	(0.22)		(0.22)		(0.18)	
Control Variables						
Firm Performance	0.00		0.00	*	0.00	
	(0.00)		(0.00)		(0.00)	
Firm Size	0.46	***	0.48	***	0.39	***
	(0.05)		(0.05)		(0.04)	
Number of Analysts Covering the Industry	0.01	***	0.04	***	-0.99	
	(0.00)		(0.00)		(32.24)	
Firm's Yearly Number of Patents	0.00	***	0.00	***	0.00	***
	(0.00)		(0.00)		(0.00)	
Firm's Technological Quality	0.19	***	0.19	***	0.17	***
	(0.02)		(0.02)		(0.02)	
Firm's Geographic Scope	-0.36	***	-0.36	***	-0.28	***
	(0.08)		(0.08)		(0.06)	
Innovation intensity of firm's industry	-12.42	**	-27.83	***	1,217.59	
	(4.25)		(3.22)		(39,073.83)	
Knowledge overlap between the analyst and the firm	4.50	***	4.39	***	4.44	***
	(0.10)		(0.09)		(0.13)	
Regulation FD (dummy)	-4.45	***	-9.49	***	206.30	
	(0.94)		(0.41)		(6,860.84)	
Year Dummies	Included		Included		Included	
Constant	-7.570	***	-7.173	***		
Number of Observations	1,025,863		1,025,863		125,710	
Model log likelihood	-11,933.02				-7,395.46	
Wald X 2	2996.74	***			2844.54	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 37
Robustness to Different Industry Groupings - Study 2
Logistic Regression Estimates of Analyst's Increasing Favorability of Recommendation

	Medical Devices Industry (SIC 3841 - 3845) Logit Model 1		Computer Hardware Industry (SIC 3570 - 3572) Logit Model 2
Knowledge Distance (P7 < 0)	-0.56		-1.65
	(0.53)		(1.53)
Knowledge Overlap (P8 < 0)	-0.83		-0.96
	(0.83)		(2.15)
Control Variables			
Inverse Mills Ratio	-0.18		-0.38
	(0.15)		(0.34)
Firm Size	0.17		-0.14
	(0.20)		(0.35)
Firm Performance	0.00		0.00
	(0.00)		(0.00)
Average Analysts Recomendation	0.57	***	0.45
	(0.17)		(0.34)
Firm's Yearly Number of Patents	0.00		0.00
	(0.00)		(0.00)
Firm's Technological Quality	0.00		-0.21
	(0.05)		(0.15)
Firm's Knowledge Diversity	0.00		0.01
	(0.02)		(0.02)
Firm's Geographic Scope	-0.35	***	0.59
	(0.11)		(0.40)
Degree to which analysts' firms explore new knowledge	-0.13		0.66
	(0.74)		(0.96)
Analyst Experience	0.00		0.02
	(0.01)		(0.02)
Analyst Accuracy	0.00		0.01
	(0.07)		(0.03)
Regulation FD (dummy)	0.23		0.10
	(0.21)		(0.37)
Constant	-1.321		0.719
Number of Observations	1,414		621
Model log likelihood	-575.47		-305.79
Wald X 2	41	***	19.65

+ p<.10;* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 38

Robustness to Alternative Measures - Study 2

Logistic Regression Estimates of Analyst's Increasing Favorability of Recommendation

	Medical Devices (SIC 3841 & 3842) Logit Model 1		Computer Hardware (SIC 3570-3579) Logit Model 2		Computer Software (SIC 7372) Logit Model 3	
Knowledge Distance (P7 < 0)	-1.55		-1.24		-1.10	
	(3.35)		(1.57)		(1.22)	
Knowledge Overlap (P8 < 0)	-2.15	*	0.60		-0.33	
	(0.97)		(0.85)		(0.52)	
Control Variables						
Inverse Mills Ratio	-1.34	***	-0.38	*	-0.09	
	(0.33)		(0.16)		(0.16)	
Firm Size	-0.64		-0.30		0.01	
	(0.33)		(0.14)		(0.14)	
Firm Performance	0.00		0.00	*	0.00	
	(0.00)		(0.00)		(0.00)	
Average Analysts Recomendation	0.40		0.73	***	0.70	**
	(0.25)		(0.20)		(0.22)	
Firm's Yearly Number of Patents	0.00		0.00		0.00	**
	(0.01)		(0.00)		(0.00)	
Firm's Technological Quality	0.04		0.04		-0.02	
	(0.09)		(0.08)		(0.10)	
Firm's Knowledge Diversity	0.03		0.00		-0.04	
	(0.02)		(0.01)		(0.02)	
Firm's Geographic Scope	-0.39	*	0.11		0.17	
	(0.19)		(0.14)		(0.28)	
Degree to which analysts' firms explore new knowledge	0.18		-0.47		0.25	
	(1.03)		(0.67)		(0.65)	
Analyst Experience	0.01		0.01		-0.02	
	(0.02)		(0.01)		(0.01)	
Analyst Accuracy	0.06		0.00		0.00	
	(0.07)		(0.02)		(0.01)	
Regulation FD (dummy)	0.08		0.01		0.12	
	(0.30)		(0.18)		(0.23)	
Constant	6.189		-0.581		-1.747	
Number of Observations	758		1,412		1,916	
Model log likelihood	-286.86		-588.96		-857.21	
Wald X 2	33.21	**	37.04	**	83.74	***

* p < .05; ** p < .01; *** p < .001

Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 39
Robustness to Different Models For Medical Devices - Study 2
Logistic Regression Estimates of Analyst's Increasing Favorability of Recommendation

	Medical Devices Industry (SIC 3841 & 3842)		
	Regression Model 1	Firm Fixed Effects Logit Model 2	
Knowledge Distance (P7 < 0)	0.06	-2.53	
	(0.43)	(1.86)	
Knowledge Overlap (P8 < 0)	0.28	-6.47	
	(0.60)	(6.27)	
Control Variables			
Inverse Mills Ratio	0.28	-1.03	
	(0.18)	(0.60)	
Firm Size	0.27	-2.84	*
	(0.18)	(1.24)	
Firm Performance	0.00	0.00	
	(0.00)	(0.00)	
Average Analysts Recomendation	0.20	0.83	*
	(0.13)	(0.34)	
Firm's Yearly Number of Patents	0.00	0.01	
	(0.00)	(0.01)	
Firm's Technological Quality	-0.01	0.79	
	(0.05)	(0.49)	
Firm's Knowledge Diversity	0.00	0.06	
	(0.01)	(0.04)	
Firm's Geographic Scope	0.05	-0.79	
	(0.06)	(0.62)	
Degree to which analysts' firms explore new knowledge	0.23	0.50	
	(0.54)	(1.30)	
Analyst Experience	0.00	0.02	
	(0.01)	(0.02)	
Analyst Accuracy	-0.01	0.05	
	(0.02)	(0.07)	
Regulation FD (dummy)	0.19	0.26	
	(0.15)	(0.60)	
Constant	0.054		
Number of Observations	293	705	
Model log likelihood		-243	
Wald X 2		34.34	**

* p < .05; ** p < .01; *** p < .001
Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 40
Robustness to Different Models For Computer Hardware - Study 2
Logistic Regression Estimates of Analyst's Increasing Favorability of Recommendation

	Computer Hardware Industry (SIC 3570-3579)			
	Regression Model 1		Firm Fixed Effects Logit Model 2	
Knowledge Distance (P7 < 0)	-0.03		-3.97	**
	(0.36)		(1.51)	
Knowledge Overlap (P8 < 0)	0.17		-2.42	
	(0.55)		(4.55)	
Control Variables				
Inverse Mills Ratio	0.01		0.04	
	(0.09)		(0.36)	
Firm Size	-0.03		-0.61	
	(0.07)		(0.42)	
Firm Performance	0.00		0.00	
	(0.00)		(0.00)	
Average Analysts Recomendation	0.02		0.87	***
	(0.10)		(0.24)	
Firm's Yearly Number of Patents	0.00		0.00	
	(0.00)		(0.00)	
Firm's Technological Quality	-0.02		-0.15	
	(0.03)		(0.20)	
Firm's Knowledge Diversity	0.00		0.00	
	(0.00)		(0.01)	
Firm's Geographic Scope	-0.02		-0.43	
	(0.06)		(0.47)	
Degree to which analysts' firms explore new knowledge	0.19		-0.26	
	(0.39)		(0.85)	
Analyst Experience	0.01		0.02	
	(0.01)		(0.01)	
Analyst Accuracy	0.00		0.00	
	(0.01)		(0.02)	
Regulation FD (dummy)	0.09		-0.07	
	(0.08)		(0.34)	
Constant	2.235	***		
Number of Observations	602		1,380	
Model log likelihood			-571.31	
Wald X 2			28.96	*

* p < .05; ** p < .01; *** p < .001
Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 41
Robustness to Different Models For Computer Software - Study 2
Logistic Regression Estimates of Analyst's Increasing Favorability of Recommendation

	Computer Software Industry (SIC 7372)			
	Regression Model 1		Firm Fixed Effects Logit Model 2	
Knowledge Distance (P7 < 0)	0.14		-1.28	
	(0.20)		(1.27)	
Knowledge Overlap (P8 < 0)	0.52	*	1.11	
	(0.23)		(2.40)	
Control Variables				
Inverse Mills Ratio	-0.24	*	0.33	
	(0.11)		(0.43)	
Firm Size	-0.18	*	0.37	
	(0.08)		(0.48)	
Firm Performance	0.00		0.00	
	(0.00)		(0.00)	
Average Analysts Recomendation	0.23	*	0.89	***
	(0.09)		(0.24)	
Firm's Yearly Number of Patents	0.00	*	0.00	*
	(0.00)		(0.00)	
Firm's Technological Quality	-0.04		-0.65	
	(0.04)		(0.36)	
Firm's Knowledge Diversity	0.02	*	-0.03	
	(0.01)		(0.03)	
Firm's Geographic Scope	0.04		-0.24	
	(0.10)		(0.81)	
Degree to which analysts' firms explore new knowledge	-0.27		-0.12	
	(0.27)		(0.62)	
Analyst Experience	0.00		-0.02	
	(0.01)		(0.01)	
Analyst Accuracy	0.00		0.00	
	(0.00)		(0.01)	
Regulation FD (dummy)	0.14		0.30	
	(0.08)		(0.35)	
Constant	2.991	***		
Number of Observations	807		1,863	
Model log likelihood			-749.12	
Wald X 2			30.17	**

* p < .05; ** p < .01; *** p < .001
Standard errors in parentheses. Two-tailed test for hypotheses and control variables.

Table 42
Robustness to Different Models For Medical Devices - Study 3
Estimates of Investor's Hazard of Increasing Investment in the Focal Firm

	Cloglog Model 1		RELOGIT Model 2		Investor Fixed Effects Logit Model 3	
Standard Deviation of Securities Analysts' Recommendations	0.29	***	0.26	***	0.26	***
	(0.03)		(0.03)		(0.03)	
Contingency Variables						
Investor's Industry Experience	0.03	***	0.05	***	0.00	
	(0.00)		(0.00)		(0.00)	
Investor's Time Horizon	0.15	**	0.02		-0.06	
	(0.05)		(0.05)		(0.09)	
Firm's Scope of Innovation Portfolio	0.00	***	0.00	***	0.00	***
	(0.00)		(0.00)		(0.00)	
Firm's Ability To Commercialize Innovations	0.02	***	0.02	***	0.02	***
	(0.00)		(0.00)		(0.00)	
Other Control Variables						
Firm's Innovative Inputs	0.12	***	0.12	***	0.10	***
	(0.01)		(0.02)		(0.01)	
Securities Analysts' Favorability of Focal Firm's Recommendation	0.10	***	0.12	***	0.14	***
	(0.02)		(0.00)		(0.02)	
Number of Securities Analysts Covering Focal Firm	-0.01	***	0.00		0.00	
	(0.00)		(0.00)		(0.00)	
Firm's Products' Average Age	0.03	***	0.04	***	0.04	***
	(0.00)		(0.00)		(0.00)	
Firm's Products % of Total Products in its Categories	2.58	***	2.92	***	2.95	***
	(0.38)		(0.39)		(0.39)	
Firm's Number of Competing Products in its Product Categories	0.00		0.00		0.00	***
	(0.00)		(0.00)		(0.00)	
Firm Performance	0.00		0.00		0.00	
	(0.00)		(0.00)		(0.00)	
Firm Size	0.26	***	0.29	***	0.30	***
	(0.03)		(0.03)		(0.02)	
Firm's Share Price	0.01	***	0.01	***	0.01	***
	(0.00)		(0.00)		(0.00)	
Firm's Annual Dividend	-0.56	***	-0.72	***	-0.75	***
	(0.07)		(0.09)		(0.06)	
Investor's Portfolio Value	0.06	***	0.08	***	0.07	***
	(0.00)		(0.00)		(0.01)	
Investor's Number of Distinct Industries	0.11	***	0.10	***	0.04	***
	(0.00)		(0.00)		(0.00)	
Investor's Prior Number of Shares in the Focal Firm	0.06	***	0.15	***	0.13	***
	(0.00)		(0.00)		(0.00)	
Annual Inflation (CPI)	0.13	***	0.05	***	0.04	***
	(0.00)		(0.00)		(0.02)	
U.S. Government T-Bill Rate	0.06	***	0.06	***	0.03	
	(0.02)		(0.02)		(0.02)	
Annual US Equities Index	-0.02	***	-0.02	***	-0.02	***
	(0.00)		(0.00)		(0.00)	
Constant	-13.316	***	-13.975	***		
Number of Observations	566,472		566,472		368,488	
Model log likelihood	-53,376.32				-44,572.72	
Wald X 2	33915.93	***			21968.28	***

* p < .05; ** p < .01; *** p < .001
Standard errors in parentheses. Two-tailed test for all variables. Includes investor dummies for pension and investment fund ownership

Table 43
Robustness to Different Investors For Medical Devices - Study 3
Logistic Regression Estimates of Investor's Hazard of Increasing Investment in the Focal Firm

	New Investors Logit Model 1		Existing Investors Logit Model 2	
Standard Deviation of Securities Analysts' Recommendations	0.21	***	0.22	***
	(0.04)		(0.05)	
Contingency Variables				
Investor's Industry Experience	0.08	***	0.01	***
	(0.00)		(0.00)	
Investor's Time Horizon	-0.74		1.60	***
	(0.06)		(0.09)	
Firm's Scope of Innovation Portfolio	0.00	*	0.00	
	(0.00)		(0.00)	
Firm's Ability To Commercialize Innovations	0.02	***	0.02	***
	(0.00)		(0.00)	
Other Control Variables				
Firm's Innovative Inputs	0.18		0.04	*
	(0.02)		(0.02)	
Securities Analysts' Favorability of Focal Firm's Recommendation	0.21		0.06	
	(0.03)		(0.03)	
Number of Securities Analysts Covering Focal Firm	0.02	***	-0.02	***
	(0.00)		(0.00)	
Firm's Products' Average Age	0.06	***	0.00	
	(0.00)		(0.00)	
Firm's Products % of Total Products in its Categories	4.54	***	-1.61	*
	(0.45)		(0.67)	
Firm's Number of Competing Products in its Product Categories	0.00	*	0.00	*
	(0.00)		(0.00)	
Firm Performance	0.00	***	0.00	*
	(0.00)		(0.00)	
Firm Size	0.36	***	-0.01	
	(0.04)		(0.00)	
Firm's Share Price	0.01	***	0.01	***
	(0.00)		(0.00)	
Firm's Annual Dividend	-1.06	***	-0.12	
	(0.12)		(0.08)	
Investor's Portfolio Value	0.12	***	0.09	***
	(0.01)		(0.01)	
Investor's Number of Distinct Industries	0.12	***	0.00	
	(0.00)		(0.00)	
Annual Inflation (CPI)	0.06	***	0.03	***
	(0.00)		(0.00)	
U.S. Government T-Bill Rate	0.01		0.12	***
	(0.00)		(0.03)	
Annual US Equities Index	-0.03	***	-0.01	***
	(0.00)		(0.00)	
Constant	-15.335	***	-7.890	***
Number of Observations	539,839		26,633	
Model log likelihood	-32,900.89		-16,540.13	
Wald X 2	13735.62	***	1341.35	***

* p < .05; ** p < .01; *** p < .001
Standard errors in parentheses. Two-tailed test for all variables. Includes investor dummies for pension and investment fund ownership

Table 44
Robustness to Different Dependent Variable For Medical Devices - Study 3
Logistic Regression Estimates of Investor's Hazard of Decreasing Investment in the Focal Firm

	New DV Sales Logit Model 1	
Standard Deviation of Securities Analysts' Recommendations	-0.06 (0.05)	
Contingency Variables		
Investor's Industry Experience	-0.03 (0.00)	***
Investor's Time Horizon	-0.32 (0.09)	***
Firm's Scope of Innovation Portfolio	0.00 (0.00)	
Firm's Ability To Commercialize Innovations	-0.02 (0.00)	***
Other Control Variables		
Firm's Innovative Inputs	0.00 (0.02)	
Securities Analysts' Favorability of Focal Firm's Recommendation	-0.05 (0.03)	
Number of Securities Analysts Covering Focal Firm	0.00 (0.01)	
Firm's Products' Average Age	0.01 (0.01)	
Firm's Products % of Total Products in its Categories	2.23 (0.51)	***
Firm's Number of Competing Products in its Product Categories	0.00 (0.00)	*
Firm Performance	0.00 (0.00)	
Firm Size	0.11 (0.04)	**
Firm's Share Price	0.00 (0.00)	*
Firm's Annual Dividend	0.04 (0.07)	
Investor's Portfolio Value	-0.06 (0.00)	***
Investor's Number of Distinct Industries	0.07 (0.00)	***
Investor's Prior Number of Shares in the Focal Firm	0.64 (0.00)	***
Annual Inflation (CPI)	0.00 (0.00)	
U.S. Government T-Bill Rate	-0.21 (0.03)	***
Annual US Equities Index	0.00 (0.00)	
Constant	-5.704	***
Number of Observations	566,472	
Model log likelihood	-21,851.27	
Wald X 2	35,555.65	***

* p < .05; ** p < .01; *** p < .001
Standard errors in parentheses. Two-tailed test for all variables. Includes dummies for pension and investment fund ownership

Table 45
Summary of Empirical Findings Study 1, 2 and 3

	Medical Devices	Computer Hardware	Computer Software	
Proposition 1 (P1): The greater the firm's knowledge diversity, the lower the likelihood that a securities analyst will cover the firm.	Yes	No	Yes	**Partially Supported**
Proposition 2 (P2): The more extensively the firm explores distant knowledge, the lower the likelihood that a securities analyst will cover the firm.	Yes	Yes	Yes	**Supported**
Proposition 3 (P3): The greater the knowledge overlap between the firm and its industry rivals, the greater the likelihood that a securities analyst will cover the firm.	Yes	Yes	No	**Partially Supported**
Proposition 4 (P4): The greater the knowledge overlap between the analyst and the firm, the less negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm.	No	No	No	**Not Supported**
Proposition 5 (P5): The greater the innovation intensity of the firm's industry, the more negative the effect that exploration of distant knowledge will have on the likelihood an analyst will cover the firm.	No	No	No	**Not Supported**
Proposition 6 (P6): The greater the innovation intensity of the firm's industry, the less positive the effect of knowledge overlap between the firm and its industry rivals on the likelihood an analyst will cover the firm.	Yes	Yes	No	**Partially Supported**
Proposition 7 (P7): Exploring distant knowledge will have a negative impact on the favorability of the analyst's recommendation for the firm.	No	No	No	**Not Supported**
Proposition 8 (P8): Greater knowledge overlap between the firm and its rivals will have a negative impact on the favorability of the analyst's recommendation for the firm.	No	No	No	**Not Supported**
Proposition 9 (P9): The greater the analyst's experience, the less negative the effect that exploration of distant knowledge will have on the favorability of the recommendation.	No	No	No	**Not Supported**
Proposition 10 (P10): The more extensively other firms covered by the analyst explore external knowledge, the less negative the effect that exploration of distant knowledge will have on the favorability of the recommendation.	No	No	No	**Not Supported**
Proposition 11 (P11): The lower the level of consensus among securities analysts' recommendations about the firm, the greater the likelihood that the investor will buy shares in the firm.	Yes			**Supported**
Proposition 12 (P12): The greater the investor's industry experience, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.	Yes			**Supported**
Proposition 13 (P13): The longer the investor's time horizon, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.	Yes			**Supported**
Proposition 14 (P14): The greater the scope of the firm's innovation portfolio, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.	Yes			**Supported**
Proposition 15 (P15): The greater the firm's ability to commercialize innovations, the more likely the investor will be to buy shares in the firm when consensus is low among securities analysts' recommendations.	Yes			**Supported**

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