Title
Do Analysts Understand Innovation? Evidence from Patents and Trademarks

Author
Li, Qin

Publication Date
2016

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA,
IRVINE

Do Analysts Understand Innovation? Evidence from Patents and Trademarks

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Management

by

Qin Li

Dissertation Committee:
Professor Siew Hong Teoh, Chair
Professor Terry Shevlin
Professor Alexander Nekrasov

2016

DEDICATION

To

My parents and grandparents

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

First and foremost, I would like to thank my advisor Professor Siew Hong Teoh. Her passion for research and for mentoring students has greatly inspired me ever since the first time I talked to her. Her caring for students and kindness touched me so much. I truly appreciate that she was always willing to meet and discuss whenever I faced hurdles in research. The countless discussion with her on research in general and on my dissertation in particular was enjoyable and fruitful. I am extremely grateful to her for stimulating me to think deeply and for training me to be a good writer.

I am also very thankful to other members on my committee. I am indebted to Professor Lucile Faurel for her invaluable encouragement and guidance at different stages of my dissertation, especially during tough times. I am deeply grateful for what Professor Terry Shevlin taught in his Ph.D. seminars, which helped me tremendously in mastering empirical research methods. My dissertation benefited greatly from his constructive suggestions about positioning, writing with clarity, and empirical tests. I am also thankful to Professor Alex Nekrasov for his insightful questions, which helped me improve the empirical design of my dissertation.

In addition, I gratefully acknowledge the helpful comments and suggestions from Professor Jiawei Chen (outside member on my proposal committee), Professor Joanna Ho, Professor Ben Lourie, Professor Mort Pincus, Professor Devin Shanthikumar, Professor Angela Davis (discussant), and workshop participants at University of California, Irvine, George Washington University, National University of Singapore, Florida International University, Hong Kong Polytechnic University, California State University, Fullerton, and the 2015 AAA Western Regional meeting, and the 2015 Haskell & White Corporate Reporting & Governance Conference.

I thank University of California, Irvine, the Paul Merage School of Business, and the California Society of Certified Public Accountants for their generous funding.

I would like to express my appreciation to the following people for their support: John Bae, Stephen Campbell, Meng Chen, Novia Chen, Peng-Chia Chiu, Tim Haight, Paula Hao, Ian Ho, Yoojin Lee, Tiana Lehmer, Yifan Li, Sun Lin, Esther Rihawi, Guojun Wang, Patricia Wellmeyer, Lijie Yao, and Yingjie Zhang. It has been a pleasure to work with and hang out with these fellow students or friends. I also want to extend my sincere gratitude to elderly brothers and sisters at Church in Irvine for their care and shepherding.

I would like to thank my husband Qiguang Wang for being my companion in the Ph.D. pursuit. Words cannot describe how thankful I am to the Lord for bringing you to my life and leading you to become my classmate, friend and dear husband. Lastly, a special thank you goes to my parents and grandparents for always loving me and supporting me in all my pursuits.

CURRICULUM VITAE

Qin Li

2004	B.S. in Economics, Fudan University
2009	M.S. in Accounting and Finance, London School of Economics and Political Science
2010-2016	Research & Teaching Assistant, The Paul Merage School of Business, University of California, Irvine
2016	Ph.D. in Management, University of California, Irvine

FIELD OF STUDY

Accounting

WORKING PAPERS

Do Analysts Understand Innovation? Evidence from Patents and Trademarks (Dissertation)

CEO Incentives and New Product Development: Insights from Trademarks (with Lucile Faurel, Devin Shanthikumar, and Siew Hong Teoh)

The Value of New Product Development (with Lucile Faurel, Devin Shanthikumar, and Siew Hong Teoh)

ABSTRACT OF THE DISSERTATION

Do Analysts Understand Innovation? Evidence from Patents and Trademarks

By

Qin Li

Doctor of Philosophy in Management

University of California, Irvine, 2016

Professor Siew Hong Teoh, Chair

This study examines whether analysts efficiently impound information about innovation into their short-term (quarterly and annual) and long-term forecasts. I use patents to measure technological innovation outputs, and trademarks to measure non-technological product and marketing innovation outputs. Analysts appear to understand that patents increase only long-term earnings growth whereas trademarks increase both short-term earnings and long-term earnings growth. However, their forecasts contain systematic errors. Analysts underreact to the short-term earnings implications of trademarks, and overreact to the long-term earnings implications of both patents and trademarks. In addition, analysts' short-term forecast errors predicted from trademarks partially explain investor mispricing of trademarks. Collectively, my findings improve our knowledge of whether analysts understand innovation and how analysts' inefficient use of information about innovation affects the stock market valuation of innovation.

CHAPTER 1: Introduction

During 1993-2010, nearly 80% of S&P 1500 firms have owned patents and/or trademarks, indicating the prevalence of innovation in U.S. public firms. Innovation activities, although crucial to future firm performance and intrinsic value, are uncertain and thus it is difficult for investors to assess how they affect firm value (Cohen, Diether, and Malloy (2013)). Given the importance of innovation to firm value and the difficulty to assess innovation, the role of analysts as information intermediaries becomes particularly important for innovative firms. Barth, Kasznik, and McNichols (2001) find that firms with more intangible assets both attract more analysts and elicit greater effort from the analysts. In my sample of S&P 1500 firms between 1993 and 2010, firms with patents and/or trademarks are followed by about three more analysts than firms with neither patents nor trademarks. In this paper, I examine whether analysts understand innovation by investigating whether they make efficient use of information contained in innovation output measures when making earnings forecasts.

I focus on two innovation output measures: patents and trademarks. [1] The traditional view of innovation narrowly focuses on new scientific discovery and technological advances, and these types of innovation generally culminate in new patents. However, the Organisation for Economic Co-operation and Development (OECD, 2005) suggests more broadly that *"an innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices,*

[1] I focus on innovation *outputs* rather than innovation inputs because innovation outputs capture the successful usage of all inputs, observable or unobservable, into innovation (He and Tian (2013)). The research question of this study is, therefore, about whether analysts understand how much future earnings can be generated from innovation outputs, and not about whether analysts understand if investment in innovation as measured by innovation inputs such as R&D expenditures will successfully lead to innovation outputs.

workplace organization or external relations."[2] This broader definition of innovation therefore includes a non-technological facet. Among all types of non-technological innovation, product and marketing innovation—which I regard as development of new or improved products/services and new marketing methods—bears particular importance because it results in new products/services that can be brought to the market and thus leads directly to sales and profits. This paper goes beyond prior literature on innovation by also focusing on product and marketing innovation and using trademarks to measure this type of innovation. A short-hand distinction between the two innovation output measures is that patents reflect the technological aspect of innovation whereas trademarks capture more of the commercial aspect of innovation (Millot (2009)).[3] For example, the patent titled "Method and Apparatus for Localization of Haptic Feedback" captures Apple Inc.'s new no-look typing technology while the trademark "UberEATS" refers to Uber's new on-demand meal delivery service.

Not all firms engage in both technological and non-technological types of innovation. Some firms focus on only one or the other, and some others have both or neither. Among the 3,311 unique firms in S&P 1500 between 1993 and 2010, there are 1,068 firms (32.26%) that have never filed patents but owned trademarks and 218 firms (6.58%) that have never filed trademarks but had patents, indicating that product and marketing innovation is more prevalent than technological innovation. Technology-intensive industries such as Electrical Equipment focus mainly on invention of new technologies that culminate in patents, whereas non-

[2] With the traditional view of innovation, our knowledge of innovation is limited to technology-intensive firms. Despite the fact that innovation is also pervasive in a large set of firms that do not rely so much on new technologies, we know little about how these firms innovate. It is thus important for researchers to take a broad view of innovation and expand the scope of research to innovation in those firms that have not received much attention in the past literature on innovation.

[3] Trademarks can be registered for new products/services or new marketing campaigns. I do not distinguish between the two because new products are often accompanied by new marketing campaigns. Product innovation and marketing innovation are grouped together as one type of non-technological innovation.

technology-intensive industries such as Food Products and Financial Services can create new products/services without inventing new technologies and thus own trademarks but not patents. In the same sample, 1,376 firms (41.56%) create both patents and trademarks. These firms usually develop new technologies and then turn the new technologies into new products/services.[4] For example, Apple Inc.'s product "iPhone" was developed from a combination of nearly 1,300 patents that the company had filed (Gaze and Roderick (2012)). This post-patenting step of converting new technologies to new products/services is crucial, especially for consumer-facing firms, because most patents are not directly commercializable due to the lack of concrete useful applications (Millot (2009)) and thus firms cannot realize profits from most technological inventions until new products/services are developed from those new technologies.

Prior literature on analysts' forecasts suggests that analysts care about their reputation and strive for accurate forecasts (see, e.g., Mikhail, Walther, and Willis (1999) and Hong and Kubik (2003)), which can be achieved through efficient use of innovation-related information. Moreover, the capital market views analysts as having expertise about hard-to-value firms, such as those with high innovation activities. Barth, Kasznik, and McNichols (2001) confirm that analysts like to follow firms with more intangible assets and exert more effort into analyzing these firms. Given these points, analysts have both the incentives to gather information contained in innovation output measures and the expertise to use it. If this is the case, I expect that analysts will likely understand and use information contained in patents and trademarks.

[4]Creating a new product or service may or may not need new technologies. In industries where product development relies on technologies, product innovation particularly refers to the post-patenting stage in which firms integrate technologies to design or improve products/services that will be directly marketable.

On the other hand, there is past evidence showing that analysts are inefficient users of new information (see, e.g., Abarbanell and Bernard (1992), Abarbanell and Bushee (1997), Bradshaw, Richardson, and Sloan (2001), and Teoh and Wong (2002)). The earnings prospects of innovation are generally uncertain, imposing challenges even for analysts. Due to proprietary costs, innovative firms are often reluctant to provide information about their innovation activities, which further increase difficulty for analysts to understand firm innovation. Moreover, greater information opacity and paucity in innovative firms raise analysts' reliance on managers for private information, thereby increasing analysts' tendency to issue biased forecasts for connection-building purposes. Innovative firms, which often face high growth opportunities, have greater need for external financing and thus have incentives to exploit analysts' intention to please firms. Therefore, due to these agency problems, analysts may not truthfully incorporate their understanding of innovation into forecasts. These counter-arguments point to a conjecture that analysts may not appear to efficiently use information contained in the two innovation output measures-patents and trademarks.

This paper focuses on S&P 1500 firms with analyst coverage between 1993 and 2010. The sample includes 550,239 patents and 107,336 trademarks registered by 3,241 unique firms.[5] The question of whether analysts understand innovation consists of two parts: (1) whether analysts use information contained in innovation output measures, and (2) whether analysts use the information efficiently. To address these two questions, I test (1) whether analysts revise their earnings forecasts contemporaneously in response to new patents and new trademarks, and (2) whether analysts' forecast errors are predictable by new patents and new trademarks.

[5] For each firm that has ever been included in S&P 1500 between 1993 and 2010, I track all available periods of that firm in Compustat. Because the composition of the stock market index changes over time (i.e., firms can be added into or removed from S&P 1500), there are more than 1,500 unique firms in S&P 1500.

Analysts make quarterly, annual and long-term earnings growth forecasts. Accordingly, I focus on these three different windows in the tests.

I first verify the predictability of patents and trademarks for future earnings and see that new trademarks—and not patents—predict one-quarter-ahead earnings and one-year-ahead earnings whereas both new patents and new trademarks predict five-year earnings growth. This is consistent with the notion that it takes a longer period of time for patents to be monetized and included in earnings. In the main tests, I find that (1) analysts revise their quarterly and annual earnings forecasts upwards more when there are more new trademarks but not when there are more patents granted; (2) errors in analysts' quarterly and annual earnings forecasts are positively associated with the number of new trademarks but not with the number of new patents;[6] (3) analysts upgrade their long-term earnings growth forecasts when there are new patents and/or new trademarks; and (4) errors in analysts' long-term earnings growth forecasts are negatively associated with both the number of new patents and the number of new trademarks. Taken together, these findings indicate that (1) analysts use information contained in new trademarks about short-term earnings but underreact to this information; (2) analysts correctly perceive that new patents do not contain information about earnings in next quarter or next year; (3) analysts recognize the long-term earnings implications of both new patents and new trademarks but are overly optimistic about them.

This paper contributes to the literature in several major ways. I adopt a broad view of innovation and offer a comprehensive analysis of analysts' role in understanding both technological and non-technological innovation captured by new patents and new trademarks

[6] Errors in short-term earnings forecasts (long-term earnings growth forecasts) are defined as actual short-term earnings (actual long-term earnings growth) minus analysts' forecasted short-term earnings (forecasted long-term earnings growth).

respectively. By linking innovation outputs to analyst forecasts, I extend prior studies that relate analysts forecast errors to innovation inputs such as R&D costs that are expensed or capitalized as intangibles (see, e.g., Barron et al. (2002), Gu and Wang (2005), Ciftci (2012), and Curtis, McVay, and Toynbee (2015)).[7] It is critical to study innovation outputs, because outputs capture the successful usage of all inputs, observable or unobservable, into innovation (He and Tian (2013)). To my knowledge, Gu (2005) is the only paper that relates innovation outputs to analyst forecasts. That paper examines the relations between analysts' forecast errors and change in patent citations. However, change in citations reflects the relevance of previously patented technologies but does not capture new technological innovation for which new patent is a more appropriate measure.[8] Most importantly, my study is the first to examine whether analysts understand non-technological product and marketing innovation captured by trademarks. Distinct from previous studies, which focus on short-term earnings only, I allow for innovation outputs to be monetized and realized into earnings over different future periods and examine forecast revisions and forecast errors in both short and long windows.

My findings contribute to our knowledge of whether analysts have expertise in assessing innovation. The role of analysts as information intermediaries is crucial for the efficient functioning of the capital market. If analysts fail to properly evaluate innovation, investors relying on their judgement would therefore fail to efficiently value innovative firms. In a further analysis, I find that the inability of analysts to fully appreciate the annual earnings implications

[7] Barron et al. (2002) find that analyst consensus (i.e., the correlation in analysts' earnings forecast errors) decreases in a firm's level of intangible assets. Gu and Wang (2005) document a positive relation between analyst earnings forecast errors and a firm's industry-adjusted level of intangible assets. They measure intangible assets with R&D expenses, advertising expenses and balance sheet intangibles. Ciftci (2012) and Curtis, McVay, and Toynbee (2015) relate analysts' long-term forecasts to R&D expenditures.
[8] It is doubtful to what extent citations measure the importance or quality of patents (Alcácer, Gittelman, and Sampat (2009)). Most valuable patents are not always cited more (Abrams, Akcigit, and Popadak (2013)).

of trademarks is a contributory source of stock market mispricing of trademarks documented in Faurel et al. (2016). My evidence can also help understand the real economic effects of analyst coverage on corporate innovation. If analysts have expertise in assessing the value of innovation, their coverage of innovative firms can help reduce information asymmetry about firm innovation and thus increase investors' tolerance for short-term failure, which would encourage innovation (Manso (2011)).

The rest of the paper is organized as follows. Section 2 discusses the theoretical motivation for hypothesizing a link between patents and trademarks and analyst forecasts. Section 3 describes the sample, data and test design. Section 4 presents main results. Section 5 is an additional analysis that links analysts' forecast errors to stock mispricing of trademarks. Section 6 concludes the paper.

CHAPTER 2: Theoretical Motivation

In Section 2.1, I discuss how patents and trademarks capture innovation. Section 2.2 provides the motivation for why analysts would or would not use information contained in patents and trademarks about innovation.

2.1 Patents and Trademarks as Innovation Measures

A patent is "*a limited duration property right relating to an invention, granted by the United States Patent and Trademark Office in exchange for public disclosure of the invention* (USPTO, 2016)." For an invention to be patentable, it must be (1) a patentable subject matter; (2) novel; (3) non-obvious or involving an inventive step; and (4) useful or susceptible to industrial application. These criteria ensure that patent is a measure of technological innovation. Previous studies on innovation mainly use patents as an output measure of innovation (see, e.g., Griliches (1981), Griliches, Hall, and Pakes (1987)).[9]

Non-technological innovation, particularly product and marketing innovation, is generally not patentable. Faurel et al. (2016) propose trademark as an output measure of product and marketing innovation in the US setting.[10] A trademark is "*a word, phrase, symbol, and/or design that identifies and distinguishes the source of the goods or service of one party from those of others* (USPTO, 2016)." The mapping from new trademarks to new products/services or new marketing methods hinges on two features of trademark: (1) distinctiveness and (2) use in commerce. The distinctive character of trademark means that a trademark can be used to identify the goods/services of a particular provider and distinguish them from goods/services of other providers and also from existing goods/services of the same provider (Economides (1987)). Hence, when a firm has a new product/service or marketing campaign, it would want to file a new trademark, which is essentially a new name, to uniquely identify this new product/service or marketing campaign. For example, before launching its kid-targeted yogurt, Yoplait filed a new trademark "Pro-Force" in order to distinguish this new product from existing yogurt products on the market. In addition, the "evidence of use in commerce" requirement ensures that a new trademark has been used on an actual product/service or marketing campaign by the time of registration. Put more clearly, trademarks measure product and marketing innovation because a

[9] Academics and practitioners have raised concerns on whether patents are a good measure of technological innovation, due to such issues as patent trolling (i.e., preemptive filings of patents with trivial substance). Some patents are marginal while others capture ground-breaking technologies. From an empirical perspective, the inclusion of those patents with limited value in the analysis biases against finding a significant mean effect.

[10] For other studies that examine trademarks in non-US settings or in small US settings, please see, e.g., Krasnikov, Mishra, and Orozco (2009), González-Pedraz and Mayordomo (2012), and Millot (2012). Studies using survey data in European countries show that trademarks are linked to innovation. For example, by using survey data on 377 German firms that provide knowledge-intensive services, Schmoch (2003) shows that trademarks are positively related to the share of revenues associated with new products, which is another indicator of innovation activities.

trademark is a proxy for an underlying new product/service or new marketing method. For example, Uber trademarked "UBEREATS" and "UBERRUSH" respectively for its new meal delivery and package delivery services. Coca-Cola trademarked hashtag slogans "#SMILEWITHACOKE" and "#COKECANPICS" for future marketing campaigns on Twitter.

Both technological innovation and product and marketing innovation create competitive advantages and are important to future firm performance and growth. As output measures for different types of innovation, patents and trademarks contain complementary information.[11] Moreover, patents and trademarks are incremental to innovation input measures. Innovation inputs do not necessarily result in outputs. In addition, commonly-used input measures such as R&D expenses do not fully capture innovation inputs. For example, many firms do not report all their costs incurred in innovation activities as R&D expenses (Koh and Reeb (2015)).[12]

2.2 Analysts' Use of Information Contained in Patents and Trademarks

Anecdotal evidence suggests that analysts monitor firms' technological invention and product development. For example, Morgan Stanley analysts reported that "On March 19, 2015, the US Patent & Trademark Office published a patent application from Apple Inc. for a virtual keyboard made of the material of Apple's current trackpad but with haptics under each virtual key, according to Patently Apple." Suntrust Robinson Humphrey analysts said in their January 2015 report for Mattel Inc. that "Toys typically have a short shelf life (70-80% annual turnover), necessitating strong product development and innovation capabilities. In the event the company

[11] Not only do the implications of patents and trademarks for future fundamentals rely on the fact that they capture innovation but also come from the legal rights embedded in patents and trademarks.
[12] In the sample of S&P 1500 firms between 1993 and 2010, 60.29% firm-year observations report zero or missing R&D expenses. Among the firm-year observations that report zero or missing R&D, 8.51% (34.3%) have new patents (trademarks). These findings are consistent with the idea that missing R&D expenses do not indicate a lack of innovation activities (Koh and Reeb (2015)). Moreover, there are 67.7% firm-year observations that report zero or missing advertising expenses. Among the firm-year observations that report zero or missing advertising expenses, 36.22% have new trademarks.

is not able to introduce popular products, it could lose market share which could alter financial performance." An article released by Zacks Equity Research on May 22, 2015 mentioned that "Shake Shack Inc. shares soared 8.5% on May 21 after SSE IP, a unit of the company, reportedly filed an application to trademark the name "chicken shack". ......Restaurant companies generally file applications before announcing new items or initiatives."

Prior literature shows that forecast accuracy is important to analysts. Mikhail, Walther, and Willis (1999) and Hong and Kubik (2003) posit that relative forecast accuracy determines analysts' career outcomes. Leone and Wu (2007) find that analysts with better forecast accuracy are more likely to be ranked by the Institutional Investor magazine. The desire for accurate forecasts would lead analysts to gather information about innovation. In addition, innovation activities are associated with greater information asymmetry (Aboody and Lev (2000)). Investors' greater demand for innovation-related information enhances analysts' incentives to collect such information. As innovation output measures, patents and trademarks are one major source of information about innovation.[13]

Relative to naïve investors, analysts have superior abilities, skills and resources to process information about innovation, which is supposedly complex. The use of information contained in patents and trademarks requires a thorough analysis of the road from patents to marketable products and from marketable products to earnings. As specialists with industry knowledge, analysts are more able to perform that task. Based on these arguments, analysts are

[13] There are many possible ways for analysts to gather information about patents and trademarks, e.g., searching in the USPTO's patent and trademark system, reading Official Gazette published by the USPTO, and subscribing to electronic news services (e.g., Patently Apple) that provide updates on patents and trademarks.

expected to impound information contained in patents and trademarks into their earnings forecasts.

However, analysts do not always use new information efficiently (Bradshaw (2011)).[14] One strand of literature documents analysts' underreaction to new information. Abarbanell and Bushee (1997) show that analysts' forecast revisions do not fully incorporate information contained in fundamental signals about future earnings. Gu (2005) finds that analysts do not fully appreciate the earnings implications of change in patent citations. Another strand of literature is centered on analysts' optimism about news (see, e.g., Easterwood and Nutt (1999)). For example, Teoh and Wong (2002) show that analysts issue overly optimistic forecasts for the sample of high-accrual firms that are issuing seasoned new equity.

Firms with innovation activities tend to have high uncertainty in fundamentals as well as opacity and paucity of information (Bhattacharya and Ritter (1983), Freeman and Soete (1997), Aboody and Lev (2000), Kothari, Laguerre, and Leone (2002), and Gu and Wang (2005)). Zhang (2006) posits that analysts' behavioral biases such as pessimism are greater in the presence of information uncertainty, which he defines as poor information and high uncertainty in fundamentals. So, analysts may fail to grasp the implications of the two innovation output measures for future earnings. In addition, analysts that follow high-innovation firms are likely more subject to conflict of interest because of their greater reliance on managers for private information. High-innovation firms that need external financing to fund innovation also have incentives to bribe or mislead analysts. These agency problems can also defer analysts from

[14] Prior studies have proposed a variety of potential explanations for analysts' inefficient use of new information, including psychological biases, incentives or analysts' reputation concerns (see, e.g., Elliot, Philbrick, and Wiedman (1995), Lim (2001), and Raedy, Shane, and Yang (2006)). I do not intend to present a thorough review of this literature but instead focus on the factors that are of high relevance to the setting of innovation.

efficiently using information contained in patents and trademarks. Therefore, whether analysts understand and make efficient use of information contained in patents and trademarks about innovation remains an empirical question.

CHAPTER 3: Research Design

3.1 Data and Sample Selection

I use US patent data collected by Kogan et al. (2012). Prior studies on innovation use patent data from the National Bureau of Economics Research (NBER) patent data file. However, the latest version of the NBER patent data file only contains patent data up to 2006. Kogan et al. (2012) extend the CRSP-merged patent data to 2012. I use US trademark data from Faurel et al. (2016), which is the first to compile a large cross-sectional set of US trademark data. I obtain analyst forecast data from I/B/E/S, financial data from Compustat annual file, and return data from CRSP.

My sample covers S&P 1500 firms between 1993 and 2010. For each firm that has ever been included in S&P 1500 between 1993 and 2010, I track all available periods of that firm in Compustat. The sample period starts in 1993 because, prior to the regime shift in early 1990s, I/B/E/S did not adjust actual EPS for items that analysts did not forecast (Abarbanell and Lehavy (2007), Cohen, Hann, and Ogneva (2007)), which would lead to inaccurate measurement of earnings forecast errors in the pre-1993 period. The sample period ends in 2010 because the number of patents in more recent periods appears small in the data provided by Kogan et al. (2012).

[To Insert Table 1 Here]

Table 1, Panel A summarizes the sample selection procedure. I start with 41,960 firm-year observations in S&P 1500 between 1993 and 2010. The requirement for I/B/E/S data reduces the sample to 36,077 firm-year observations. I further exclude 658 firm-year observations with negative book value of equity. Unlike most prior studies, I do not exclude financial industries because firms in these industries often engage in the creation of new services, which is a form of non-technological innovation. The final sample includes 35,419 firm-year observations of 3,241 unique firms, with 550,239 patents and 107,336 trademarks in total.

Table 1, Panel B shows the sample representation of Fama-French 12 industry sectors. The distribution of firm-year observations across the 12 industry sectors confirms that S&P 1500 is a good representation of the US stock market. Panel B also presents the average number of patents or trademarks per firm-year. Firms in non-technology-intensive sectors such as Consumer Nondurables, Wholesales, Retails and Some Services, and Finance have few patents but own a significant number of trademarks, indicating that trademarks complement patents in measuring innovation because trademarks can capture innovation outputs in these industries that are not technology-oriented.

3.2 Innovation Measures

The patent data collected by Kogan et al. (2012) and the trademark data collected by Faurel et al. (2016) both originate from the USPTO patent and trademark databases.[15] The USPTO records filing date, publication date and grant date for patents and filing date, published-for-opposition date and registration date for trademarks. I use grant date for patents and registration date for trademarks to avoid look-ahead bias because (1) a patent application becomes public 18 months after filing at latest; (2) if a trademark is filed on an "intent-to-use" basis, analysts do not know whether this trademark will actually be used on any specific product or service until the registration date, even though the application itself is made available in

[15] Please refer to Faurel et al. (2016) for details about how the trademark data were cleaned and merged to Compustat.

USPTO's electronic search system once it is filed.[16] In order to select trademarks that are most likely to capture product and marketing innovation, I impose a restriction that the trademark must be owned by a single corporate owner throughout the filing and registration process. I then count the number of patents granted and the number of trademarks registered by each firm in each period (fiscal quarter or fiscal year). I scale the number of patents granted and the number of trademarks registered in each period by the beginning-of-period total assets because larger firms, by nature, have larger patent and trademark portfolios.

3.3 Test Design

3.3.1 Predicting Future Earnings

I start the analysis with an examination of the ability of patents and trademarks to predict future earnings, which will establish a baseline for main tests on analyst forecasts.

$$\begin{aligned} ROA_{i,t+1}\ or\ Earn\_Growth_{i,[t+1,t+5]} &= \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * Size_{i,t} + \beta_3 * MB_{i,t} \\ &+ \beta_4 * Age_{i,t} + \beta_5 * Leverage_{i,t} + \beta_6 * ROA_{i,past} + \beta_7 * \Delta ROA_{i,past} + \beta_8 * R\&D_{i,t} + \beta_9 * ADV_{i,t} \\ &+ \beta_{10} * CAPEX_{i,t} + \beta_{11} * OPEX_{Other\,i,t} + \sum \delta_j Time_j + \sum \mu_k Firm_k + \varepsilon_{i,t+1} \qquad (1) \end{aligned}$$

(Please refer to Appendix for variable definitions)

The regression model shown in Equation (1) follows Hirshleifer, Hsu, and Li (2013). The key independent variable $Innovation\ Measure_{i,t}$ refers to $Patent_{i,t}$ or $Trademark_{i,t}$, which is measured as the natural log of one plus the number of patents granted or trademarks registered in period t scaled by the beginning-of-period total assets. Period t refers to quarter t in quarterly tests and year t in annual and long-term tests. The dependent variable is $ROA_{i,t+1}$ (quarterly return on assets in quarter t+1 or annual return on assets in year t+1) or $Earn\_Growth_{i,[t+1,t+5]}$ (the annualized earnings growth rate between year t+1 and year t+5). Following Rajgopal,

[16] A trademark can be filed on a "use-in-commerce" basis or an "intent-to-use" basis. "Use-in-commerce" basis means that the applicant started to use the trademark in commerce before filing. "Intent-to-use" basis means that "*a party with a bona fide intention to use a specific mark in commerce in relation to specific goods or services can file an application and submit evidence of use before registration* (USPTO, 2014)."

Shevlin, and Venkatachalam (2003), I use the realized earnings per share (EPS) and the realized five-year earnings growth from I/B/E/S to compute $ROA_{i,t+1}$ and $Earn\_Growth_{i,[t+1,t+5]}$, because I/B/E/S adjusts actual earnings by excluding items that analysts do not forecast and thus the scope of I/B/E/S realized earnings is more consistent with that of analysts' forecasted earnings.[17,18] To see if the predictive power of new patents and new trademarks is incremental, I control for ROA in prior period (i.e., ROA in quarter t-3 in quarterly window or ROA in year t in annual window), change in ROA in prior period (i.e., change in ROA from quarter t-7 to quarter t-3 in quarterly window or change in ROA from year t-1 to year t in annual window) as well as R&D expenses, advertising expenses, capital expenditures, and total operating expenses excluding R&D expenses and advertising expenses in period t, which approximate direct or indirect inputs into innovation.[19] To mitigate the effects of unobservable time-invariant factors and common economic, technological or product market shocks, I include firm fixed effects and time fixed effects (quarter or year) in this regression. Standard errors are clustered by firm to adjust for time-series correlations (Petersen (2009)).

3.3.2 Analysts' Short-term Earnings Forecasts (Quarterly and Annual Forecasts)

I then examine the revisions and forecast errors in analysts' quarterly and annual earnings forecasts. I test quarterly forecast revisions for the purpose of gauging how prompt analysts' reaction to new patents and new trademarks is. I use I/B/E/S unadjusted summary files to construct measures of quarterly and annual earnings forecast revisions and forecast errors to

[17] Results are similar and, in fact, stronger, if I define ROA as income before extraordinary items adjusted for special items, which approximate items that analysts do not forecast (Bradshaw and Sloan (2002)).
[18] A few prior studies (see, e.g., Pandit, Wasley, and Zach (2011), Ciftci and Cready (2011)) measure ROA with income before extraordinary items adjusted for R&D expenses, advertising expenses, and depreciation expenses. Given that analysts' earnings forecasts take into account these expenses, I do not add them back for consistency.
[19] Advertising expenses and capital expenditures are not reported on a quarterly basis. Thus, in quarterly tests, these two variables do not appear as controls.

avoid concerns about rounding in split-adjusted forecast data (Payne and Thomas (2003), Cheong and Thomas (2011)). To adjust for stock splits, I adopt So (2013)'s approach to multiply each EPS consensus forecast or actual EPS by the ratio of the number of shares outstanding on the day of the consensus forecast or actual EPS over the number of shares outstanding at the beginning of the period.

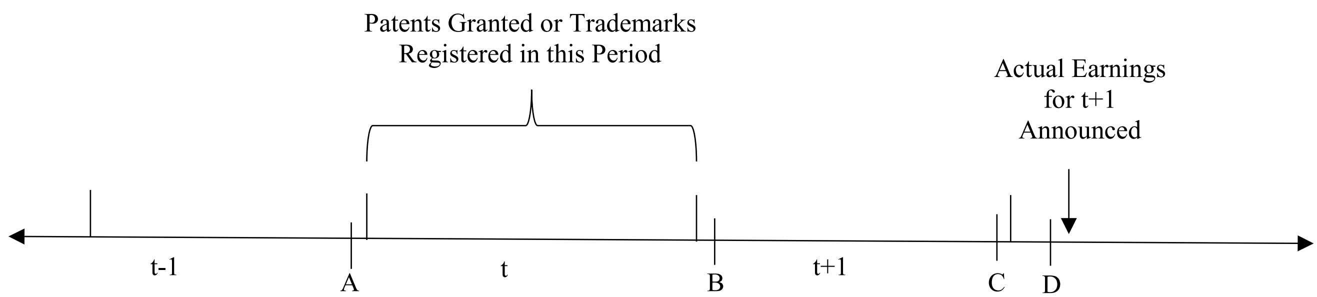

Figure 1 Short-term Forecasts

The timeline in Figure 1 illustrates how I measure revisions and errors in quarterly and annual earnings forecasts. Patents are granted or trademarks are registered in period t, which refers to quarter t in the quarterly forecast tests and year t in the annual forecast tests. To check whether analysts react contemporaneously to new patents and new trademarks, I examine the revisions in consensus forecasts for period t+1's earnings during period t. Similar to Abarbanell and Bushee (1997) and Barth and Hutton (2004), I measure earning forecast revision as the difference between the first consensus forecast for period t+1 that is made after the end of period t (at point B, Figure 1) and the last consensus forecast for period t+1 that is made before the start of period t (at point A, Figure 1). I then scale this difference by the beginning-of-period total assets per share in period t (i.e., the beginning-of-period total assets divided by the beginning-of-period number of shares outstanding). I use total assets per share as a deflator instead of stock price to avoid a spurious relation that may result from the possibility that stock prices capture analysts' earnings forecasts (Mian and Teo (2004), So (2013)). I denote this revision variable as

$Earn\_Rev_{i,t}^{t+1}$.[20] The superscript "t+1" means the period being forecasted is t+1, while the subscript "t" means the forecast revision is measured over the interval of period t.

$$
\begin{aligned}
Earn\_Rev_{i,t}^{t+1} = {} & \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * Earn_{Rev}{}_{i,t-1}^{t} + \beta_3 * Size_{i,t} + \beta_4 * MB_{i,t} \\
& + \beta_5 * Age_{i,t} + \beta_6 * Leverage_{i,t} + \beta_7 * ROA_{i,past} + \beta_8 * \Delta ROA_{i,past} + \beta_9 * R\&D_{i,t} + \beta_{10} \\
& * ADV_{i,t} + \beta_{11} * CAPEX_{i,t} + \beta_{12} * OPEX\_Other_{i,t} + \sum \delta_j Time_j + \sum \mu_k Firm_k + \varepsilon_{i,t} \quad (2)
\end{aligned}
$$

(Please see Appendix for variable definitions)

I use the regression described in Equation (2) to examine whether analysts revise their quarterly and annual earnings forecasts contemporaneously in response to patents granted and trademarks registered. The variable of interest is $Innovation\ Measure_{i,t}$. If analysts revise their earnings forecasts upwards more when there are more patents granted or trademarks registered, β_1 will be positive. In the regression, I include $Earn\_Rev_{i,t-1}^{t}$, which is the revision in period t-1 for period t earnings, to control for inter-temporal patterns in analyst forecast revisions. Firm size, growth, age, time fixed effects (quarter or year) and firm fixed effects are also included in the regression to mitigate potential impacts of correlated omitted variables. Moreover, to rule out confounding information signals that may drive analysts to revise their short-term earnings forecasts, I control for ROA in prior period, change in ROA in prior period, R&D expenses, advertising expenses, total operating expenses excluding R&D and advertising expenses, and capital expenditures in period t. Standard errors are clustered by firm to adjust for time-series correlations (Petersen (2009)).

$$
\begin{aligned}
Earn\_FE_{i,t+1}^{t+1} = {} & \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * Earn\_FE_{i,t}^{t} + \beta_3 * \Delta Earn\_COV_{i,t+1} + \beta_4 * Size_{i,t} + \beta_5 \\
& * MB_{i,t} + \beta_6 * Age_{i,t} + \beta_7 * Leverage_{i,t} + \beta_8 * Earn\_Vol_{i,[t-4,t]} + \beta_9 * RD_{i,t} + \beta_{10} * ADV_{i,t} \\
& + \beta_{11} * CAPEX_{i,t} + \beta_{12} * OPEX\_Other_{i,t} + \sum \delta_j Time_j + \sum \mu_k Firm_k + \varepsilon_{i,t+1} \qquad (3)
\end{aligned}
$$

(Please see Appendix for variable definitions)

[20] I use the consensus forecast made immediately before the start of period t instead of the first forecast made within period t because the first forecast made within period t may have incorporated information in patents granted or trademarks registered in the early part of period t. I use the consensus forecast made immediately after the end of period t because there may be patents granted or trademarks registered after the last forecast made in period t.

Equation (3) shows the regression model that is used to test the association between quarterly or annual earnings forecast errors and the number of patents granted or trademarks registered. $Earn\_FE_{i,t+1}^{t+1}$ is measured as actual EPS of period t+1 minus the last consensus EPS forecast for period t+1 that is made before period t+1's earnings is announced (at point D, Figure 1), scaled by the beginning-of-period assets per share in period t+1. β_1 will indicate whether quarterly or annual forecast errors can be predicted by new patents or new trademarks.

In this regression, I include forecast errors for prior period, $Earn\_FE_{i,t}^{t}$, because Abarbanell and Bernard (1992) document a positive serial correlation in analyst forecast errors. I control for change in analyst coverage to take into account the fact that consensus forecasts tend to be more accurate when there are more analysts acquiring information for the same firm. I also control for historical earnings volatility because Dichev and Tang (2009) show that earnings volatility can predict analysts' forecast errors. The inclusion of firm fixed effects is particularly important in this test because it alleviates concerns about time-invariant firm-specific factors that impact both innovation and the likelihood of receiving biased forecasts from analysts.

3.3.3 Analysts' Long-term Earnings Growth Forecasts

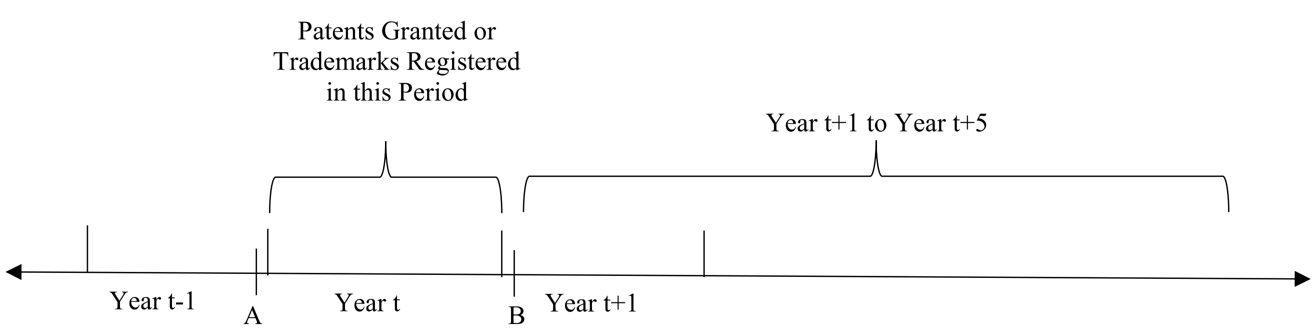

Figure 2 Long-term Forecasts

In this section, I examine whether analysts revise their long-term earnings growth forecasts upwards more when they are more patents granted or more trademarks registered. As shown in Figure 2, patents are granted or trademarks are registered in year t. I measure long-term earnings growth forecast revision as the difference between the first long-term earnings growth forecast after the end of year t (at point B, Figure 2) and the last long-term earnings growth forecast before the start of year t (at point A, Figure 2) and denote it as $LTG\_Rev_{i,t}$. The “t” in the subscript means the revision is measured over the interval of year t. Because long-term earnings growth forecast is reported in I/B/E/S as a percentage, I do not need to further scale this difference.

$$\begin{aligned} LTG\_Rev_{i,t} = \beta_0 &+ \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * LTG\_Rev_{i,t-1} + +\beta_4 * Size_{i,t} + \beta_5 * MB_{i,t} + \beta_6 * Age_{i,t} \\ &+ \beta_6 * Leverage_{i,t} + \beta_7 * ROA_{i,past} + \beta_8 * \Delta ROA_{i,past} + \beta_9 * RD_{i,t} + \beta_{10} * ADV_{i,t} + \beta_{11} \\ &* CAPEX_{i,t} + \beta_{12} * OPEX\_Other_{i,t} + \sum \delta_j Year_j + \sum \mu_k Firm_k + \varepsilon_{i,t} \end{aligned} \tag{4}$$

(Please see Appendix for variable definitions)

In Equation (4), $LTG\_Rev_{i,t}$ is regressed on $Patent_{i,t}$ or $Trademark_{i,t}$. Control variables are included for the same reasons discussed in Section 3.3.2. If analysts revise their long-term earnings growth forecasts upwards to incorporate information contained in patents or trademarks, the coefficient $\beta_1$will be significantly positive.

$$\begin{aligned} LTG\_FE_{i,t} = \beta_0 &+ \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * LTG\_FE_{i,t-1} + \beta_3 * \Delta LTG\_COV_{i,t} + \beta_4 * Size_{i,t} + \beta_5 * MB_{i,t} \\ &+ \beta_6 * Age_{i,t} + \beta_7 * Leverage_{i,t} + \beta_8 * Earn\_Vol_{i,[t-1,t-4]} + \beta_9 * RD_{i,t} + \beta_{10} * ADV_{i,t} + \beta_{11} \\ &* CAPEX_{i,t} + \beta_{12} * OPEX\_Other_{i,t} + \sum \delta_j Year_j + \sum \mu_k Firm_k + \varepsilon_{i,t} \end{aligned} \tag{5}$$

(Please see Appendix for variable definitions)

Then I use the test shown in Equation (5) to examine whether analysts fully exploit information contained in new patents and new trademarks about long-term earnings growth. I use signed error in long-term earnings growth forecasts, which is measured as the difference between actual five-year earnings growth between year t+1 and year t+5 and the first consensus long-term earnings growth forecast after the end of year t (at point B, in Figure 2). Following Edmans (2011), I construct a measure of actual five-year earnings growth rate by using the variable “FVYRGRO” (i.e., the average annualized EPS growth over the past 20 quarters) from I/B/E/S dataset “ACTPSUMU_EPSUS”. If analysts do not fully incorporate the long-term earnings implications of patents and trademarks into forecasts, β_1 will be significantly different from 0.

CHAPTER 4: Main Results

4.1 Descriptive Statistics

The descriptive statistics of key variables are reported in Table 2. As seen in Panel A, the median (mean) number of total patents at the firm level is 0 (121.16), whereas the median (mean) number of trademarks is 6 (28.72). The mean of patents at the firm-year level is 12.43 and the mean of trademarks at the firm-year level is 2.73. The median of patents and the median of trademarks at the firm-year level are both zero.[21] The distribution of patents is more skewed than that of trademarks, which is consistent with the fact that patents are highly concentrated into certain industries. In my sample, each firm is followed by 9.33 analysts on average in each year. The long-term earnings growth forecast errors have a negative mean (-6.62%) and a negative median (-5.44%), suggesting that analysts’ long-term earnings growth are overly optimistic in general. All variables in the tests except for returns are winsorized at the top and bottom 0.5% (Frank and Goyal (2008)).[22]

[To Insert Table 2 Here]

Table 2, Panel B depicts the correlations between patents and trademarks and various expenses, which directly or indirectly relate to innovation inputs. The correlation between patents and trademarks is 0.1759. Moreover, both patents and trademarks are positively correlated with R&D expenses but the correlation is much higher for patents. Advertising

[21] In untabulated robustness tests, I repeat all tests after removing firms with 0 patent and/or 0 trademark between 1993 and 2010 and the regression results remain similar.
[22] Winsorization is necessary because the maximum number of patents (trademarks) is 4422 (754) at firm-year level in the unwinsorized sample. Results are similar if all variables are winsorized at the top and bottom 1%.

expenses are positively correlated with the number of trademarks but negatively correlated with the number of patents. These differences are consistent with the notion that patents and trademarks capture different types of innovation.

4.2 The Predictability of Patents and Trademarks for Future Fundamentals

Results in Table 3 show that (1) the number of new trademarks predicts higher one-quarter-ahead earnings (Panel A) and higher one-year-ahead earnings (Panel B); (2) there is no evidence that the number of new patents predicts higher one-quarter-ahead earnings (Panel A) or one-year-ahead earnings (Panel B); (3) the number of new patents predicts five-year earnings growth (Panel C); and (4) the number of new trademarks predicts five-year earnings growth (Panel C). In addition, the predictability of patents and trademarks is incremental to that of innovation input measures such as R&D expenses.

[To Insert Table 3 Here]

These findings suggest that both patents and trademarks contain information about future earnings and that only trademarks contain information about short-term (quarterly and annual) earnings whereas both patents and trademarks contain information about long-term earnings growth. Trademarks are proxies for new products/services that are directly sellable on the market or new ways of marketing products/services, and thus can generate immediate improvement in earnings. Trademarks are also associated with long-term earnings growth perhaps because, for firms with long product cycles such as pharmaceutical companies, the benefits of a new product/service can continue to generate profits for several years. In contrast, patents do not predict short-term earnings but predict long-term earnings growth, consistent with the idea that most patents are not directly commercializable due to the lack of concrete useful applications

(Millot (2009)).[23] If analysts understand the earnings implications of patents and trademarks, they should revise their quarterly and annual earnings forecasts upwards in response to new trademarks only and revise their long-term earnings growth forecasts upwards in response to both new patents and new trademarks.

4.3 Quarterly Earnings Forecast Revisions and Errors

[To Insert Table 4 Here]

Table 4 presents results from quarterly earnings forecast revision test. The three columns in the left panel show results on contemporaneous revisions made in quarter t. The coefficient on $Trademark_{i,t}$ is positive and significant at 10% level, indicating that analysts increase their forecasts for quarter t+1 earnings during quarter t when there are more trademarks registered in quarter t. The coefficient on $Patent_{i,t}$ is insignificant in all specifications, suggesting that analysts, on average, do not seem to revise their quarterly earnings forecasts upwards in response to patents granted. These findings suggest that analysts are aware of information contained in new trademarks about quarterly earnings and incorporate it promptly by revising their quarterly forecasts upwards and that analysts perceive new patents as not having implications for future annual earnings.

I conduct an additional test to examine the subsequent revisions in earnings forecasts for quarter t+1 during quarter t+1. The next three columns in the right panel show results on subsequent revisions. I replace the dependent variable in Equation (2) with $Earn\_Rev_{i,t+1}^{t+1}$, which is measured as the scaled difference between the last consensus forecast before the end of quarter t+1 (at point C, Figure 1) and the first consensus forecast made after the end of quarter t

[23] Firms can also gain from licensing or selling patents. However, I do not expect sale of patents to be a major source of income for S&P 1500 firms, because these firms are unlikely to be IP specialist firms that monetize patents mainly through licensing or trading patents.

(at point B, Figure 1). As seen in the table, there is a significantly positive association between trademarks registered in quarter t and subsequent revisions in quarterly earnings forecasts during quarter t+1, indicating that analysts continue to react to new trademarks in quarter t+1.

[To Insert Table 5 Here]

Table 5 includes quarterly forecast error results. $Trademark_{i,t}$ is positively associated with signed errors in quarterly earnings forecasts. Combining with the finding that analysts revise their quarterly earnings forecasts upwards in response to new trademarks, this significantly positive association suggests that analysts underreact to information in new trademarks about quarterly earnings, even though they do not completely ignore that information. The coefficient on $Patent_{i,t}$ is insignificant. Recall that the number of new patents does not predict one-quarter-ahead earnings and analysts do not revise their quarter forecasts upwards in response to new patents. The absence of evidence on a significant association between $Patent_{i,t}$ and signed errors in quarterly earnings forecasts is consistent with the idea that analysts correctly perceive new patents as not having implications for immediate future earnings.

4.4 Annual Earnings Forecast Revisions and Errors

[To Insert Table 6 Here]

The revision results on annual earnings forecasts are presented in Table 6. Again, the first three columns are for contemporaneous revisions. As expected, the coefficient on $Patent_{i,t}$ is insignificant. The coefficient on $Trademark_{i,t}$ is positive but insignificant. A deeper look reveals that the loss of significance is merely due to controlling for ROA and change in ROA of year t. Controlling for ROA and change in ROA of year t is, in fact, conservative in this contemporaneous revision test, because analysts do not see the actual ROA of year t until it is announced in year t+1.

Similar to the quarterly setting, I also check subsequent revisions in earnings forecasts for year t+1 during year t+1. The dependent variable is now $Earn\_Rev_{i,t+1}^{t+1}$, which is measured as the scaled difference between the last consensus forecast before the end of year t+1 (at point C, Figure 1) and the first consensus forecast made after the end of year t (at point B, Figure 1). Results in the three columns of the right panel show a significantly positive association between trademarks registered in year t and the subsequent revisions in annual forecasts during year t+1. This is not surprising because, with more collaborating information becoming available during year t+1, analysts can better assess the implications of trademarks registered in year t for earnings of the whole year t+1.

[To Insert Table 7 Here]

Results on annual forecast errors are shown in Table 7. As seen in the table, the coefficient on $Patent_{i,t}$ is insignificant, which means that analysts understand that new patents do not lead to higher earnings in next year. However, $Trademark_{i,t}$ positively predicts errors in annual earnings forecasts.[24] Overall, the annual forecast results are consistent with the quarterly forecast results, confirming that analysts understand partially the short-term earnings implications of trademarks.

[24] In a robustness test, I follow Rajgopal, Shevlin, and Venkatachalam (2003) to regress the forecasted earnings of year t+1 on trademarks registered in year t (measured at various points—B, C or D in Figure 1) and compare this coefficient to the coefficient from regressing realized earnings of year t+1 on trademarks registered in year t. I find a significantly negative difference between the coefficient based on the forecasted earnings and the coefficient based on realized earnings, which confirms my results from the forecast error test in Equation (3).

4.5 Long-term Earnings Forecast Revisions and Errors

[To Insert Table 8 Here]

In Table 8, I find that both $Patent_{i,t}$ and $Trademark_{i,t}$ are positively associated with the revisions in analysts' long-term earnings growth forecasts during year t. This association remains significantly positive when both $Patent_{i,t}$ and $Trademark_{i,t}$ are included in the same regression. Given the finding in Table 3, Panel C that both the number of patents and the number of trademarks predict higher five-year earnings growth, the positive association between patents and trademarks and revisions in analysts' long-term earnings growth forecasts suggests that analysts use information contained in both new patents and new trademarks about long-term earnings growth.

[To Insert Table 9 Here]

The results in Table 9 show a significantly negative coefficient on both $Patent_{i,t}$ and $Trademark_{i,t}$, indicating that analysts overreact to the long-term earnings implications of both types of innovation output measures. This overreaction echoes analysts' overreaction to R&D expenses in the post-1996 period documented by Curtis, McVay, and Toynbee (2015).

Findings from the quarterly and annual earnings forecast tests in Section 4.3 and Section 4.4, however, suggest that analysts underreact to the immediate earnings implications of new trademarks. In fact, this disparity is very consistent with the differences in incentives that underlie analysts' short-term forecasts and long-term forecasts. Hong and Kubik (2003) argue that the average career of analysts is 4 years. So, analysts may exert great effort to improve short-term earnings forecasts but have less incentives to make their long-term forecasts accurate. Moreover, while analysts may lower their short-term forecasts to allow firms to meet or beat their forecasts (Richardson, Teoh, and Wysocki (2004)), analysts' long-term forecasts are generally found to be overly optimistic due to conflict of interest (see, e.g., Dechow, Hutton, and Sloan (2000), Chan, Karceski, and Lakonishok (2003), and Barniv et al. (2009)). Da and Warachka (2011) also document significant disparity between short-term and long-term forecasted earnings growth (i.e., firms with high long-term earnings growth forecasts and low short-term earnings growth forecasts; firms with low long-term earnings growth forecasts but high short-term earnings growth forecasts).

CHAPTER 5: Additional Analysis

Given that investors are likely to rely on analysts' judgement when valuing innovation, it is important to explore the potential impacts of analysts' inefficient use of innovation-related information on the stock market valuation of innovation. Faurel et al. (2016) find that the number of trademarks registered in year t predicts one-year-ahead future returns. Results in Table 10, Panel A confirm that the positive future return predictability of trademarks also exists in my sample of S&P 1500 firms with analyst coverage, while patents do not seem to predict future returns in this sample.[25] The positive future return predictability of trademarks points to a likely investor underreaction to trademarks, which is consistent with analysts' underreaction to the annual earnings implications of trademarks. Therefore, in this section, I focus on whether analysts' errors in annual forecasts can explain part of stock market mispricing of trademarks. To address this question, I use the following two-stage procedure modified from Teoh and Wong (2002).

[25] Hirshleifer, Hsu, and Li (2013) find that innovation efficiency as measured by the number of new patents scaled by R&D capital predict positive future returns. The differences in the innovation measure, the sample coverage and the time period between Hirshleifer, Hsu, and Li (2013) and my study may explain why there is no evidence on the future return predictability of patents. It is not the objective of this paper to formally document the future return predictability of either patents or trademarks.

$$1st\ Stage \quad Earn\_FE_{i,t+1}^{t+1} = \beta_0 + \beta_1 * Trademark_{i,t} + \sum \delta_h Other\ Predictor_h + \sum \delta_j Year_j + \sum \mu_k Firm_k + \varepsilon_{i,t}$$

$$2nd\ Stage \quad Log(1 + RET_{i,t+1}) = \beta_0 + \beta_1 * FE\_TM_{i,t+1} + \beta_2 * FE\_Other_{i,t+1} + \beta_2 * FE\_Residual_{i,t+1} + \sum \delta_j Year_j + \sum \mu_k Industry_k + \varepsilon_{i,t+1}$$

(Please see Appendix for variable definitions)

The goal of the 1st stage is to estimate the predicted forecast errors from trademarks. In the 1st stage regression, forecast errors are regressed on $Trademark_{i,t}$ and other predictors as well as firm and year fixed effects.[26] Other predictors refer to control variables in the regression depicted in Equation (3) of Section 3.3.2. I denote the fitted value and residual from the 1st stage regression as $FE\_TM_{i,t+1}$, $FE\_Other_{i,t+1}$, and $FE\_Residual_{i,t+1}$.

In the 2nd stage, I regress one-year-ahead returns on forecast errors predicted from trademarks ($FE\_TM_{i,t+1}$), forecast errors predicted from other predictors ($FE\_Other_{i,t+1}$), and unpredicted predicted errors ($FE\_Residual_{i,t+1}$). The dependent variable $Log(1 + RET_{i,t+1})$ is computed as the natural log of one plus the buy-and-hold return compounded over the 12 months of year t+1 adjusted for value-weighted market return over the same period. Variables in the 2nd stage regression are standardized to make coefficients on the three components directly comparable. Standard errors are clustered by year to control for the cross-sectional correlations in returns.

[To Insert Table 10 Here]

[26] This regression is the same as the one used to test the relations between short-term forecast errors and trademarks in Section 3.3.2, except that the forecast errors in this regression are measured based on the first consensus forecast for year t+1 that is made after the end of year t (at Point B, Figure 1).

The 2nd stage regression results are reported in Table 10, Panel B. The variable of interest in the 2nd stage regression is $FE\_TM_{i,t+1}$. The coefficient on $FE\_TM_{i,t+1}$ is significantly positive. The magnitude of this key coefficient is smaller than the magnitude of the coefficient on predicted forecast errors from other predictors but comparable to the magnitude of the coefficient on unpredicted forecast errors. This finding suggests that analysts' underreaction to the implications of trademarks for next year's earnings partially explains stock market mispricing of trademarks.

CHAPTER 6: Conclusions

This paper examines whether analysts use information contained in patents and trademarks about future earnings when forecasting earnings, and if they do, whether they do so efficiently. Because patents capture technological innovation and trademarks capture product and marketing innovation, both types of innovation have implications for future earnings but over different horizons. Only trademarks predict one-quarter-ahead earnings and one-year-ahead earnings whereas both patents and trademarks predict five-year earnings growth.

This paper finds that (1) analysts revise their quarterly and annual earnings forecasts upwards in response to new trademarks but not new patents; (2) errors in analysts' quarterly and annual earnings forecasts are positively associated with the number of new trademarks but are not related to the number of new patents; (3) analysts revise their long-term earnings growth forecasts upwards when there are new trademarks and/or new patents; (4) errors in analysts' long-term earnings growth forecasts are negatively associated with both the number of new patents and the number of new trademarks; and (5) annual earnings forecast errors predicted from trademarks exhibits a positive association with one-year-ahead return. I conclude from these findings that (1) analysts use but underreact to information contained in new trademarks about short-term earnings; (2) analysts understand that new patents do not contain information about short-term earnings; (3) analysts use information in patents and trademarks about long-term earnings growth but are overly optimistic about long-term earnings implications of both; and (4) analysts' inefficient use of information contained in trademarks about next year's earnings potentially contributes to the stock market failure of pricing non-technological product and marketing innovation captured by trademarks.

REFERENCES

Abarbanell, Jeffery S., and Victor L. Bernard, 1992, Tests of Analysts' Overreaction/ Underreaction to Earnings Information as an Explanation for Anomalous Stock Price Behavior, *The Journal of Finance* 47, 1181–1207.

Abarbanell, Jeffery S., and Reuven Lehavy, 2007, Letting the "Tail Wag the Dog": The Debate over GAAP versus Street Earnings Revisited, Contemporary Accounting Research 24, 675–723.

Abarbanell, Jeffrey S., and Brian J. Bushee, 1997, Fundamental Analysis, Future Earnings, and Stock Prices, *Journal of Accounting Research* 35, 1–24.

Aboody, David, and Baruch Lev, 2000, Information Asymmetry, R&D, and Insider Gains, *The Journal of Finance* 55, 2747–2766.

Abrams, David S., Ufuk Akcigit, and Jillian Popadak, 2013, Patent Value and Citations: Creative Destruction or Strategic Disruption?, Working Paper, National Bureau of Economic Research.

Alcácer, Juan, Michelle Gittelman, and Bhaven Sampat, 2009, Applicant and Examiner Citations in U.S. Patents: An Overview and Analysis, *Research Policy* 38, 415–427.

Barniv, Ran, Ole-Kristian Hope, Mark J. Myring, and Wayne B. Thomas, 2009, Do Analysts Practice What They Preach and Should Investors Listen? Effects of Recent Regulations, *The Accounting Review* 84, 1015–1039.

Barron, Orie E., Donal Byard, Charles Kile, and Edward J. Riedl, 2002, High-Technology Intangibles and Analysts' Forecasts, *Journal of Accounting Research* 40, 289–312.

Barth, Mary E., and Amy P. Hutton, 2004, Analyst Earnings Forecast Revisions and the Pricing of Accruals, *Review of Accounting Studies* 9, 59–96.

Barth, Mary E., Ron Kasznik, and Maureen F. McNichols, 2001, Analyst Coverage and Intangible Assets, *Journal of Accounting Research* 39, 1–34.

Bhattacharya, Sudipto, and Jay R. Ritter, 1983, Innovation and Communication: Signalling with Partial Disclosure, *The Review of Economic Studies* 50, 331–346.

Bradshaw, Mark Thomas, 2011, Analysts' Forecasts: What Do We Know after Decades of Work?, SSRN Scholarly Paper, Social Science Research Network, Rochester, NY.

Bradshaw, Mark T., Scott A. Richardson, and Richard G. Sloan, 2001, Do Analysts and Auditors Use Information in Accruals?, *Journal of Accounting Research* 39, 45–74.

Bradshaw, Mark T., and Richard G. Sloan, 2002, GAAP versus the Street: An Empirical Assessment of Two Alternative Definitions of Earnings, *Journal of Accounting Research* 40, 41–66.

Chan, Louis K. C., Jason Karceski, and Josef Lakonishok, 2003, The Level and Persistence of Growth Rates, *The Journal of Finance* 58, 643–684.

Cheong, Foong Soon, and Jacob Thomas, 2011, Why Do EPS Forecast Error and Dispersion Not Vary with Scale? Implications for Analyst and Managerial Behavior, *Journal of Accounting Research* 49, 359–401.

Ciftci, Mustafa, 2012, Do Analysts Underestimate Future Benefits of R&D?, *International Business Research* 5.

Ciftci, Mustafa, and William M. Cready, 2011, Scale Effects of R&D as Reflected in Earnings and Returns, *Journal of Accounting and Economics* 52, 62–80.

Cohen, Daniel A., Rebecca N. Hann, and Maria Ogneva, 2007, Another Look at GAAP versus the Street: An Empirical Assessment of Measurement Error Bias, *Review of Accounting Studies* 12, 271–303.

Cohen, Lauren, Karl Diether, and Christopher Malloy, 2013, Misvaluing Innovation, *Review of Financial Studies* 26, 635–666.

Curtis, Asher, Sarah E. McVay, and Sara Toynbee, 2015, The Changing Implications of Research and Development Expenditures for Future Profitability, SSRN Scholarly Paper, Social Science Research Network, Rochester, NY.

Da, Zhi, and Mitch Warachka, 2011, The Disparity between Long-term and Short-term Forecasted Earnings Growth, *Journal of Financial Economics* 100, 424–442.

Dechow, Patricia M., Amy P. Hutton, and Richard G. Sloan, 2000, The Relation between Analysts' Forecasts of Long-Term Earnings Growth and Stock Price Performance Following Equity Offerings, *Contemporary Accounting Research* 17, 1–32.

Dichev, Ilia D., and Vicki Wei Tang, 2009, Earnings Volatility and Earnings Predictability, *Journal of Accounting and Economics* 47. Accounting Research on Issues of Contemporary Interest, 160–181.

Easterwood, John C., and Stacey R. Nutt, 1999, Inefficiency in Analysts' Earnings Forecasts: Systematic Misreaction or Systematic Optimism?, *The Journal of Finance* 54, 1777–1797.

Economides, Nicholas S., 1987, The Economics of Trademarks, *TradeMark Register*, 78, 523–539.

Edmans, Alex, 2011, Does the Stock Market Fully Value Intangibles? Employee Satisfaction and Equity Prices, *Journal of Financial Economics* 101, 621–640.

Elliot, John A., Donna R. Philbrick, and Christine I. Wiedman, 1995, Evidence from Archival Data on the Relation Between Security Analysts' Forecast Errors and Prior Forecast Revisions, *Contemporary Accounting Research* 11, 919–938.

Faurel, Lucile, Qin Li, Devin Shanthikumar, and Siew Hong Teoh, 2016, CEO Incentives and New Product Development: Insights from Trademarks, Working Paper, University of California, Irvine.

Faurel, Lucile, Qin Li, Devin Shanthikumar, and Siew Hong Teoh, 2016, The Value of New Product Development, Working Paper, University of California, Irvine.

Frank, Murray Z., and Vidhan K. Goyal, 2008, Chapter 12 - Trade-off and Pecking Order Theories of Debt, in B. Espen Eckbo ed.: *Handbook of Empirical Corporate Finance*. Handbooks in Finance (Elsevier, San Diego).

Freeman, Christopher, and Luc Soete, 1997, *The Economics of Industrial Innovation* (Psychology Press).

Gaze, Laura, and Roderick, John, 2012, Inside the iPhone Patent Portfolio, *Thomson Reuters IP Market Report*, Thomson Reuters.

González-Pedraz, Carlos, and Sergio Mayordomo, 2012, Trademark Activity and the Market Performance of U.S. Commercial Banks, *Journal of Business Economics and Management* 13, 931–950.

Griliches, Zvi, 1981, Market Value, R&D and Patents, *Economics Letters* 7, 183–187.

Griliches, Zvi, Bronwyn H. Hall, and Ariel Pakes, 1987, The Value of Patents as Indicators of Inventive Activity, in Partha Dasgupta and in Paul Stoneman ed.: *Economic Policy and Technological Performance* (Cambridge University Press, Cambridge, UK).

Gu, Feng, 2005, Innovation, Future Earnings, and Market Efficiency, *Journal of Accounting, Auditing & Finance* 20, 385–418.

Gu, Feng, and Weimin Wang, 2005, Intangible Assets, Information Complexity, and Analysts' Earnings Forecasts, *Journal of Business Finance & Accounting* 32, 1673–1702.

He, Jie (Jack), and Xuan Tian, 2013, The Dark Side of Analyst Coverage: The Case of Innovation, *Journal of Financial Economics* 109, 856–878.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2013, Innovative Efficiency and Stock Returns, *Journal of Financial Economics* 107, 632–654.

Hong, Harrison, and Jeffrey D. Kubik, 2003, Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts, *The Journal of Finance* 58, 313–351.

Huberty, Katy L., Shawn Kim, Bill Lu, Jasmine Lu, Shoji Sato, and Sharon Shih, 2015, Technology: Apple's Force Touch to Touch More of Apple?, Morgan Stanley Research.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2012, Technological Innovation, Resource Allocation, and Growth. NBER Working Paper, National Bureau of Economic Research.

Koh, Ping-Sheng, and David M. Reeb, 2015, Missing R&D, *Journal of Accounting and Economics* 60, 73–94.

Kothari, S. P., Ted E. Laguerre, and Andrew J. Leone, 2002, Capitalization versus Expensing: Evidence on the Uncertainty of Future Earnings from Capital Expenditures versus R&D Outlays, *Review of Accounting Studies* 7, 355–382.

Krasnikov, Alexander, Saurabh Mishra, and David Orozco, 2009, Evaluating the Financial Impact of Branding Using Trademarks: A Framework and Empirical Evidence, *Journal of Marketing* 73, 154–166.

Leone, Andrew J., and Joanna Shuang Wu, 2007, What Does it Take to Become a Superstar? Evidence from Institutional Investor Rankings of Financial Analysts, SSRN Scholarly Paper, Social Science Research Network, Rochester, NY.

Lim, Terence, 2001, Rationality and Analysts' Forecast Bias, *The Journal of Finance* 56, 369–385.

Manso, Gustavo, 2011, Motivating Innovation, *The Journal of Finance* 66, 1823–1860.

Mian, G. Mujtaba, and Terence G. L Teo, 2004, Do Errors in Expectations Explain the Cross-Section of Stock Returns?, *Pacific-Basin Finance Journal* 12, 197–217.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 1999, Does Forecast Accuracy Matter to Security Analysts?, *The Accounting Review* 74, 185-200.

Millot, Valentine, 2012, Trademark Strategies and Innovative Activities, Working Paper, University of Strasbourg.

Millot, Valentine, 2009, Trademarks as an Indicator of Product and Marketing Innovations, OECD Science, Technology and Industry Working Papers, Organisation for Economic Co-operation and Development, Paris.

OECD/Eurostat, 2005, *Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data (3rd edition),* The Measurement of Scientific and Technological Activities (OECD Publishing, Paris)

Pandit, Shail, Charles E. Wasley, and Tzachi Zach, 2011, The Effect of Research and Development (R&D) Inputs and Outputs on the Relation between the Uncertainty of Future Operating Performance and R&D Expenditures, *Journal of Accounting, Auditing & Finance* 26, 121–144.

Payne, Jeff L., and Wayne B. Thomas, 2003, The Implications of Using Stock-Split Adjusted I/B/E/S Data in Empirical Research, *The Accounting Review* 78, 1049–1067.

Petersen, Mitchell A., 2009, Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, *Review of Financial Studies* 22, 435–480.

Raedy, Jana Smith, Philip Shane, and Yanhua Yang, 2006, Horizon-Dependent Underreaction in Financial Analysts' Earnings Forecasts, *Contemporary Accounting Research* 23, 291–322.

Rajgopal, Shivaram, Terry Shevlin, and Mohan Venkatachalam, 2003, Does the Stock Market Fully Appreciate the Implications of Leading Indicators for Future Earnings? Evidence from Order Backlog, *Review of Accounting Studies* 8, 461–492.

Richardson, Scott, Siew Hong Teoh, and Peter D. Wysocki, 2004, The Walk-down to Beatable Analyst Forecasts: The Role of Equity Issuance and Insider Trading Incentives, *Contemporary Accounting Research* 21, 885–924.

Schmoch, Ulrich, 2003, Service Marks as Novel Innovation Indicator, *Research Evaluation* 12, 149–156.

So, Eric C., 2013, A New Approach to Predicting Analyst Forecast Errors: Do Investors Overweight Analyst Forecasts?, *Journal of Financial Economics* 108, 615–640.

Swartz, Michael A., and D. Mitch Van Zelfden, 2015, Mattel Inc. (MAT): Plenty of Work Ahead; Lowering Ests/PT to $28, SunTrust Robinson Humphrey Research.

Teoh, Siew Hong, and T. J. Wong, 2002, Why New Issues and High-accrual Firms Underperform: The Role of Analysts' Credulity, *The Review of Financial Studies* 15, 869–900.

USPTO, 2016, Trademark, Patent, or Copyright?, United States Patent and Trademark Office.

USPTO, 2014, Basic Facts about Trademarks, United States Patent and Trademark Office.

Zacks Equity Research, 2015, Shake Shack (SHAK) Rises on 'Chicken Shack' Trademark Filing, Zacks Investment Research.

Zhang, X. Frank, 2006, Information Uncertainty and Analyst Forecast Behavior, *Contemporary Accounting Research* 23, 565–590.

APPENDIX: Variable Definitions

Innovation Measures

$Trademark_{i,t}$	The natural log of one plus the number of trademarks registered in period t scaled by beginning-of-period total assets in t. Period refers to a fiscal quarter in quarterly window or a fiscal year in annual window.
$Patent_{i,t}$	The natural log of one plus the number of patents registered in period t scaled by beginning of-period total assets in t.

Analyst Forecast Measures

$Earn\_Rev_{i,t}^{t+1}$	Revision in consensus EPS forecast for period t+1 during period t, which is measured as the difference between the first consensus forecast for period t+1 that is made within period t+1 (at point B, Figure 1) and the last consensus forecast for period t+1 that is made within period t-1 (at point A, Figure 1), scaled by the beginning-of-period total assets per share in period t.
$Earn\_Rev_{i,t-1}^{t}$	Revision in consensus EPS forecast for period t during period t-1, which is measured as the difference between the first consensus forecast for period t that is made within period t and the last consensus forecast for period t that is made within period t-2, scaled by the beginning-of-period total assets per share in period t-1.
$Earn\_Rev_{i,t+1}^{t+1}$	Revision in consensus EPS forecast for period t+1 during period t+1, which is measured as the difference between the last consensus forecast for period t+1 that is made within period t+1 (at point C, Figure 1) and the first consensus forecast for period t+1 that is made within period t+1 (at point B, Figure 1), scaled by the beginning-of-period total assets per share in period t+1.
$Earn\_Rev_{i,t}^{t}$	Revision in consensus EPS forecast for period t during period t, which is measured as the difference between the last consensus forecast for period t that is made within period t and the first consensus forecast for period t that is made within period t, scaled by the beginning-of-period total assets per share in period t.
$Earn\_FE_{i,t+1}^{t+1}$	Actual EPS of period t+1 minus the last consensus EPS forecast before the earnings announcement for period t+1 (at point D, Figure 1), scaled by the beginning-of-period assets per share in period t+1.
$Earn\_FE_{i,t}^{t}$	Actual EPS of period t minus the last consensus EPS forecast before the earnings announcement for period t, scaled by the beginning-of-period assets per share in period t.
$LTG\_Rev_{i,t}$	Revision in consensus long-term earnings growth forecast during year t, which is measured as the difference between the first consensus long-term earnings growth forecast after the end of year t (at point B, Figure 2) and the last long-earnings growth forecast before the start of year t (at point A, Figure 2).
$LTG\_Rev_{i,t-1}$	Revision in consensus long-term earnings growth forecast during year t-1, which is measured as the difference between the first consensus long-term earnings growth forecast after the end of year t-1 and the last long-earnings growth forecast before the start of year t-1.
$LTG\_FE_{i,t}$	Actual five-year earnings growth rate minus the first consensus long-term earnings growth forecast after the end of year t (at point B, Figure 2).

$LTG\_FE_{i,t-1}$	Actual five-year earnings growth rate minus the first consensus long-term earnings growth forecast after the end of year t-1.
$\Delta Earn\_COV_{i,t+1}$	The percentage change from period t to period t+1 in the number of individual EPS forecasts that constitute the last consensus EPS forecast before the announcement of earnings of period t+1.
$\Delta LTG\_COV_{i,t}$	The percentage change from year t-1 to year t in the number of individual long-term earnings growth forecasts that constitute the first consensus long-term earnings growth forecast after the end of year t.
Firm Characteristics	
$RD_{i,t}$	R&D expenses in period t scaled by total sales in period t, missing R&D expenses are set to be zero
$ADV_{i,t}$	Advertising expenses in period t scaled by total sales in period t, missing advertising expenses are set to be zero
$OPEX\_Other_{i,t}$	Operating expenses excluding R&D expenses and advertising expenses in period t scaled by total sales in period t
$CAPX_{i,t}$	Capital expenditure in period t scaled by total sales in period t
$Size_{i,t}$	The natural log of market value of equity at the end of period t
$MB_{i,t}$	The market value of equity at the end of period t divided by the book value of equity at the end of period t
$Age_{i,t}$	The natural log of the number of months during which a firm has been in CRSP until the end of period t
$Leverage_{i,t}$	The sum of short-term debt and long-term debt at the end of period t divided by the sum of short-term debt, long-term debt and the market value of equity at the end of period t
$ROA_{i,t+1}$	The realized EPS from I/B/E/S actual file scaled by beginning of-period total assets per share in period t+1
$ROA_{i,past}$	The realized EPS from I/B/E/S actual file scaled by beginning of-period total assets per share in quarter t-3 (i.e., the same quarter of the last year) or in year t
$\Delta ROA_{i,past}$	The change in ROA from quarter t-7 to quarter t-3 (i.e., the same quarter of the prior 2 years) or from year t-1 to year t
$Earn\_Growth_{[t+1,t+5]}$	The realized annual EPS growth rate from I/B/E/S actual file from year t+1 to year t+5. I/B/E/S estimates the realized long-term growth in the following way: “The average annual earnings per share growth for a company over the past five years. The average annual growth in EPS for the past five years is calculated by measuring the slope of a log-linear line fit to the reported earnings. It is expressed as a percentage. If quarterly data is available, the line is fitted to the last 21 observations of rolling four quarter EPS. The resultant growth (slope) is raised to the fourth power to obtain an annualized growth factor. If semi-annual data is available, the curve is fitted to the last 11 observations of the semi-annual data. The resultant growth (slope) is raised to the second power to obtain the annual growth factor. If only annual observations are available, the curve is fitted to the last 6 annual observations (5 time periods) and the

	slope is used to represent the growth factor. Zero and negative observations are excluded from the calculations.”
$Earn\_Vol_{[t-4,t]}$	The standard deviation in realized EPS from I/B/E/S actual file scaled by the beginning-of-period total assets per share during the period [t-4, t] (i.e., the prior 5 quarters or the prior 5 years)
$Log(1 + RET_{i,t+1})$	The natural log of one plus the buy-and-hold compounded return over the 12 months of year t+1, adjusted for value-weighted market return over the same period.

Table 1 Sample Selection and Industry Distribution

This table presents the sample selection procedure in Panel A and the industry distribution of the sample in Panel B. 565 firm-years with missing industry classifications are excluded from Panel B.

Panel A Sample Selection

	# Obs	# Firms	# Patents	# Trademarks
All S&P 1500 firms between 1993 and 2010	41,960	3,311	574,275	117,377
Removing firm-year observations that are not in I/B/E/S	36,077	3,248	560,686	109,265
Removing firm-year observations with negative book value of equity	35,419	3,241	550,239	107,336

Panel B Industry Distribution

ID	Industry Name	# of Firm-year Obs	% of the Sample	# of Patents Per Firm-year	# of Trademarks Per Firm-year
1	Consumer NonDurables (Food, Tobacco, Textiles, Apparel, Leather, Toys)	2,133	6.02%	3.47	6.88
2	Consumer Durables (Cars, TV's, Furniture, Household Appliances)	973	2.75%	27.02	4.37
3	Manufacturing (Machinery, Trucks, Planes, Off Furn, Paper, Com Printing)	4,261	12.03%	23.18	2.97
4	Oil, Gas, and Coal Extraction and Products	1,429	4.03%	10.77	1.15
5	Chemicals and Allied Products	962	2.72%	35.02	6.64
6	Business Equipment (Computers, Software, and Electronic Equipment)	6,290	17.76%	30.68	2.18
7	Telephone and Television Transmission	676	1.91%	10.97	6.46
8	Utilities	1,718	4.85%	0.15	0.79
9	Wholesale, Retail, and Some Services (Laundries, Repair Shops)	4,066	11.48%	0.35	2.83
10	Healthcare, Medical Equipment, and Drugs	2,808	7.93%	14.76	3.00
11	Finance	5,608	15.83%	0.34	1.86
12	Other (Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment)	3,930	11.10%	3.40	1.85

Table 2 Descriptive Statistics

This table presents summary statistics of main variables in Panel A and pairwise correlations between patents and trademarks and various expenses in Panel B. Variables are defined in Appendix and are measured in year t, unless denoted otherwise. #Analyst Coverage is measured as the number of analyst forecasts that constitute the last consensus forecast for year t+1 before the announcement of earnings of year t+1.Total Assets and Sales are in millions. #Patents means the raw number of patents. #Trademarks means the raw number of trademarks. All variables are winsorized at the top and bottom 0.5%. * represents p-value<0.0001.

Panel A Summary Statistics

Innovation Output Measures

Variable	N	Mean	Std Dev	25th Pctl	Median	75th Pctl	Maximum
# Patents (firm level)	3,241	121.16	552.84	0	0	17	5,264
# Trademarks (firm level)	3,241	28.72	70.42	0	6	23	525
# Patents (firm-year level)	35,419	12.43	56.58	0	0	2	567
# Trademarks (firm-year level)	35,419	2.73	7.06	0	0	2	58

Analyst Forecast Measures

Variable	N	Mean	Std Dev	25th Pctl	Median	75th Pctl
$Earn\_Rev_{i,t}^{t+1}$	22,805	-0.0074	0.0531	-0.0186	-0.0016	0.0076
$Earn\_Rev_{i,t+1}^{t+1}$	34,165	-0.0027	0.0264	-0.0061	0.0000	0.0041
$Earn\_FE_{i,t+1}^{t+1}$	35,085	-0.0003	0.0209	-0.0010	0.0004	0.0029
# Analyst Coverage$_{t+1}$	35,334	9.33	7.25	4	7	13
$LTG\_Rev_{i,t}$	30,622	-0.0051	0.0486	-0.0180	0.0000	0.0095
$LTG\_FE_{i,t}$	22,706	-6.62%	25.02%	-19.33%	-5.44%	4.68%

Firm Characteristics

Variable	N	Mean	Std Dev	25th Pctl	Median	75th Pctl
Total Assets	35,419	8,283.26	29,520.93	355.80	1,165.88	4,384.94
Sale	35,419	3,707.80	9,371.83	280.28	828.00	2,682.83
ROA	33,911	0.06	0.09	0.02	0.05	0.10

MB	35,402	3.32	4.04	1.49	2.22	3.58
Earn_Growth	25838	9.84%	25.57%	-3.73%	8.82%	20.61%
Age (in years)	35411	20.02	18.01	6.67	14.42	28.00
R&D	35419	0.05	0.19	0.00	0.00	0.03
ADV	35419	0.01	0.03	0.00	0.00	0.01
OPEX_Other	35419	0.77	0.19	0.67	0.80	0.88
CAPX	33394	0.09	0.16	0.02	0.04	0.08

Panel B Pairwise Correlations between Patents and Trademarks and Expenses

	Patent	*Trademark*	*R&D*	*ADV*	*OPEX_Other*	*CAPX*
Patent	1					
Trademark	0.1759*	1				
R&D	0.3926*	0.1035*	1			
ADV	-0.0129	0.1296*	0.0169	1		
OPEX_Other	-0.0491*	0.0368*	-0.014	-0.0704*	1	
CAPX	0.019	-0.0245*	0.1938*	-0.0478*	-0.1382*	1

Table 3 The Ability of Patents and Trademarks to Predict Future Firm Fundamentals

This table presents the regression results of the ability of innovation output measures—patents and trademarks—to predict future firm fundamentals. Panel A includes the results on one-quarter-ahead earnings. Panel B includes the results on one-year-ahead earnings. Panel C includes the results on long-term (i.e., five-year) earnings growth. Variables are defined in Appendix. Independent variables are measured in period t, unless denoted otherwise. All variables are winsorized at the top and bottom 0.5%. The numbers shown in parentheses below coefficients are t-values based on standard errors that are heteroskedasticity-consistent and clustered at firm level. *, **, and *** represent significance at 10%, 5%, and 1%, respectively.

Panel A Predicting One-quarter-ahead Earnings

$$ROA_{i,t+1} = \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * Size_{i,t} + \beta_3 * MB_{i,t} + \beta_4 * Age_{i,t} + \beta_5 * Leverage_{i,t} + \beta_6 * ROA_{i,past} + \beta_7 * \Delta ROA_{i,past} + \beta_8 * R\&D_{i,t} + \beta_9 * OPEX\_Other_{i,t} + \sum \delta_j Quarter_j + \sum \mu_k Firm_k + \varepsilon_{i,t+1}$$

	ROA$_{t+1}$	*ROA$_{t+1}$*	*ROA$_{t+1}$*
Patent	0.0410		0.0394
	(1.23)		(1.18)
Trademark		0.0748**	0.0726*
		(1.97)	(1.93)
Size	0.0016***	0.0016***	0.0016***
	(7.33)	(7.27)	(7.40)
MB	0.0007***	0.0007***	0.0007***
	(14.23)	(14.22)	(14.19)
Age	-0.0005*	-0.0005*	-0.0005*
	(-1.92)	(-1.86)	(-1.90)
Leverage	-0.0175***	-0.0175***	-0.0175***
	(-19.30)	(-19.26)	(-19.24)
ROA	0.3875***	0.3869***	0.3876***
	(29.66)	(29.64)	(29.65)
ΔROA	-0.0429***	-0.0425***	-0.0429***
	(-5.00)	(-4.95)	(-5.00)
R&D	-0.0529***	-0.0529***	-0.0529***
	(-18.32)	(-18.35)	(-18.32)
OPEX_Other	-0.0409***	-0.0409***	-0.0409***
	(-17.20)	(-17.22)	(-17.20)
Intercept	0.0279***	0.0280***	0.0278***
	(13.44)	(13.52)	(13.34)
Firm Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
SE Clustered	By Firm	By Firm	By Firm
Adjusted R-square	0.6231	0.6231	0.6231
No. of Obs	130115	130115	130115

Panel B Predicting One-year-ahead Earnings

$$ROA_{i,t+1} = \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * Size_{i,t} + \beta_3 * MB_{i,t} + \beta_4 * Age_{i,t} + \beta_5 * Leverage_{i,t} + \beta_6 * ROA_{i,t} + \beta_7 * \Delta ROA_{i,past} + \beta_8 * R\&D_{i,past} + \beta_9 * ADV_{i,t} + \beta_{10} * CAPEX_{i,t} + \beta_{11} * OPEX\_Other_{i,t} + \sum \delta_j Year_j + \sum \mu_k Firm_k + \varepsilon_{i,t+1}$$

	ROA_{t+1}	ROA_{t+1}	ROA_{t+1}
Patent	0.0441		0.0242
	(0.62)		(0.34)
Trademark		0.4175***	0.4146***
		(3.62)	(3.59)
Size	-0.0009	-0.0005	-0.0005
	(-0.74)	(-0.41)	(-0.38)
MB	0.0025***	0.0024***	0.0024***
	(8.17)	(8.12)	(8.09)
Age	-0.0020	-0.0017	-0.0017
	(-1.22)	(-1.01)	(-1.01)
Leverage	-0.0768***	-0.0758***	-0.0756***
	(-15.94)	(-15.62)	(-15.69)
ROA	0.3731***	0.3702***	0.3707***
	(19.89)	(19.73)	(19.76)
ΔROA	0.0333**	0.0328**	0.0324**
	(2.48)	(2.46)	(2.41)
R&D	-0.1838***	-0.1843***	-0.1844***
	(-8.00)	(-7.99)	(-7.99)
ADV	-0.1791***	-0.1776***	-0.1775***
	(-3.01)	(-3.03)	(-3.03)
CAPEX	-0.0442***	-0.0443***	-0.0442***
	(-3.55)	(-3.58)	(-3.56)
OPEX_Other	-0.0953***	-0.0959***	-0.0958***
	(-6.00)	(-6.07)	(-6.04)
Intercept	0.1312***	0.1272***	0.1267***
	(9.31)	(9.01)	(8.90)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
SE Clustered	By Firm	By Firm	By Firm
Adjusted R-square	0.6373	0.6383	0.6383
No. of Obs	30973	30973	30973

Panel C Predicting Five-year Earnings Growth

$$Earn\_Growth_{i,[t+1,t+5]} = \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * Size_{i,t} + \beta_3 * MB_{i,t} + \beta_4 * Age_{i,t} + \beta_5 * Leverage_{i,t} + \beta_6 * ROA_{i,past} + \beta_7 * \Delta ROA_{i,past} + \beta_8 * R\&D_{i,t} + \beta_9 * ADV_{i,t} + \beta_{10} * CAPEX_{i,t} + \beta_{11} * OPEX\_Other_{i,t} + \sum \delta_j Year_j + \sum \mu_k Firm_k + \varepsilon_{i,[t+1,t+5]}$$

	$Earn\_Growth_{[t+1,t+5]}$	$Earn\_Growth_{[t+1,t+5]}$	$Earn\_Growth_{[t+1,t+5]}$
Patent	0.5925**		0.5656**
	(2.15)		(2.03)
Trademark		0.5878**	0.5249*
		(1.99)	(1.76)
Size	-0.0825***	-0.0828***	-0.0819***
	(-13.52)	(-13.58)	(-13.43)
MB	0.0035***	0.0036***	0.0035***
	(4.03)	(4.06)	(3.99)
Age	-0.0448***	-0.0439***	-0.0443***
	(-4.09)	(-4.00)	(-4.04)
Leverage	-0.1381***	-0.1394***	-0.1365***
	(-4.79)	(-4.83)	(-4.73)
ROA	-0.8936***	-0.9020***	-0.8969***
	(-12.27)	(-12.37)	(-12.33)
ΔROA	0.4214***	0.4304***	0.4201***
	(10.15)	(10.47)	(10.13)
R&D	0.1456	0.1439	0.1435
	(1.27)	(1.25)	(1.25)
ADV	-0.1486	-0.1313	-0.1413
	(-0.66)	(-0.58)	(-0.63)
CAPEX	-0.0422	-0.0418	-0.0425
	(-0.76)	(-0.75)	(-0.76)
OPEX_Other	0.2001***	0.1985***	0.1991***
	(2.94)	(2.91)	(2.93)
Intercept	0.7968***	0.8007***	0.7906***
	(12.22)	(12.27)	(12.09)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
SE Clustered	By Firm	By Firm	By Firm
Adjusted R-square	0.3616	0.3613	0.3617
No. of Obs	24047	24047	24047

Table 4 Revisions in Quarterly Earnings Forecasts

This table presents the regression results of the quarterly earnings forecast revision tests. The left panel includes the results on contemporaneous revisions in earnings forecasts for quarter t+1 during quarter t. The right panel includes the results on subsequent revisions in earnings forecasts for quarter t+1 during quarter t+1. Variables are defined in Appendix. Independent variables are measured in quarter t, unless denoted otherwise. All variables are winsorized at the top and bottom 0.5%. The numbers shown in parentheses below coefficients are t-values based on standard errors that are heteroskedasticity-consistent and clustered at firm level. *, **, and *** represent significance at 10%, 5%, and 1%, respectively.

$$Earn\_Rev_{i,t}^{t+1} = \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * Earn\_Rev_{i,t-1}^{t} + \beta_3 * Size_{i,t} + \beta_4 * MB_{i,t} + \beta_5 * Age_{i,t} + \beta_6 * Leverage_{i,t} + \beta_7 * ROA_{i,past} + \beta_8 * \Delta ROA_{i,past} + \beta_9 * R\&D_{i,t} + \beta_{10} * OPEX\_Other_{i,t} + \sum \delta_j Quarter_j + \sum \mu_k Firm_k + \varepsilon_{i,t}$$

	Contemporaneous Revisions			**Subsequent Revisions**		
	$Earn\_Rev_{i,t}^{t+1}$	$Earn\_Rev_{i,t}^{t+1}$	$Earn\_Rev_{i,t}^{t+1}$	$Earn\_Rev_{i,t+1}^{t+1}$	$Earn\_Rev_{i,t+1}^{t+1}$	$Earn\_Rev_{i,t+1}^{t+1}$
Patent	0.0045		0.0040	-0.0014		-0.0016
	(0.39)		(0.35)	(-0.19)		(-0.22)
Trademark		0.0259*	0.0257*		0.0142*	0.0143*
		(1.72)	(1.70)		(1.85)	(1.85)
$Earn\_Rev_{i,t-1}^{t}$	0.2888***	0.2888***	0.2888***	0.1506***	0.1506***	0.1506***
	(32.51)	(32.50)	(32.51)	(19.62)	(19.65)	(19.62)
Size	0.0009***	0.0009***	0.0009***	0.0001***	0.0001***	0.0001***
	(14.14)	(14.05)	(14.15)	(3.80)	(3.86)	(3.87)
MB	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(9.07)	(9.06)	(9.04)	(8.95)	(8.89)	(8.90)
Age	-0.0003***	-0.0003***	-0.0003***	-0.0001***	-0.0001***	-0.0001***
	(-3.53)	(-3.48)	(-3.49)	(-3.21)	(-3.18)	(-3.18)
Leverage	-0.0011***	-0.0011***	-0.0011***	-0.0004***	-0.0004**	-0.0004**
	(-4.51)	(-4.43)	(-4.44)	(-2.64)	(-2.52)	(-2.57)
ROA	-0.0513***	-0.0514***	-0.0513***	-0.0173***	-0.0173***	-0.0173***
	(-15.85)	(-15.86)	(-15.84)	(-9.21)	(-9.18)	(-9.21)
ΔROA	0.0062**	0.0062**	0.0062**	0.0014	0.0014	0.0014
	(2.08)	(2.09)	(2.07)	(0.88)	(0.87)	(0.88)

R&D	-0.0106***	-0.0106***	-0.0106***	-0.0021***	-0.0021***	-0.0021***
	(-9.55)	(-9.56)	(-9.56)	(-4.25)	(-4.25)	(-4.25)
OPEX_Other	-0.0095***	-0.0095***	-0.0095***	-0.0033***	-0.0033***	-0.0033***
	(-15.51)	(-15.51)	(-15.50)	(-10.78)	(-10.77)	(-10.78)
Intercept	0.0015**	0.0015**	0.0015**	0.0020***	0.0019***	0.0019***
	(2.19)	(2.12)	(2.10)	(5.91)	(5.75)	(5.78)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	By Firm	By Firm	By Firm	By Firm	By Firm	By Firm
Adjusted R-square	0.2459	0.2460	0.2460	0.1110	0.1110	0.1110
No. of Obs	99416	99416	99416	110593	110593	110593

Table 5 Quarterly Earnings Forecast Errors

This table presents the regression results of the quarterly earnings forecast error test. The quarterly earnings forecast error is measured as actual EPS of quarter t+1 minus the last consensus EPS forecast for quarter t+1 that is made before the earnings announcement for quarter t+1, scaled by the beginning-of-quarter assets per share in quarter t. Other variables are defined in Appendix. Independent variables are measured in quarter t, unless denoted otherwise. All variables are winsorized at the top and bottom 0.5%. The numbers shown in parentheses below coefficients are t-values based on standard errors that are heteroskedasticity-consistent and clustered at firm level. *, **, and *** represent significance at 10%, 5%, and 1%, respectively.

$$Earn\_FE_{i,t+1}^{t+1} = \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * Earn\_FE_{i,t}^{t} + \beta_3 * \Delta Earn\_COV_{i,t+1} + \beta_4 * Size_{i,t} + \beta_5 * MB_{i,t} + \beta_6 * Age_{i,t} + \beta_7 * Leverage_{i,t} + \beta_8 * Earn\_Vol_{i,[t-4,t]} + \beta_9 * RD_{i,t} + \beta_{10} * OPEX\_Other_{i,t} + \sum \delta_j Quarter_j + \sum \mu_k Firm_k + \varepsilon_{i,t+1}$$

	$Earn\_FE_{i,t+1}^{t+1}$	$Earn\_FE_{i,t+1}^{t+1}$	$Earn\_FE_{i,t+1}^{t+1}$	$Earn\_FE_{i,t+1}^{t+1}$	$Earn\_FE_{i,t+1}^{t+1}$	$Earn\_FE_{i,t+1}^{t+1}$
Patent	0.0056	0.0087			0.0050	0.0082
	(0.48)	(0.75)			(0.43)	(0.70)
Trademark			0.0292*	0.0262*	0.0289*	0.0258*
			(1.93)	(1.78)	(1.92)	(1.75)
$Earn\_FE_{i,t}^{t}$	0.2269***	0.2243***	0.2268***	0.2243***	0.2268***	0.2242***
	(22.79)	(22.59)	(22.79)	(22.59)	(22.79)	(22.60)
$\Delta Earn\_COV_{i,t+1}$	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(7.41)	(7.51)	(7.40)	(7.50)	(7.40)	(7.50)
Size	-0.0001*	-0.0002**	-0.0001*	-0.0002**	-0.0001*	-0.0002**
	(-1.96)	(-2.50)	(-1.93)	(-2.51)	(-1.88)	(-2.43)
MB	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(6.63)	(6.49)	(6.60)	(6.47)	(6.59)	(6.46)
Age	-0.0001	-0.0002	-0.0001	-0.0001	-0.0001	-0.0002
	(-1.37)	(-1.53)	(-1.32)	(-1.48)	(-1.34)	(-1.51)
Leverage	-0.0027***	-0.0027***	-0.0027***	-0.0027***	-0.0027***	-0.0027***
	(-8.99)	(-8.68)	(-8.98)	(-8.70)	(-8.92)	(-8.62)
$Earn\_Vol_{i,[t-4,t]}$		0.0038		0.0038		0.0037
		(0.51)		(0.51)		(0.50)

R&D		0.0001		0.0002		0.0001
		(0.16)		(0.17)		(0.16)
OPEX_Other		-0.0019***		-0.0019***		-0.0019***
		(-3.04)		(-3.04)		(-3.03)
Intercept	0.0019***	0.0033***	0.0018***	0.0033***	0.0018***	0.0033***
	(3.12)	(4.50)	(3.07)	(4.47)	(3.01)	(4.42)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	By Firm	By Firm	By Firm	By Firm	By Firm	By Firm
Adjusted R-square	0.1580	0.1610	0.1581	0.1610	0.1581	0.1611
No. of Observations	129004	125880	129004	125880	129004	125880

Table 6 Revisions in Annual Earnings Forecasts

This table presents the regression results of the annual earnings forecast revision tests. The left panel includes the results on contemporaneous revisions in earnings forecasts for year t+1 during year t. The right panel includes the results on subsequent revisions in earnings forecasts for year t+1 during year t+1. Variables are defined in Appendix. Independent variables are measured in year t, unless denoted otherwise. All variables are winsorized at the top and bottom 0.5%. The numbers shown in parentheses below coefficients are t-values based on standard errors that are heteroskedasticity-consistent and clustered at firm level. *, **, and *** represent significance at 10%, 5%, and 1%, respectively.

$$Earn\_Rev_{i,t}^{t+1} = \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * Earn\_Rev_{i,t-1}^{t} or\ Earn\_Rev_{i,t1}^{t} + \beta_3 * Size_{i,t} + \beta_4 * MB_{i,t} + \beta_5 * Age_{i,t} + \beta_6 * Leverage_{i,t} + \beta_7 * ROA_{i,past} + \beta_8 * \Delta ROA_{i,past} + \beta_9 * R\&D_{i,t} + \beta_{10} * ADV_{i,t} + \beta_{11} * CAPEX_{i,t} + \beta_{12} * OPEX\_Other_{i,t} + \sum \delta_j Year_j + \sum \mu_k Firm_k + \varepsilon_{i,t}$$

	Contemporaneous Revisions			Subsequent Revisions		
	$Earn\_Rev_{i,t}^{t+1}$	$Earn\_Rev_{i,t}^{t+1}$	$Earn\_Rev_{i,t}^{t+1}$	$Earn\_Rev_{i,t+1}^{t+1}$	$Earn\_Rev_{i,t+1}^{t+1}$	$Earn\_Rev_{i,t+1}^{t+1}$
Patent	-0.1041		-0.1111	-0.0180		-0.0245
	(-1.06)		(-1.13)	(-0.56)		(-0.76)
Trademark		0.1334	0.1545		0.1204**	0.1237**
		(0.89)	(1.03)		(2.38)	(2.47)
Earn_Rev	-0.0419*	-0.0412*	-0.0418*	-0.1247***	-0.1241***	-0.1242***
	(-1.89)	(-1.85)	(-1.89)	(-6.38)	(-6.33)	(-6.35)
Size	0.0106***	0.0109***	0.0108***	-0.0003	-0.0002	-0.0002
	(8.04)	(8.35)	(8.15)	(-0.64)	(-0.31)	(-0.39)
MB	0.0008***	0.0008***	0.0008***	0.0004***	0.0004***	0.0004***
	(3.83)	(3.74)	(3.79)	(3.49)	(3.32)	(3.35)
Age	-0.0030	-0.0029	-0.0029	-0.0014**	-0.0013*	-0.0013*
	(-1.56)	(-1.53)	(-1.49)	(-1.98)	(-1.82)	(-1.81)
Leverage	0.0250***	0.0262***	0.0254***	-0.0068***	-0.0063***	-0.0064***
	(4.84)	(5.05)	(4.92)	(-3.42)	(-3.12)	(-3.23)
ROA	0.2369***	0.2377***	0.2361***	-0.0006	-0.0011	-0.0014
	(8.80)	(8.76)	(8.72)	(-0.07)	(-0.12)	(-0.16)
ΔROA	0.2581***	0.2559***	0.2579***	0.0538***	0.0530***	0.0535***

	(12.28)	(12.54)	(12.28)	(7.70)	(7.56)	(7.64)
R&D	-0.0129	-0.0139	-0.0128	-0.0175	-0.0180	-0.0179
	(-0.49)	(-0.51)	(-0.48)	(-1.48)	(-1.52)	(-1.52)
ADV	0.0065	0.0068	0.0071	-0.0481**	-0.0478**	-0.0475**
	(0.14)	(0.14)	(0.15)	(-2.23)	(-2.23)	(-2.22)
CAPEX	-0.0462***	-0.0461***	-0.0464***	-0.0211***	-0.0210***	-0.0211***
	(-3.08)	(-3.08)	(-3.09)	(-4.05)	(-4.03)	(-4.06)
OPEX_Other	0.0157	0.0156	0.0153	-0.0077	-0.0078	-0.0078
	(0.64)	(0.63)	(0.62)	(-1.10)	(-1.10)	(-1.12)
Intercept	-0.0982***	-0.1017***	-0.0999***	0.0150**	0.0129*	0.0134**
	(-4.26)	(-4.43)	(-4.34)	(2.30)	(1.95)	(2.05)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	By Firm	By Firm	By Firm	By Firm	By Firm	By Firm
Adjusted R-square	0.4346	0.4344	0.4347	0.1146	0.1154	0.1155
No. of Obs	17,345	17,345	17,345	29,009	29,009	29,009

Table 7 Annual Earnings Forecast Errors

This table presents the regression results of the annual earnings forecast error test. The annual earnings forecast error is measured as actual EPS of year t+1 minus the last consensus EPS forecast for year t+1 that is made before the earnings announcement for year t+1, scaled by the beginning-of-year assets per share in year t. Other variables are defined in Appendix. Independent variables are measured in year t, unless denoted otherwise. All variables are winsorized at the top and bottom 0.5%. The numbers shown in parentheses below coefficients are t-values based on standard errors that are heteroskedasticity-consistent and clustered at firm level. *, **, and *** represent significance at 10%, 5%, and 1%, respectively.

$$Earn\_FE_{i,t+1}^{t+1} = \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * Earn\_FE_{i,t}^{t} + \beta_3 * \Delta Earn\_COV_{i,t+1} + \beta_4 * Size_{i,t} + \beta_5 * MB_{i,t} + \beta_6 * Age_{i,t} + \beta_7 * Leverage_{i,t} + \beta_8 * Earn\_Vol_{i,[t-4,t]} + \beta_9 * RD_{i,t} + \beta_{10} * ADV_{i,t} + \beta_{11} * CAPEX_{i,t} + \beta_{12} * OPEX\_Other_{i,t} + \sum \delta_j Year_j + \sum \mu_k Firm_k + \varepsilon_{i,t+1}$$

	$Earn\_FE_{i,t+1}^{t+1}$	$Earn\_FE_{i,t+1}^{t+1}$	$Earn\_FE_{i,t+1}^{t+1}$	$Earn\_FE_{i,t+1}^{t+1}$	$Earn\_FE_{i,t+1}^{t+1}$	$Earn\_FE_{i,t+1}^{t+1}$
Patent	-0.0116	-0.0100			-0.0150	-0.0130
	(-0.43)	(-0.38)			(-0.55)	(-0.49)
Trademark			0.0726**	0.0649**	0.0744**	0.0665**
			(2.37)	(2.06)	(2.37)	(2.06)
$Earn\_FE_{i,t}^{t}$	0.0800***	0.0664***	0.0795***	0.0661***	0.0794***	0.0660***
	(3.58)	(3.11)	(3.55)	(3.09)	(3.56)	(3.10)
$\Delta Earn\_COV_{i,t+1}$	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***
	(5.33)	(5.26)	(5.25)	(5.19)	(5.26)	(5.19)
Size	0.0010**	0.0004	0.0011**	0.0005	0.0010**	0.0005
	(2.39)	(1.13)	(2.49)	(1.30)	(2.52)	(1.27)
MB	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.25)	(-0.35)	(-0.39)	(-0.48)	(-0.36)	(-0.45)
Age	-0.0006	-0.0007	-0.0005	-0.0006	-0.0005	-0.0006
	(-1.11)	(-1.28)	(-1.02)	(-1.19)	(-1.01)	(-1.18)
Leverage	-0.0049***	-0.0051***	-0.0046**	-0.0048**	-0.0047***	-0.0048**
	(-2.73)	(-2.65)	(-2.52)	(-2.47)	(-2.62)	(-2.54)
$Earn\_Vol_{i,[t-4,t]}$	0.0105	0.0155**	0.0099	0.0149*	0.0100	0.0150*
	(1.33)	(2.00)	(1.23)	(1.91)	(1.25)	(1.92)

R&D		-0.0192**		-0.0191**		-0.0191**
		(-2.33)		(-2.31)		(-2.32)
ADV		-0.0466**		-0.0461**		-0.0461**
		(-2.23)		(-2.22)		(-2.22)
CAPEX		-0.0020		-0.0019		-0.0020
		(-0.46)		(-0.45)		(-0.46)
OPEX_Other		-0.0156***		-0.0155***		-0.0155***
		(-3.41)		(-3.37)		(-3.38)
Intercept	-0.0027	0.0115***	-0.0037	0.0104**	-0.0035	0.0107**
	(-0.78)	(2.61)	(-1.10)	(2.38)	(-1.03)	(2.41)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	By Firm	By Firm	By Firm	By Firm	By Firm	By Firm
Adjusted R-square	0.1482	0.1544	0.1488	0.1548	0.1488	0.1548
No. of Observations	31,975	30,173	31,975	30,173	31,975	30,173

Table 8 Revisions in Long-term Earnings Growth Forecasts

This table presents the regression results from the long-term earnings growth forecast revision test. Variables are defined in Appendix. Independent variables are measured in year t, unless denoted otherwise. All variables are winsorized at the top and bottom 0.5%. The numbers shown in parentheses below coefficients are t-values based on standard errors that are heteroskedasticity-consistent and clustered at firm level. *, **, and *** represent significance at 10%, 5%, and 1% respectively.

$$LTG\_Rev_{i,t} = \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * LTG\_Rev_{i,t-1} + \beta_3 * Size_{i,t} + \beta_4 * MB_{i,t} + \beta_5 * Age_{i,t} + \beta_6 * Leverage_{i,t} + \beta_7 * ROA_{i,past} + \beta_8 * \Delta ROA_{i,past} + \beta_9 * RD_{i,t} + \beta_{10} * ADV_{i,t} + \beta_{11} * CAPEX_{i,t} + \beta_{12} * OPEX\_Other_{i,t} + \sum \delta_j Year_j + \sum \mu_k Firm_k + \varepsilon_{i,t}$$

	$LTG\_Rev_{i,t}$	$LTG\_Rev_{i,t}$	$LTG\_Rev_{i,t}$	$LTG\_Rev_{i,t}$	$LTG\_Rev_{i,t}$	$LTG\_Rev_{i,t}$
Patent	0.2030***	0.1246**			0.1970***	0.1156**
	(3.82)	(2.37)			(3.73)	(2.20)
Trademark			0.2296***	0.1837**	0.2002**	0.1677*
			(2.61)	(2.04)	(2.30)	(1.87)
$LTG\_Rev_{i,t-1}$	-0.1473***	-0.1466***	-0.1472***	-0.1465***	-0.1473***	-0.1466***
	(-10.40)	(-10.31)	(-10.44)	(-10.33)	(-10.43)	(-10.32)
Size	0.0039***	0.0063***	0.0048***	0.0063***	0.0050***	0.0065***
	(4.43)	(6.28)	(6.28)	(6.24)	(6.53)	(6.37)
MB	0.0014***	0.0011***	0.0014***	0.0012***	0.0014***	0.0011***
	(7.28)	(6.27)	(7.29)	(6.27)	(7.19)	(6.21)
Age	0.0035**	0.0020	0.0034**	0.0023	0.0033**	0.0022
	(2.16)	(1.17)	(2.08)	(1.32)	(2.02)	(1.29)
Leverage	-0.0100**	-0.0066		-0.0067		-0.0062
	(-2.27)	(-1.39)		(-1.41)		(-1.31)
ROA		-0.0469***		-0.0490***		-0.0481***
		(-3.03)		(-3.15)		(-3.10)
ΔROA		0.1307***		0.1329***		0.1303***
		(11.40)		(11.68)		(11.37)
R&D		-0.0250		-0.0247		-0.0262

		(-1.05)		(-1.04)		(-1.11)
ADV		0.0241		0.0273		0.0253
		(0.48)		(0.54)		(0.50)
CAPEX		0.0226*		0.0227*		0.0225*
		(1.89)		(1.90)		(1.88)
OPEX_Other		0.0419***		0.0417***		0.0413***
		(2.92)		(2.89)		(2.88)
Intercept	-0.0525***	-0.0832***	-0.0586***	-0.0837***	-0.0608***	-0.0851***
	(-5.50)	(-5.97)	(-6.44)	(-6.00)	(-6.64)	(-6.09)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	By Firm	By Firm	By Firm	By Firm	By Firm	By Firm
Adjusted R-square	0.0581	0.0736	0.0569	0.0735	0.0582	0.0739
No. of Obs	25,179	23,628	25,179	23,628	25,179	23,628

Table 9 Long-term Earnings Growth Forecast Errors

This table presents the regression results from the long-term earnings growth forecast error test. The long-term earnings growth forecast error is measured as actual five-year earnings growth rate minus the first consensus long-term earnings growth forecast after year t. Other variables are defined in Appendix. Independent variables are measured in year t, unless denoted otherwise. All variables are winsorized at the top and bottom 0.5%. The numbers shown in parentheses below coefficients are t-values based on standard errors that are heteroskedasticity-consistent and clustered at firm level. *, **, and *** represent significance at 10%, 5%, and 1% respectively.

$$LTG\_FE_{i,t} = \beta_0 + \beta_1 * Innovation\ Measure_{i,t} + \beta_2 * LTG\_FE_{i,t-1} + \beta_3 * \Delta LTG\_COV_{i,t} + \beta_4 * Size_{i,t} + \beta_5 * MB_{i,t} + \beta_6 * Age_{i,t} + \beta_7 * Leverage_{i,t} + \beta_8 * Earn\_Vol_{i,[t-4,t]} + \beta_9 * RD_{i,t} + \beta_{10} * ADV_{i,t} + \beta_{11} * CAPEX_{i,t} + \beta_{12} * OPEX\_Other_{i,t} + \sum \delta_j Year_j + \sum \mu_k Firm_k + \varepsilon_{i,t}$$

	$LTG\_FE_{i,t}$	$LTG\_FE_{i,t}$	$LTG\_FE_{i,t}$	$LTG\_FE_{i,t}$	$LTG\_FE_{i,t}$	$LTG\_FE_{i,t}$
Patent	-0.4556**	-0.4479**			-0.4091*	-0.4049*
	(-2.13)	(-2.06)			(-1.91)	(-1.86)
Trademark			-0.8798***	-0.8255***	-0.8259***	-0.7720**
			(-2.93)	(-2.76)	(-2.74)	(-2.57)
$LTG\_FE_{i,t-1}$	0.5694***	0.5614***	0.5687***	0.5607***	0.5695***	0.5616***
	(54.89)	(51.86)	(54.56)	(51.52)	(54.95)	(51.90)
$\Delta LTG\_COV_{i,t}$	-0.0058**	-0.0046*	-0.0059**	-0.0047*	-0.0058**	-0.0046*
	(-2.31)	(-1.73)	(-2.35)	(-1.78)	(-2.30)	(-1.73)
Size	-0.0579***	-0.0526***	-0.0580***	-0.0527***	-0.0585***	-0.0533***
	(-13.24)	(-11.72)	(-13.28)	(-11.81)	(-13.32)	(-11.84)
MB	-0.0033***	-0.0031***	-0.0033***	-0.0031***	-0.0032***	-0.0030***
	(-4.58)	(-4.36)	(-4.55)	(-4.34)	(-4.47)	(-4.26)
Age	-0.0010	-0.0012	-0.0023	-0.0025	-0.0021	-0.0023
	(-0.13)	(-0.15)	(-0.30)	(-0.31)	(-0.27)	(-0.28)
Leverage	0.0924***	0.0921***	0.0918***	0.0915***	0.0903***	0.0898***

	(4.54)	(4.19)	(4.51)	(4.16)	(4.42)	(4.07)
$Earn\_Vol_{i,[t-4,t]}$	0.2568***	0.2230***	0.2611***	0.2272***	0.2613***	0.2273***
	(3.63)	(3.17)	(3.70)	(3.25)	(3.70)	(3.25)
R&D		0.3226***		0.3249***		0.3257***
		(3.59)		(3.63)		(3.61)
ADV		-0.2927*		-0.3123*		-0.3041*
		(-1.79)		(-1.91)		(-1.86)
CAPEX		0.0863*		0.0864*		0.0858*
		(1.69)		(1.70)		(1.68)
OPEX_Other		0.2325***		0.2287***		0.2293***
		(3.90)		(3.86)		(3.86)
Intercept	0.3588***	0.1803***	0.3649***	0.1887***	0.3703***	0.1939***
	(8.35)	(3.03)	(8.46)	(3.17)	(8.57)	(3.25)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	By Firm	By Firm	By Firm	By Firm	By Firm	By Firm
Adjusted R-square	0.5613	0.5646	0.5614	0.5647	0.5616	0.5648
No. of Obs	20,963	19,742	20,963	19,742	20,963	19,742

Table 10 Explaining Mispricing of Trademarks with Short-term Forecast Errors Predicted by Trademarks

This table presents the results from the additional test of whether analysts' annual forecast errors predicted by trademarks explain stock market mispricing of trademarks. Panel A shows the future return predictability of patents and trademarks. $Log(1 + RET_{i,t+1})$ is computed as the natural log of one plus the buy-and-hold return compounded over the 12 months of year t+1, adjusted for value-weighted market return over the same period. Independent variables are measured in year t, unless denoted otherwise. Panel B shows the results from a two-stage estimation procedure. In the 1st stage, forecast errors are regressed on trademarks, other predictors, and fixed effects. This regression is the same as the one in Table 7, except that the forecast error in this 1st stage regression is measured based on the first consensus forecast for year t+1 that is made after the end of year t (at Point B, Figure 1). $\mathrm{FE\_TM}_{i,t+1}$, $\mathrm{FE\_Other}_{i,t+1}$, and $\mathrm{FE\_Residual}_{i,t+1}$ denote forecast errors predicted from trademarks, forecast errors predicted from other predictors, and residuals from the 1st stage. In the 2nd stage, $\mathrm{Log}(1 + \mathrm{RET}_{i,t+1})$ is regressed on $\mathrm{FE\_TM}_{i,t+1}$, $\mathrm{FE\_Other}_{i,t+1}$, and $\mathrm{FE\_Residual}_{i,t+1}$ as well as year and firm fixed effects. All variables are winsorized at the top and bottom 0.5%, except for returns. All variables used in the 2nd stage regression are standardized for easy comparison of coefficients. The numbers shown in parentheses below coefficients are t-values based on standard errors that are heteroskedasticity-consistent and clustered by year. *, **, and *** represent significance at 10%, 5%, and 1% respectively.

Panel A The Future Return Predictability of Patents and Trademarks

	$Log(1 + RET_{i,t+1})$	$Log(1 + RET_{i,t+1})$	$Log(1 + RET_{i,t+1})$
Patent	0.5989		0.5088
	(1.15)		(0.99)
Trademark		1.5995***	1.4972***
		(3.12)	(3.06)
Size	-0.0226**	-0.0214**	-0.0212**
	(-2.77)	(-2.59)	(-2.58)
MB	-0.0030	-0.0032	-0.0034
	(-0.91)	(-0.97)	(-1.01)
Intercept	0.1162*	0.1080*	0.1040*
	(2.09)	(1.89)	(1.85)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
SE Clustered	By Year	By Year	By Year
Adjusted R-square	0.0574	0.0578	0.0580
No. of Observations	34,483	34,483	34,483

Panel B Explaining Mispricing of Trademarks with Short-term Forecast Errors Predicted by Trademarks

$$1st\ Stage \qquad Earn\_FE_{i,t+1}^{t+1} = \beta_0 + \beta_1 * Trademark_{i,t} + \sum \delta_h Other\ Predictor_h + \sum \delta_j Year_j + \sum \mu_k Firm_k + \varepsilon_{i,t}$$

$$2nd\ Stage \qquad Log(1 + RET_{i,t+1}) = \beta_0 + \beta_1 * FE\_TM_{i,t+1} + \beta_2 * FE\_Other_{i,t+1} + \beta_3 * FE\_Residual_{i,t+1} + \sum \delta_j Year_j + \sum \mu_k Firm_k + \varepsilon_{i,t+1}$$

	$Log(1 + RET_{i,t+1})$
$FE\_TM_{i,t+1}$	8.8097**
	(2.31)
$FE\_Other_{i,t+1}$	12.1295***
	(5.70)
$FE\_Residuals_{i,t+1}$	7.6033***
	(13.86)
Intercept	0.0948***
	(6.54)
Firm Fixed Effects	Yes
Year Fixed Effects	Yes
SE Clustered	By Year
Adjusted R-square	0.2086
No. of Observations	29775