PATENTING ACTIVITY, FIRM INNOVATION CHARACTERISTICS, AND FINANCIAL PERFORMANCE: AN EMPIRICAL INVESTIGATION

by

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Submitted in partial fulfillment of the requirements
For the degree of Doctor of Philosophy

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*We also certify that written approval has been obtained for any proprietary material contained therein.
DEDICATION

This dissertation is dedicated to my mother Fouziyah and my father Abdul-Razzak (may God bless his soul).
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ACKNOWLEDGMENTS

First, I must thank God, the Merciful and the Compassionate for answering countless prayers. This dissertation and all my achievements would not be possible without His blessings. I also thank Prophet Mohammed and his household who continually inspired me when I experienced challenges while completing this project.

I would like to acknowledge my dissertation committee for providing support and guidance: Dr. Timothy J. Fogarty (chair), Dr. Gary J. Previts, Dr. Larry M. Parker, and Dr. Claudia Coulton. My dissertation chair, Dr. Fogarty, has been patient with me. Working under his supervision was such an honor and a rewarding experience. Dr. Previts contributed so much to my academic and professional development. It was such a privilege to be one of his students. I would also like to thank the Ph.D. program director Dr. Julia Grant for her valuable contributions, especially during the coursework stage.

To my mother and so many friends, thank you for your prayers, support, and encouragement. I also thank my oldest brother, Faisal, who set the high standard by earning a Ph.D. in 1973. My other brother, Ali, maintained that standard by earning his Ph.D. in 1993, and he is the one who guided me to the road of academia. Last, I thank my brother Reyadh for the support he provided since my undergraduate years. Thank you for encouraging me to continue my academic pursuit in accounting.

Finally, I acknowledge the financial support provided by the State of Kuwait through Kuwait University’s accounting department. I would like to thank Dr. Sadik Al-Bassam, chair of the accounting department at Kuwait University, for his support.
This study investigates whether firm innovation characteristics and patenting activity are incrementally informative in terms of predicting future financial performance for a sample of publicly traded U.S. based firms. It also investigates how a firms’ patenting activity might have a mediating effect in the relationship between innovation characteristics and financial performance. Projecting the future performance of high technology firms is a particularly difficult task. Due to the inherently historical focus of financial accounting data, it has limited utility in terms of informing users about a firm’s future prospects. The success of high-techs depends upon up-to-date technological development, yet this aspect of firm activity is not reflected in financial reports. This study aims to address this complex issue. Building upon existing literature, this study will make three important contributions to the field: first, by exploring the relationships among intangibles, patenting activity, and financial performance; second, by addressing the existing literature related to the value-relevance of nonfinancial performance measures by using six patent measures to empirically test a model that includes firm innovation characteristic (intangibles, research and development and accounting
goodwill) to predict financial performance (ROA, ROS and ROE); and third, by using structural equation modeling to simultaneously test four research hypotheses. Results from this study indicate that while goodwill and intangibles can directly influence financial performance, research and development’s relationship with future financial performance is mediated by five patenting activity measures. Results also show that a firm’s patenting activity can be predicted by firm innovation characteristics, with research and development serving as the strongest predictor of patenting activity. This study’s findings can benefit investors and policy makers by empirically showing the significant role nonfinancial performance measures, specifically patents, contribute to predicting firm financial performance in the high-technology sector.
CHAPTER 1
INTRODUCTION

Over the past three decades, developed economies such as the United States’ have shifted from a manufacturing-based economy toward a technology-based economy (Singh and Van der Zahn 2008). Firms increasingly strive to develop institutional knowledge to achieve growth, to gain economic returns, and to maintain competitive advantages (Bismuth and Tojo 2008). Consequently, the proportion of market value attributed to intellectual property has noticeably increased for many firms. Bagley and Savage (2006) state that in 2004 intellectual property represents about 87 percent of an average firm’s value compared to 62 percent in 1992 and 38 percent in 1982 (p.367). Intellectual property is often developed internally but it may also be acquired as an intangible asset (i.e., accounting goodwill). Valuation of intellectual property presents a unique set of challenges. Policy makers have not developed a unified policy stipulating how financial disclosure of intellectual property should be structured. Scholars, practitioners, and policymakers continue to debate issues pertaining to valuation and accounting for so-called “soft assets” (e.g., Lev and Sougiannis 1996).

Intellectual property is a sub-set of intangible assets that includes patents, trademarks, and copyrights, as well as other types of “know-how” that may be less easily defined. Bagley and Savage (2006, p. 367) define intellectual property as “any product or result of a mental process that is given legal protection against unauthorized use.” Firms invest substantial resources in research and development (R&D) programs to create intellectual property and other intangible assets that provide competitive advantages to
generate future revenues and growth opportunities. Alternatively, firms invest in intellectual property and other intangibles by acquiring other firms. The premium paid in an acquisition (i.e., the difference between purchase price and fair value of net assets) reflects intangibles that cannot be separately identified, measured, and disclosed in financial statements. These intangibles are disclosed as accounting goodwill.

In 1974 the Financial Accounting Standards Board (FASB) issued SFAS No. 2, *Accounting for Research and Development Costs*, which requires firms to expense R&D expenditures as they are incurred. Because R&D investments generate future benefits in periods extending beyond the one in which they incurred, compliance with SFAS No. 2 unavoidably may result in a violation of the matching principle. In order to avoid this problem, some scholars have argued that investments in R&D should be capitalized (Chan et al. 2001; Lev and Sougiannis 1996; Hall et al. 2005). The former accounting standard, Accounting Principles Board (APB) Opinion No. 17 *Intangible Assets*, permitted the capitalization and inclusion of R&D expenditures on the balance sheet as intangible assets. In defense of SFAS No. 2, the FASB points out that three studies (e.g., Newman 1968; Johnson 1967; Milburn 1971) indicate that there is no direct relationship between R&D and future revenues (FASB 1974). The only exception to this is SFAS No. 86, which permits the capitalization of costs such as R&D in firms that develop computer software.

In 2001 the FASB superseded APB Opinion No. 17 by issuing SFAS No. 142, *Goodwill and Other Intangible Assets*. SFAS No. 142 significantly changed the accounting treatment and disclosure of goodwill and other intangibles resulting from business combination transactions. The report states, goodwill and intangible assets are
“increasingly important economic resource for many entities and are an increasing proportion of the assets acquired in many transactions” (FASB 2001b, p.5). SFAS No. 142 requires firms to use fair values to initially record goodwill and other intangibles at acquisition. It also eliminates the amortization approach for assets with an infinite useful life. The new standard requires firms to conduct an impairment test on an annual basis to determine the carrying value of goodwill and other intangibles and the amount of impairment loss. This new approach, according to the FASB, will improve financial reporting by providing users timely and relevant information related to goodwill and intangible assets.

The accounting treatment (e.g., recognition and valuation) of intangible assets is of particular significance to technology-intensive firms, whose very success depends on innovations developed internally through R&D programs. High-tech firms invest heavily in terms of financial and human resources in R&D to improve future performance and growth opportunities. Despite the indications that R&D is important in determining a firm’s value, prior empirical studies investigating R&D expenditures do not provide conclusive evidence regarding the exact nature of their economic impact (e.g., Kothari et al. 2002; Lev and Sougiannis 1996; Sougiannis 1994; Francis and Schipper 1999; Aboody and Lev 2000).

The value-relevance of nonfinancial measures, in general, and patent measures, in particular, has been demonstrated in prior literature (e.g., Pakes 1985; Megna and Klock 1993). For example, Hall et al. (1986) argue that publicly available patent data can be used as a proxy measuring R&D efforts in firms. Deng et al. (1999) provide further
empirical support for the incremental value of patent measures in explaining stock performance.

This study investigates whether nonfinancial performance measures, such as patents, can assist investors in making predictions about the financial performance of high-tech firms by providing additional information overlooked by the current reporting model. First, I examine whether certain firm innovation characteristics (R&D, intangible assets, and accounting goodwill) can predict future financial performance. Although previous studies tend to focus on R&D as an indicator of a firm’s innovation characteristics, this study goes beyond prior research by looking at additional sources that may indicate potential innovation characteristics. This includes intangible assets and the unamortized portion of accounting goodwill as reported in the balance sheet of high-tech firms. Second, I will investigate the relationship between firm innovative characteristics and a firm’s patenting activity using six different measures. Third, I examine the strength of the direct relationship between financial and nonfinancial performance measures. Finally, I will investigate the mediating role of patent activity to explain the relationship between firm innovation characteristics and firm performance.

This dissertation makes three major contributions to the existing literature. First, this study builds upon the existing literature related to the value-relevance of nonfinancial performance measures (patents), as well as studies that explore their relationship with firm financial performance. This study analyzes a sample of U.S. publicly traded high-tech firms that are listed by the Patent Board as being among the top 500 patenting companies worldwide. While several studies analyze patent information and firm performance in the 1990s, this study covers from 2002 through 2006. This period is of
particular interest not only because it is recent, but also because it represents a period of stability for the U.S. high-tech industry after several years of fluctuation. The phenomenal stock market activity in the period surrounding the new millennium is often referred to as the “dot-com bubble.” But beginning in 1999, investors increasingly valued stocks of all types with an optimism that could not be justified on the basis of financial disclosure. This trend sharply reversed itself early in 2000 (Kwon et al. 2006). Firms holding large amounts of intangible assets, such as technology firms, tended to be hard-hit by the dot-com correction. In fact, the NASDAQ exchange was exceptionally affected precisely because of its heavy representation of high-tech firms (Rombel 2004). The dot-com episode shows the importance of identifying alternative measures and key performance drivers of firm value when traditional accounting information is inadequate.

The second contribution pertains to the unique and proprietary database of patent measures. Although a limited number of prior studies have utilized similar databases (e.g., Deng et al. 1999; Hirschey et al. 2001b; Matolcsy and Wyatt 2008), this study uses the *Patent Board 500* patent measures as a starting point for the sample selection process. Finally, this study uses structural equation modeling to test four research hypotheses.

The remainder of the dissertation is organized as follows. Chapter 2 reviews background and relevant prior literature. Chapter 3 presents the theoretical framework and hypotheses development. Chapter 4 outlines the sample selection, variable measurement, and research design. Chapter 5 shows the results. The study will conclude with Chapter 6, which includes a discussion, review of findings, implications, limitations of this study, and future research.
CHAPTER 2

LITERATURE REVIEW

Over the past three decades, academics, policy makers, and executives throughout the world have become increasingly interested in intellectual property rights. Technological innovations have led to the increased significance of intellectual property (e.g., patents and copyrights). Patents, and the current patent system that support them, have a long history preceding our current information era. During the Industrial revolution, patents played an important role in promoting economic growth. Patent history can be traced back to the Renaissance period in Europe and some historians argue that patents date back into antiquity.¹ This chapter traces the history of patents, outlines previous research trends, and highlight studies that indicate the important role that patents and intangible assets play in business development.

In order to trace their origins and relevant laws in Europe and in the United States, this chapter begins with section 2.1, a brief historical background of patents. A summary of relevant accounting standards issued by the Accounting Principal Board (APB) and its successor, the Financial Accounting Standard Board (FASB), will be examined. Section 2.2 reviews research that identifies weakness in the current financial reporting model and suggests ways to improve the system. Section 2.3 summarizes research demonstrating the value of using various nonfinancial performance measures and patent measures in particular. Section 2.4 highlights research related to high-tech industries and R&D

¹ Some evidence indicates that the history of patents could be traced back as far as the third century B.C. and that the first to use patents are the ancient Greeks (see Bundy 2002, Chapter 2 Creativity in the Ancient World and the Middle Ages).
studies. Finally, Section 2.5 provides a summary and then outlines the important contributions this study will make to the field.

2.1 Patents: Historical Background

2.1.1 Origins of Patents

Agreements between states and inventors have a long history with some historians going as far to say that patents can be traced back as far as the third century B.C. While the lack of documentary evidence for patents and patenting systems from the ancient period makes this claim difficult to prove, substantial evidence, often in the form of contracts and legal documents, point to their origins during the Renaissance in what is now modern day Italy. It likely transferred from its birthplace in Italy to England and then from England to the colonies in the Americas. In 1421 the government of Florence granted exclusive rights to Filippo Brunelleschi to prevent others from replicating his innovative vessel that could efficiently transport heavy goods (e.g., marble) on the Arno River (Flynn 2006). Brunelleschi kept his invention secret during the development stage, but the city of Florence encouraged him and other entrepreneurs to patent their innovations by granting three years monopoly rights and other monetary incentives in the form of tax exemptions and land. Brunelleschi’s vessel, Bundy contends, “was the first known patented invention”(2002, p.22).

In Renaissance Europe, governments granted inventors exclusive rights to profit from new ideas for a limited time, an agreement that is similar to how patents function today. Venice, another Italian city-state, granted exclusive monopolies for limited periods to protect inventors and encourage them to develop new technologies. At the
beginning of the 15th century, Venice was a major trade center in Europe that was also famous for its glass manufacturing industry. The successful Venetian glass and mirror industry prompted the government of Venice to promote innovations in other areas and enacted the first law with economic significance in Europe in 1474. Venetian patent law protected inventors’ rights to benefit from their inventions. This law protected inventors for a period of ten years, and in some circumstances longer than ten years. The process of applying for a patent in Venice was similar to modern day patent systems in the U.S. and other parts of the world. Flynn writes, “an inventor in Venice was required to disclose the invention to the General Welfare board after it had been reduced to perfection so that it can be used and practiced” (Flynn 2006, p.9).

During the fifteenth and sixteenth centuries, each Italian city-state and other polities throughout Europe attempted to stimulate economic activities by importing ideas from other parts of the world. Some monopolies were granted for individuals who brought innovations to the region that could economically benefit the society. During the sixteenth century, England lagged behind the economically superior France and Italy. The ruler of England at that time, Queen Elizabeth I, attempted to stimulate industrial activities by importing new technologies. In 1561, Queen Elizabeth started granting patent of monopoly to foreigners and locals who brought new inventions to England. These patents gave exclusive monopolies up to twenty-one years. However, the practice of granting patents and exclusive monopolies raised some controversy in the Parliament. Queen Elizabeth, however, argued that she was not interfering with Parliamentary rights because granting patents was a royal privilege. King James I, who succeeded Queen Elizabeth in 1603, condemned monopolies but continued to grant patents to some favored
individuals. He pledged to only grant patents for new inventions that could potentially benefit society. After granting several controversial patents, parliament objected and revoked some of monopolies granted by King James, which led to the first patent statute in England in 1624, the Statute of Monopolies. This statute became codified in common law (Stobbs 2000). British colonies in America also granted patents based on the English common laws and patent system which later on laid the foundation for the United States patent system.2

2.1.2 U.S. Patents History

Advancement of scientific knowledge and innovation has deep foundations that are embedded in the U.S. constitution. The U.S. constitution stresses the importance of patents and copyright protection laws by giving Congress the power “to promote the progress of Science and useful arts, by securing for limited times to authors and inventors the exclusive rights to their respective writings and discoveries” (Article I, Section 8, Clause 8). In the 1790s Congress passed the first federal patent laws in the United States (Campbell 1891; Stobbs 2000; Flynn 2006). President George Washington signed the Patent Act of 1790 and the Patent Act of 1793. The current U.S. Patent Office was established in 1836 under the commissioner of patents. Prior to establishing the Patent Office, inventors had to submit a request to a patent committee that consisted of three members: the Secretary of State, Secretary of War, and Attorney General (Dienner 1939; Flynn 2006). The committee evaluated inventions and granted patents for a period not exceeding fourteen years. Inventors had to pay an application fee ranging between four

2 During the 1600s Massachusetts and Connecticut were the most active colonies granting patents based on the English system (see Flynn 2006, p. 67).
and five dollars (Stobbs 2000, p.14). The Secretary of State, Thomas Jefferson, was heavily involved in making decisions about granting patents, although the decision to grant a patent could be determined by any two members of the committee. In 1813 Jefferson served as the first patent expert witness in a lawsuit case brought by Oliver Evans who held U.S. patent number three, which was issued in 1790 (Stobbs 2000). Jefferson, with inventions of his own, had a strong interest in new inventions and patents. Nevertheless, Jefferson did not patent his ideas because of his strict view about government granted monopolies. In fact, he only granted fifty-seven patents during his three-year tenure serving as a patent examiner.

Similar to Thomas Jefferson, Abraham Lincoln had strong interest in new inventions and patents. Lincoln is the only U.S. president to have a patented idea. In 1849, while Lincoln was serving in the House of Representatives, he received U.S. patent number 6,469 for an invention described as "Buoying Vessels over Shoals."

Furthermore, Lincoln gave several speeches and lectures where he stressed the importance of new inventions. One of the famous quotes from his lectures states that “The patent system... added the fuel of interest to the fire of genius, in the discovery and production of new and useful things.”

After several decades of granting patents, U.S. courts and inventors sought a reform to the patent law. As a result, in 1836 a new patent statute was enacted to replace the 1793 patent law. The new law is more comprehensive and required a detailed examination of patent applications. In addition, the Patent Office was established to handle all matters related to patents. The Patent Office was under the Department of State and administered by a Commissioner of Patents. In 1849 the Patent Office was

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3 See Abraham Lincoln, Second Lecture on Discoveries and Inventions (Feb. 11, 1859).
transferred to the Department of Interior and in 1925 was transferred to the Department of Commerce and Labor. The office name was changed to *the Patent and Trademark Office* in 1975 (Flynn 2006).

Another factor that contributed to the increased awareness about patents and new inventions in the U.S. is the publication of *Scientific American* beginning in 1845. This magazine published information about recent U.S. patents and other information about the Patent Office (Flynn 2006). During the twentieth century several revisions to the patent law were enacted. Constant revisions to the patent law were necessary because of economic and political changes, as well as other factors that might have affected patent laws. New technologies (e.g., computer software) require new laws that enable courts to protect inventors.

### 2.1.3 Intangibles Accounting Standards

Accounting for intangibles is specified in the Accounting Principles Board (APB) No. 17, the Financial Accounting Standards Board (FASB) Statement of Financial Accounting Standards (SFAS) No. 2, SFAS 141, and SFAS 142. APB Opinion 17 related to intangible assets was issued in August 1970. Nearly three decades later in June 2001, the FASB issued SFAS 142, which superseded No. 17. Under APB Opinion No. 17, intangible assets purchased from other entities are recorded at cost and disclosed in the balance sheet as intangible assets. After determining the intangible asset useful life, which cannot exceed 40 years, an amortization expense will be deducted annually. Therefore, the balance of the intangible asset will be eventually eliminated at the end of its estimated useful life. When intangible assets cannot be identified separately or
developed internally, the costs associated with these intangibles will be expensed as incurred and will not be recognized as an asset on the balance sheet.

The FASB issued Statement No. 2 *Accounting for Research and Development* in 1974 after considering four alternatives of accounting for research and development costs. This document points out that firms can, “a.) Charge all costs to expense when incurred; b.) Capitalize all costs when incurred; c.) Capitalize costs when incurred if specified conditions are fulfilled and charge all other costs to expense; d.) Accumulate all costs in a special category until the existence of future benefits can be determined” (FASB 1974, p.12). After evaluating these four alternatives, the FASB required expensing research and development costs when incurred.

In 2001, the FASB issued SFAS 141 and 142. Both statements have implications for accounting issues related to intangible assets. SFAS 141, *Business Combinations*, supersedes APB No. 16 and SFAS 38. Prior accounting standards allowed managers to choose one of two methods to account for business combination transactions: the *pooling of interest* method and the *purchase* method. SFAS 141 eliminated the pooling of interest option; hence, all business combination transactions will be accounted for by using the purchase method. The new standard, SFAS 141, improves disclosure of intangible assets since the purchase method allows the recognition of intangible assets acquired in a business combination transaction (FASB 2001a).

SFAS 142, *Goodwill and Other Intangible Assets*, does not allow the amortization of goodwill. Instead it requires entities to perform annual impairment test to determine the fair value and carrying amount of goodwill. SFAS 142 applies only to intangible assets that are developed internally or purchased either individually or as a
group that were not part of a business combination transaction (FASB 2001b). The rule allows for the disclosing of intangible assets and requires that they be recognized based on their fair value. However, when it is not possible to identify an intangible asset on a balance sheet, such as an internally developed intangible asset, it should be expensed when incurred. An intangible asset with a finite useful life is amortized over its estimated useful life. Entities are required to estimate the useful life of an intangible asset by taking into account contractual, economic and legal factors. The FASB provides examples to assist entities in determining the useful life of intangible assets. In the absence of factors that may indicate the limits of an intangible asset’s useful life, it is considered to have an indefinite useful life and straight-line amortization can be used. The FASB emphasizes the distinction between intangible assets with an indefinite useful life and intangible assets with an infinite life.

Contrary to APB 16, which also permitted negative goodwill, the new standard does not allow the amortization of goodwill, but requires entities to perform an annual impairment test based on fair value. Prior to SFAS 142, goodwill was treated as an asset, which subsequently was amortized over a period not exceeding 40 years. The standard also gave entities discretion in the process of evaluating the carrying value of goodwill.

First, goodwill has to be assigned to a reporting unit that is expected to economically benefit from goodwill resulting from a business combination transaction. Second, the unit’s carrying value is compared with its fair value to determine if an impairment charge is needed. If the carrying value is less than the fair value then no additional testing is required. Otherwise, additional steps are required to measure the implied fair value of goodwill. To determine the fair value of goodwill, the fair value of
net assets is deducted from the fair value of the reporting unit. Third, an impairment loss may have an effect on net income and income taxes depending on the timing of the charge. Under the new rule, managers have some discretion to consider taking larger impairment losses at the time of adoption, which will appear in the income statement between _extraordinary items_ and _net income_, or defer all or some of the impairment charges in hope that the fair value will increase in future periods. The risk that managers take when they defer impairment losses to periods after adopting the rule is that impairment losses must be disclosed in the income statement as a line item before net income.

To summarize, recent accounting standards issued by the FASB (e.g., SFAS 141 and SFAS 142) address issues related to intangible assets and goodwill. Among the objectives of these standards is measurement of accounting and disclosures of intangible assets, including goodwill, because of the increased significance of intangible assets in today’s economy.

### 2.2 Patents: Nonfinancial Performance Measures

Patents are vital in high-tech industries, because innovation for technological firms leads to superior market performance. Thornhill (2006) demonstrates this relation using revenue growth as a proxy for market performance. Firms often patent new inventions to gain exclusive rights to the economic benefits from the commercialization of new products and services. Patents can be viewed as value drivers for financial performance. Several studies use patent activity as nonfinancial performance measures,

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4 See Section 40 of SFAS 142 – _Goodwill and Other Intangible Assets_ (FASB 2001).
and provide evidence that patent measures complement traditional financial measures in predicting future financial performance. There are two main sources for patent data: The first source of patent data comes from public or well known research organizations, such as the United States Patent and Trademark Office (USPTO) and the National Bureau of Economic Research (NBER); and the second source includes private commercial research institutions, such as, CHI Research Inc. Both sources provide patent data with some limitations. Public sources (e.g., USPTO) provide a large database of patent data that includes patent number count and other technical information that can be further enhanced in different ways, such as patent citations.

Deng et al. study a sample of high-tech firms and use patent-related measures to address the following questions: first, is the economic value of patents fully reflected in contemporaneous book value ratios? Second, are patent measures leading indicators of future stock returns for high-tech firms? Deng et al. (1999) provide evidence that patent measures do appear to be economically relevant to the stock market. In their examination of 235 high-tech firms for the period 1985-1995, their study shows a significant association between patent-related attributes and market-to-book ratios. A somewhat weaker association is found between patent activity and subsequent stock returns.

Deng et al. (1999, p. 21) focus on three patent measures. First, citation impact is a measure of “forward citation” that shows whether a firm’s most current patent received higher or lower citations compared to the past five year’s average. Second, since patent applications often include citations to other patents as well as scientific research papers, Science link is a measure that specifically focuses on the number of citations in a patent application to scientific papers. This measure shows a relationship between a firm’s R&D
programs and current scientific developments. It is, therefore, a “backward citation” indicator. Third, technology cycle time is a measure that focuses on the “median age of U.S. patents cited in a patent application” (p.22). In addition to these three citation measures, Deng et al. also include a patent count measure, which shows the number of U.S. patents granted during a particular year. Deng et al.’s work shows that patents of successful firms tend to be cited often in the patent applications of other firms. Further, developments at such firms tend to occur at a more rapid pace and involve “pure Science” innovations to a greater extent than is true of less-successful competitors.

Using alternative patent measures, Mazzucato and Tancioni (2008) investigate factors leading to stock price volatility in high-tech industries (pharmaceutical and biotechnology) for the years 1974 through 1999. The authors use firm-specific patent data to empirically demonstrate a relationship between stock price volatility and innovation. Results provide evidence for a significant, positive relationship between idiosyncratic risk, R&D intensity, and several unique patent measures. The authors confirm results from earlier studies (e.g. Campbell et al. 2001) which argue that over the past four decades firm-specific volatility resulting from new technologies, (i.e., information technology) has increased.

As previously discussed, analysis of patent data is not limited to a simple count of patent applications or patents granted per firm. Hall et al. (2005) study a large sample of patents and patent citations for the period 1963-1995 to investigate the relationship between patent citations and Tobin’s q (equity market value plus liabilities divided by equity book value plus liabilities book value). By construction, Tobin’s q provides a measure of a firm’s excess market value over book value. Conceptually, Tobin’s q has
been interpreted as a reflection of market sentiment regarding a firm’s future prospects or an approximation of the value of the firm’s intellectual capital. The authors regress Tobin’s q on R&D, patent measures, and book value of assets. In their analysis, they find that patent measures are statistically significant predictors of Tobin’s q after controlling for R&D expenses. Because R&D expense is the best evidence of a firm’s technological development that accounting disclosure provides, the finding that patent information is a significant predictor of Tobin’s q controlling for R&D expense shows that patenting activity is incrementally informative when used as a supplement to accounting data. Hall et al. (2005), also, model a patent citation measure as the output of R&D and find that the market selectively values high-quality R&D outputs as measured by patent citation intensity.

In a related study, Hirschey et al. (2001b) find that the relationship between R&D expenditures and equity is relatively weak for firms whose patents are of low quality (that is, firms whose patents are cited infrequently by subsequent patent applicants). In their study, the inclusion of a patent quality index adds to the predictive value of a model regressing firm value on R&D expenditures, without reducing the significance of R&D expenditures. The authors suggest that footnote disclosure of patent information would increase the “informativeness” of financial statement disclosure for high tech firms. Similarly, Lanjouw et al. (1998) stress that publicly-available patent data is a rich source of information. For example, the frequency of citations for a patent, as well as renewal data, provides more specific information about the likely value of the underlying innovation and its economic lifespan. Harhoff et al. (1999) indicate that patents with high economic value tend to be cited more than patent which are perceived to have low
economic value. Pakes (1985) also finds that successful patent applications incrementally contribute to a model where firms’ R&D expenditures are used to predict stock returns.

2.3 Value Relevance of Financial Reporting

Over the past three decades, business organizations have experienced unprecedented changes on several fronts. Technological advancements (e.g., low cost portable computing and telecommunication devices, internet), globalization, increased competition, and deregulation are examples of changes that firms have experienced and the impact of these realities should be reflected in financial reports (Lev and Zarowin 1999; Bismuth and Tojo 2008). Brown et al. (1999) document a decline in the relevance of financial statement information to firm value. According to the authors, this trend began after World War II and coincides with the decline of hard assets as the primary source of value for most firms. In the late 1990s, several other accounting researchers voiced concerns about the value relevance of financial statements and the financial reporting model (e.g., Francis and Schipper 1999; Lev and Zarowin 1999).

Criticism of the current financial reporting model was also offered by the American Institute of Certified Public Accountants (American Institute of Certified Public Accountants (AICPA)), and the Financial Accounting Standard Board (FASB). Due to similar concerns, the Securities and Exchange Commission (SEC) has begun to require

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6 In 1994, the AICPA’s Special Committee on Financial Reporting released a comprehensive report that addresses shortcomings in the U.S.’s financial reporting model. The committee was chaired by Edmund L. Jenkins and the issued report, which is frequently cited and debated, is widely referred to as “the Jenkins Report.” In brief, the report calls for a shift from financial reporting to a more comprehensive “business reporting,” in which nonfinancial information such as operating and performance data, risk factors and industry trends would factor prominently. In 2001, the FASB released “Improving Business Reporting: Insights into improving Voluntary Disclosures.” The report resulted from a two-year project in which a group of accounting professionals under the direction of a FASB steering committee studied current voluntary disclosure practices of many firms across eight industries. Disclosure of (often nonfinancial) measures used by management in assessing its own effectiveness was a key recommendation of the FASB report.
the inclusion of key performance metrics, including nonfinancial performance measures that are material and used to manage business, in the section of the SEC 10-K filings containing management’s discussion and analysis (SEC 2003). One of the critiques that several authors make against the current financial reporting model is its failure to reflect the transformation from the industrial era to the new information and technology era (Elliott and Jacobson 1991). Francis and Schipper (1999, p.321) assert that “some observers have attributed the putative decline in the relevance of financial reporting to the increase in relative importance of technology-based industries, for which the current reporting model is alleged to be particularly ill-suited”. Ittner and Larcker (2000) provide additional insight into this development. They contend that, because of financial accounting’s focus on historical data, it inherently discounts intangible assets and, as a consequence, discourages long-term investment. R&D is an example of the type of investment financial accounting fails to adequately value. Ittner and Larcker (2000) point out that certain nonfinancial performance measures (such as those involving intellectual property and innovation) relate to sources of value that are less quantifiable. They conclude that the inclusion of such measures in firm valuation is helpful because it can balance the analysis of a firm’s prospects. For instance, patent activity measures may provide an alternative means of assessing the future performance prospects of high-tech firms, whose market value cannot be as easily estimated using financial statement information.

Several empirical studies address the value relevance issue of the current financial reporting model by demonstrating the incremental value of nonfinancial measures and other intangible investments (e.g., Hirschey and Weygandt 1985; Chauvin and Hirschey
The value of supplementing corporate financial reports with nonfinancial performance measures is justified in prior research on the premise that nonfinancial measures are leading indicators of financial performance (Ittner and Larcker 1998; Banker et al. 2000).

Although several studies show that nonfinancial performance measures provide additional information content that can supplement current financial reports, Biddle et al. (1995) take this issue a step further by distinguishing between the types of values that can be obtained from additional information (i.e., nonfinancial performance measures). The authors argue that information might have either an incremental information content, which is to “assess whether an accounting measure (or set of measures) provides information content beyond that provided by another” or relative information content, which is “whether one measure provides greater information content than another” (p.3). While Biddle et al. acknowledge that most analyses attempt to identify an incremental contribution of alternative information sources, the authors point out that both approaches are appropriate in a world where accounting information is costly and resources are limited.

Sundaram et al. (1996) study the announcement effects of R&D expenditure and a measure of competitive strategy on firm’s stock prices. The study shows the positive influence of R&D spending announcements on stock prices and a negative association between competitive strategy measure and stock price. The authors’ findings support the idea that investors value R&D expenditure because it provides firms with an advantage over their competitors.
In an attempt to document the predictive value of nonfinancial performance measures in for financial performance (and whether those measures benefit investors), researchers studied several industries and nonfinancial performance measures commonly used within each specific industry. Three studies by Amir and Lev, Behn and Riley, and Banker and et al. document the association of nonfinancial measures with firm performance in different industries. Amir and Lev (1996) examine the value relevance of nonfinancial performance measures (e.g., rights acquired by potential subscribers and penetration of markets) in the wireless communications industry. The authors argue investors cannot rely on financial information (e.g., earnings and book values) alone for high-tech industries because these industries experience rapid change. The study shows that traditional financial statement information is inadequate to meet the information needs of investors in the wireless communications industry and that nonfinancial performance is a strong indicator of the value of wireless firms. Amir and Lev contend that results obtained from studying the wireless industry can be generalized to other high-tech, high-growth, and science-based industries. In a similar study, Behn and Riley (1999) evaluated the association between nonfinancial information and financial performance in the U.S. airline industry and find similar results. Finally, Banker et al. (2005) focus on the lodging industry and use two nonfinancial performance measures (i.e., likelihood of a return visit and complaints taken from hotel guests’ comment cards) to predict future financial performance of a hotel chain. The study shows that the likelihood guests might return to the hotel is positively associated with future revenues and operating profits, while guest complaints are negative indicators of future firm performance. In a related study, Ittner and Larcker (1998) examine the role of customer
satisfaction ratings as possible indicators of firms’ financial performance. In that study, the authors also investigate the impact of customer satisfaction measures on firm value.

As stated earlier, the FASB’s rule pertaining to R&D expensing (SFAS No. 2) contributed to the value-relevance controversy. Aboody and Lev (2000) demonstrate that intangible assets are valued by investors, as measured by market equity. Further, the authors show that firms making significant expenditures on R&D are associated with substantially larger insider gains from trading. They theorize that information asymmetry is greater in R&D-intensive firms precisely because investors find it difficult to determine the future value of intangible assets that current R&D expenditures will create.

2.4 High-Tech Industries and Research and Development

The designation of high technology as it applies to firms is somewhat fluid, but the use of complex, cutting-edge technology in production or in finished products is one attribute of a high-tech firm. High-tech firms belong to a variety of industries, but share a commitment to the development of technological innovation as evidenced by significant expenditures on R&D. Industries commonly designated as high-tech include pharmaceuticals, computers and electronics (Francis and Schipper 1999). Chan et al. (2001) stress the importance of the high-tech industry by observing that the technology and pharmaceutical firms account for about 40 percent of the S&P index. It should be noted that some of the high-tech firms invest more than earnings in research and development.

Corporate investments in R&D have captured the attention of researchers from various disciplines due to the economic significance and magnitude of the investments
involved. The growth and survival of firms in certain industries depends upon their ability to develop new products and technologies to maintain current market share and become more competitive. Although it has been more than three decades since the FASB issued *SFAS No. 2*, which requires firms to expense R&D cost, the debate over the accounting treatment of R&D continues. The FASB’s only exception to the R&D expensing rule is *SFAS No. 86*, which permits software development costs to be capitalized. On one hand, some researchers and practitioners argue that R&D spending results in benefits that go beyond a single financial period. As discussed previously, to the extent that this is true, expensing of R&D has been identified as a violation of the matching principle in the historical cost model. Very large R&D projects artificially depress earnings in early years, before the benefits associated with R&D investment are apparent. On the other hand, early advocates of expensing the costs of R&D, including the FASB, argued that the goals of objectivity and conservatism are served by expensing R&D in the period costs are incurred, and that these benefits outweigh the costs.

The current accounting treatment for R&D expenditures has other implications as shown in the literature. For example, prior studies investigate how managers make decision to increase or decrease R&D spending for reasons other than improving financial performance. Chen (2004) investigates whether managers reduce R&D spending for personal gain (i.e., increase their own compensation). Managers often can reduce R&D spending to improve financial performance. Chen examines the role of the compensation committee plays in detecting opportunistic reductions in R&D to mitigate losses or to manage earnings, which in turn increase managers’ compensations. Chen finds that compensation committees are able to detect such behavior. In another study,
Aboody and Lev (2000) investigate whether R&D expenditures can lead to increased insider trading and insider gains. The authors argue that managers might act on the information asymmetry related to R&D expenditures because managers have more details about the quality of their own R&D programs than investors, which only have aggregate number. This study shows that insider gains are more common among firms with intensive R&D programs than firms without R&D programs. Aboody and Lev conclude that R&D accounting could increase information asymmetry and insider trading. Both studies, Chen (2004) and Aboody and Lev (2000), show the potential contribution of supplementing patent data, as a nonfinancial measure, to reduce opportunistic behavior by managers because patents provide an output measure for R&D as demonstrated in prior studies.

2.5 Summary and Implications

As prior literature has shown, gauging the value of firms’ efforts toward innovation remains problematic. This study attempts to address this issue by building upon existing literature in demonstrating the value of nonfinancial performance measures. Such measures can serve as a supplement to available accounting disclosures in addressing the problem of measuring the efficacy of firms’ technology initiatives. Several studies have shown that investors consider R&D efforts useful indicators for investment decisions, that capital markets value firms’ investments in R&D, and that stock prices reflect the benefits (cost) of R&D.

Previous studies provide evidence that nonfinancial performance measures provide investors with useful information about high-tech firms’ potential future
performance. As a source of nonfinancial information, patent activity data is useful to the entire community of stakeholders, including investors, managers, creditors and policy makers. Published research (e.g., Lev and Sougiannis 1996; Hall et al. 2005; Oswald and Zarowin 2007; Yang 2007) has shown that patent activity measures can be used as an output measure for a firm’s technological innovation as measured by R&D investments, which can be viewed as the input measure. Therefore, throughout this study I will maintain the assumption that patenting activity measures the success of R&D investments as suggested by prior studies. In addition, this study goes beyond earlier studies by using a simultaneous approach for investigating the relationship among firm innovation characteristics, nonfinancial performance measures (patent activity), and firm performance.

This research project will make a timely contribution because innovation and scientific development among American firms has been identified by the federal administration as a public policy priority in the effort to manage the effects of the current economic downturn. Patel and Pavitt (1991) suggest that innovation and new technology are positively related to economic growth. An increase in productivity, innovation, and technology will have a positive effect on the economy during economic recessions.
CHAPTER 3
HYPOTHESIS DEVELOPMENT

There are two major streams of research related to this study: studies that focus on the relationship between firm nonfinancial performance measures and financial performance and studies that examine the relationship between firm characteristics and financial performance (e.g., Hendricks and Singhal 2001a). Prior empirical studies show that, after controlling for firm characteristics known to influence long-term financial performance, nonfinancial performance measures have incremental value in modeling financial performance (Smith and Wright 2004; Thornhill 2006; Yang 2007; Joos and Zhdanov 2008). Some empirical studies that specifically investigate issues pertaining to high-tech industries have used patent activity as nonfinancial performance measures to predict firm stock performance (e.g., Pakes 1985; Deng et al. 1999; Hirschey et al. 2001b; Yang 2007).

Although prior studies mainly focus on internally developed intangibles through investment in R&D, other types of intangible assets also contribute to the innovation process and the success of firms in the high-tech industries. For example, goodwill is an intangible asset that is a consequence of a firm acquiring another firm (e.g., mergers or buyouts) and paying an additional premium over the book value of the acquired firm. Gaining access to exclusive resources, such as human resources, new technologies, and gaining competitive advantages are among the benefits that justify the premium paid in an acquisition transaction. Sawhney et al. (2006) argue that innovation is not limited to the development of new products and services. Instead, they provide a broader definition
of innovation as “the creation of substantial new value for customers and the firm by creatively changing one or more dimensions of the business system” (p. 76). This study contends that high-tech firms strive to maintain leadership in their industries through innovation and that they often share common characteristics that facilitate the innovation process. Hence, firms invest in R&D, goodwill, and other intangible assets to maintain or gain new markets through new innovative products and services. Wyatt (2008) classifies intangible assets into three main categories. First, technology resources that include R&D and other intellectual properties. The second category includes human capital. The last category includes intangibles related to production resources (e.g., advertising, brands, customer loyalty, competitive advantage, and goodwill). Taking into account the insight of these earlier studies, this study focuses on three proxies for firm innovation characteristics: R&D expense, goodwill and other intangible assets.

Prior studies identify R&D expenditures and the economic value of intangible assets as predictors of financial performance. With the exception of Chauvin and Hirschey (1994) and Hirschey and Richardson (2002b), studies often exclude goodwill from the analysis. Chauvin and Hirschey (1994), however, document the positive influence of accounting goodwill on firm profitability and market value. The authors argue that “accounting goodwill numbers are regarded as a potentially useful, albeit imperfect, indicator of intangible assets which give rise to higher rates of profitability…[and] are considered as a potentially useful indicator of the important intangible asset dimension of the value of the firm” (p.161). Chauvin and Hirschey’s argument is based on the premise that accounting goodwill numbers signal to investors a firm’s commitment to produce high-quality goods and invest in “reputational” capital,
such as, brand names. The authors also assume that investors recognize the value of investing in goodwill and other intangible assets and expecting future financial benefits from these types of investments. Chauvin and Hirschey (1994) however, provide limited evidence on the accounting goodwill numbers that investors use to predict future abnormal returns. In fact, the positive and statistically significant relationship between goodwill and market value is limited to the nonmanufacturing firms. They did not find a significant result for the manufacturing firms in their sample. Based on these limited findings, and since these findings reflect the significance of accounting goodwill numbers that were reported based on accounting standards superseded by the newer SFAS 141 and 142, this issue is worth investigating. Therefore, I contend that these recent accounting standards related to goodwill and intangibles might provide investors with new information related to goodwill and intangibles that might help them evaluate firms’ intangible assets.

Since FASB issued SFAS No. 2 in 1974, investors can directly observe firms R&D spending as disclosed in the income statement. In general, R&D expenditures disclosed in accordance with GAAP are aggregates that fail to accurately reflect the magnitude of a firm’s R&D spending. Evidence from several studies shows that investors incorporate information related to firms annual R&D expenditures in the stock prices (e.g., Hirschey 1982; Jaffe 1986; Bublitz and Ettredge 1989; Chan et al. 2001). Prior studies indicate that R&D expenditures can be directly linked with future revenue generation. Nakamura (1999) contends that in some industries (e.g., pharmaceuticals and electronic) firms recoup investment in R&D from just a few, highly successful projects. In another study, Sougiannis (1994) examines a sample of 573 firms that consistently
invest in R&D over a ten-year period (1975-1985). The study shows that R&D expenditures are positively associated with earnings and market value. Specifically, over a period of seven years, a one-dollar increase in R&D spending is related to an increase in gross profit and market value of two and five dollars respectively. Perry and Grinaker (1994) examine the relationship between R&D expenditures and earnings expectations. Empirical evidence indicates that managers increase R&D spending during good economic periods and decrease R&D spending during bad economic periods. The study also reveals that managers tend to use R&D spending to manage earnings and meet analyst’s earnings expectations. Perry and Grinaker conclude that allowing firms to capitalize R&D expenditures might strengthen the U.S. economy.

While prior studies focus on R&D and other areas of discretionary spending, such as advertising (e.g., Hirschey and Weygandt 1985; Hirschey 1982; Bublitz and Ettredge 1989; Chauvin and Hirschey 1993), other studies focus on intangible assets and accounting goodwill to identify firm attributes that are predictive of future financial performance for high-tech firms. Taking into account two streams of research, this study argues that high-tech firms invest in three types of firm innovation characteristics, R&D, goodwill, and other intangibles to enhance their financial performance. To simplify the hypotheses, these three firm innovation characteristics will be tested simultaneously. Additionally, three financial performance measures will also be tested. These include three profitability measures: return on assets (ROA), return on sales (ROS), and return on equity (ROE). Therefore, the first research hypothesis follows:

**H₁:** There are positive relationships between firms’ innovation characteristics (R&D, intangibles, and goodwill) and their financial performance (ROA, ROS, and ROE).
Prior studies identify a variety of nonfinancial performance measures that relate to particular industries. For example, four studies focus on high-tech industry and use patent data as a nonfinancial performance measure (e.g., Deng et al. 1999; Hirschey et al. 2001b; Hall et al. 2005; Yang 2007). Other industries, including biotechnology, electronics, lodging, wireless communications and the airline industry have all been explored in studies involving nonfinancial performance measures (Amir and Lev 1996; Behn and Riley Jr 1999; Hendricks and Singhal 2001b; Banker et al. 2005).

Studies that investigate the role of nonfinancial performance measures, such as patents, in predicting financial performance in high-tech industries also consider the effect of R&D expenditures. For instance, Hall et al. (2005) use patents as an observable proxy for R&D “success.” Patents, thus, are used to measure the benefits derived from R&D spending. Deng et al. (1999) include R&D intensity (R&D divided by sales) as an independent variable predicting future market-to-book ratios and stock returns. While R&D intensity is a useful predictor for the market-to-book ratios, it is not as useful for predicting stock returns. Francis and Schipper (1999) analyzed a sample of high and low-tech firms and showed that high-tech firms on average spend significantly more on R&D than low-tech firms. The same study indicates that high-tech firms have higher market-to-book ratios than low-tech firms. This suggests that high-tech firms depend on R&D investments to generate revenues and maintain economic growth (Klette and Griliches 2000). A likely explanation for the linkage established in prior literature between R&D expenditures and financial performance is that R&D expenditures increase patenting activity to secure exclusive rights to profit from new innovations in products and
services. This study argues that firms with high patenting activity require investments in intangible assets to support the invention process. For example, prior to inventing and patenting new products, a firm needs intellectual capital, trademarks, copyrights and other intangible assets. Therefore, the following hypothesis provides a partial test of this relation:

\textbf{H2: There are positive relationships between firms’ innovation characteristics (R&D, intangibles, and accounting goodwill) and their patenting activity.}

Prior studies focusing on patent measures as a proxy for successful R&D projects indicate a positive relationship between firms patenting activity and market valuation. Although the number of patents held by a high-tech firm is a useful indicator of a firm’s patenting activity, newly developed patent measures provide both qualitative and quantitative indicators to assist researchers in obtaining accurate and reliable proxies. Hall et al. (2005) use three measures: R&D expenditure, patent count, and a patent citation measure. The authors’ results show that patent citation provides additional information on the market value of firms when added to other patent measures. The link between patent activities and market performance is an intuitively appealing model if patent activities are understood as a proxy for the output of high-tech firms. Although a patent does not always generate profits, this study argues that firms strengthen the patent portfolio by obtaining new patents. Consequently, firms can profit from individual patents or the strategic accumulation of a patent portfolio. Accordingly, the following hypothesis is formed to test the direct relationship between firms’ patenting activity and financial performance:
**H3:** There are positive relationships between firms’ patenting activity and their financial performance.

Hypotheses one through three address the direct relationship between the following: first, firm innovation characteristics (R&D, intangibles, accounting goodwill) and firm performance (H1); second, firm characteristics and patenting activity (H2); and third, patenting activity and firm performance (H3). The final hypothesis leads to an investigation of the mediating\(^7\) effect of patenting activity in the proposed model. Baron and Kenny’s study (1986, p.1173) indicates that mediator variables function as a third variable, “which represents the generative mechanism through which the focal independent variable is able to influence the dependent variable of interest.” Therefore, this study will empirically test this possible mediation role of nonfinancial performance measures in enhancing the prediction power of future financial performance. Consequently, the six patent measures included in the model will function as another group of endogenous variables that will mediate the relationship between three exogenous variables and three outcome variables.

While the majority of prior studies include nonfinancial performance measures as predictors of financial performance, limited research investigates complex models that may show indirect or contextual relationships between similar measures and financial performance (Banker and Mashruwala 2007). Prior economic research regards patent measures as a proxy for firm innovation. Patent measures are also considered an outcome for successful R&D investment (Hall et al. 2005; Griliches 1990). Although the number

\(^{7}\) In the accounting literature, interaction among variables is a widely used concept. However, the mediation concept is common in other disciplines such as psychology, and represents one of the contributions of this study. For a detailed overview of the mediation variable concept and a distinction between mediator and moderator variables see Baron and Kenny (1986).
of patents held by high-tech firms is a useful indicator of firm patent activity, newly
developed patent measures provide both qualitative and quantitative indicators to better
assess the relationship among firm innovation characteristics, patenting activities, and
financial performance. The empirical model developed in this study illustrates that
nonfinancial performance measures, specifically patent measures, might mediate the
relationship between firm innovation characteristics and financial performance. This
study will investigate whether nonfinancial performance measures provide incremental
information as argued in prior literature. Further, prior studies that have investigated the
relationship between nonfinancial measures (e.g., patents), R&D, and financial
performance present mixed results. Examining the mediating role of nonfinancial
performance measures, in addition to the direct effects, could provide a new perspective
that will clarify the exact nature of the relationships among the three groups of variables
included in this study. Therefore, the fourth hypothesis is proposed:

**H4: Firms’ patenting activity mediates the relationships between their
innovation characteristics and financial performance.**

Figure 1 illustrates and summarizes the theoretical framework and hypotheses,
which will be tested by using structural equation modeling technique. The first
hypothesis examines the direct relationship between a firm’s innovation characteristics
(R&D, intangibles and accounting goodwill) and its performance (return on assets, return
on sales and return on equity). The second hypothesis examines the relationship between
a firm’s innovation characteristics and patenting activity. It posits that a firm’s intangible
assets, investment in R&D, and accounting goodwill will have a positive effect on its
patenting activity. The third hypothesis tests the direct relationship between a firm’s
patenting activity and a firm’s performance. Hypothesis four examines the mediating
effect of a firm’s patenting activity on firm’s performance.

[Insert Figure 1 here]

In conclusion, this chapter presents four research hypotheses investigating
relationships among firm innovation characteristics, patenting activity, and financial
performance. Researchers are interested in issues related to firms’ innovation capabilities
because they see that innovation and technological resources provide firms with
sustainable competitive advantage that cannot be easily replicated by competitors
(Coombs and Bierly 2006). High-tech firms likely benefit from investing in intangible
assets, which are either developed internally by investing in R&D or acquired from other
types. Firms often acquire intangible assets directly if the separation and identification of
intangibles is possible. The other alternative is acquiring the entire firm, and its tangible
and intangible assets, where they pay an additional premium to compensate for the
potential benefits from the unrecognized intangible assets. This study covers these three
possible sources of intangible assets. It also builds upon prior studies (e.g., Hirschey et al.
2001a; Jaffe 1986; Cockburn and Griliches 1988; DeCarolis and Deeds 1999; Deng et al.
1999; Yang 2007) by investigating the direct and mediating relationships between
nonfinancial performance measures (patenting activity), firm innovation characteristics,
and financial performance.

The next chapter provides an overview of the research design, variable
measurements, and descriptive statistics for the variables included in the analysis. To test
the theoretical model presented in this chapter, this study uses structural equation modeling technique to simultaneously test the entire model. Chapter five presents the test results for each of the four hypotheses, and chapter six presents the conclusion of this study.
CHAPTER 4
RESEARCH DESIGN

This chapter outlines the research design and data incorporated in this study. Section 4.1 explains the sample selection process. Section 4.2 discusses the measurement of variables used in the analysis. Section 4.3 briefly overviews the empirical model testing method using Structural Equation Modeling. Finally, section 4.4 presents descriptive statistics used in the sample.

4.1 Sample Selection

Several private research organizations maintain databases to assist researchers, businesses, and others in conducting analyses related to patents. The current leader among private research institutions specializing in analyzing intellectual property such as patents is Patent Board Inc., which was originally founded in 1968 as CHI Research Inc. This study includes six patenting activity measures acquired from the Patent Board Inc. One of the Patent Board’s databases, the Patent Board 500,\(^8\) includes various measures of patenting activity for five hundred of the foremost patenting companies. This list includes foreign, private, and public companies with patents registered with the United States Patent Office. Although the Patent Board data’s quality and reliability cannot be measured directly, prior accounting studies (e.g., Deng et al. 1999; Hirschey et al. 2001b; Matolcsy and Wyatt 2008) have successfully used earlier versions of this database (e.g., CHI Research database, and TECH-LINE). In an online Newsweek article, Chang (2008)

\(^8\) The Patent Board 500 is a registered trademark owned by the Patent Board, Inc.
mentions that companies such as Abbott Laboratories are among the clients benefiting from the Patent Board patent valuation services. Furthermore, Chang attests to the high quality of the system that the Patent Board has implemented to analyze various aspects of patents granted by the United States Patent Office.

A criterion for sample selection is the availability of data for each U.S. public firm included in the Patent Board 500 and Compustat. Foreign and private firms were excluded from sample because of the limited access to their financial information and the different legal and accounting compliance issues. To identify U.S. public firms, a manual search (by firm name) was conducted using the Securities and Exchange Commission’s (Electronic Data Gathering and Retrieval (EDGAR) online reporting system. Another objective of this manual search was to obtain a Central Index Key (CIK) code for each firm to identify firms in the Compustat database and for matching firms’ financial data with the Patent Board 500 database. Since SFAS No. 86 permits software companies to capitalize R&D costs that are directly related to software development, I excluded 7 software companies from the sample. Furthermore, the patenting activity and nature of patents for the software industry is different from other industries (see Stobbs 2000).

These restrictions yield a final sample of 210 firms for the year 2006 with the five-year average measures covering the period from 2002 to 2006. Table 2 provides a summary for the sample selection procedure. The sample includes large, high-tech firms representing sixteen industries. Due to the limitation of the sample size, grouping firms

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9 These seven firms include the following: Microsoft Inc., Oracle Corp., Symyx Technologies Inc., McAfee Inc., Symantec Corp., Navteq, and Cadence Design Systems Inc.

10 Industries represented by firms in the Patent Board 500: Aerospace & defense, automotive & transportation, biotechnology, chemicals, consumer electronics, consumer products, electronics & instruments, energy & environmental, food, beverages, & tobacco, heavy equipment, industrial components & fixtures, industrial materials, information technology, medical devices & services, pharmaceuticals, and semiconductors.
based on industry classification and including them in the analysis as separate groups is not viable. The high-tech firms included in the sample, however, share common characteristics of high R&D expenditures, intangible assets, and accounting goodwill.

Table 2 presents the distribution of sample firms among different groups according to the Standard Industrial Classification (SIC) code. The sample of firms represents five industries: first, chemicals, allied products, petroleum, and coal (SIC 2800-2899); second, industrial machinery and equipment (SIC 3500-3599); third, electronic and other electric equipment (SIC 3600-3699); fourth, transportation equipment (SIC 3700-3799); and fifth, instruments and related products (SIC 3800-3899). Industries with a few firms representing them in the sample are grouped together and labeled as “other industries.” The largest group of firms “other industries” represents 23% of the sample firms. The second largest group (SIC 2800), is comprised of chemical and allied products industry, represents 20% of the sample. The smallest group (SIC 3700), representing the transportation equipment, consists of 10% of the sample.

4.2 Variable Measurement

4.2.1 Measures of Firm Innovation Characteristics

This study focuses on three innovation characteristics that are related to intangibles. Innovation, according to Edwards and Gordon (1984, p.1), is defined as “a
process that begins with an idea, proceeds with the development of an invention, and
results in the introduction of a new product, process or service to the marketplace.”
Firms invest in intangibles, such as R&D, to gain a competitive advantage and to earn
higher returns. In recent years, the significance of intangible assets has been recognized
as a key diver of financial performance, growth and competitiveness. (Stallworth and
DiGregorio 2004; Bismuth and Tojo 2008). Furthermore, Nakamura (2001), assert that
“the wealth of U.S. households has increased dramatically, and much of this increase has
taken the form of these stock market capital gains due to successful investments in
intangible assets” (p.28). Because intangible assets are not always separately identifiable
to be reported on the financial statements, previous studies usually focus on R&D as an
intangible measure (Bismuth and Tojo 2008). Although SFAS No. 2 requires firms to
expense R&D investments, firms and investors anticipate future benefits from these
investments. In this study, I use R&D investments as an exogenous predictor of firm
patenting activity and financial performance because the nature of R&D expenditures is
viewed to be closely related to investments in intangible assets than other ordinary
expenditures. Other studies also focus on accounting goodwill, which includes
intangibles such as customer lists and business reputation (Stallworth and DiGregorio
2004). In addition, firms report other separately identifiable intangibles, such as
trademarks, copyrights, and other intellectual assets as a group of intangible assets under
the assets section of the balance sheet.

In the accounting literature, several studies investigating the relationship between
R&D expenditures and financial performances report significant linkages between the
two (e.g., Jerry et al. 1984; Aboody and Lev 2000; Sundaram et al. 1996; Sougiannis
1994; Perry and Grinaker 1994). Prior studies characterized the relationship between R&D and a firm’s patenting activity as an input/output relationship, and patenting activity as the “successful” outcome of R&D (e.g., Aboody and Lev 2000; Hall et al. 2005). Other studies focus on goodwill by investigating the possible economic benefits that might be obtained from such intangibles (Sorescu et al. 2007). Chauvin and Hirschey (1994) contend that in the early 1990s “goodwill and other intangible assets constitute a much larger portion of the value of the firm, and a larger part of the acquired companies, than was previously the case” (p.160). Drawing from the insight from earlier research, this study uses a theoretical model that includes R&D, goodwill and other intangibles as reported in the annual income statement and balance sheet. These three independent (exogenous) variables obtained from Compustat\textsuperscript{11} will be included in the analysis to test the research hypotheses developed and presented in the previous chapter.

Since the process of inventing and patenting new ideas often takes several years, I computed a three-year average that covers the years 2002-2004 for R&D, goodwill, and intangibles. Prior studies investigating the time lag between R&D and patenting activity report different time-lag periods ranging from two year to five years (e.g., Griliches and Schmookler 1963; Comanor and Scherer 1969; Branch 1974; Hausman et al. 1984; Hall et al. 1986). Often, there is a delay between the initial investments in new ideas and the patenting phase of those ideas. This study takes this into account by lagging firm innovation characteristics variables two years.

\textsuperscript{11} In 2007, Compustat-Fundamentals Annual introduced Xpressfeed format, hence, the new variable names: Research and development expense (XRD); total intangible assets (INTAN); other intangibles (INTANO); and accounting goodwill (GDWL). It is important to notice that total intangibles also include goodwill, and other intangibles equal total intangibles less goodwill. To avoid multicollinarity, I will use INTANO to measure the net intangible assets, and measure goodwill separately using GDWL.
4.2.2 Measures of Patenting Activity

Earlier studies used a simple patent count as an outcome measure of the innovation process (e.g., Scherer 1965; Schmookler 1966). Although a simple patent count (e.g., the number of patents granted to a firm during a period of time) could provide useful information, researchers identified several limitations associated with this measure. Among the limitations of patent counts measures is the lack of information about the quality of patents (e.g., technological implications), and more importantly the economic benefits expected from these patent counts cannot be determined. Furthermore, Coombs and Bierly (2006) and Griliches (1990) contend that patent counts is a problematic measure because the technological implication and the economic value of a patent widely varies.

Researchers addressed this limitation by developing patenting activity measures that are based on patent citation analysis to extract additional information from patent documents, which are publicly available and can be obtained from the United States Patent and Trade Mark Office. Narin et al. (2002) provide an explanation of the basic premise of patent citation analysis: a patent with a valuable technology provides a foundation for newer inventions to build upon. Therefore, the more valuable a patent, the more citation a patent receives in subsequent patents. Patent documents also often include citations to scientific and research documents, which provides another valuable source of information about patent documents.

The new Patent Board 500 database provides an opportunity to extend prior studies by providing six measures. These six measures cover four categories

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12 A confidentiality agreement was signed with the Patent Board Inc for the Patent Board 500 database. Patent data cannot be disclosed without a written permission.
pertaining to a firm’s patent portfolio: (1) quality, (2) quantity, (3) Science, and (4) speed. The first category includes technology strength and industry impact. The second category, quantity, includes a measure of patent count. The third category includes two measures that link patents with Science, and includes a measure of Science strength and a measure of research intensity. The last category, innovation cycle time, tells us whether or not a patent is timely and referenced by new technologies. The database includes firms that are ranked according to various measures, such as the total number of patents granted in 2006. It also includes a five-year average calculated for each measure.

The Patent Board Inc. defines each of these measures as follows:

- **Technology Strength** provides an aggregate assessment of patents and innovation by considering the combined quality and quantity aspects of a company’s portfolio. A normalized metric used for ranking in the 500.
- **Industry Impact** a quality measure that quantifies how influential a company’s patent portfolio is on the development of technologies in other companies compared to the rest of the industry.
- **Patent Count** the quantity measure equals the full portfolio of U.S. patents granted in a given year, excluding design and other special-case inventions. Average age is calculated on the entire portfolio. Percent (%) lapsed reflects the portion of the entire portfolio that has been allowed to expire at any of the standard. Maintenance point.
- **Science Strength** a quality and quantity measure provides an aggregate assessment of the degree to which company’s patent portfolio is linked to core Science.
- **Research Intensity** a quality measure tracks a company’s level of fundamental research in a given industry compared to other companies, portfolios and patents across the same technology areas.
- **Innovation Cycle Time** measures how close a company is to “newer” or “older” technologies within its industry. Identifies the average age of all patents referenced by newly granted patents. Quality measured in years, a lower number is most desirable.14

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13 Five of these measures, Technology Strength, Industry Impact, Innovation Cycle Time, Research Intensity, and Science Strength are trademark protected by the Patent Board.

Previous studies (e.g., Deng et al. 1999; Hirschey et al. 2001b; Li and Simerly 2002; Narin et al. 2002; Coombs and Bierly 2006; Matolcsy and Wyatt 2008) have used similar patent measures or earlier versions of the above-mentioned measures. For example, Deng et al. (1999) use four patent measures to predict firm and market performance: *Science link*, a patent measure that shows the number of references to scientific papers in a company patent; *technology cycle time*, a measure that shows the age of patents cited by other patent; *citation impact*, a measure that indicates the number of citations in a given year to the company’s previously-registered patents; and finally, *patent count*. Li and Simerly (2002) also use comparable patent measures and report a significant relationship between these measures and R&D per employee. Deng et al. (1999) use similar patenting activity measures, such as patent count, citation impact, Science link, and technology cycle.

Coombs and Bierly (2006) use similar patenting activity measures and attempt to form a *technological capability* construct by using factor analysis. However, they conclude, “a factor analysis of the technological capability variables did not provide clearly distinct components” (p.438). To explore the possibility of reducing and summarizing the six patenting activity measures, an exploratory factor analysis was performed. A principal components analysis, with *Varimax* and *Oblique* rotations, was tried but did not yield results. One explanation is that the six patenting activity measures are unique observed variables and grouping these variables to form a unified latent constructs is not feasible. Since these results confirm prior findings by Coombs and Bierly (2006), I will include in the analysis the six patent activity measures as individual endogenous variables to test my research hypotheses.
4.2.3 Measures of Financial Performance

Prior studies investigating issues related to firm financial performance often use various proxies to measure financial performance. The two main categories of financial performance measures are either accounting-based measures or market-based measures. Few studies include a mix of accounting and market measures (e.g., Coombs and Bierly 2006). While several studies related to firms’ patenting activities provide empirical support for a relationship between a firm’s patenting activity and market performance (e.g., Pakes 1985; Deng et al. 1999; Yang 2007), the relationship between a firm’s patenting activity and its earnings performance needs to be further examined. This study focuses on three accounting-based financial performance measures, which have been traditionally used in the accounting literature as outcome variables (e.g., Cochran and Wood 1984; Coombs and Bierly 2006; Ballester et al. 2003). I use (1) return on assets (ROA), sometimes referred to as return on investment, (2) return on sales (ROS), and (3) return on equity (ROE). The first profitability ratio, ROA measures a firm’s ability to generate profits by utilizing the total assets owned by the firm. Investors and financial analysts believe that ROA is an important profitability measure because it indicates the efficiency level of management in utilizing their assets to generate profits. To compute ROA, I divide earnings before interest and taxes by the average operating assets. Furthermore, I use an average of assets during a period to exclude assets not used in operations (Marshall et al. 2007). The second profitability measure is return on sales (ROS). This ratio shows the ability of a firm to generate profits from sales revenue. ROS is a relevant ratio to be included in this study because it can be expected that innovative firms with exclusive patented technologies have a competitive advantage that will allow
them to earn higher profit margins. To compute ROS, I divide earnings before interest and taxes by sales revenue generated during a financial period. Analysts recommend the exclusion of interest and taxes to obtain a better measure of firms’ ability to generate profits from every dollar of sales revenue generated from selling products and services (Marshall et al. 2007). The third profitability measure is return on equity (ROE). This is a measure that is most relevant to current investors and potential investors. Prior studies (e.g., Lev and Zarowin 1999) shows that firms with high intangible assets have higher rate of returns than other firms. ROE is most relevant to current investors and potential investors because this profitability ratio provides a rate of return for the direct investment in a firm’s owner’s equity. To compute ROE, I divide net income by the average owner’s equity for the year.

I used data from Compustat to calculate these three financial performance measures. The outcome variables were calculated for 2007, producing a one-year lag between the five-year average patenting activity measures and a three-year lag between the firm innovation characteristics measures and financial performance. Earlier studies have demonstrated various methods for computing financial performance ratios (e.g., Berman et al. 1999; Peters and Mullen 2009).

4.3 Empirical Model Testing

This study uses structural equation modeling to simultaneously test the hypothesized set of relationships among variables of interest (Tabachnick and Fidell 2001; Hoyle 1995; Hair et al. 2006). Structural equation modeling offers several advantages over other multivariate techniques. First, unlike other statistical methods,
which assume that variables are perfectly measured, this method allows measurement
error associated with exogenous and endogenous variables. Second, structural equation
modeling simultaneously calculates the model parameter estimates using maximum
likelihood estimation (i.e., all estimates of model parameters are calculated at the same
time). Third, this method provides a method for testing complex relationships (e.g.,
mediation and moderation) in one step. In addition, structural equation modeling provides
goodness of fit indices to assess how well the data fits the hypothesized model.

Researchers (e.g., Bollen and Long 1993; Kline 2005) recommend several steps
of structural equation modeling. First, the researcher specifies a model based on theory or
prior literature, which includes the research hypotheses in the form of structural equation
model. Second, the researcher must determine whether model identification is possible
using a statistical program. That is whether or not a statistical program can calculate
unique values for each parameter specified in the model. Third, screen and refine
variables included in the model and select an estimation technique. Fourth, test the initial
model and determine if the model is consistent with the data. Finally, evaluate the model
fit, modify initial model to improve the fit, and retest using the same data.

Following these steps, I begin the process by specifying the theoretical model,
which was developed in the previous chapter, and include in the model the measured
variables. Figure 2 shows the theoretical model and hypothesized relationships among the
variables with operational measures. I will then follow the remaining steps and provide
results in the next chapter. To test the model and analyze the data, I use AMOS 16.0. This
statistical software is commonly used for structural equation modeling.
One of the major advantages of using the AMOS program for structural equation modeling is the ability to utilize Full Information Maximum Likelihood (FIML) for handing missing data. The FIML method offers several advantages over other methods, such as listwise and pairwise deletion. First, the FIML method represents a direct approach for handing missing data because it is based on maximum likelihood estimation and hence it is a theoretically based method (Arbuckle 1996; Byrne 2001). Second, this method retains an effective sample size and provides more accurate and less biased standard error calculations. Third, this method provides unbiased parametric estimates. Pairwise estimation, in contrast, cannot produce standard error estimates or provide a technique for testing hypotheses. Therefore, the FIML method for estimating missing data has several advantages over other methods, enabling researchers to retain more data and a higher level of accuracy than other commonly used methods.\textsuperscript{15}

4.4 Sample Descriptive Statistics

Descriptive statistics for the final sample are summarized in Table 3. The means, standard deviations, and ranges for each of the variables in the model are illustrated. Column 1 also contains the abbreviated variable names for all variables; these abbreviations will be used extensively in the next chapter. All data presented in Table 3 are based on raw (i.e., untransformed) form.

\footnote{For additional details about the FIML method, see Arbuckle (1996)}
There are no missing observations for the patenting activity measures. However, there are some random missing observations for the other variables. Among the three firm characteristics variables, goodwill includes 7 missing cases (3% of the sample), intangibles include 8 missing cases (4% of the sample), and R&D includes 13 missing cases (6% of the sample). Among the outcome variables, ROA includes 9 missing cases (4% of the sample), ROS includes 12 missing case (6% of the sample), and ROE includes 10 missing cases (5% of the sample).

Panel A of Table 3 shows the six patent activity measures included in the analysis. An initial examination of these variables shows that the sample is broadly distributed, and the distributional statistics are consistent with prior studies using similar measures (e.g., Coombs and Bierly 2006). The average (median) patent count is 167 (66). The relatively high average number of patents held by firms included in the sample indicates that they are heavily engaged in developing and patenting new technologies. Additionally, the average (median) science strength is 601.17 (1224.40), which could indicate that a firm’s patent portfolio is linked to core science. Therefore, patented technologies of these firms could provide opportunities for scientific breakthroughs. The average (median) innovation cycle time is 9.89 (9.62). Since this measure provides an indication on how close a firm’s patent portfolio is to newer technologies within its industry, an average measure near the median indicates a firm is focusing on newer technological inventions.

Panel B of Table 3 shows the three exogenous variables that are proxies for firm innovation characteristics, included in the analyses. Average (median) goodwill for the
sample firms is about $2.2 billion ($650 million), and the average (median) for intangible assets is $1.2 billion ($121 million). The average (median) R&D expenditure for the sample is $593 million ($152 million).

Panel C of Table 3 provides descriptive statistics for the financial performance variables. The average (median) ROA ratio is 4% (7%). The average (median) ROS ratio is -12% (8%). The average (median) ROE is 14% (18%). According to Marshall et al. (2007), the historical ROE ranges from 10% to 15% for American merchandising and manufacturing firms. Therefore, while the ROA and ROE ratios for the sampled firms seem to be accordance with the expected return, an extreme range for ROS is noticeable.

I transformed these variables to normalize the financial performance measures and to reduce skewness and kurtosis to acceptable levels as suggested by Tabachnick and Fidell (2001). A log transformation produced optimum levels of normality for ROE, while an inverse transformation produced optimum results for ROA and ROS.

Goodwill, intangibles, and R&D means are each larger than their corresponding medians, indicating skewness in the data and justifying the use of the logarithmic transformation of these variables. For example, the mean of R&D is $592.97 million, while the median is $151.94. Other variables have been transformed to reduce skewness and kurtosis to acceptable levels. A log transformation produced optimum levels of normality for all variables. With the exception of ROA and ROS, an inverse transformation produced optimum results.

To summarize, the 2006 Patent Board 500 provides the sample for this study. The sample includes large high-tech firms (e.g., minimum R&D = $4.23 million) representing five major industries and a group of firms representing several other industries. Three
exogenous variables are used to measure firm innovation characteristics that captures different sources of intangible assets as reported in the income statement (e.g., R&D) and the balance sheet (e.g., goodwill and intangibles). Six different patenting activity measures, acquired from the Patent Board Inc., cover various aspects of a firm’s patenting activity quantity and quality. Three outcome variables (ROA, ROS and ROE) measure firm financial performance. Using these variables, this study simultaneously tests the theoretical model using structural equation modeling. The next chapter begins with a correlation analysis of the exogenous and endogenous variables included in the model. Results of this study and tests of the research hypotheses will be presented using AMOS and AMOS Graphics.
CHAPTER 5
RESULTS AND FINDINGS

This chapter presents the empirical test results for the four research hypotheses that were outlined in chapter 3. Section 5.1 provides bivariate analyses showing correlations among variables included in the analysis. Section 5.2 describes the main steps that were taken to test the empirical model using structural equation modeling and their initial results. Section 5.3 discusses the results of the empirical tests and hypotheses in detail. Section 5.4 summarizes the study’s results and findings.

5.1 Bivariate Correlations

Table 4 provides a correlation matrix of the variables included in the structural equation model. As expected, correlations among the financial performance variables (ROA, ROS, and ROE) are significantly positive. Out of all the variables included in the analysis, the correlation between ROA and ROS is the highest ($r = .81, p < .01$). Each variable, however, provides distinct information because they are correlated with other variables at different levels. For example, ROA is significantly negatively correlated with SCIENCS ($r = -.18, p < .01$), however the correlation between ROS and SCIENCS is not significant ($r = -.08, p = .27$). Both ROA and ROS will be used in the analysis in order to provide additional information regarding firm profitability.

[insert Table 4 here]
The three financial performance variables are significantly positively correlated with goodwill and intangibles. Among the three profitability ratios, however, ROS is the only one that correlates positively with RD ($r = .15$, $p < .05$). For example, the correlation between ROA and RD is insignificant ($r = .11$, $p = .12$). These findings provide preliminary support for H1. In addition, ROA and ROE are significantly correlated with four patenting activity measures, while ROS correlates positively with TECHST and PATENTC, ($r = .26$, $p < .01$; $r = .25$, $p < .01$, respectively). These initial findings provide preliminary support for H3.

Correlations among the three firm innovation characteristics variables, goodwill, intangibles and R&D, are positive and significant. Goodwill and intangibles are highly correlated ($r = .71$, $p < .01$). They both, however, provide additional information based on correlations with other variables. R&D correlates negatively with industry impact and INNOVCYC ($r = .38$, $p < .01$). This result was expected because INNOVCYC measures the average age of patent references, with a lower number representing newer technology included in patents. Goodwill and intangibles are significantly correlated with TECHST, INDUST, and PATENTC, and in turn, provide preliminary support for H2. There is a positive relation between a firm’s innovation characteristics (R&D, intangibles, and accounting goodwill) and its patenting activity.

The six patenting activity measures are significantly correlated with one another. The only exception is PATENTC, which not sign related to INDUST ($r = -.01$, $p = .88$), and RESINT ($r = -.01$, $p = .92$). Although not significant, RESINT is somewhat positively correlated with TECHST ($r = .10$, $p = .158$).
To identify multicollinearity, I conduct several tests as recommended by Hair et al. (2006). First, although few variables are highly correlated, these correlations are lower than .90. Second, I test for possible existence of multicollinearity by running the collinearity diagnostic test found in the multiple linear regression procedure in SPSS. I examine the tolerance and variance inflation factor to detect collinearity between variables. Results reveals that potential moderate collinearity may exist between SCIENCE and PATENTC, however never reach the maximum levels as recommended by Hair et al. (2006). Given the definitions of these two measures and how they are constructed, some level of conceptual overlap is expected because they are both related to a firm’s patent portfolio. In addition, these two variables are correlated with other variables at different levels, therefore, will be included in the analyses.

To summarize, results from the correlation analysis shows significant correlations among firm innovation characteristics, patenting activity, and financial performance. Previous studies focus on the relationship between R&D and patenting activities. The correlation analysis of this study provides results that are consistent with their findings (e.g., R&D is the only variable significantly correlated with all of the patenting activity measures). The analysis also provides initial support for H1, H2, and H3. This allows us to move to the next step of the analysis by testing the proposed theoretical model using structural equation modeling with AMOS.

5.2. Developments and Test of the Model

Based on the theoretical model developed in this study, I construct an initial model using AMOS 16.0. I begin with an initial model that includes all possible
directional regression paths among the variables. As shown in Figure 3a, I start the analyses with a fully saturated model. The model also includes correlations among the three exogenous variables (goodwill, intangibles, and R&D) to account for the possible associations among these variables. The standard procedure in structural equation modeling for correlating endogenous variables is to correlate their residual error terms. AMOS cannot calculate a correlation (covariance) between two endogenous variables without calculating it through the residuals error term. It should be noted that the patenting activity measures and the financial performance variables are endogenous. Therefore, correlations among their error terms were added as shown in Figure 3b. All possible correlations among the error term residuals were added to the initial saturated model.

[insert Figure 3a here]

[insert Figure 3b here]

Figure 4 shows the initial saturated model with all possible regression paths and correlations/covariances (see figure 5). Test results for the structural models are evaluated by using four indicators: (1) the $\chi^2$ goodness-of-fit statistic, (2) the Tucker Lewis Index (TLI), (3) the Comparative Fit Index (CFI), and (4) the Root Mean Square Error of Approximation (RMSEA). Bentler and Chou (1987), suggest using CFI and TLI and scores greater than .90 to indicate a good fitting model. Browne and Cudeck (1992) recommend RMSEA score of .08 or less as good fitting model. Researchers using structural equation modeling (e.g., Hair et al. 2006; Hoyle 1995) emphasize using several indicators of model fit as opposed to relying on the $\chi^2$ statistic. They have two reasons:

16 See Hoyle (1995) for more details about model fitting indices.
first, the $\chi^2$ test is mathematically influenced by the sample size and second, because the number of observed variables influences this test. The final model fit, therefore, will be evaluated using the optimum overall fit among the four indicators.

Table 5 shows the results of testing the initial model, which includes all possible regression paths and covariances. With several insignificant paths, the model fit, based on the CFI and RMSEA indicators, is not optimum ($\chi^2 = 39.87$, df = 4, $p < .001$, TLI = .634, CFI = .978, RMSEA = .207). As a result, seventeen insignificant regression paths and two covariance paths were removed from the model. They were removed one path at a time in a step-by-step process. Figure 6 shows the final model with an overall improvement of model fit based on the four indicators, and TLI and RMSEA indicators in particular ($\chi^2 = 62.21$, df = 23, $p < .001$, TLI = .930, CFI = .976, RMSEA = .090).

Table 6 shows the regression results for the final model. In addition, Figure 6a shows the final structural model with the standardized regression weights, and Figure 6b shows the correlations/covariances among endogenous and exogenous variables. The results pertaining to each of the four hypotheses will be discussed for each hypothesis in the following sections.
Table 7 shows the result of the structural equation modeling of estimated correlations/covariances among the exogenous variables and among the residuals associated with the endogenous variables. These results are consistent with results of bivariate correlations as previously discussed and presented in Table 4. The amount of variance explained by the model can be addressed by examining the $R^2$ values associated with each endogenous variable. Among the outcome variables, which represent firm financial performance, the explained variance of ROA is .27. In addition, the amount of variance explained by ROS and ROE is .31 and .16 respectively. Among the endogenous variables representing patenting activity, the model explained .51 of PATENTC’s variance. Additionally, the model explained .31 of the variance associated with SCIENCS, .27 of the variance associated with INNOVCYC, .22 of the variance associated with TECHST, .11 of the variance associated with INDUST, and .06 of the variance associated with RESINT.

[insert Table 7 here]

5.3 Tests of Research Hypotheses

5.3.1 Test Results of H1

The first research hypothesis (H1) investigates whether there are positive relationships between firms’ innovation characteristics (R&D, intangibles, and goodwill) and their financial performance (ROA, ROS, and ROE). Results in this section pertain only to the impact of firm innovation characteristics on the financial performance measures. Table 6 provides the results for each of the paths included in the structural
model with standardized beta, unstandardized beta, standard error, and p-values. Panel A of Table 6 provides the regression results for the first and third hypotheses.

Results show that only goodwill predicts ROA, with higher levels of goodwill predicting higher levels of ROA ($\beta = .30, p<.001$). Among the three exogenous variables (goodwill, intangibles, and R&D), there were no other significant predictors for ROA. Two firm innovation characteristics variables (goodwill and intangibles) predict ROS. Therefore, results show that firms with higher level of goodwill also have higher level of ROS ($\beta = .31, p < .001$). In addition, higher levels of intangibles are associated with higher level of ROS ($\beta = .19, p < .001$). Figure 7 highlights the regression paths and shows the standardized regression weights related to testing H1. The R&D regression path, however, was not significant and consequently removed from the model. ROE has only one predictor—goodwill. Results indicate that investors who invest in firms with higher levels of goodwill earn higher ROE. Although R&D did not significantly predict any of the three financial performance ratios, results partially support H1. For example, goodwill predicted ROA, ROS, and ROE and intangibles predicted ROS.

[insert Figure 7 here]

5.3.2 Test Results of H2

The second research hypothesis (H2) investigates whether there are positive relationships between firms’ innovation characteristics (R&D, intangibles, and accounting goodwill) and their patenting activity. Panel B of Table 6 provides the results
of regressing the six patenting activity measures by the three firm innovation characteristics variables.

Results show that patenting activity measures, including INDUST, PATENTC, SCIENCS, INNOVCYC, and RESINT, significantly predict GW (all significant, p < .01, except RESINT significant p < .05). TECHST is the only patenting activity that is not a predictor of GW. Results show that while firms with higher goodwill assets are associated with lower industry impact, Science strength, and research intensity, firms with higher goodwill are predicted to have higher patent count and innovation cycle time. In other words, goodwill is positively associated with patenting activity measures that focus on quantity and negatively associated with the quality measures. Among the other firm innovation characteristics, only two patenting activity measures predicted INTAN. As expected, INTAN’s impact on SCIENCS is significantly positive (β = .17, p < .01). This suggests that firms with high intangibles (e.g., intellectual property and human resources) hold patents that are linked to core Science (e.g., patents include more citations of scientific research). Additionally, the significant negative impact of INTAN on INNOVCYC (β = -.17, p < .05) is expected because low scores of this measure are desirable. A low measure indicates that, within a particular industry, a firm’s patent portfolio includes newer technologies as indicated by the average age of patents cited (i.e., newer patents citations referenced recently issued patents). Therefore, higher levels of intangibles resulted in higher (lower) levels of SCIENCS and INNOVCYC (β = .17, p < .01, and β = -.17, p < .05 respectively). Finally, among the three firm innovation characteristics, results show that each of the six patenting activity measures predicted R&D. Figure 8 highlights the regression paths and shows the standardized regression
weights related to testing H2. This result is consistent with previous research findings (e.g., Aboody and Lev 2000; Hall et al. 2005). Importantly, it confirms the proposition that R&D and patents’ relationship can be described as an input and output relationship. In other words, as firms increase investment in R&D, their patenting activity also increases. For example, R&D positively and significantly predicts PATENTC (β = .65, p < .01). Therefore, results show that firm innovation characteristics can predict firm patenting activity, with R&D being the strongest predictor. These results support hypothesis H2.

5.3.3 Test Results of H3

The third research hypothesis (H3) investigates whether there are positive relationships between firms’ patenting activity (TECHST, INDUST, PATENTC, SCIENCS, RESINT, INNOVCYC) and their financial performance (ROA, ROS and ROE). Results in this section pertain only to the impact of firm patenting activity on financial performance. Panel A of Table 6 provides the regression results for the third hypothesis.

The following results show significant relationships where patenting activity predicts financial performance. Results show that TECHST and RESINT positively predicted ROA (β = .34, p < .001; β = .30, p < .05) respectively. Additionally, INDUST and SCIENCS negatively predict ROA (β = -.11, p = .05; β = -.50, p < .001). The other financial performance measure, PATENTC and RESINT positively predicted ROS (β = .24, p < .001; β = .36, p < .001). Last, ROE is negatively significantly predicted by SCIENCS (β = -.51, p < .001). Finally, ROE is positively predicted by TECHST and
RESINT (β = .38, p < .001; β = .27, p < .05) respectively. Additionally, PATENTC and SCIENCS negatively predict ROA (β = -.16, p < .05; β = -.37, p < .001). Figure 9 highlights the regression paths and shows the standardized regression weights related to testing H3.

The above findings suggest that RESINT is the only predictor among all of the patenting activity measures that consistently (e.g., positively significantly) that predicts the financial performance measures (ROA, ROS, and ROE). TECHST association with ROA and ROE is also positively significant. However, no relationship was detected between ROS and TECHST. These results are consistent with H3 and provide partial support for the hypothesized relationship. The negatively significant relationship among other patenting activity measures and financial performance measures are worth further examination in future studies.

[insert Figure 9 here]

5.3.4 Test Results of H4

The fourth and final research hypothesis (H4) investigates whether firms’ patenting activity mediates the relationships between their innovation characteristics and financial performance. The independent variable influence on the dependent variable through another variable is mediation (Baron and Kenny 1986). Therefore, all significant paths examined in testing H1 will be disregarded in order to detect the full mediation effect of the patenting activity measures. In addition, the exogenous variables (e.g., firm innovation characteristic variable) should be a significant predictor of the mediation
variables (e.g., patenting activity measures) as discussed in the H2 test. Furthermore, the mediation variables should be significant predictors of the outcome variables (ROA, ROS, and ROE) as discussed in H3 test. In other words, a firm’s innovation characteristic variable cannot be a predictor of a financial performance variable. However, it must be a significant predictor of a patent activity measure. In turn, a patent activity measure should be a significant predictor of one of the outcome variables.

Among the three firm innovation characteristics, goodwill’s relationship with ROA, ROS, and ROE was not mediated by any of the six patent activity measures. This is because goodwill predicts ROA, ROS, and ROE. The impact of INTAN on ROA was mediated by SCIENCS such that higher levels of INTAN resulted in higher levels of SCIENCS (β = .17, p < .01) and firms with higher levels of SCIENCS had lower level of ROA (β = -.50, p < .001). The relationship between INTAN and ROE was also mediated by SCIENCS, such that firms with higher levels of INTAN had a higher score of SCIENCS (β = .17, p < .001). And those firms with high SCIENCS had lower levels of ROE (β = -.51, p < .001).

The impact of R&D on the financial performance measures was mediated by four patenting activity measures. R&D relationship with ROA was mediated by TECHST, industry impact, SCIENCS, and RESINT. A closer look at these mediated relationships, reveals that firms with higher TECHST scores (β = .47, p < .001) also had higher levels of ROA (β = .37, p < .001). Furthermore, firms with high R&D spending had lower scores of industry impact and firms with lower levels of industry impact had higher level of ROA (β = -.11, p < .001). Firms with higher levels of R&D spending had higher scores of RESINT (β = .24, p < .001) and firms with higher RESINT have higher ROA (β = .30,
The relationship between R&D and ROS was mediated by TECHST, PATENTC, SCIENCS, and RESINT. An examination of the mediation between R&D and ROS, reveals that firms with higher levels of R&D had high scores of TECHST ($\beta = .47$, $p < .001$) and higher scores of TECHST correlate to higher levels of ROS ($\beta = .38$, $p < .001$).

Firms with higher levels of R&D had higher numbers of PATENTC ($\beta = .65$, $p < .001$) and firms with a higher number of PATENTC had lower levels of ROS ($\beta = -16$, $p < .001$). Another mediation between R&D and ROS is through SCIENCS, where firms with high R&D spending had higher scores for SCIENCS ($\beta = .54$, $p < .001$) and firms with high SCIENCS scores had lower levels of ROS ($\beta = -.37$, $p < .001$). Firms with higher levels of R&D spending had a higher level of RESINT ($\beta = .24$, $p < .001$) and firms with higher scores of RESINT had higher levels of ROS ($\beta = .27$, $p < .001$).

Finally, the relationship between R&D and ROE is mediated by PATENTC, SCIENCS and RESINT. A closer examination of these mediation relationships reveals that firms with higher R&D spending had a higher level of PATENTC ($\beta = .65$, $p < .001$) and firms with higher PATENTC had higher ROE ($\beta = .24$, $p < .001$). In addition, firms with higher R&D spending had high scores of SCIENCS ($\beta = .54$, $p < .001$) and firms with higher levels of SCIENCS have lower level of ROE ($\beta = -.51$, $p < .001$). In other words, lower R&D spending leads to a lower SCIENCS scores, in turn leading to higher ROE. Finally, firms with high R&D spending have high levels of RESINT ($\beta = .24$, $p < .001$) and firms with higher levels of RESINT had higher levels of ROE ($\beta = .36$, $p < .001$). Figure 10 highlights the regression paths and shows the standardized regression weights related to H4. It should be noted that INNOVCYC did not mediate any
relationship between firm innovation characteristics and financial performance, hence, not shown in Figure 10.

[insert Figure 10 here]

5.3.5 Test of Direct, Indirect and Total Effects: Additional Test of Mediation

Another method for addressing mediation in structural equation modeling is by examining the direct, indirect, and total effect of firm innovation characteristics on financial performance. As shown in Table 8, the impact of R&D on the three financial performance variables is based on indirect effect. The total effect of R&D on ROA is ($\beta = -0.029$), which consists of direct effect ($\beta = 0.000$) and indirect effect ($\beta = -0.029$). The total effect of R&D on ROS is ($\beta = -0.062$), consisting of direct effect ($\beta = 0.000$) and indirect effect ($\beta = -0.062$). The total effect of R&D on ROE is ($\beta = -0.039$), which consists of direct effect ($\beta = 0.000$) and indirect effect ($\beta = -0.099$). In other words, R&D affects ROA, ROS, and ROE through indirect relationships.

The impact of INTAN on two financial performance variables (ROA and ROE) is based on indirect effect. The total effect of INTAN on ROA is ($\beta = -0.083$), which consists of direct effect ($\beta = 0.000$) and indirect effect ($\beta = -0.083$). The total effect of INTAN on ROE is ($\beta = -0.085$), which consists of direct effect ($\beta = 0.000$) and indirect effect ($\beta = -0.085$). The total effect of INTAN on ROS, however, consists of direct effect ($\beta = 0.191$) and indirect effect ($\beta = -0.061$), with the total effect equaling ($\beta = 0.133$). Table 8 shows the impact of GW on financial performance based on direct and indirect effects. For example, the total effect of GW on ROA is ($\beta = 0.459$), which consists of direct effect ($\beta = 0.304$) and indirect effect ($\beta = 0.155$). Results from the analysis of direct, indirect, and total
effect offer additional evidence and partial support for H4. Hence, the relationship between firm innovation characteristics and financial performance is mediated by patenting activity.

[insert Table 8 here]

5.4 Summary of Results

To summarize, the structural modeling results indicate that the data moderately fit the hypothesized model. As shown in Table 5, the results suggest that goodwill and intangibles have a significant effect on financial performance. However, R&D expenditures are not directly related to financial performance. Instead, R&D’s relation to financial performance is mediated by five different patenting activity measures. In addition, firm innovation characteristics have significant relationships with patenting activity. As expected, R&D is a consistent predictor for various patenting activity measures. This result confirms prior studies’ results, suggesting that the relationship between R&D and patents can be described as an input/output relationship. The results also indicate that goodwill and intangibles are important assets and contribute to increasing firms’ financial performance. Researchers argue that R&D costs should be capitalized and treated as assets instead of the current accounting treatment practices. This study, however, provides clear evidence that R&D’s association with financial performance and patenting activity is different from that of goodwill and intangibles. The test of H1 indicates that goodwill has a significant positive association with ROA, ROS, and ROS. However, intangibles only have a significant positive association with ROS. In addition, R&D is an insignificant predictor of financial performance. Furthermore, the
test of H2 provides mixed results with different degrees of association between firm innovation characteristics and financial performance. However, among the three innovation characteristics variables, R&D is positively significantly associated with four patenting activity measures, technology strength, patent count, Science strength, and research intensity. The test of H3 provides some evidence suggesting that nonfinancial performance measures, such as patent activity measures, could predict financial performance. For instance, research intensity has a significant positive association with ROA, ROS, and ROE. Finally, the test of the mediating role of the patenting activity measures in H4 reveals that the relationship between R&D and financial performance is completely mediated by five patenting activity measures. In addition, the relationship between intangibles and two financial performance measures (ROA and ROE) is mediated by Science strength.

The next chapter begins with discussion of the main findings, and the conclusion of this study. It will also address this study’s contributions, limitations, and potential directions for future research.
CHAPTER 6
DISCUSSION, CONTRIBUTIONS, LIMITATIONS,
AND FUTURE RESEARCH

This chapter begins with a discussion of the main results and the conclusions of this study. Section 6.2 highlights the contributions this study makes to the accounting literature. Section 6.3 discusses the limitations of this study. The final section, explores future research opportunities that this study has brought to light.

6.1 Discussion

This study has empirically examined the relationship between firm innovation characteristics, patenting activity, and financial performance. It builds upon several streams of research, including several studies focusing on intangibles and intellectual property, those which explore the value relevance of nonfinancial performance measures, and studies that examine patents and innovation and how both relate to firms’ future financial performance. This study uses structural equation modeling for and a sample of 210 high-tech firms to test a theoretical model that was developed in order to explore the relationship between firm innovation characteristics and financial performance. It includes six various patenting activity measures to investigate the value relevance of nonfinancial performance measures in predicting future financial performance.

Previous studies (e.g., Hand and Lev 2003; Lev and Sougiannis 1996) investigating issues related to intangibles show that firms with higher levels of intangibles often earn higher returns. The majority of these studies focus on market performance measures, such as stock returns, to demonstrate that investors value the
potential benefits generated from intangibles. These studies also tend to focus on corporate R&D expenditures as a source of intangibles that are generated internally. Other studies (Chauvin and Hirschey 1994; Hirschey and Richardson 2002a) focus on other sources of intangibles, such as business combinations and goodwill associated with these transactions. This study makes an important contribution to the literature by positing that R&D, goodwill, and other intangibles reflect firms’ innovation characteristics. Since prior studies suggest that firm innovation leads to an increase in competitiveness and high growth rates among high-tech firms, I hypothesize that firm innovation characteristics are positively related to firms’ future financial performance (H1). Results from this study indicate that goodwill and intangibles can directly predict future financial performance. Although previous studies have shown contrary, this study indicates that R&D does not directly predict financial performance. Aboody and Lev (2000) suggest that firms with high R&D expenditures have larger information asymmetry, which indicate that insiders know more about the nature of R&D than outsiders. Hence, more information should be disclosed to the public to evaluate the potential benefits of R&D. Deng et al. (1999) show that R&D intensity (R&D divided by sales) is a highly significant predictor of firms’ market performance. These mixed results indicate that further investigation is needed to evaluate the potential future benefits of R&D expenditures and their impact on financial performance.

Consistent with earlier research, this study provides additional empirical evidence that support the notion that various patent measures are useful output indicators of R&D. Investors, for example, may better evaluate the benefits obtained from R&D investments, if they can observe an important step in the innovation process. One of the benefits of
using patent information to assess firms’ innovation and growth potential is that newly
developed patent measures provide an assessment of the quality, as well as the quantity,
of firms’ patents. This study also investigates whether firm innovation characteristics,
which include R&D, can help predict patent quantity and quality (H2). Results from this
study indicate that this is the case. Among the three firm innovation characteristics, R&D
is the only variable significantly associated with all six patenting activity measures.

Although few firms disclose details about their patenting activity, patent measures
based on citation analysis provide a rich source of information that can predict future
financial performance. This finding corresponds with H3. Results show that technology
strength, in particular, is a strong predictor of three profitability measures (ROA, ROS,
and ROE). This result was anticipated since this patent measure provides information
related to both the quantity and quality of patents.

Various patent measures provide additional information beyond the current
disclosure requirements. This study, therefore, investigates the potential role of
nonfinancial performance measures that can link various financial indicators (e.g.,
accounting-based profitability measures, such as ROA, ROS and ROE). For instance, the
last hypothesis (H4) investigates the mediation role of the various patent measures.
Results show that patenting activity mediates the relationship between some firm
innovation characteristics and financial performance. Limited prior research (e.g., Banker
and Slaughter 2000; Banker and Mashruwala 2007) investigates this type of complex
relationship (i.e., mediation and moderation). This study provides evidence that
nonfinancial performance measures can function as mediators, and in turn could benefit
investors with additional information about a firm’s prospects.
There are several important implications that arise from this study. First, the study’s findings suggest that nonfinancial performance measures, particularly patent measures, provide incremental information beyond the historical financial information that is disclosed in the financial statements. Therefore, policy makers should require public firms to include this information in the financial statements. Second, prior empirical literature has debated whether R&D costs should be capitalized. Some argue that since R&D investments produce future benefits, hence, they should appear on the balance sheet instead of the income statement. This study shows that when R&D is grouped with other intangibles to predict financial performance, R&D does not have predictive power, but it does through the patenting activity variables. In contrast, goodwill performs like other assets and is a strong predictor of financial performance.

6.2 Contributions

This study makes four major contributions to the existing literature. First, this study builds upon the existing literature related to the value-relevance of nonfinancial performance measures. In particular, this study extends prior studies that focus on the relationships among intangibles, patenting activity, and financial performance (e.g., (Deng et al. 1999; Hirschey et al. 2001a; Hall et al. 2005; Yang 2007) by investigating relationships among goodwill, intangibles, patenting activity, and accounting-based financial performance. The evidence in this study suggests that goodwill has a direct impact on financial performance and R&D directly impacts patenting activity and indirectly impacts financial performance.
The second contribution pertains to the unique and proprietary database of patent measures, which includes six various patent measures covering the quantity and quality aspects of firms’ patenting activity. Studies investigating issues related to nonfinancial performance measures often rely on proprietary information and attempt to investigate its economic value and usefulness in making investment decisions.

Finally, this study provides evidence that nonfinancial measures could be a useful source of information for investors. The AICPA special committee on financial reporting and the SEC could mandate nonfinancial performance measures as a useful supplement to current financial reports as recommended.

Fourth, this study contributes to the literature by using a structural equation modeling approach to simultaneously test four research hypotheses. A few accounting studies use this sophisticated statistical technique. One of the main benefits obtained from this approach is testing the mediation effect of nonfinancial performance measures in a single step.

### 6.3 Limitations

This study’s findings are subject to several limitations. The first potential limitation of this study relates to the limited sample size. This study focuses only on U.S. publicly traded firms included in the Patent Board 500. It analyzes a sample of 210 large high-tech firms representing various industries. A second potential limitation of this study is that results are sensitive to general economic factors, such as economic recessions and market bubbles. For that reason, this study covers a relatively limited time-period 2002 to 2007. Although this study focuses on a relatively stable period, it uses multiple-year
averages to account for minor changes in the economic environment. Extending the time-period of this study or finding another relatively comparable period has proven to be challenging. However, several economic adjustment methods could be used to overcome this limitation. Finally, this study focuses on three accounting-based financial performance measures and does not include market-based financial performance measures. Future research could attempt to overcome some of these limitations.

6.4 Future Research

There are several possible avenues for future research. While this study uses six patenting activity measures obtained from a private data source, future studies could validate these results by obtaining other patenting activity measures from other sources (e.g., the National Bureau of Economic Research). Although patent measures might come from different sources, the main source of patent data is the information disclosed in the original patent and as published by the United States Patent and Trade Mark Office. Therefore, I would expect that results from future studies to validate the findings of this study. Second, the theoretical model developed in this study could be tested by using data specific to other countries. Third, future research might also further explore other types of nonfinancial performance measures such as trademarks and trade secrets.
TABLE 1
Summary of Sample Selection Process

<table>
<thead>
<tr>
<th>Description</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firms listed in the Patent Board 500 database</td>
<td>500</td>
</tr>
<tr>
<td>Exclusion of foreign and private firms</td>
<td>283</td>
</tr>
<tr>
<td>Exclusion of software firms</td>
<td>7</td>
</tr>
<tr>
<td>Final Sample</td>
<td>210</td>
</tr>
</tbody>
</table>
### TABLE 2
Distribution of Sample Firms within a Four-digit SIC Code

<table>
<thead>
<tr>
<th>SIC Codes</th>
<th>Industries</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>2800 - 2899</td>
<td>Chemicals and Allied Products (including Petroleum and</td>
<td>41</td>
<td>20%</td>
</tr>
<tr>
<td>3500 - 3599</td>
<td>Industrial Machinery and Equipment</td>
<td>38</td>
<td>18%</td>
</tr>
<tr>
<td>3600 - 3699</td>
<td>Electronic and other Electric Equipment</td>
<td>31</td>
<td>15%</td>
</tr>
<tr>
<td>3700 - 3799</td>
<td>Transportation Equipment</td>
<td>20</td>
<td>10%</td>
</tr>
<tr>
<td>3800 - 3899</td>
<td>Instruments and Related Products</td>
<td>31</td>
<td>15%</td>
</tr>
<tr>
<td>Various</td>
<td>Others</td>
<td>49</td>
<td>23%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>210</td>
<td>100%</td>
</tr>
</tbody>
</table>
TABLE 3  
Descriptive Statistics

Summary Statistics for Untransformed Variables Included in the Analysis

Panel A Patenting Activity Measures

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>TECHST (Technology Strength)</td>
<td>210</td>
<td>236.94</td>
<td>495.30</td>
<td>64.53</td>
<td>7.20</td>
<td>3687.60</td>
</tr>
<tr>
<td>INDUST (Industry Impact)</td>
<td>210</td>
<td>1.45</td>
<td>1.03</td>
<td>1.18</td>
<td>.27</td>
<td>7.21</td>
</tr>
<tr>
<td>PATENTC (Patent Count)</td>
<td>210</td>
<td>167.32</td>
<td>338.24</td>
<td>66.10</td>
<td>4.70</td>
<td>3338.20</td>
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<tr>
<td>SCIENCS (Science Strength)</td>
<td>210</td>
<td>601.17</td>
<td>1224.40</td>
<td>144.30</td>
<td>.00</td>
<td>11123.00</td>
</tr>
<tr>
<td>RESINT (Research Intensity)</td>
<td>210</td>
<td>1.27</td>
<td>1.01</td>
<td>1.01</td>
<td>.00</td>
<td>6.52</td>
</tr>
<tr>
<td>INNOVCYC (Innovation Cycle Time)</td>
<td>210</td>
<td>9.89</td>
<td>3.05</td>
<td>9.62</td>
<td>4.80</td>
<td>21.80</td>
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</table>

Panel B. Firm Innovation Characteristics

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>GW (Goodwill)</td>
<td>203</td>
<td>2191.92</td>
<td>3639.70</td>
<td>650.07</td>
<td>0</td>
<td>52605.33</td>
</tr>
<tr>
<td>INTAN (Intangibles)</td>
<td>202</td>
<td>1174.39</td>
<td>4995.80</td>
<td>120.75</td>
<td>0</td>
<td>45767.00</td>
</tr>
<tr>
<td>RD (Research &amp; Development)</td>
<td>197</td>
<td>592.97</td>
<td>1222.55</td>
<td>151.94</td>
<td>4.23</td>
<td>8704.67</td>
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</table>

Panel C. Financial Performance Measures

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROA (Return on Assets)</td>
<td>201</td>
<td>0.04</td>
<td>0.17</td>
<td>0.072</td>
<td>-0.75</td>
<td>0.33</td>
</tr>
<tr>
<td>ROS (Return on Sales)</td>
<td>198</td>
<td>-0.12</td>
<td>0.97</td>
<td>0.08</td>
<td>-7.61</td>
<td>0.61</td>
</tr>
<tr>
<td>ROE (Return on Equity)</td>
<td>200</td>
<td>0.14</td>
<td>0.47</td>
<td>0.18</td>
<td>-2.60</td>
<td>2.68</td>
</tr>
</tbody>
</table>

* Summary statistics is based on the original values for all variables. All variables were transformed using log or inverse transformation to reduce skewness and kurtosis.
<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 ROA</td>
<td>1.000</td>
<td>0.811</td>
<td>0.561</td>
<td>0.397</td>
<td>0.291</td>
<td>0.108</td>
<td>0.213</td>
<td>-0.114</td>
<td>0.253</td>
<td>-0.182</td>
<td>-0.080</td>
<td>0.160*</td>
</tr>
<tr>
<td>2 ROS</td>
<td>1.000</td>
<td>0.563</td>
<td>0.455</td>
<td>0.416</td>
<td>0.151</td>
<td>0.264</td>
<td>-0.033</td>
<td>0.247</td>
<td>-0.077</td>
<td>0.005</td>
<td>0.126</td>
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<tr>
<td>3 ROE</td>
<td>1.000</td>
<td>0.289</td>
<td>0.151</td>
<td>0.116</td>
<td>0.068</td>
<td>-0.138</td>
<td>-0.142</td>
<td>-0.168</td>
<td>-0.034</td>
<td>0.187**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 GW</td>
<td>1.000</td>
<td>0.707</td>
<td>0.294</td>
<td>0.169</td>
<td>-0.284</td>
<td>0.375</td>
<td>-0.074</td>
<td>-0.102</td>
<td>0.175*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 INTAN</td>
<td>1.000</td>
<td>0.298</td>
<td>0.209</td>
<td>-0.202**</td>
<td>0.384**</td>
<td>0.118</td>
<td>-0.020</td>
<td>-0.018</td>
<td></td>
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</tr>
<tr>
<td>6 RD</td>
<td>1.000</td>
<td>0.437</td>
<td>0.215**</td>
<td>0.698**</td>
<td>0.497**</td>
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a. All variables have been transformed.
* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).
Step-by-step development of structural Equation model, and insignificant paths removed from the model (p = < .05).

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***$p<.001$
### TABLE 6
Regression Paths Between Observed Variables

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<th>Unstandardized Regression Weights</th>
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<th>P-value</th>
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<td>.00</td>
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<td>.01</td>
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<td>SCIENCS → ROA</td>
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<td>RESINT → ROA</td>
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*p<.05
**p<.01
*** p<.001
TABLE 7
Covariances and Correlations of Exogenous Variables and Residuals Associated with Endogenous Variables

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**p<.01
*** p<.001
TABLE 8
Standardized Direct, Indirect, and Total Effects of Path Model: Regression Coefficient Estimates

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FIGURE 1
Theoretical Framework and Hypotheses

Firm Innovation Characteristics \( \rightarrow \) Patenting Activity \( \rightarrow \) Financial Performance

Hypotheses:

- H1: Firm Innovation Characteristics \( \rightarrow \) Financial Performance
- H2: Firm Innovation Characteristics \( \rightarrow \) Patenting Activity
- H3: Patenting Activity \( \rightarrow \) Financial Performance
- H4: Firm Innovation Characteristics \( \rightarrow \) Patenting Activity (bidirectional relationship)
FIGURE 2
Theoretical Framework and Hypotheses with Operational Measures

Firm Innovation Characteristics

Performance

Intangibles
Goodwill
R&D

Financial

ROA
ROS
ROE

Patenting Activity

Technology Strength
Industry Impact
Patent Count
SCIENCE Strength
Research Intensity
Innovation Cycle Time

H1
H2
H3
H4
FIGURE 3a

Initial Model with All Regression Paths
This figure illustrates the correlations among the exogenous variables (goodwill, intangibles, and R&D), covariances among endogenous (patenting activity measures), and covariances among outcome variables (ROA, ROS, and ROE). Based on bivariate correlation results, three insignificant covariances were not included in the model (e.g., \( e_2 \leftrightarrow e_3 \), \( e_1 \leftrightarrow e_5 \), and \( e_3 \leftrightarrow e_5 \)). Other regression paths are not shown in the structural model to enhance the visual illustration of correlations/covariances additions to the model.
FIGURE 4
Initial Saturated Structural Model
FIGURE 5

Final Structural Model
FIGURE 6b

Final Model Correlations/Covariances

The figure shows the results of the correlations among the exogenous variables (goodwill, intangibles, and R&D), covariances among endogenous (patenting activity measures), and covariances among outcome variables (ROA, ROS, and ROE). In the final model, two insignificant covariance paths removed, e2 $\leftrightarrow$ e5 and e5 $\leftrightarrow$ e6. Other regression paths are not shown in the structural model to enhance the visual illustration of correlations/covariances results of the final model.
This figure shows the standardized test results of H1. Other paths, variables, and correlations/covariances are not shown for illustration purposes.
FIGURE 8
Test Results of H2

This figure shows the standardized test results of H2. Other paths, variables, and correlations/covariances are not shown for illustration purposes.
FIGURE 9

Test Results of H3

This figure shows the standardized test results of H3. Other paths, variables, and correlations/covariances are not shown for illustration purposes.
FIGURE 10

Test Results of H4

This figure shows the standardized test results of H4. Other paths, variables, and correlations/covariances are not shown for illustration purposes.
REFERENCES


