**The Impact of Absorptive Capacity on the Innovation Performance of
Pharmaceutical Firms**

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**A thesis submitted to the Faculty of Graduate Studies and
Research in partial fulfillment of the requirements for the degree
of Doctor of Philosophy in Management**

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Abstract

This thesis reviews the theoretical and empirical studies in the literature that cover various disciplines including innovation and technology management, strategic management, R&D management, and marketing management. The thesis develops a comprehensive framework that outlines the relationships among absorptive capacity, innovation performance, functional integration, and commercialization strategy that a pharmaceutical firm formulates to achieve the maximum benefits from its innovation. It also examines the importance of building higher levels of absorptive capacity to improve the innovation performance of the pharmaceutical firms.

Innovation performance is considered a multi-dimensional construct that consists of financial and non-financial criteria including sales revenue, customer criteria, opportunities criteria, and the number of new drugs that a pharmaceutical company introduces to market. This thesis measures absorptive capacity by the amount of R&D and sales, general, and administration (SGA) investments made by a company. The conceptual framework was tested on a dataset of 65 responses received from senior executives (CEOs, presidents, and vice-presidents of R&D, marketing, business development, and commercialization) of Canadian and U.S. pharmaceutical firms.

The linear and Poisson regression techniques were applied to analyze and investigate the association among variables in this thesis. In addition, this thesis tests the ways functional integration and commercialization strategy moderate the relationship between absorptive capacity and firm performance. The results show that both R&D and SGA investments have a positive and significant impact on the innovation

performance of pharmaceutical firms. Moreover, the findings of this research show that functional integration and commercialization strategy moderate the relationships among investments in R&D and SGA (i.e., absorptive capacity) and some of the dimensions of innovation performance.

This thesis significantly contributes to the theory and body of knowledge in the innovation and technology management discipline by synthesizing and extending the previous disparate studies and by developing and empirically testing a model for the relationship between absorptive capacity and firm performance.

Following a comprehensive literature review, the model in this study outlines the relationship between absorptive capacity as measured by investments in both R&D and SGA and firm's innovation performance. It also examines the moderating effects of functional integration and commercialization strategy on the relationship between absorptive capacity and four dimensions of firm performance. This thesis also contributes to the body of knowledge by identifying four types of commercialization strategy (i.e., in-house drug development strategy, developing complementary asset strategy, integration strategy and licensing strategy) that pharmaceutical companies can formulate to commercialize their innovative drugs.

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Ali R. Hassanlou

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Chapter 1: Introduction

1.1 Preamble

Technology is of critical importance in the growth of world economies. The 1987 Nobel Prize in Economic Science was awarded to Dr. Robert M. Solow for his contribution to the theory of capital and economic growth and for demonstrating that approximately 88 percent of the doubling in gross output per hour of work in the U.S. economy was due to technology (i.e., technical change) in the broadest sense (Solow, 1957). More recently, authors have even suggested that without technical advancements (i.e., innovation) there would be no economic growth at all (Usher, 1980).

The generation of wealth from technology is dependent on an initial discovery (i.e., invention), which is often fundamental in nature, followed by the commercial application of this discovery, a process often referred to as commercialization of technology. Considering the importance of technology in wealth creation, companies jealously guard technologies developed through in-house research, hoping to commercially exploit them. At the same time, other companies in the same industry or in other industries, depending on the type of technology, aggressively try to purchase or license-in technologies that have the potential to make their firms more productive and profitable. Purchasing technology and

obtaining exclusive or even non-exclusive access to it is often as useful as having a firm invent and commercialize its own technologies.

Recent increases in the number of strategic cooperative agreements (e.g., strategic alliances, mergers and acquisitions, and strategic take-over and partnerships) in all industries, especially in the pharmaceutical industry (Eisberg, 2009), and a management focus on improving the efficiency and effectiveness of a firm's innovation processes by formulating various strategies have been shown to have a positive impact on the firm's innovation performance. As an example of increase in a cooperative strategic agreement, consider the case of GlaxoSmithKline, which recently signed three strategic alliances and collaborations with Archemix, Dynavax Technologies, and Biotica Technology to outsource its research and development on anti-inflammatories (Eisberg, 2009). In another case, Wyeth Pharmaceuticals, a division of Wyeth, has acquired Thiakis, a privately held biotechnology company based in the U.K. (Company strategy, headlines, 2009).

The impact of the above factors on the innovation performance of pharmaceutical firms is highly significant because innovation has a double effect in the pharmaceutical industry. Innovation in this industry is important to both the health of people and the economic health of a company. Not only does innovation in this industry save lives and improve the quality of life worldwide, but it also has a significant impact on the growth and profitability of a company.

During the last 25 years, the pharmaceutical industry has become especially cognizant of the importance of innovation (i.e., invention and commercialization) on its performance. Some companies in this industry have chosen a strategy that enables them to bring a larger number of new drugs to the market. These companies invest heavily in in-house research to build internal knowledge in addition to searching for and licensing-in new external knowledge. They also invest heavily in sales and marketing to make their innovative products globally available. As a result of the strategy taken by these companies, they have been able to build a higher level of absorptive capacity – the identification, assimilation, transformation, and exploitation of all components of knowledge (Cohen and Levinthal, 1990). Many authors have suggested that this practice (i.e., building a higher level of absorptive capacity) improves the performance of organizations. In the pharmaceutical industry, it results in an increase in the number of new drugs that come to market; improves the quality of life; increases the profitability of the pharmaceutical companies involved in the discovery, development, and commercialization of new drugs; and, in general, brings significant growth to the industry and to the world economy.

While several companies in this industry in some industrialized nations – including Switzerland, France, and England – have benefited from the growth of the industry in the past due to higher levels of invention and commercialization of new drugs, many others have been unable to benefit from the growth of the industry. According to the “Pharmaceutical Industry Competitive Task Force” (2002 and 2005), a U.K.-based organization that analyzes the competitiveness of the U.K. pharmaceutical

industry and develops performance indicators for the industry activities across industrialized nations, the proportion of New Molecular Entities (NMEs)¹ first marketed by the Canadian pharmaceutical companies during 1993-2002 was at about 2 percent, compared to 11 percent for the U.K. and more than 40 percent for U.S. companies. According to Reichert and Windover (2002), the Canadian pharmaceutical industry had a trade deficit (imports exceeding exports) of \$4.7 billion in 2001, an increase of more than 160 percent from 1997. The degree of self-sufficiency in the pharmaceutical industry in Canada has dropped from 58 percent in 1996 to 42.5 percent in 1999 (Reichert and Windover, 2002). In terms of the pharmaceutical trade balance per capita, Canada ranked last in 2001 among OECD industrialized nations that have been involved in the discovery, development, and commercialization of new pharmaceutical products (OECD, 2003). Reichert and Windover (2002) argue that a lack of a large Canadian Multi-National Company (MNC) and the inability of the firms in this industry to commercialize their own inventions are the main reasons for the poor performance of the pharmaceutical industry in Canada.

The author's previous study (Hassanlou *et al.*, 2006) on the performance of pharmaceutical companies in Canada and comparing it with the performance of companies in the world provide similar results as the findings of the Pharmaceutical

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¹According to Olson (2002), "NMEs represent the newest, most innovative drug products. Their development and approval are deemed to have the greatest social benefits". Based on the Chandy and Tellis (1998) taxonomy and the Food and Drug Administration in the U.S., NMEs fall into two categories of radical innovation and technological breakthrough products.

Industry Competitive Task Force (2002). Hassanlou *et al.* (2006) investigated the flow of technical and business knowledge from the sources of discovery to the places of marketing of new molecular entities that received FDA approved during 1993-2002 and found that Canadian pharmaceutical performs better in the early stages of innovation (i.e., discovery) but is incapable of bringing its own invention to the market. Therefore, to be able to bring their discoveries to the market, the pharmaceutical companies in Canada either license out their discovery or partner with multi-national companies in other countries. The author's previous research on the performance of pharmaceutical industry was a motivating factor for this thesis in continuing the research in the same field to better understand the reasons for the poor performance of the pharmaceutical industry in Canada and to better contribute to the body of knowledge in the innovation and technology management literature.

The innovation process in the pharmaceutical industry encompasses the discovery, development, and commercialization of drugs. This process is a lengthy and costly undertaking. After an initial investigation of a disease and discovery of a compound that could be further developed to treat the disease, it takes an average of 12 years to develop and introduce the drug to the market (DiMasi, 2002; Lappin and Gardner, 2003). This time period includes all the steps that drug companies need to take from drug discovery to preclinical tests of the drug on animals; clinical tests on humans in phases I, II, and III; and the regulatory review and approval of the safety and efficacy of the drug. The process is very costly and extremely risky. Numerous studies in the past have attempted to calculate the average cost of a drug innovation.

Each study has come up with a different cost number, depending on the factors that researchers had considered in their cost calculation. A widely cited study conducted in 2001 by the Tufts Center for the Study of Drug Development determines the cost of developing a new drug at about \$800 million U.S. Using a different methodology and considering the commercialization cost of new drug development, a study conducted by the consulting firm Bain & Co calculates the cost of a drug innovation at about \$1.7 billion U.S. (Gilbert *et al.*, 2003). DiMasi *et al.* (2003) compared their own results to an earlier study with a similar methodology and found that the total capitalized costs have increased at an annual rate of 7.4 percent above general price inflation.

In such a high-risk environment, a pharmaceutical company is incapable of innovating efficiently without relying on many types of external sources of knowledge. Therefore, identification of the external sources of knowledge, assimilation of this knowledge, and the transformation and exploitation of it for commercial use, i.e., absorptive capacity (Cohen and Levinthal, 1990), has become an important factor in the innovation process of pharmaceutical companies.

Absorptive capacity and its effect on the success of innovation and performance of organizations have been widely studied in the past. Following Cohen and Levinthal (1990), many authors have contributed to the literature by either conceptually or empirically examining various factors that affect or are affected by absorptive capacity (Cohen and Levinthal, 1990; Zahra and George, 2000; Lane and Lubatkin,

1998; Newey and Shulman, 2004; Daghfous, 2004; Stock *et al.*, 2001; Lenox and King, 2004; Castellani and Zanfei, 2003; Grunfeld, 2003; Van den Bosch *et al.*, 1999; Narasimhan *et al.*, 2006). However, the literature on absorptive capacity is characterized by incomplete, contradictory, and ambiguous research findings due to failure to understand the construct. Central questions such as how to define and measure absorptive capacity have remained unresolved. In addition to the ambiguity in the literature, there is no evidence of empirical investigation to study the impact of absorptive capacity on the innovation performance of pharmaceutical companies with various drug innovation and commercialization strategies. This is indeed surprising since the commercialization environment, the microeconomic and strategic conditions facing a firm translating an “idea” into a valuable proposition for customers (Gans and Stern, 2003), innovation approaches (Andrew and Sirkin, 2003), and effective commercialization strategies (Gans and Stern, 2003) all have a great impact on the competitive dynamics and performance of organizations. Absorptive capacity makes a firm receptive to external knowledge and helps in invention and discovery of new drugs, but it does not guarantee that a firm can benefit from its inventions (Zahra and George, 2000). Pharmaceutical firms must take an effective commercialization strategy to successfully develop their discoveries and bring their products to market.

Recent literature on technology innovation puts more emphasis on commercialization. Tijssen (2004) states that “... corporate research is an ongoing

process of structural change characterized by a stronger emphasis on the appropriation and commercialization of in-house research results”.

In this thesis, the author considers the theories that are related to building higher levels of absorptive capacity. It is argued in the literature that higher levels of absorptive capacity increase a firm's competitive advantage relative to firms with lower levels of absorptive capacity. The arguments that lie behind this are based largely on intuitive reasoning and are articulated by Cohen and Levinthal (1990). While they focus on absorptive capacity in general and consider it in terms of accumulation and application of knowledge over the years in an organization, the author considers their arguments as they apply to the accumulation and transformation of knowledge in a pharmaceutical company.

First, Cohen and Levinthal (1990) argue that absorptive capacity is critical to the firm's innovative capabilities and that the level of new knowledge that could be absorbed by a firm is history and path-dependent and it is a function of firm's prior related knowledge. Therefore, one would expect that firms that have been in business for many years would have accumulated more knowledge and be capable of innovating more than the new firms. In this context, it is worth noting that according to Hassanlou *et al.* (2006) about 57 percent of the new drugs have been developed and marketed by smaller pharmaceutical companies during 1993-2002.

Second, Cohen and Levinthal (1990) state that absorptive capacity is linked to organizational learning, and it is important in the commercial application of external

knowledge. The Lane and Lubatkin (1998) study confirms this statement, as the authors refer to a shift from traditional resource-based and risk-sharing alliances to learning alliances and develop a model of how inter-organizational learning alliances should be structured and managed.

Third, central questions such as how to define and measure absorptive capacity have remained unresolved. Zahra and George (2000) reviewed the literature on absorptive capacity and re-conceptualized the construct by introducing “Potential” and “Realized” absorptive capacity. In their study, potential absorptive capacity encompasses the first two dimensions of the construct (i.e., identification and assimilation of new knowledge) and realized absorptive capacity includes the other two dimensions (i.e., transformation and exploitation of knowledge). The authors argue that potential absorptive capacity makes a firm receptive to external knowledge but does not necessarily contribute to the bottom line and profitability of the firm. Realized absorptive capacity, on the other hand, helps the firm in its efforts in exploiting the new knowledge and applying it for commercial use. According to Zahra and George (2000), it is realized absorptive capacity that is positively related to future value creation of the firm which affects the firm’s performance and, therefore, more resources should be devoted in improving it to be able to successfully leverage the knowledge that has previously been captured.

Investments in R&D and sales, general, and administration (SGA) affect absorptive capacity and innovation performance of pharmaceutical firms (Lin *et al.*, 2006;

Narasimhan *et al.*, 2006). Improving the efficiency and effectiveness of R&D activities through internal business process improvements, such as integrating the functional units of a firm, will enable pharmaceutical companies to increase the number of new drug discoveries. Formulating an effective commercialization strategy by pharmaceutical firms ensures that R&D will be transformed into a safe and effective marketable drug that becomes globally available to patients, which affects a firm's innovation performance. Absorptive capacity, functional integration, and commercialization strategies taken by small and large pharmaceutical firms influence the success of innovation, and it is, therefore, important to investigate the effects of these variables on the innovation performance of pharmaceutical firms.

1.2 Objectives of the Study

Despite the vast theoretical and empirical studies investigating the impact of absorptive capacity on firm performance, there is no systematic empirical evidence that confirms that absorptive capacity improves the innovation performance of pharmaceutical firms. As will be presented in the literature review of this study, there is conflicting opinion in the literature on what factors should be measured to investigate this relationship. Therefore, the question under investigation in this research is: how important is absorptive capacity in the performance of pharmaceutical firms? What are the factors that pharmaceutical firms should consider to achieve the benefits of building absorptive capacity? Does R&D expenditure improve a firm's innovation performance, is it the expenditure on SGA

that is more important in improving performance, or are both necessary to improve performance? What factors moderate the relationship between absorptive capacity and a firm's innovation performance?

The purpose of this study is twofold. The main objective of the study is to develop a framework and empirically test the impact of absorptive capacity on the innovation performance of pharmaceutical firms. Specifically, the study examines the relationship between investments in R&D and SGA with various dimensions of innovation performance (i.e., financial criteria, customer criteria, opportunity criteria, and the number of new drugs introduced to the market) in the pharmaceutical firms. The second objective of the study is to investigate the moderating effect of integrating functional units of a pharmaceutical firm and formulating various commercialization strategies on the relationship between absorptive capacity and innovation performance.

The thesis contributes conceptually and empirically to the literature in a number of ways. First, it synthesizes and extends the previous theoretical and empirical studies in the literature. It develops a comprehensive framework to investigate the importance of building absorptive capacity by investing in both R&D and SGA to identify, assimilate, transform, and exploit knowledge. Second, the study considers innovation performance in the pharmaceutical industry as a multi-dimensional construct. Following an extensive literature review on firm performance, this study identified four dimensions (i.e., financial, customer, opportunity, and number of new

drugs) to measure the innovation performance of pharmaceutical firms. Third, it explores commercialization strategies that pharmaceutical firms can formulate to develop and bring new drugs to the market. Fourth, the study examines the indirect impact of integrating functional units of a firm on its innovation performance. Finally, the study contributes to the literature by empirically testing the relationship between dependent (i.e., innovation performance), independent (i.e., absorptive capacity), and moderating variables (i.e., commercialization strategy and functional integration) that are identified through a comprehensive literature review.

In addition, previous research has conflicting results about the effect of firm size on the firm's innovation performance. This study also considers the size of the firm (i.e., number of employees) as a control variable and investigates its effect on the performance to determine whether larger firms innovate more than do smaller firms.

1.3 Outline of the study

The structure of this thesis is as follows. Chapter 2 explains the innovation process in the pharmaceutical industry. Chapter 3 reviews the literature on four topics, which include absorptive capacity, innovation performance, commercialization strategy, and functional integration to understand variables that need to be considered in developing a theoretical framework for this research. It also identifies any deficiency or gap in the literature. Based on the review of the literature, a theoretical framework is developed in Chapter 4. This chapter also explains the relationship between

variables and develops four sets of hypotheses to be tested in this study. Chapter 5 explains the methodology that has been applied to investigate, explore, analyze, and understand the relationship between variables in the study. This chapter also explains the statistical techniques (i.e., simple, multiple, and Poisson regression) that the author applied to test the hypotheses developed in this thesis. Chapter 6 provides descriptive statistics on some key variables of the research. It highlights and tests some of the differences between U.S. and Canadian pharmaceutical companies. Data preparation techniques used to prepare the data for statistical tests are explained in Chapter 7. This chapter covers the techniques that were used to analyze missing values and screen outliers and extreme points in the data. The thesis then briefly explains regression techniques and assumptions underlying each technique in this chapter. Non-response bias, tests of reliability of the constructs, factor analysis to reduce the number of items in each construct and hypotheses tests are also covered in Chapter 7. Chapter 8 provides the results of the study. A discussion of important findings of the research is presented in this chapter. Chapter 9 concludes the thesis and provides information on research limitation and future research directions.

Chapter 2- Innovation Process in the Pharmaceutical Industry

The innovation process in the pharmaceutical industry begins with research by scientists in the university, industry, and government laboratories using various drug discovery techniques including drug design, high throughput synthesis, target screening, genetic approaches to drug discovery, computer-assisted drug discovery techniques (Spilker, 1989), and recent advances in functional Genomics, Proteomics, Micro arrays, High-through-put screening, and Combinatorial Chemistry CDNA libraries (Smarta, 2003) to identify a compound that could be further developed to treat a disease. The pharmaceutical industry, government, and universities spend billions of dollars² every year to fund basic scientific research with the hope that their spending in scientific research would result in discovering new drugs. After the successful discovery of a compound, depending on the business strategy of the discovering entity (e.g., scientists in the universities and industry) and the type of compound, the inventors might decide to apply for a patent to protect their intellectual property right and their discoveries³. The compound then passes through a number of stages in the innovation process (e.g., testing the compound on animals and humans and applying for marketing approval with the regulatory agencies) to become a marketable drug. The process ends with a marketing authorization issued by government regulatory agencies that allows the drug to enter into the market and

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² OECD- R&D investment in the world

³ Patent law incorporates limits as to what is patentable. For example, elements of the human body in their natural state cannot be patented, as cannot natural compounds extracted and purified from plants. In addition, some firms or inventors may choose not to patent their discoveries for various strategic or financial reasons.

become available to patients, physicians, and pharmacists. Figure 1 summarizes the stages that drug developers need to take to bring a new drug to market.

Figure 1: Drug Innovation Process

Drug development is a very complex process and involves thousands of various activities at different stages of development. Research and development productivity in the pharmaceutical industry is very uncertain (LaFrancis *et al.*, 1994) and drug attrition rate from one stage to another is usually high (Spilker, 1989). According to Spilker (1989), out of 10,000 synthesized compounds in the U.S. only 10 reach the stage of human testing. In Japan, 7,000 compounds are investigated to develop one promising drug (Yoshikawa, 1989), and the estimate for Europe ranges as high as 10,000 to one. Such a high attrition rate poses a high financial risk for drug companies. However, after discovering a compound, the average drug development success rate (i.e., from the first test on human to registration) is dependent on the

therapeutic area and is approximated to be at about 11 percent for all therapeutic areas (Kola and Landis, 2004).

To increase the chances of success, drug companies usually collaborate with each other in developing drugs in various therapeutic areas. They also work and cooperate with the regulatory agencies in providing all the necessary documents to evaluate the safety and efficacy of drugs and in reducing the drug review process time. In the U.S., for example, early in the drug development process, the drug company files a New Drug Application (NDA) with the FDA and provides technical and statistical information to be used by the FDA's drug evaluators to evaluate the safety and efficacy of the developed drug. Table 1 illustrates the FDA classification system used to classify and review NDAs.

Table 1: FDA classification of NDAs

Priority Review	Standard Review	Chemical Type
Significant improvement compared to marketed products in the treatment, diagnosis, or prevention of a disease.	The drug appears to have therapeutic qualities similar to those of one or more already marketed drugs.	1 – New molecular entity 2 – New ester, new salt, or other noncovalent derivative 3 – New formulation 4 – New combination 5 – New manufacturer 6 – New indication (beginning in 1994, type 6's were tracked as efficacy supplements, not as NDAs.) 7 – Drug already marketed but without an approved NDA

Source: Food and Drug Administration, U.S., 2003

The FDA classifies NDAs based on their therapeutic potential and chemical type. There are two types of therapeutic potential for a drug. "Priority Review" represents a significant therapeutically improved drug as compared to marketed products in the

treatment, diagnosis, or prevention of a disease. “Standard Review” represents drugs that have therapeutic qualities similar to those of one or more drugs already on the market. In this classification, the chemical type has seven classes. The first class of the chemical type is the NME, which is defined by the FDA as drugs that have never been marketed in the U.S.

Chandy and Tellis (1998) reviewed the literature on radical product innovation and proposed a taxonomy that distinguishes between four types of innovation; depending on the extent to which a new product incorporates new technology and the extent to which it satisfies customer needs (Table 2). The authors define radical product innovation as the propensity of a firm to introduce new products that incorporate substantially different technology from existing products and can fulfill customer needs better than the existing products. According to the proposed taxonomy by Chandy and Tallis (1998) and the FDA classification of NDAs, only the first class of chemical type in the FDA classification (i.e., New Molecular Entity) is considered radical product innovation. Olson (2002) states: “NMEs represent the newest, most innovative drug products. Their development and approval are deemed to have the greatest social benefits.” Many drugs in this class become blockbusters, defined as drugs with more than one billion dollars annual sales revenue (e.g., Vioxx and Singulaire). The other classes of chemical type in the FDA classification are considered as incremental innovation.

Table 2: Types of Product Innovations

Newness of Technology		Customer Need Fulfillment	
		Low	High
	Low	Incremental Innovation	Market Breakthrough
	High	Technological Breakthrough	Radical Innovation

Source: Chandy and Tallis (1998)

The sensitive nature of drug products and the high cost of R&D and commercialization of drugs in the pharmaceutical industry have led to numerous regulations by governments in all countries to protect the public and to ensure the availability, safety, and efficacy of drug products (LaFrancis *et al.*, 1994). The industry is highly regulated and governments across the world have policies in place to ensure that the most effective drugs will be available to physicians and patients at an affordable price. These policies relate to the health care system, price review, inclusion or exclusion of drugs in their insurance systems, R&D incentives, intellectual property right and patent protection, compulsory licensing, generic drug production, pre-clinical and clinical tests, good manufacturing practices, restrictions to direct consumer advertising, labeling, and packaging. These regulations, which are intended to protect consumers from malpractices or mistakes conducted by some firms in the industry, increase the cost and time of introducing new drugs to the market.

The risk associated with an increase in cost and time of drug innovation has forced pharmaceutical companies to search for new ways of doing business in conducting research, improving business processes, and commercializing the drug products. To be more productive in R&D, pharmaceutical firms build absorptive capacity not only through investing in in-house research but also by searching the world for sources of new related knowledge. For example, GlaxoSmithKline has recently signed strategic collaboration agreements with Archemix, Dynavax Technologies, and Biotica Technology to develop an anti-inflammatory drug. They also try to reach a larger market for their new products by following a commercialization strategy (e.g., marketing cooperative agreement) that brings them more revenue and gives them competitive advantage (e.g., QLT Inc. and Novartis for developing and marketing Visudyne).

In the next section of the thesis, a comprehensive review of the literature is presented to highlight the factors that affect the creation and application of knowledge (i.e., absorptive capacity), innovation performance, commercialization strategy, and functional integration in pharmaceutical firms. The study continues with developing a framework to investigate direct and indirect relationships between variables in this research.

Chapter 3: Literature Review

An extensive review of the literature on absorptive capacity, innovation performance, commercialization strategy, and functional integration is presented in this chapter. Many researchers have studied the factors that contribute to and affect the success of innovation in different industries. Some of the main factors that influence innovation and have been reviewed include R&D spending and the position of the firm in the industry (Tsai, 2001); the impact of absorptive capacity on a firm's profitability (Narasimhan *et al.*, 2006); knowledge bases and knowledge processing similarities (Lane and Lubatkin, 1998); commercialization strategies (Gans and Stern, 2003); and internal and external human resources, technological capabilities, and formal and informal integration (Zahra and Nielsen, 2002). Other essential factors reviewed are SGA expenses (Lin *et al.*, 2006); the impact of marketing, sales, and operations capabilities on high-technology firm performance (Dutta *et al.*, 1999); characteristics of the product and organizational work (Brown and Eisenhardt, 1995); and knowledge stock (Lin *et al.*, 2006). Based on this critical review of the literature and identifying factors that influence performance, the last section of this chapter identifies and presents a number of gaps in the literature.

3.1 Absorptive Capacity

Cohen and Levinthal (1990) were the first to introduce the absorptive capacity construct in the literature. They defined absorptive capacity as the ability of a firm to identify the value of external knowledge, assimilate and apply it to commercial ends. The authors argue that absorptive capacity is critical to the firm's innovative capabilities and that the level of new knowledge that could be absorbed by a firm is history and path dependent; and it is a function of a firm's prior related knowledge. They state that absorptive capacity is linked to organizational learning, and it is important in the commercial application of external knowledge. Following their pioneering research, many authors have contributed to the literature by studying the factors that determine or affect absorptive capacity at the firm and industry level, and they have tried to find an association between absorptive capacity and innovation performance. Narasimhan *et al.* (2006), for example suggested that marketing, R&D, and operations capabilities have a significant impact on a firm's absorptive capacity. Van den Bosch *et al.* (1999), on the other hand, suggested that the organizational form (i.e., functional, divisional, or matrix form) and combinative capabilities (i.e., system, coordination, and socialization capabilities) should be considered as determinants of absorptive capacity; further, these factors affect the level of new knowledge that could be identified, assimilated, and applied for commercial use. Daghfous (2004) categorized factors that affect absorptive capacity in two broad categories: internal and external factors. Internal factors include organizational

structure, size, strategy, prior knowledge base, and organizational responsiveness while external factors encompass the firm's position in the knowledge network.

Zahra and George (2000) reviewed the literature on absorptive capacity and re-conceptualized the construct by introducing "Potential" and "Realized" absorptive capacity. In their study, potential absorptive capacity encompasses the first two dimensions of the absorptive capacity construct (i.e., identification and assimilation of new knowledge) and realized absorptive capacity includes the last two dimensions (i.e., transformation and exploitation of knowledge). The authors argue that potential absorptive capacity makes the firm receptive to external knowledge but does not necessarily contribute to the bottom line and profitability of the firm. Realized absorptive capacity, on the other hand, helps the firm in its efforts to exploit the new knowledge and apply it for commercial use. According to Zahra and George (2000), it is realized absorptive capacity that is positively related to future value creation of the firm and affects the firm's performance; therefore, more resources should be devoted toward improving it to be able to successfully leverage the knowledge that has previously been captured.

Absorptive capacity has an impact on new product development (NPD) performance. Kamien and Schwartz (1982), who studied market structure and innovation, observed a strong correlation between innovation output and innovational efforts such as R&D intensity. Stock *et al.* (2001) empirically tested the relationship between absorptive capacity and NPD performance on 24-year data in the computer

modem industry, and they were able to fit a quadratic function (i.e., an inverted parabola) to their data. The authors concluded that NPD performance, measured by the yearly average transmission rate of newly introduced modem products, improves as the absorptive capacity of firms, measured by the intensity of a firm's R&D expenditure, increases. However, because of the inverted parabola shape of the curve, the increase in performance is only true up to a certain point; beyond that point any increase in R&D expenditure or absorptive capacity makes the performance worse.

Building a higher level of absorptive capacity would improve the NPD performance of firms by giving them the ability to identify and locate outside sources of knowledge more easily. Tsai (2001) suggested that firms will have a better understanding of their external environment and will perform better in capturing and harnessing the new knowledge if they have a higher level of absorptive capacity. Chen (2004) provides a similar suggestion.

In measuring absorptive capacity at the firm level, many authors have used traditional measures such as R&D intensity (i.e., the amount of R&D spending divided by sales) in their empirical studies to investigate the association between variables in their models. Stock *et al.* (2001) for example, state "...prior research has shown an empirical relationship between R&D intensity and learning, which provides evidence that R&D intensity can be thought of as an observable manifestation of the more general construct of absorptive capacity". In addition,

Allen (1997) supports using this measure to operationalize absorptive capacity and states that a major reason for firms to invest in R&D is to be able to acquire and use external scientific and technical information.

Other authors have criticized using such measures in operationalizing absorptive capacity. Zahra and George (2000), for example, criticized using this measure and argued that R&D spending does not reflect expenditure on all dimensions of identification, assimilation, transformation, and exploitation of knowledge. Minbaeva *et al.* (2003) state: “the literature offers multiple methods to conceptualize and operationalize absorptive capacity, often not capturing the various facets of absorptive capacity”. Lane and Lubatkin (1998), who re-conceptualized absorptive capacity and called it “Relative Absorptive Capacity” as a dyad-level construct (i.e., student-teacher), tested the traditional measure of R&D intensity against their relative measures and found that their measure has greater explanatory power than the traditional measures.

SGA expenditure consists of advertising expenses and the payroll costs of salaries, commissions, and travel expenses of executives and sales people employees. This expenditure is necessary in exploiting the new product and in bringing it to market and therefore, it does make sense to include it as a measure of absorptive capacity.

In addition to researcher disagreement on how to measure the construct, the literature is also mixed about applying a cause-and-effect relationship (i.e., causal study) or a correlational relationship (i.e., correlational study) between absorptive capacity and a

firm's innovation performance. While some authors, including Tsai (2001) and Stock *et al.* (2001), apply a cause-and-effect relationship to investigate the association between R&D investments and firm performance, others (Cohen and Levinthal, 1989 and 1990) use a correlational relationship between variables.

A critical review of empirical research articles that are relevant to this thesis have been conducted to help in understanding various factors that affect absorptive capacity. Specifically, this thesis reviews studies conducted by Tsai (2001), Stock *et al.* (2001), and Lane and Lubatkin (1998) to understand the theoretical framework; dependent, independent, moderating and control variables; sources of primary and secondary data; statistical analysis techniques; and the conclusion achieved in each study.

Tsai's (2001) study of knowledge transfer in inter-organizational networks investigated the effects of network position and absorptive capacity on the business unit innovation and performance. The author argued that business units in an organization produce more innovation and perform better if two conditions apply: 1) they spend more on R&D and 2) they are positioned at the center of a network that has more access to new knowledge developed by other units. The author collected data from two multinational companies (MNCs) – a pharmaceutical company that has 24 business units with total annual revenue of \$10.7 billion U.S. and a food manufacturing company with 36 business units with annual revenue of \$4.1 billion U.S. to investigate the relationship between variables in the study. Each unit within

the MNCs was responsible for developing, manufacturing, and selling its products. Tsai (2001) sent a questionnaire to the director and deputy director of each business unit within the two companies and, because the MNC's top management supported the study, he received 120 responses from the two companies, a 100-percent response rate. Following Cohen and Levinthal (1990) and Stock *et al.* (2001), R&D intensity was used to measure absorptive capacity. Network centrality was measured through a survey. Dependent variables (i.e., number of new products developed and business profitability) were measured through company records. The author also used unit size (i.e., number of employees and unit sales), local competition, and past innovation as control variables. Figure 2 depicts Tsai's framework in this study.

Figure 2: Effects of Network Positions and Absorptive Capacity on Business Unit Innovation and Performance Framework

To explore the relationship between variables in this study, Tsai (2001) used hierarchical regression analysis and found that absorptive capacity is significant and positively associated with business innovation and performance ($\beta = 4.09$, $p < 0.01$ and $\beta = 1.24$, $p < 0.05$, respectively). The interaction between absorptive capacity and network centrality was also positive and significant. The result of this study suggests that absorptive capacity is positively related to innovation and business performance, which means that business units perform better when they build a higher level of absorptive capacity through R&D spending. Tsai's study is both relevant and useful to this thesis as it provides empirical evidence of the relationship between absorptive capacity and a firm's innovation performance.

Stock *et al.* (2001) investigated the relationship between absorptive capacity, measured by R&D intensity of a firm, and new product development performance in the telephone modem industry over the period of 1970-1993. The dependent variable in their study, measured by new product development performance, was based on the technical performance of the modems introduced in the market during the above time period. The authors used two sets of data (i.e., yearly modem industry overview report from DataPro Research and Standard and Poor's Compustat Database) to obtain secondary information about the technical performance, firm size, and R&D spending. The authors had to limit their study to publicly traded firms in the computer industry and, as a result, their study included 131 observations.

To analyze the relationship between variables, the authors used regression analysis and found that new product development performance is positively correlated with R&D intensity ($r = 0.2027$), not high in magnitude but significant. They also used firm size, measured by the number of employees, and a trend variable (i.e., year of introduction) as control variables. The results of this study show a negative correlation between the dependent variable and the firm size ($R = -0.2709$). However, there is a strong positive correlation between the trend control variable and the new product development performance. This strong positive correlation supports the positive trend in the computer and communication products over the past two decades. Figure 3 illustrates the conceptual framework in Stock *et al.* (2001) study.

Figure 3: Absorptive Capacity and New Product Development Framework

The Stock *et al.* (2001) study is useful and relevant in developing a framework for this thesis, as the authors empirically tested and identified a positive relationship

between absorptive capacity and organizational performance. In addition, the process of obtaining secondary data in their study provides some guidelines for this thesis.

Lane and Lubatkin (1998) developed and tested a model of inter-organizational learning by shifting the unit of analysis from the firm level to the student-teacher analysis, a learning-dyad pair, as relative absorptive capacity. The authors argued that the ability of a firm to learn from another firm is determined by the relative characteristics of the student and teacher firms. The authors proposed that a student firm's ability to value, assimilate, and apply new knowledge from the teacher firm is dependent upon the type of knowledge offered by the teacher firm, similarities between organizational structure and compensation practices of both firms, and the student firm's knowledge of the teacher firm's organizational problems.

The authors refer to a shift from traditional resource-based and risk-sharing alliances to learning alliances and state that: "... capability development places a premium on a firm's ability to identify, assimilate, and utilize partner's knowledge". They developed a model of how inter-organizational learning alliances should be structured and managed. The dependent variable in their study, inter-organizational learning in the pharmaceutical and biotechnology firms, was measured using a 5-point scale developed in consultation with experts in evaluating alliances formed between pharmaceutical and biotechnology firms. The independent variables, knowledge bases, problem similarities and knowledge processing similarities were measured using CRP proprietary database and experts' opinions. The study includes

four control variables: a pharmaceutical firm's average R&D spending; the relevance of biochemical knowledge and the number of shared research communities; the interaction and relevance of non-biochemical knowledge and the number of shared research communities; and both forms of knowledge relevance (biochemical and non-biochemical). Figure 4 depicts the conceptual framework in the Lane and Lubatkin (1998) study.

Figure 4: Inter-organizational Learning Alliance Framework

Data for this study was collected from two primary sources: a panel of six experts to evaluate the performance of 69 alliances that were formed during 1985-1993 and a

two-page survey instrument that was sent to top human resources executives to capture data on organizational structure and compensation practices.

Multiple regression analysis was used to statistically analyze and investigate the relationships between variables. Three models that include R&D spending, eight relative absorptive capacity variables, and three interaction terms were tested and all found to be highly significant. The result of this study suggests that R&D spending alone has a weak association with inter-organizational learning ($p < 0.10$). Out of the three classes of independent variables (i.e., valuing new knowledge, assimilating new knowledge, and commercializing new knowledge), the highest β value relates to commercializing new knowledge ($\beta = 0.83$, $p < 0.01$), which signifies the importance of considering this factor as a determinant of success in organizational learning and the performance of firms.

The Lane and Lubatkin (1998) study is relevant and useful to this thesis in at least three different ways. First, the study focuses on the pharmaceutical and biotechnology industry and identifies some important factors that need to be considered in this industry to develop a framework for this thesis. Second, this study differs from other studies that used R&D intensity as a proxy to measure absorptive capacity (Cohen and Levinthal, 1990; Stock *et al.*, 2001; Tsai, 2001; Lin *et al.*, 2006; Allen, 1997) to investigate the relationship between variables and organizational performance; this study, however, collects data through survey and expert opinion as a way to measure the three components of absorptive capacity (identification,

assimilation, and commercialization). Third, the result of this study suggests that commercialization of new knowledge is very important and needs to be considered in the study of the pharmaceutical industry.

In addition to the above studies, Narasimhan *et al.* (2006) investigated the determinants of absorptive capacity and found that R&D and marketing expenditure positively affect absorptive capacity ($b = 0.2649, p < 0.01$ and $b = 0.4185, p < 0.01$). In addition, the authors found that a firm's prior technological stock has a strong impact on its absorptive capacity ($b = .637, p < .01$). Table 3 summarizes three important empirical studies in the literature on the relationship between absorptive capacity and firm performance that are relevant to this thesis.

Table 3: Summary of the literature review articles on Absorptive Capacity

Author	Framework	Sample size, data collection, and statistical analysis	Variable	Industry of study
Tsai (2001)	Effects of absorptive capacity and network centrality of innovation and performance	2 MNCs, 120 observations, survey, publicly available information and company records Hierarchical regression analysis	DV ¹ : innovation and performance INDV ² : absorptive capacity and network position CV ³ : unit size, local competition, and past innovation	Pharmaceutical and food manufacturing MNCs
Stock <i>et al.</i> (2001)	Effects of absorptive capacity on new product technical performance	131 observations from publicly traded firms, secondary data Regression Analysis	DV: technical performance of modems introduced during 1970-1993 INDV: absorptive capacity measured by R&D intensity CV: firm size and trend	Computer modem industry
Lane and Lubatkin (1998)	Effects of knowledge bases and knowledge problem similarities on inter-organizational learning	69 alliances that were formed during 1985-1993; Primary and secondary sources; Multiple regression analysis	DV: inter-organizational learning INDV: knowledge bases and problem similarities CV: average R&D spending; the relevance of biochemical knowledge and the number of shared research communities	Pharmaceutical and Biotechnology industry

1 Dependent Variable   2 Independent Variable   3 Control Variable

3.2 Innovation Performance

The pharmaceutical industry is a scientific, technology-based industry, which is both highly patient-physician oriented (Smarta, 2003) and very competitive. Innovation is the life-blood of the industry (Gambardella, 1995; Scherer, 2000; Chressanthis, 2008) and millions of patients worldwide rely on the new products developed by the industry to treat various diseases, alleviate their health problems, and improve their quality of life. Firms in this industry spend billions of dollars every year on research and development with the hope of bringing new drugs to the market that will not only satisfy patient-physician needs but also improve firm profitability and market share.

The literature is loaded with research investigating firm performance in different industries. A large number of studies – including Day and Fahey (1988); Griffin and Page (1993); Srivastava, *et al.* (1999); Narver and Slater, (1990); Matsuno *et al.* (2002); Hurley and Hult, (1998); Sorescu *et al.* (2003); Oltra and Flor, (2003); Collins and Smith, (2006); Graves and Langowitz, (1993); Nesta and Saviotti, (2005); Alam, (2003); Storey and Easingwood, (1999); Storey and Kelly, (2001); and Storey and Easingwood, (1996) – have investigated the link between performance and various variables in their empirical studies. However, the literature is mixed on the type of variables that should be considered in measuring performance. Some authors – including Day and Fahey (1988) and Srivastava, *et al.* (1999) – call for adopting performance measures such as stock market indicators that

can be directly related to shareholder value. Dutta *et al.* (1999) measured the profitability of firms in investigating the impact of R&D, marketing, and operation capability on firm performance. Griffin and Page (1993) suggest that firms use multiple constructs to measure the performance of their innovation. Many researchers including de Brentani (1989), Cooper *et al.* (1994), Storey and Eisingwood, (1996), and Edgett and Snow (1996) used financial measures of performance and considered factors such as enhanced profitability, sales growth, increased market share, reduced operating cost, and increased return on investment.

Recent literature on performance suggests measuring non-financial factors such as customer satisfaction, increased number of new customers, fewer customer complaints, opening new markets, and increased customer loyalty. For example, Edgett and Snow (1996) proposed measuring three dimensions – customer satisfaction, service quality, and new service performance. They suggested that a quantitative analysis of unit sales and profitability present only part of the success equation.

More recent literature suggests using both financial and non-financial factors to measure innovation performance. Storey and Kelly (2001) proposed three dimensions of performance – financial measures, customer measures and internal measures. Similarly, Alam (2003) developed three performance dimensions (i.e., financial criteria, customer criteria, and opportunities criteria) to determine the success of new products. The first dimension in his model includes financial

indicators such as sales, cost, profitability, market share, and return on investment. The second dimension includes measures of customer satisfaction (e.g., whether a new product attracts new customers or opens up new markets). Finally, the third criterion, which is much broader in scope, provides information about the opportunities that new products may bring to a firm (e.g., a new product may improve the profitability of other products, a new product provides a platform for other new products, and a firm gains experience and skills in NPD projects). Table 4 refers to a number of studies that provide information about recent advancements in developing new product performance dimensions by introducing financial, customer, and opportunities criteria.

Table 4: New Product Performance Dimensions

Performance Dimensions	Measures	Studies
Financial criteria	Enhanced profitability Sales growth against objective Increased market share Reduced operating cost Increased return on investment	de Brentani (1989) Cooper <i>et al.</i> (1994) Edgett & Snow (1996) Storey & Easingwood (1996) Storey & Kelly (2001)
Customer criteria	Customer satisfaction with new products Increase in the number of new customers Opening up new market Increase customer loyalty Enhanced image with the customers Fewer customer complaints	de Brentani (1989) Cooper <i>et al.</i> (1994) Edgett & Snow (1996) Storey & Easingwood (1999) Storey & Kelly (2001)
Opportunities criteria	Improved profitability of other products Provided a platform for other new products Improved NPD capabilities	Cooper <i>et al.</i> (1994) Easingwood & Percival (1990) Storey & Easingwood (1996 and 1999)

Source: Alam (2003)

Measuring the performance of innovation in the pharmaceutical industry is different from other industries for at least two main reasons.

First, the time lag between the start of a research project to find a new compound and the development of the compound to a drug and its introduction to market is very long. According to DiMasi (2002) the development time for a representative drug spans approximately 12 years from the time that a compound is discovered to the time that a drug is introduced to the market. Graves and Langowitz (1993) investigated the relationship between R&D expenditure, innovative productivity of developing New Chemical Entities (NCEs), and pharmaceutical firm size. They developed and tested a number of models and found that a six-year average R&D expenditure, R&D spending squared, and R&D spending cubed is the best fit for the data. The authors also compared this model with a model developed using average R&D spent over three years prior to NCE introduction and found identical result in both models in terms of both sign and significance.

Second, unlike many other industries in which the amount of demand by consumers can be used to measure the success of innovation, the demand and consumption of drugs in the pharmaceutical industry are decided in many cases by physicians and not the patients.

The pharmaceutical industry literature suggests measuring the innovation performance by considering both financial and non-financial measures. Financial measures to be considered include the number of drugs introduced to the market in a

specific time period, the number of patents issued for each drug, the number of patents that a company holds, new drug annual sales compared to total annual sales, sales and market share, return on investment, and profitability. Important non-financial measures to be considered include patient-physician satisfaction indicators.

An extensive review of empirical research articles relevant to this research and specific to the pharmaceutical industry has been conducted to understand various factors that researchers consider in measuring the performance of firms in this industry. Specifically, this thesis reviews the theoretical frameworks, variables considered, measurement of variables, methodology, data collection, statistical techniques used to analyze the relationship between variables, and the result of the analysis of studies conducted by Sorescu *et al.* (2003), Graves and Langowitz (1993), and Collins and Smith (2006).

Sorescu *et al.* (2003) investigated the financial consequences of radical innovation in the pharmaceutical industry and tried to answer the following questions in their paper:

- *Who introduces a greater number of innovations: dominant or non-dominant firms?*
- *How great are the financial rewards to radical innovations and how do these vary across dominant and non-dominant firms?*
- *Is it only the firm's resources in the aggregate or also its focus and leverage of resources that makes its innovations more financially valuable?*

- *Which are more valuable: innovations that incorporate a breakthrough technology or innovations that provide a substantial increase in customer benefits?*

The authors referred to the innovation classification taxonomy that was developed by Chandy and Tellis (1998) and the FDA classification to classify new drugs. Based on the taxonomy developed by Chandy and Tellis (1998), a new drug falls into one of the four classes of radical innovation, technology breakthrough, marketing breakthrough, and incremental innovation depending on the extent to which a new product incorporates new technology and the extent to which it satisfies customer needs. The authors used the first three classes of innovation as independent variables and the last class of innovation as a control variable. The new drugs were measured by counting the number of innovations in each category during 1991-2000. The dependent variable in this study is dominance, which is defined as the level of market power a firm wields. It incorporates three dimensions of market share, assets, and profits. Market share reflects the revenue of the firm and was measured as the amount of sales of the firms' products; assets reflect all tangible and intangible resources that a firm possesses; and profits reflect all financial resources that a firm gains from its activities. The authors used principal factor analysis to generate a common factor that captures information from all three components of dominance and operationalized dominance as the factor score associated with the factor obtained from the principal factor analysis. The focus of the Sorescu *et al.* (2003) study is innovation in the pharmaceutical industry; their sample is based on a census of

innovations from 1991-2000 that was obtained from the NDA pipeline, which is a database of drugs tracked from discovery through preclinical and clinical trial phases to approval by the FDA. The sample includes 255 new drug breakthroughs that have been introduced by 66 publicly traded firms, which have their headquarters in the U.S., the U.K., France, Belgium, Switzerland, Germany, and Japan. Data to measure different variables in the study is secondary, and it was obtained from 17 different databases including Compustat, NDA Pipeline, U.S. Patent Office, National Drug Code Directory, Thomson Datastream, and the FDA database.

Sorescu *et al.* (2003) used a two-step statistical analysis to test five hypotheses in their study. To investigate who introduces more radical innovation (e.g., the relationship between the type of innovation and dominance and the effect of the relationship on the value for the firm) a Poisson model was used. The authors state that because one of the variables in their study (i.e., the number of innovations) is a count data, ordinary least square techniques is inappropriate; further, because the data is spread over 10 years, it forms a time-series, cross-sectional panel that makes the Poisson model an appropriate method to find the relationships. Regression analysis was used to test the other four hypotheses. Figure 5 represents the theoretical framework for this research.

Figure 5: Sources and Financial Consequences of Radical Innovation Framework

The result of the study suggests that dominant firms introduced more than twice as many radical innovations and breakthroughs than did non-dominant firms. The greatest difference arises for technological breakthroughs, which suggests the effects of economies of scale in R&D for dominant firms. The result also suggests that dominant firms gain more from radical innovation. Product, technology, marketing support, and the product scope are significant and they increase the financial value of radical innovation. In addition, the authors found that radical innovation is valued significantly higher than either technological breakthrough or market breakthrough.

The Sorescu *et al.* (2003) study is both relevant and useful to this research for three main reasons. First, they investigated the pharmaceutical industry, which is the

industry of interest to be investigated in this thesis. Second, they introduced a number of new variables to measure innovation performance including dominance variables. Finally, they introduced sources of secondary data that can be used to obtain pharmaceutical industry data to measure different variables in this research.

The Graves and Langowitz (1993) study focuses on the innovative productivity and returns to scale in the pharmaceutical industry. The authors investigate the relationship between R&D expenditure, innovative productivity, and firm size in this industry. The dependent variable in their study is the number of new chemical entities (NCEs) introduced to the market during 1969-1987, which was taken from the De Haen database. Independent variables are the size of R&D efforts, measured by R&D expenditure of firms whose line of business falls into SIC 2834 (i.e., the Standard Industrial Classification system reference to pharmaceutical firms), and the size of the firm measured by the firm's total number of employees. The authors include a time trend variable to capture the effects of time on returns in developing new drugs. In addition, to investigate the impact of the regulatory approval process, mean drug approval time was measured and included in the study as an independent variable. The sample of the study is small and includes only 16 large pharmaceutical firms. To measure variables, the authors obtained secondary data from three sources (De Haen, Compustat, and the Pharmaceutical Manufacturer's Association).

Similar to Sorescu *et al.* (2003), the authors use a Poisson regression model to investigate the relationship among the variables in their study. The Poisson

regression is appropriate when the dependent variable is count, assumes small discrete values, and has some values equal to zero for some periods, which is the case for the introduction of NCEs to the market. They refer to the use of Poisson regression in similar cases by other researchers and explain why the Ordinary Least Square (OLS) and Tobit models are inappropriate in their study. To use Poisson regression, the authors assume that NCEs are introduced to the market according to a Poisson distribution. Figure 6 represents the conceptual framework for in this study.

Figure 6: Innovative Productivity and Returns to Scale in the Pharmaceutical Industry Framework

Six Poisson models were developed for the relationships between dependent and independent variables to test two propositions: 1) innovative productivity declines with increasing levels of R&D expenditures and 2) innovative productivity declines

with increasing firm size. The Poisson regression analysis suggests that their first model, which includes the six-year average R&D expenditure, R&D spending squared, and R&D spending cubed is the best fit for the data.

The study concludes that the increased R&D expenditure has a positive effect while the firm size has a negative effect on the rate of NCE introduction. However, the increasing level of R&D spending, which is mostly associated with larger firms, is counterproductive in innovation output. The authors also found that the relationship between innovation output and other variables in the model (e.g., firm size, trend, and the mean approval time) is not statistically significant.

The Graves and Langowitz (1993) study is relevant and useful to this research for its focus on the pharmaceutical industry, the sources of secondary data, the research methodology, and the statistical techniques used in analyzing the data. The conclusion of the study that an increase in R&D spending is counterproductive in innovation output is of significant importance in this study. Stock *et al.* (2001) also provided a similar conclusion that spending in R&D in excess of a certain point does not improve performance.

Collins and Smith (2006) study knowledge exchange, combination, and the role of human resource practices in the performance of high-technology firms. They explore the effects of commitment-based human resource practices on organizational performance by creating an organizational social culture that facilitates knowledge exchange among employees (Figure 7).

The independent variable in this study is commitment-based human resources practices, and the dependent variable is firm performance. The authors argue that human resources commitment-based practices measured by employee selection; training and development; and pay incentives indirectly affect performance through mediating variables of creating a social organizational culture (measured by trust, cooperation, and shared codes and languages) that encourages and facilitates knowledge sharing among knowledge workers. A survey instrument was designed and sent to human resource managers and employees of 136 high technology firms in six different industries, including pharmaceuticals, to capture information on various independent and mediating variables in the study. The dependent variable, however, was measured through an interview with the CEOs of the firms one year after collecting information from the human resource managers to solicit their opinion about revenue from new products. In addition, secondary data for the sales growth was obtained from the Compustat database. The study includes variables to control for the size of the firm and the differences among the types of industry on the relationship between human resource practices and firm performance. The number of employees and the number of locations for each company in the sample were measured to capture information about firm size.

Figure 7: Framework for linking commitment HR practices to firm performance

Source: Collins and Smith (2006)

The statistical analysis shows a significant correlation between independent and dependent variables and some collinearity among independent variables in this study. Six independent ordinary and least square regression models were developed to test the following three hypotheses:

1. *Commitment-based HR practices are positively related to an organization's social climate for trust, cooperation, and shared codes and languages.*
2. *Organizational social climate for trust, cooperation, and shared codes and languages are positively related to firm performance (revenue from new products and services and one-year sales growth) through their effects on knowledge exchange and combination.*
3. *Commitment-based HR practices partially affect employee knowledge exchange and combination and subsequent firm performance through organizational social climates for trust, cooperation and shared codes and languages.*

The authors found that commitment-based HR practices were significantly associated with trust ($\beta = .47, p < 0.1$), cooperation ($\beta = .48, p < 0.1$), and shared codes and languages ($\beta = .43, p < 0.1$) after controlling for firm size, number of locations, and industry type. This supports the first hypothesis that commitment-based HR practices positively affect organizational social culture. In another run of the regression model, considering knowledge exchange and the combination variable as dependent and measures of organizational social culture and HR practices as independent variables, the authors also found support for the second hypothesis, confirming that HR practices have a positive and significant effect on the level of knowledge that can be shared or combined by a firm's employees. Finally, the authors found support for their third hypothesis that knowledge exchange among employees partially mediates the effects of organizational social culture and firm performance.

The Collins and Smith (2006) study is one of the few cases that investigates the mediating effects of variables on firm performance and it is relevant and useful to this research. Measures of a firm's performance (sales growth and revenue from new products) and shared knowledge among employees are of particular use to this research. In addition, the methodology; sources of primary and secondary data; and statistical analysis in this study provide some insight. Moreover, the study includes four sets of survey questions that the authors designed to capture information on different variables, which is of significant use in the design and reliability test of

survey questions in this research. Table 5 summarizes three important empirical studies in the literature on the relationship among different variables and firm performance that are relevant and useful to this thesis.

Table 5: Summary of the literature review articles on Innovation Performance

Author	Framework	Sample size, data collection, and statistical analysis	Variables	Industry of study
Sorescu <i>et al.</i> (2003)	Effects of innovation, support and scope on dominance	255 new drugs introduced by 66 firms Secondary data Two-step statistical analysis: Poisson regression and regression analysis	DV ¹ : Dominance (market share, asset, and profit) INDV ² : Radical innovation, technology and market breakthrough MODV ⁴ : Product, market and technology support and product scope CV ³ : Incremental innovation, number of patents, and country	Pharmaceutical industry
Graves and Langowitz (1993)	Effects of R&D expenditure, firm size, drug approval time, and year drug introduced on the number of New Chemical Entities (NCE) introduced during 1969-1987	380 NCEs Secondary data Poisson regression	DV: Number of NCEs INDV: R&D expenditure, number of employees, introduction year	Pharmaceutical industry
Collins and Smith (2006)	Effects of commitment-based HR practices on firm performance through creating a social culture and knowledge exchange	136 observations Primary and secondary data Regression analysis	DV: sales growth and revenue from new products INDV: Recruitment and selection, compensation, training and development MEDV ⁵ : Trust, cooperation shared codes and languages and knowledge exchange	6 different industries including pharmaceuticals

1 Dependent Variable 2 Independent Variable 3 Control Variable 4 Moderating Variable 5 Mediating Variable

3.3 *Commercialization of Technology*

Commercialization of new technology is an important part of the innovation process. Successful commercialization is linked to improved organizational performance (Zahra and Nielsen, 2002). The management challenge today is to implement strategies that ensure a promising translation of new technology into a stream of financial and economic returns for the inventors of new technology. In other words, the main problem today has become the commercialization, but not the invention, of new technology (Gans and Stern, 2003). Recognizing the importance of commercialization in the success of innovation and in wealth generation, many authors have empirically or conceptually studied the topic (Morck *et al.*, 1988; Erickson and Jacobson, 1992; Zahra and Nielsen, 2002; Gans and Stern, 2003; Wind, 2005; Lin *et al.*, 2006) and provided some insights for its impact on firm performance.

According to Mitchell and Singh (1996) technology commercialization is "... the process of acquiring ideas, augmenting them with complementary knowledge, developing and manufacturing salable goods, and selling goods in the market". Lin *et al.* (2006) adopt the commercialization definition given by Lockett and Wright (2005). They define commercialization as "... the process of bringing science and technology capabilities or R&D results to the market place". The definition given by Mitchell and Singh (1996) is different from the one given by Lockett and Wright (2005) as it includes acquisition and assimilation of knowledge in the

commercialization process. As explained in section 3.1, and according to Zahra and George (2000), acquisition and assimilation of knowledge is potential absorptive capacity, which is the result of the R&D process. Therefore, this research adopts the latter definition, which is more relevant for the purpose of this study as it tries to investigate and understand the direct and indirect effects of R&D and commercialization strategies on innovation performance.

Gans and Stern (2003) developed a framework that links commercialization strategy to the commercialization environment – the microeconomic and strategic conditions facing a firm translating an idea into a valuable proposition for customers. The authors argue that innovators either cooperate or compete with other established firms in bringing their inventions to the market. They suggest that the existence of a “market for ideas” is the crucial determinant of cooperation or competition strategies taken by innovators.

According to Gans and Stern (2003), central elements included in the commercialization environment are the nature of technology appropriability (e.g., whether inventors can benefit from their inventions and prevent other firms from imitating their technology) and the distribution of ownership and control over complementary assets such as production, distribution, and marketing capabilities. In addition to these elements, the dominant design paradigm (i.e., market acceptance of a new design and subsequent standards set by market and the industry for the winning design) affects the commercialization environment (Teece, 1986). These

elements and the interaction between them shape the strategic directions (e.g., cooperation or competition) that inventors can take in bringing new ideas to the market (Teece, 1986). Haeussler (2008) built on the Gans and Stern (2003) framework and elaborated different commercialization environments of biotechnology companies and the impact of various commercialization environments on the commercialization choice. Their study highlights the difficulty of innovators in developing the complementary assets and, therefore, making the environment more suitable to developing a cooperative agreement on profitable commercialization. Table 6 represents the commercialization strategy environment framework developed by Gans and Stern (2003).

Table 6: Commercialization Strategy Environment

		Do incumbents' complementary assets contribute to the value proposition from the new technology?	
		No	Yes
Can innovation by the start-up preclude effective development by the incumbent?	No	The attacker's advantage	Reputation-based ideas trading
	Yes	Greenfield competition	Ideas factories

Source: Gans and Stern (2003)

A number of factors, including a strong intellectual property protection mechanism and control over complementary assets, are needed to ensure successful commercialization of technology. A strong intellectual property protection

mechanism guarantees that innovators can protect their inventions and prevent other established firms from imitating their new technologies. Control over complementary assets (e.g., manufacturing and marketing) provides a competitive advantage for innovator firms to commercialize their inventions without the fear of their inventions being copied by other firms. As shown in Table 6, innovators of new technologies can use four commercialization strategy possibilities to formulate a strategy, depending on the level of the possibility of imitation of new technology by other firms and control over complementary assets.

According to Gans and Stern (2003), the attacker's advantage represents a situation in which a strong intellectual property protection law does not exist (i.e., patents are not applied for nor issued) and control over complementary assets to develop the innovation is not important. A fierce competition between innovators and other established firms could result in an environment where innovators try to keep their technology secret and formulate an appropriability mechanism (e.g., speed-to-market or product design) to gain the maximum benefit from their inventions. In contrast, the "ideas factory" signifies a situation in which imitation can be prevented by the existence of a strong intellectual property protection mechanism (i.e., patents), and access to complementary assets becomes of extreme importance in the commercialization of new products. In such an environment, investments in obtaining complementary assets is very high and, at the same time, innovators are assured that their new technology may not be imitated if they cooperate with other firms. Therefore, different types of cooperation agreements (e.g., licensing, royalty,

profit sharing) will be established between firms to bring new technology into the market. While the “Attacker’s Advantage” and “Ideas Factory” commercialization strategies explain two extreme cases of competition or cooperation among firms, the other two possibilities in Table 6 (i.e., Greenfield competition and reputation-based ideas trading) explain how firms can establish a cooperative relationship with other firms to work together in developing a new product and bringing it to the market.

Andrew and Sirkin (2003) introduced three innovation approaches (i.e., Integrator, Orchestrator, and Licensor) that firms can take to commercialize a new product. Each of these approaches influences the way a firm conducts business in terms of investment profile, risk profile, skill requirements, and financial returns. Integrators need high capital investment to manage all the necessary steps to generate profit from an idea. They need to develop capabilities in forming strong cross-functional links, product design, and manufacturing and marketing skills within their organizations. According to the authors, this strategy works well if speed-to-market is not crucial, the new technology is proven to be needed by customers, and innovation is incremental. Orchestrators focus on some steps of the innovation process and link with partners to carry out the rest. The investment requirement in this approach is medium. Firms need to be strong in collaborating with several partners simultaneously, and they also need to have strong project management skills. This strategy works well if the new technology is in its early stages, a strong substitute exists in the market, intense competition exists, and there is a mature supplier base. Finally, Licensors are firms that license their innovations to another

company to take it to market. The investment requirement in this approach is low as marketing and manufacturing investments are borne by other firms. However, these firms need to have strong intellectual property management skills, basic research capabilities, contracting skills, and an ability to influence standards. This approach is best when there is a strong intellectual property protection mechanism, the market is new to innovators, the innovator's brand is not very important, and significant infrastructure is needed but not yet developed.

To understand the factors that affect the successful introduction of a new product to the market and various commercialization strategies that firms formulate to successfully commercialize their new products, this thesis reviews a number of empirical research studies that have examined commercialization of technology and are relevant to this research. In specific, this thesis reviews studies conducted by Shan (1990), Lin *et al.* (2006), and Zahra and Nielsen (2002) to understand variables involved in the commercialization of technology, conceptual framework, methodology, sources of collecting data, and statistical analysis, which help in developing a framework for this research.

Shan (1990) investigated the determinants of forming a cooperative relationship for commercializing new high-technology products in biotechnology firms. Cooperative arrangements such as complete merger, equity and contractual joint ventures, joint R&D agreements, licensing agreements, manufacturing and marketing arrangements are crucial organizational ingredients of corporate strategies in commercializing new

products. Shan's research focuses on the organizational and strategic motivations behind forming a contractual agreement in the commercialization of new technology. Referring to the literature, the author suggests that transaction cost and strategic behavior are important variables that motivate firms to form cooperative arrangements. The author argues that firms adopt a strategy that allows them access to the least costly complementary assets to commercialize their new products, although access to the complementary assets through a cooperative agreement may trade away the long-term profitability of the firms.

The dependant variable in Shan's study is the organizational form that a biotechnology firm adopts in commercializing its new technology. This is a categorical variable, which is set to one if the firm cooperates with other firms in commercializing its new products and zero if it does not. The author identifies three independent variables (i.e., competitive position of the firm in the industry, firm size, and product diversity). The competitive position of a biotechnology firm is ranked by the firm's position in marketing a new product compared to its rivals. The firm can be a Lone-Star (no competition), a Leader, a Follower, or a Distant Follower, in which a value of 0, 1, 2, or 3 is assigned to each case, respectively. The number of employees in a firm is the proxy for firm size as the second independent variable, and the number of products introduced by a firm in the market is a measure of product diversity. In addition, the author introduces a control variable (i.e., Nation) to investigate the market location of the new product. This is a dummy variable that

takes a value equal to zero if the largest market for the product is the U.S. and one, if it is not. Figure 8 presents the framework in their research.

Figure 8: Organizational Strategies by Entrepreneurial High-Technology Firms Framework

Data on the competitive status of 278 new biotechnology firms in the U.S. is obtained from the Paine Webber's Biotechnology Industry and the 1986 Fact Book and was statistically analyzed using SAS logistic regression procedure. The author found that the competitive position of a firm has significant impact on the firm's

decision to cooperate. In other words, the further behind the firm is in competition with its rivals, the more likely it is to commercialize its products through a cooperative agreement. On the other hand, an industry leader tends to commercialize its new products independently. A firm's size is negatively related to its decision on forming cooperative agreements with other firms to commercialize new technology. Larger firms are less likely to engage in partnerships to introduce new products to the market because of access to complementary assets. The result of the study also shows that product diversity is positively correlated with the dependent variable, but not significant ($p = 0.1134$). The Nation variable is positively correlated and strongly significant, which confirms that firms seek cooperative agreements with foreign firms to enter international markets.

Similar to Gans and Stern (2003), Shan's research confirms that access to complementary assets is a determinant of success in commercialization of new products. It also suggests that the level of access to complementary assets is a base for decisions on entering into cooperative agreements. This is one of the most important factors that companies consider when they formulate a strategy for commercializing their innovation. Large pharmaceutical companies have both the assets and marketing power that are needed to develop a drug and take it to different countries in the world. Smaller firms, on the other hand, lack the resources they need and rely on a fair relationship with larger companies to market their drugs. As an example of a cooperative agreement in commercializing a drug, consider the case of QLT Inc., a Canadian-based biopharmaceutical company. University researchers at

the University of British Columbia discovered Visudyne, a drug for age-related macular degeneration (AMD) and vision-related concerns, and they established QLT, a university spin-off. Due to a lack of resources to develop and market Visudyne, QLT entered into a cooperative agreement with Novartis, a Swiss-based multinational pharmaceutical company. Based on the terms and conditions of the agreement, QLT is responsible for manufacturing and Novartis is responsible for marketing, distribution, and sales of Visudyne worldwide. Both QLT and Novartis equally share the profits gained in developing, marketing, and selling the drug.

Other researchers also considered the importance of commercialization of new products in their studies. For example, *Lin et al.* (2006) study R&D intensity and commercialization orientation effects on financial performance. The study investigated the effects of R&D intensity as measured by the ratio of R&D spending to total assets, commercialization orientation of the firm measured by the firm's total sales, general and administration (SGA) expenses divided by total assets, and knowledge stocks measured by the number of patents granted to a firm on the firm's financial performance. *Lin et al.* (2006) also investigated the interaction effects among the above variables. The authors operationalized a firm's financial performance using Tobin's Q as an indicator of the firm's long-term performance. Tobin's Q is an index that measures firm value and managerial quality at the same time. Figure 9 illustrates the theoretical framework in this study.

Figure 9: R&D Intensity and Commercialization Orientation Effects on Financial Performance

Obtaining secondary data from various databases (e.g., the U.S. patent office, the NBER, and Compustat) for 258 U.S. public firms in six industry types and adopting a multilevel statistical method for analyzing the relationships, the authors found that the relationship between R&D intensity and financial performance is not significant. They conclude that spending on R&D alone does not improve financial performance. On the other hand, there is a positive association between commercialization orientation and financial performance of the firms, meaning that spending on SGA improves a firm's financial performance. This result is consistent with the finding of Wuyts *et al.* (2004), but differs from the result of the study conducted by Pearl (2001), who suggested that R&D and sales expenditure negatively impact financial

performance. This suggests that the literature does not provide consistent results on the effect of R&D and commercialization of technology on the performance of high technology firms. Lin *et al.* (2006) relate the inconsistent findings in the literature to the differing nature of the technology stock of firms. In addition, they state that R&D and marketing strategies are part of the corporate strategy, and the interaction effects of the two functional strategies should be considered in the decision-making process.

Lin *et al.* (2006) also found that the interaction between R&D intensity and commercialization orientation is significant and positively affects performance. The authors argue that R&D and commercialization are complementary assets and both are important in successful innovation. A firm's knowledge stock has a positive impact on financial performance, but it is not significant in this study.

Zahra and Nielsen (2002) study sources of capabilities, integration, and technology commercialization using the resource-based view of the firm. The resource-based view of the firm suggests that a company can achieve a competitive advantage by having strong manufacturing capabilities (Stalk *et al.*, 1992). Their study examines the effect of internal and external company resources (i.e., human resources and technology) on four dimensions of technology commercialization (i.e., frequency, speed, radicalness, and patents). Zahra and Nielsen (2002) suggest that internal and external manufacturing sources including the firm's people, skills, knowledge, processes, systems, and equipment can determine success in technology

commercialization. These capabilities enable the firm to develop more new products faster. The authors also investigate the role of formal and informal integration as a moderating variable on the relationship between the dependant (i.e., commercialization) and independent variables (i.e., manufacturing capabilities – internal and external HR and technology). Figure 10 represents the framework for studying sources of capabilities, integration, and technology commercialization.

Figure 10: Sources of Capabilities, Integration and Technology Commercialization framework

Source: Zahra and Nielsen (2002)

Applying a longitudinal research design and obtaining primary and secondary data from 119 companies in different industries, the authors found that internal sources of

manufacturing capabilities are positively associated with the successful commercialization of technology. The use of external human resources (i.e., consultants) was positively associated with the frequency and speed of technology commercialization and negatively associated with radicalness and number of patents issued. In addition, internal proprietary technological sources were positively associated with all dimensions of technology commercialization while external technological sources (e.g., outsourcing and alliances) were only positively associated with new product radicalness and technology commercialization speed. The result of this study also supported the moderating effect of integration.

Zahra and Nielsen (2002) used company size, age, industry type, and past performance as control variables and found that company size was positively related to the frequency of new products launched, but negatively related to patents. Company age was negatively associated with radicalness and speed of technology commercialization. In addition, they found that companies in the high technology sector produce more patents, are involved in more radical innovation, and commercialize the innovations faster than other companies. A company's past performance did not affect technology commercialization.

Zahra and Nielsen's (2002) study is relevant to this research, as it identifies appropriability mechanisms (i.e., frequency, speed, radicalness, and patents) that the authors consider to be important in commercialization of technology. Table 7 summarizes the empirical studies reviewed in this section.

Table 7: Summary of the literature review articles on Commercialization of Technology

Author	Framework	Sample size, data collection, and Statistical analysis	Variables	Industry of study
Shan (1990)	Effects of competitive position, firm size, and product diversity on organizational form	278 observations Secondary data Logistic regression procedure	DV ¹ : Organizational form (cooperation or not) INDV ² : competitive position (Lone-Star, Leader, Follower, or Distant Follower), number of employees, number of products commercialized by the firm CV ³ : Nation	Biotechnology firms
Lin <i>et al.</i> (2006)	Effects of knowledge stock, R&D intensity and commercialization orientation of financial performance	258 publicly traded firms, Secondary data, SAS MIXED Multiple analysis	DV: Tobin's Q INDV: Knowledge stock measured by number of patents, commercialization orientation measured by SGA and R&D intensity	Various industries
Zahra and Nielsen (2002)	Effects of manufacturing capabilities and integration on technology commercialization	119 observations, primary data, Longitudinal study Hierarchical multiple regression analysis	DV: Number of new products, radical new products, number of patents, and speed INDV: Internal and external sources of capabilities MODV ⁴ : Coordination between functional units CV: company size, age, industry type, past performance	20 different U.S. industries

1 Dependent Variable   2 Independent Variable   3 Control Variable   4 Moderating Variable

3.4 Functional Integration

Numerous studies have been conducted investigating ways to improve New Product Development (NPD) performance. Some of the most effective ways that have been identified in the literature for improving NPD performance include functional integration, simultaneous product development, use of computer packages for product design such as CAD, quality function deployment, and customer-supplier involvement (Crawford, 1996). However, integrating functional units of an organization by forming cross-functional teams is suggested to be one of the most effective ways of improving NPD performance (Swink *et al.*, 1996). A cross-functional team is a team comprised of members of various functional units of an organization including design, R&D, manufacturing, marketing, suppliers, and customers (Boyle *et al.*, 2005) working together on NPD projects. A key organizational objective in forming cross-functional teams is to achieve efficiency and effectiveness in various aspects of NPD performance. Troy *et al.* (2008) found that cross-functional integration has a direct impact on the success of new product development but the combination of integration with other variables might be of greater importance. The authors identified nine managerial and industry-specific controlled variables that affect the relationship between integration and performance and suggest that firms should design cross-functional integration to maximize their effectiveness. The authors also point to the research methodological decisions and

suggest that “care should be taken when designing and interpreting the results of such studies.”

The literature provides evidence of a positive relationship between functional integration by the use of cross-functional teams and a firm’s innovation performance (Droge *et al.*, 2000; McDonough, 2000; Troy *et al.*, 2008). Some of the benefits of functional integration include reduction in NPD cycle time, reduction in NPD cost, and fewer design changes (Gerwin and Barrowman, 2002; McDonough, 2000). However, despite these benefits, not all companies use functional integration. Griffin (1997) summarizes the research efforts from a survey conducted by Product Development and Management Association (PDMA) on NPD performance and finds that not all best practices use a formal cross-functional team process in their NPD projects. Boyle *et al.* (2005) identify some of the organizational factors that create or hamper support for cross-functional teams. According to the authors, the extent and quality of communication and collaboration between functional areas of an organization is the best indicator of organizational support for cross-functional teams.

The research on functional integration also suggests that functional cooperation of marketing and R&D leads to success in NPD projects. Cooper (1984) suggests that management strategies that balance R&D and marketing have a greater percentage of success. Pelz and Andrew (1966) found a positive relationship between the amount of functional interaction and firm performance. The authors also found a strong

correlation between the amount of interaction and NPD success. However, to achieve success, organizations need to remove barriers to integration. Griffin and Hauser (1996) suggest a number of barriers that include personality differences among functions; cultural differences; language differences; organizational differences on priorities, responsibilities, and reward systems; and physical barriers in achieving optimum cooperation.

To successfully innovate, firms invest in R&D and translate R&D results into a product or service. They develop an organizational culture that encourages communication and knowledge sharing among employees in various departments. R&D investment is critical as it helps the firms to develop new internal knowledge or identify and acquire new external knowledge. Through R&D, firms can improve the skills and competencies of their knowledge producing scientific employees that contribute to the firms' knowledge base (Daghfous, 2004). However, to benefit from investments in R&D, firms need to assimilate new knowledge, transform it, and apply it to commercial use. Sherman *et al.* (2005) investigate the effects of knowledge management variables and R&D-marketing integration and find that the combined effect of R&D-marketing integration and knowledge management in the form of recording, retrieving, and reviewing information has a positive interaction effect in eight of the 18 tests that the authors conducted in their research. Firms that have mechanisms in place to remove barriers to communication and encourage social interaction of employees will be able to assimilate, transform, and apply the

knowledge identified through R&D and commercialize it. In other words, they will be able to develop higher levels of absorptive capacity (Van den Bosch *et al.*, 1999).

Functional integration is considered to be an important factor in knowledge assimilation and transformation. Numerous studies have provided evidence that cooperation of various departments of a firm in a project results in projects being completed on-time, on-budget, and with fewer design change (Griffin and Hauser, 1996). By integrating functional units in a firm, knowledge-producing and knowledge-consuming employees can work together to improve assimilation and transformation capabilities of the firm (Daghfous, 2004). For example, when R&D, marketing, and production teams work together from the initiation to termination of an innovation project they will be able to improve the efficiency and effectiveness of innovation in their companies. The marketing team is closer to the end users and has a better understanding of customer needs. They can communicate these needs to R&D teams who will be able to focus their resources on developing a product that meets market needs. Communication between R&D and production teams results in inventing a product that the production department is capable of producing. Specific to the pharmaceutical industry, communication with the regulatory agencies early in the drug development process, for example, increases the possibility of drug approval and reduces the drug approval time. The sales team can be involved in the process to learn about the benefits of drugs in various therapeutic areas so that they can communicate these benefits to the patients, physicians, and pharmacists.

Griffin and Hauser (1996) reviewed and analyzed 20 years of research in the literature on integrating R&D and marketing and its role in the NPD process. One of the main findings of this analysis was that "...prior research on R&D and marketing integration is being reassessed in light of movement toward flatter organizational structures and cross-functional teams". To facilitate that reassessment, Griffin and Hauser (1996) propose several hypotheses regarding various methods employed for integrating R&D and marketing and develop a causal map for studying functional integration. This causal map links success indicators in NPD to situational dimensions, structural and process dimensions, and outcome dimensions. The situational dimensions address the amount and kind of integration needed in a project. Situational dimensions depend upon specific situations such as the phase of the project and the level of uncertainty in the project. The structural and process dimensions address the actions taken to achieve integration, which could include facility design, personnel movement, informal social systems, organizational structures, incentives and rewards, and formal integrative management processes. The outcome dimensions of the causal map in the Griffin and Hauser (1996) study measures the success of NPD projects using: 1) customer measures such as customer satisfaction, 2) financial measures such as profit goals and margins, 3) process measures such as technical performance and time to market, 4) firm-level measures such as success rate and percent of sales from new products, and finally 5) program measures such as whether the team was satisfied with the outcomes. Figure 11

represents the causal map for studying R&D and marketing integration developed by Griffin and Hauser (1996).

Figure 11: Causal map for studying the project-level marketing/R&D interface

Source: Griffin and Hauser (1996)

The literature also provides scientific evidence of the positive relationship among R&D and marketing cooperation and a firm's NPD performance. For example, Pinto and Pinto (1990) examined the relationship between patterns of communication and cross-functional cooperation in the development and management of new programs. Their study surveyed 262 team members from 72

hospital project teams and focused on assessing the relationship between two aspects of project team communication (formal versus informal modes and reasons for communication) with the level of cross-functional cooperation actually achieved within a hospital project team charged with developing a new program. The result of this study demonstrated that high cooperation teams differed from low cooperation teams both in terms of their increased use of informal methods for communication as well as their reasons for communicating. The authors find a strong relationship among cross-functional cooperation and the perceived task and psychological outcomes ($R = 0.71$).

A 10-year study of 289 projects conducted by Souder (1988) provides strong evidence that communication and cooperation of functional units strongly correlates with project success. The author also analyzed different types of problems that might occur in integrating R&D and marketing functions and discussed the effects of these observations on project outcomes. The main conclusion in Souder's (1988) study is that the greater the harmony (cooperation and communication) between marketing and R&D, the greater the likelihood of project success.

Despite the importance of functional integration, a high degree of integration is a rare phenomenon in many high technology organizations. Gupta *et al.* (1985) lists lack of communication as the number one barrier (about 31 percent of responses from marketing and R&D managers) in achieving integration between R&D and marketing. Their article explores several key reasons for this problem. The authors

collect data from 109 marketing managers and 107 R&D managers involved in new product development in 167 small- to medium-sized research-intensive firms and show that there are marked differences between R&D and marketing managers in how they look at integration issues. Other factors reported in their study identifying barriers to integration include insensitivity to another's point of view, lack of support from top management, personality difference problems, lack of market knowledge, organizational design problems, managerial problems, and cultural problems. Table 8 summarizes the empirical studies providing scientific evidence that communication among marketing and R&D enhances NPD success.

Table 8: Empirical studies providing scientific evidence that communication among marketing and R&D enhances NPD success

Researcher(s)	Sample	Type of Firm	Evidence (Partial List)
Cooper (1983)	58 Projects	Industrial	Projects that balance marketing and R&D inputs have a higher rate of success.
Cooper (1984)	122 Firms	Electronic, heavy equipment, chemicals	Management strategies that balance marketing and R&D have a greater percentage of new product successes and greater percentage of their sales coming from new products.
Cooper & de Brentani (1991)	106 Projects	Financial services	Synergy (e.g., fit with the firm's expertise, management skills, and market research resources) was the number one correlate of success.
Cooper & Kleinschmidt (1987)	125 Firms 203 Projects	Manufacturing	Market synergy and technological synergy are both significantly related to success.
de Brentani (1989)	115 Firms 276 Projects	Financial and management services, transportation, and communication	Sales, communication between functions. Correlation with sales and market share = 0.38, correlation with reduced cost = 0.29.
Dougherty (1990)	5 Firms 18 Projects	Industrial, consumer, and services	More communication and communication on all relevant topics separated successful projects from unsuccessful projects.
Gupta <i>et al.</i> (1985)	167 Firms 107 R&D managers 109 Marketing managers	High technology	Lack of communication was listed as the number one barrier to achieving integration among marketing and R&D.
Hise <i>et al.</i> (1990)	252 Marketing vice presidents	Large manufacturing firms	High level of joint effort in new product design is a significant factor in determining success. This is true for both industrial and consumer goods companies.
Moenaert and Souder (1990)	Literature review	Products and services	Function integration positively relates to innovation success.
Moenaert <i>et al.</i> (1994)	40 Belgian firms	Technology innovative firms	Significant correlation among commercial success and 1) inter-functional climate, and 2) information received by R&D.
Pinto and Pinto (1990)	72 Hospital teams 262 Team members	Health services	Strong relationship between cross-functional cooperation and the success (perceived task outcomes and psychological outcomes) of the project. Correlation = 0.71.
Souder (1988)	56 firms 289 projects	Consumer and industrial	The greater the harmony between marketing and R&D, the greater the likelihood of success.
Souder and Shakrabarti (1978)	18 firms 117 projects	Consumer and industrial	Interaction, integration, and information exchange significantly differentiate between technical and commercial success and failure.

Source: Griffin and Hauser (1996)

3.5 Critique of the Literature

Knowledge about the impact of different variables on a firm's innovation performance has improved dramatically in the last two decades. However, a critical review of the theories in the literature on strategic management, technology innovation, knowledge transfer, marketing, and commercialization suggest some conceptual and methodological limitations in the literature. Conceptual limitations refer to the range of questions that researchers have tried to answer in their studies; the dependent, independent, moderating, mediating, and control variables included in the research; and the relationship and interaction among variables that researchers have identified and included in their studies. Some authors have identified too many variables in their studies and have collected data on a small sample size (Lane and Lubatkin, 1998), which creates some concerns about a potential multicollinearity among variables, and, therefore, the results obtained in such studies are questionable. Others, on the other hand, have investigated the relationship among a few variables (Stock *et al.*, 2001) that creates some concerns about research comprehensiveness, model specification, and generalizability of the research results. Methodological limitations include difficulties and problems that researchers face in collecting reliable primary and secondary sources of data, the techniques used in collecting data, and the methods used in statistical analysis of the data. As an example of such conceptual and methodological limitations, consider the research conducted on calculating the cost of developing a new drug. Numerous studies in the past have

attempted to calculate the average cost of a drug innovation, and each study has resulted in a different cost number, depending on the variables that researchers had considered in their cost calculation. While DiMasi *et al.* (2003) report an annual increase of 7.4 percent above the general inflation rate for developing a new drug, Graves and Langowitz (1993) refer to the data from the Pharmaceutical Manufacturer's Association and report the average cost of drug development at \$125 U.S. million. Five years later, Van Arnum (1998) estimated the cost of developing a completely new drug at \$250-\$350 million U.S., more than a 20 percent annual increase in the drug development cost compared to the study by Graves and Langowitz (1993). A widely cited study conducted in 2001 by the Tufts Center for the Study of Drug Development determines the cost of developing a new drug at about \$800 million U.S. Using a different methodology and considering the commercialization cost of new drug development, a study by the consulting firm Bain & Co calculates the cost of a drug innovation at \$1.7 billion U.S. (Gilbert *et al.*, 2003).

A comprehensive survey of the literature related to the variables of interest in this thesis identifies a number of deficiencies, which will be explained in this section.

- Many authors suggest that absorptive capacity has an impact on new product development, that it is positively associated with a firm's performance (Cohen and Levinthal, 1990; Stock *et al.*, 2001; Tsai 2001; Chen, 2004, Narasimhan *et al.*, 2006), and that it is path- and history-dependent. However, there is

inconsistency among researchers on how this construct should be measured. While some researchers use the traditional measure of R&D intensity in operationalizing absorptive capacity (Cohen and Levinthal, 1990; Stock *et al.*, 2001; Tsai, 2001; Lin *et al.*, 2006; Allen, 1997), others disagree (Minbaeva *et al.*, 2003; Zahra and George, 2000; Lane and Lubatkin, 1998) and argue that R&D intensity is not appropriate to measure the construct. In addition, the history-dependent characteristic of the construct suggests that “time” is an important factor to be considered in the effect of absorptive capacity on firm performance. The effect of time on the relationship between absorptive capacity and innovation performance has been ignored in many studies.

- A number of studies in the literature have empirically investigated the relationship among absorptive capacity and other variables in industries other than pharmaceuticals. The result of such studies may not be generalized to the pharmaceutical industry because of its sensitive nature and the regulations imposed by governments on this industry. However, a few studies related to this industry exist, and these have been reviewed and explained in this thesis.
- It is not clear from the literature whether larger firms innovate more than smaller firms or if they are more productive in bringing new products to the market. Some authors believe that size matters and larger firms can be more innovative because of the resources that they possess. Larger firms have the financial, technological, and market-related (i.e., know-how) resources, which

put them in a better position to manage innovation and bring more new products to the market. They enjoy economies of scale and economies of scope in all aspects of innovation from discovery through research and development to manufacturing and marketing. Economies of scale in research and development make the firms more efficient in allocating their research money to a larger number of projects, which in turn increases the possibility of discovering new products. Economies of scope also help the firm to generate additional new ideas, which has an impact on a firm's absorptive capacity through the identification of new knowledge. However, larger firms tend to be more bureaucratic (Tornatzky and Fleischer, 1990) and are more resistant to technological change, which prevents them from spending resources on innovation. In their study of innovative productivity and returns to scale, Graves and Langowitz (1993) refer to a number of studies that provide evidence across industries that larger firms innovate proportionally less than smaller firms.

- The term “commercialization of technology” is relatively new in the literature and, therefore, there is some confusion among researchers on how and when to use this term. Some authors apply the term to explain marketing and advertising activities by firms to sell more of their new products. Others, including Lin *et al.* (2006), adapt a broader definition of the term and define it as “... the process of bringing science and technology capabilities or R&D results to the market place”, which includes all activities after the invention of

a product including manufacturing, marketing, and distribution. As shown in Figure 1 of section 2, this thesis adapts the definition given by Lin *et al.* (2006) to define commercialization of technology and uses it to formulate and investigate its effects on a firm's innovation performance.

- As explained in section 3.3, a number of studies have separately investigated the distinct relationship between absorptive capacity and commercialization of technology as this influences a firm's performance. To date, no attempt has been made to examine the joint effect of these variables on a firm's innovation performance.

In general, the literature supports the separate direct relationship between absorptive capacity, functional integration, and commercialization strategy on a firm's performance. However, no empirical study has yet been conducted that considers the relationship among all the above variables on a firm's innovation performance. This deficiency will be addressed in this thesis by developing a theoretical framework and testing the relationships among variables.

Chapter 4: Theoretical Framework

Figure 12 represents the theoretical framework to be studied in this thesis. The overall goal of this study is to investigate how absorptive capacity influences a firm's innovation performance. In particular, the study tries to discover the relationship between absorptive capacity and innovation performance and to understand whether a firm's commercialization strategy and functional integration moderate this relationship. With the support of the literature review in Chapter 3, this chapter provides detailed information about the theoretical framework and elaborates on the hypothesized relationship among dependent, independent, and moderating variables.

Figure 12: Absorptive Capacity and Innovation Performance Framework

4.1 Innovation Performance

As stated in the literature review, it is expected that building a higher level of absorptive capacity will positively influence innovation performance. Alam (2003) suggests using three criteria – financial, customer, and opportunity – to measure the performance of new product development. In addition, Graves and Langowitz (1993) measured the number of NCEs as a dependent variable in their study of innovative productivity and returns to scale in the pharmaceutical industry. Therefore, innovation performance is considered to be a multidimensional construct in this research that includes financial criteria (de Brentani, 1989; Cooper *et al.*, 1994; Edget and Snow, 1996; Storey and Easingwood, 1996; Storey and Kelley, 2001; Collins and Smith, 2006), customer criteria (de Brentani, 1989; Cooper *et al.*, 1994; Edget and Snow, 1996; Storey and Easingwood, 1999; Storey and Kelley, 2001), opportunities criteria (Cooper *et al.*, 1994; Easingwood and Percival, 1990; Storey and Easingwood, 1996 & 1999) and the number of new products introduced to the market by a company (Tsai, 2001; Graves and Langowitz, 1993).

4.1.1 Financial Criteria

Measuring financial performance is important to pharmaceutical companies in understanding how their entire business operation is performing. A number of financial measures are recommended in the literature as useful in measuring financial criteria. These include enhanced profitability (de Brentani, 1989), sales

growth (Cooper *et al.*, 1994), increased market share (Edget and Snow, 1996), reduced operating cost (Storey and Easingwood, 1996), increased return on investment (Storey and Kelley, 2001), percentage of sales revenue (Banbury and Will, 1995), and sales revenue from new products and sales growth (Collins and Smith, 2006). In this thesis, the author apply the approaches proposed by Banbury and Will (1995) and Collins and Smith, (2006) to measure annual sales revenue and sales revenue from new products by the following two items.

1- Please indicate the approximate annual sales of your company (5 categories):

- 1 = Less than \$100 million U.S.
- 2= \$100 million U.S. to less than \$1 billion U.S.
- 3 = \$1 billion U.S. to less than \$5 billion U.S.
- 4 = \$5 billion U.S. to less than \$10 billion U.S.
- 5 = \$10 billion U.S. and more

2- What percentage of the stated annual sales revenue comes from the sales of new drugs that your company developed and introduced to the market in the past three years? (5 categories):

- 1 = Less than 20 percent
- 2= 20 percent to less than 40 percent
- 3 = 40 percent to less than 60 percent
- 4= 60 percent to less than 80 percent
- 5 = 80 percent and more

Dutta *et al.* (1999) also used sales as a dependent variable in their study of success in high technology markets. In addition to the previously mentioned references for the use of sales revenue as a measure of performance, there are other factors that justify the use of sales revenue as one of the dependant variables in this research. First, sales

revenue is the perceived value of products, and higher sales revenue is associated with higher demand for the product, assuming a fixed price. As physicians prescribe the drugs, higher demand for the pharmaceutical products will not occur unless the physicians are satisfied that the drug is effective in eliminating a disease, an indication of the quality of the drug. Second, higher sales revenue illustrates higher market penetration for the product by the producing company, and, therefore, it can be used to measure the percentage of total market share for a specific product. Third, sales revenue can be used to provide information about how liquid the company is, how it is financed, and how efficient the company business processes are. Major pharmaceutical companies that are involved in innovation and commercialization of drugs constantly measure the sales revenue generated by their existing and new drugs. Drugs that generate revenue of more than \$1 billion a year are called blockbuster drugs. Blockbuster drugs account for almost 30 percent of the total pharmaceutical market. According to a report published by Urch Publishing (2007) there are more than 100 blockbuster drugs in the market; the top-selling drug is Pfizer's Lipitor, which generated more than \$12 billion in 2007. Finally, sales revenue is easy to measure.

4.1.2 Customer Criteria

Recent literature on innovation performance suggests measuring non-financial measures of performance – such as customer satisfaction with new products, increased number of new customers, opening up new markets, increased customer

loyalty, enhanced image with the customers, and fewer customer complaints (de Brentani, 1989; Cooper *et al.*, 1994; Edget and Snow, 1996; Storey and Easingwood, 1999; Storey and Kelley, 2001; Alam, 2003). Measuring non-financial factors helps a company understand how its products are perceived by the customers and whether its new products open up new markets to increase market share. Following Alam (2003), this thesis measures customer criteria through the following items:

- 1- Compared to our main competitor's drugs, customers are more satisfied with the new drugs that our company introduced to the market during the past three years.
- 2- New drugs that our company introduced to the market during the past three years increased the number of new customers significantly.
- 3- New drugs that our company introduced to the market during the past three years opened up new markets for us outside the existing markets.
- 4- Customers are loyal to our brand and buy new drugs that our company introduces to the market.
- 5- The number of customer complaints has increased recently because of the side effects of the drugs that our company introduced to the market in the past three years (Reverse coded).

The above five items are measured using a 7-point scale, where 1 = strongly disagree and 7 = strongly agree.

4.1.3 Opportunities Criteria

Every new drug that a pharmaceutical company introduces to the market brings some opportunities for the company. A new drug, if perceived as effective and safe by customers including physicians, pharmacists, and patients, might increase the sales revenue and profitability of the company through selling more of other products developed by the company. The new drug might also set a platform for other new products that the company will introduce to the market in the future. In addition, every new drug that a company develops and introduces to the market will improve the NPD capabilities of the company. This study applies the approaches taken by Cooper *et al.* (1994), Easingwood and Percival (1990), and Storey and Easingwood (1996) and measures opportunity criteria with the following four items:

- 1- Our company's revenue from selling its older products increased because of the effectiveness of the new drugs that we developed during the past three years.
- 2- Our company sets industry standards in introducing new drugs because of its perceived drug quality (e.g., safety and efficacy) by customers.
- 3- The knowledge gained in developing and introducing new drugs to market during the past three years will help us develop more new drugs in the future.
- 4- We introduced a new drug to market during the past three years that had negative side effects. This problem has negatively affected our brand and our sales revenue. (Reverse coded)

The above four items are measured using a 7-point scale, where 1 = strongly disagree and 7 = strongly agree.

4.1.4 Number of New Drugs

The number of new drugs that a pharmaceutical company develops and introduces to the market is considered to be an important indicator of its innovation performance. However, not all new drugs have the same level of therapeutic efficacy. While some drugs are considered to be life saving in a specific therapeutic area, others are only incrementally new, compared to the existing marketed drugs. As discussed in Chapter 2, the FDA classifies new drug applications into seven classes: new molecular entities; new ester, salt, or other non-covalent derivative; new formulation; new combination; new manufacturer; new indication; and drug already marketed without an approved NDA. As defined by the FDA, NMEs are drugs that have never been marketed in the U.S. According to Olson (2002), NMEs represent the newest, most innovative drug products. In evaluating drug applications, the FDA also assigns priority or standard review to each application. The former is assigned to a drug application that has significant improvement compared to marketed products in the treatment, diagnosis, or prevention of a disease. The latter is for drugs that appear to have therapeutic qualities similar to those of one or more already marketed drugs. In this thesis, the definition of “New Drug” is consistent with the FDA’s classification. New drug could be an NME or a drug that falls in the other six classes of the FDA classification. Minor or major revisions of an existing drug are also considered to be a new drug.

This study measures the fourth dimension of innovation performance – the number of new drugs – with the following question:

- 1- Please indicate the approximate number of new drugs developed by your company during the past three years .....

4.2 Absorptive Capacity

Cohen and Levinthal (1990) define absorptive capacity as the ability of a firm to identify the value of external knowledge, assimilate it, and apply it to commercial ends. The authors argue that absorptive capacity is critical to the firm's innovative capabilities that the level of new knowledge that could be absorbed by a firm is history- and path-dependent, and it is a function of the firm's prior related knowledge. The authors state that absorptive capacity is linked to organizational learning and it is important in the commercial application of knowledge.

Absorptive capacity has been examined in the innovation and technology management literature in different contexts and has been found to have a mixed impact on NPD performance. Kamien and Schwartz (1982) studied market structure and innovation and observed a strong positive correlation between innovation output and innovational efforts, such as R&D intensity. Stock *et al.* (2001) empirically tested the relationship between absorptive capacity and NPD performance on 24-year data in the computer modem industry; they found a non-linear relationship

between absorptive capacity and firm performance. The authors suggest that NPD performance improves up to a certain point in firms that invest in R&D to build absorptive capacity and then the performance becomes worse with any increase in R&D spending. Lane and Lubatkin (1998) developed and tested a model of inter-organizational learning and found that R&D spending alone has a weak association with inter-organizational learning ($p < 0.10$). The authors found a strong association between commercialization of new knowledge and their performance dependent variable ($\beta = 0.83, p < 0.01$).

The main challenges facing pharmaceutical companies are to improve productivity in research and development, ensure that patients all over the world have access to a safe and effective drug, and sustain profitability to satisfy stakeholders. To meet these challenges, firms in this industry formulate strategies that focus on investments in a number of business drivers including R&D and marketing. For example, GlaxoSmithKline, one of the largest multinational pharmaceutical firms, lists the following items as its main business drivers⁴:

- Build the best product pipeline in the industry to the benefit of patients, consumers, and society
- Continuously improve performance through commercial and operational excellence
- Improve access to medicines through a range of extensive programs, both in the developed and developing worlds

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⁴ GlaxoSmithKline's 2005 financial report available on company web site at www.gsk.com

A number of internal and external strategic decisions by pharmaceutical firms affect absorptive capacity and innovation performance. Internally, decisions made about investments in research and development could help an organization to identify, create, and absorb new knowledge. Through R&D, organizations behave proactively in creating new knowledge that could be transformed into a marketable product (DiBella and Nevis, 1998). However, acquisition and absorption of new knowledge alone do not guarantee that organizations can benefit from their R&D activities if the result of their research is not transformed into a marketable product (Zahra and George, 2000). Firms also need to make decisions that affect their competitive environment and the market for their products or services. They need to formulate strategies that enable them to find new ways of operating to respond to a variety of external pressures on the company, including increasing regulatory stringency to ensure that effective new medicines reach patients as soon as possible. For example, investments in obtaining complementary assets (e.g., manufacturing and marketing) affect an organization's ability to transform and exploit knowledge into a marketable product, and these investments are considered to be an important factor in building absorptive capacity (Gans and Stern, 2003; Lin *et al.*, 2006; Narasimhan *et al.*, 2006). In addition, integrating functional units in a firm by forming cross-functional teams of R&D, manufacturing, distribution, sales, and marketing affect a firm's innovation performance (Canner and Mass, 2005; Boyle *et al.*, 2005).

To operationalize absorptive capacity at the firm level, some researchers – including Stock *et al.* (2001) and Allen (1997) – have used traditional measures, such as R&D

intensity, in their empirical investigations. This, in fact, makes sense because a main reason for firms to invest in R&D is to acquire and use external scientific and technical knowledge (Allen, 1997). However, R&D intensity does not cover all dimensions of absorptive capacity, based on the definition given by Cohen and Levinthal (1990) and adopted for the construct in this thesis. Moreover, Zahra and George (2000) criticize using this measure and argue that R&D intensity does not reflect expenditure on all dimensions of identification, assimilation, transformation, and exploitation of knowledge. Therefore, this study operationalizes absorptive capacity by measuring both R&D and SGA expenditures. Both these variables are reported in the financial statements of publicly traded firms and are available through Standard and Poor's Compustat database.

One of the factors that needs to be considered in measuring absorptive capacity using R&D expenditure is the amount of time lag between R&D expenditure and innovation output. It takes an average of 12 years for a pharmaceutical firm to introduce a drug into the market (Dimasi, 2002). According to Graves and Langowitz (1993), R&D spending grows exponentially towards the introduction date of the drug to market and the bulk of R&D funds for a given new drug will be expended in the last few years of drug development. To consider the effect of R&D spending over the research life of a drug product, Graves and Langowitz (1993) used average R&D expenditure for the six years and three years prior to NCE introduction and found identical result in both models in terms of sign and significance. Therefore, following Graves and Langowitz (1993) and considering the availability

of reliable secondary data, this study uses the three-year average R&D spending prior to drug introduction to investigate its association with financial and non-financial performance of the pharmaceutical firms. However, to investigate the association between SGA and a firm's innovation performance, this thesis uses the reported financial data on SGA for the year just prior to the reported sales revenue. The main assumption here is that a pharmaceutical firm begins spending in sales and marketing for a drug as soon as it gets some positive signs of approval from the regulatory agencies. The SGA expenditure will result in sales revenue in the following year. This assumption is consistent with the Lin *et al.* (2006) investigation of R&D intensity and commercialization orientation effects on financial performance.

The second important factor to consider in using secondary data for calculating R&D intensity is the possibility of obtaining a ratio of greater than 1 for dividing R&D expenditure by sales revenue for some small new pharmaceutical firms. This case can occur when a new firm does not generate enough revenue from the sales of its products to support its R&D activities and relies mainly on funding from different sources including government, industry, venture capital, etc. As an example of this case, consider Lorus Therapeutics Inc., a Canadian biopharmaceutical company specializing in pharmaceutical products and technologies for cancer management. While the company generated only \$6,000 and \$26,000 revenue in 2005 and 2006, it spent more than \$14 million CDN and \$10 million CDN in R&D in 2005 and 2006, respectively. To finance its R&D and operations, the company entered into two

agreements to issue 28.8 million and 5 million common shares. Therefore, in cases similar to the case of Lorus Therapeutics, some type of adjustment needs to be performed to eliminate the possibility of a flaw in the research results. To eliminate the above problem in this thesis and following Graves and Langowitz (1993), the author investigate the association between R&D and SGA expenditures with the financial and non-financial performance of pharmaceutical firms.

Given the sensitive nature of drug products and the importance of R&D expenditure in the pharmaceutical industry, the first hypothesis in this thesis investigates the relationship between building a higher level of absorptive capacity through investments in R&D and a firm's innovation performance.

Hypothesis 1: A higher level of absorptive capacity achieved through investments in R&D will positively influence the innovation performance of pharmaceutical companies.

Hypothesis 1 can be broken down to illustrate and test the relationship among the absorptive capacity achieved through investments in R&D and each dimension of innovation performance.

Hypothesis 1a: A higher level of absorptive capacity achieved through investments in R&D will positively influence the financial criteria of a pharmaceutical firm's innovation performance.

Hypothesis 1b: A higher level of absorptive capacity achieved through investments in R&D will positively influence the customer criteria of a pharmaceutical firm's innovation performance.

Hypothesis 1c: *A higher level of absorptive capacity achieved through investments in R&D will positively influence the opportunities criteria of a pharmaceutical firm's innovation performance.*

Hypothesis 1d: *A higher level of absorptive capacity achieved through investments in R&D will positively influence the number of new drugs that a pharmaceutical firm develops and introduces to the market.*

According to Canner and Mass (2005), major U.S. firms spent more than \$180 billion on R&D in 2004 with few significant results in breakthrough innovation. A comprehensive study of success and failure in innovation over the past 40 years at Exxon Chemical revealed that significant investments in R&D produced only two breakthroughs for the company (Canner and Mass, 2005). Overall, the pharmaceutical industry has been experiencing some deficiencies in developing and introducing radical innovation (i.e., NMEs). The number of NMEs introduced into the market has been declining since 1996, even though R&D expenditure almost doubled in the last decade to \$35 billion in 2003 (Filmore *et al.*, 2004). According to Zahra and George (2000), firms need to invest in the commercialization of technology to be able to introduce their inventions into the market and benefit from their research. Tsai (2001) suggested that firms would perform better if they had a better understanding of their external environment. To obtain information about their external environment and to inform physicians, pharmacists, and patients about their new products, pharmaceutical firms spend heavily on business intelligence and on

the SGA. Table 9 provides information about the level of R&D and SGA expenditure (as a percentage of sales revenue) in 2005 for major multinational pharmaceutical companies in the world. As shown in this table, pharmaceutical firms, in trying to bring their innovations to the market, spent more on SGA in 2005 than on R&D. While R&D expenditure for the selected firms in Table 9 ranges from 8-18 percent of annual revenue in 2005, minimum spending in SGA is at about 25 percent of sales revenue.

Table 9: R&D and SGA Expenditure for major MNCs in 2005

Company	R&D Expenditure (percent of Sales)	SGA Expenditure (percent of Sales)
GlaxoSmithKline	14.48	33.47
Novartis	15.04	30.43
Abott	8.15	24.60
Pfizer	14.51	33.13
Merck	17.48	32.51
Hoffman La-Roche	18.29	27.45
Bristol Myers Squibb	14.30	34.27
AstraZeneca	14.11	36.30

Source: Annual financial reports obtained from company web sites

Lin *et al.* (2006) suggest that commercialization orientation – as measured by the SGA expenditure of high technology firms – is more important than R&D expenditure in the process of exploiting the value of technology innovation. This justifies the importance of SGA expenditure in building absorptive capacity. Therefore, the second hypothesis in this study investigates the relationship between SGA expenditure and innovation performance.

Hypothesis 2: *A higher level of absorptive capacity achieved through investments in SGA will positively influence the innovation performance of pharmaceutical companies.*

Similar to hypothesis 1, hypothesis 2 can be broken down into the four dimensions of innovation performance to illustrate and test the relationship among the dependant and independent variables:

Hypothesis 2a: *A higher level of absorptive capacity achieved through investments in SGA will positively influence the financial criteria of a pharmaceutical firm's innovation performance.*

Hypothesis 2b: *A higher level of absorptive capacity achieved through investments in SGA will positively influence the customer criteria of a pharmaceutical firm's innovation performance.*

Hypothesis 2c: *A higher level of absorptive capacity achieved through investments in SGA will positively influence the opportunities criteria of a pharmaceutical firm's innovation performance.*

Hypothesis 2d: *A higher level of absorptive capacity achieved through investments in SGA will positively influence the number of new drugs that pharmaceutical firms introduce to the market.*

4.3 The Moderating Effects of Functional Integration and Commercialization Strategy

The sensitive nature of drug products and the high cost associated with R&D and commercialization of drugs in the pharmaceutical industry have led to numerous

regulations by governments in all countries to protect the public and to ensure the availability, safety, and efficacy of drug products (LaFrancis *et al.* 1994). The industry is highly regulated and governments across the world have policies and regulations in place to ensure that the safest and most effective drug will be available to physicians and patients at an affordable price. These regulations, which are intended to protect consumers from malpractices or mistakes by some firms in the industry, create a unique competitive environment in which the pharmaceutical companies operate. To compete and remain profitable, pharmaceutical firms need to improve the efficiency and productivity of their R&D by creating an environment of cooperation among their functional units. In addition, they need to formulate a commercialization strategy that helps them transform their R&D into a salable product and make it available in the world market.

The literature in technology management suggests that functional integration in a firm improves NPD performance. Functional integration is the process of collaboration, communication, and coordination of R&D, marketing, production, sales, and logistics functions in an organization. The effect of functional integration on organizational performance has been extensively studied in technology and innovation management research. There is considerable evidence in the literature that supports a positive relationship among R&D, marketing, and a firm's new product development performance (Griffin and Hauser, 1996; Droge *et al.*, 2000; McDonough, 2000) that encourages firms to develop cross-functional teams to manage their innovation projects. Functional integration helps individuals in

different functional units to share information and help each other in better obtaining information about the market, incorporating this knowledge into the company's existing pool of knowledge, and transforming it into a commercial product that meets the market needs (i.e., improve absorptive capacity). Sales and marketing personnel in the pharmaceutical firms are closer to external knowledge (e.g., consumers and suppliers) and are better positioned to identify and understand market requirements in various therapeutic areas. By forming cross-functional teams, this knowledge of market requirements can then be conveyed to R&D teams who can invest in discovering a compound that meets the identified needs. Cooperation between R&D, marketing, production, and regulatory teams will help the firm to minimize the time that it takes to develop the drug, reduce development cost, receive approval from regulatory agencies, and bring an effective and safe drug into the market. Many large pharmaceutical companies have established procedures and created innovation centers that allow R&D, production, marketing, and regulatory teams to work together from the early stages of identifying the market needs and discovering compounds to later stages of commercialization; developing the compound to a drug, receiving regulatory approval, and bringing the drug to market. For example, at global brands at GlaxoSmithKline, a major U.K.-based pharmaceutical company, R&D teams pair closely with commercial teams in their innovation centers to identify consumer needs and to develop drugs that meet those needs. This practice at GlaxoSmithKline has increased the company's pipeline of new drug research and has increased the number of drugs that the company

introduces to the market⁵. In general, firms can build absorptive capacity by forming cross-functional teams to work on different innovation projects.

Cross-functional teams are suggested to be one of the most effective means of functional integration. Top management support of functional integration is also found to have a positive impact on the efficiency and profitability of organizations (Sethi *et al.*, 2003). Top management involvement and support is important in achieving sufficient levels of integration across functional areas (Calanton *et al.*, 1995). To facilitate integration across functions, top management can cultivate an environment that tolerates risk taking within the organization, encourages information sharing, sets up reward systems, and allocates resources to more important projects. Top management can also encourage early involvement of marketing and technical personnel in the product development process (Calanton *et al.*, 1995).

In this thesis, functional integration is measured with items based on the approaches proposed by Collins and Smith (2006) and Shu *et al.* (2005) for measuring knowledge exchange. Respondents are asked to indicate the extent to which they agree or disagree with each of the following statements:

- 1- Employees in all functional units including R&D, manufacturing, marketing and regulatory approval see benefits from exchanging and combining ideas with one another.

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⁵ 2005 annual financial report available on company's web site visited at 14:00 on December 22, 2006.

- 2- Employees in all functional units believe that by exchanging and combining ideas and knowledge they can move new drug development projects forward more quickly than by working alone.
- 3- At the end of the day, our employees feel that they have learnt from each other by exchanging and combining ideas.
- 4- Employees at this company are proficient at combining and exchanging ideas to solve problems or create new opportunities.
- 5- Employees in this company do not do a good job on sharing information to come up with new ideas, products or services. (Reverse coded)
- 6- Employees here are capable of sharing their expertise to bring new projects to completion.
- 7- The employees in this company are willing to exchange and combine information with their co-workers.
- 8- It is rare for employees in this company to exchange information to find solution to problems. (Reverse coded)
- 9- The management team in our company supports information sharing among employees in all functional units.
- 10- The management team in our company encourages employees of all functional units to share information while working on various drug development projects.
- 11- The management has incentives in place that encourages employees of all functional units to work closely to share information on various drug development projects.
- 12- Employee bonuses and incentive plans in our company are based primarily on the performance of the organization.
- 13- Incentive plans in our company are based primarily on departmental performance. (Reverse coded)
- 14- The management team creates a team of R&D, marketing, manufacturing, and regulatory approval units every time a drug project is initiated.
- 15- Communication of new ideas from one department to another is practically impossible. (Reverse coded)
- 16- The management team asks the head of all departments to meet regularly to review drug development projects.

- 17- The head of each department in our company regularly meets with the employees of her/his department to share information and review drug project within the department.

The above 17 items are measured using a 7-point scale, where 1 = strongly disagree and 7 = strongly agree.

The following hypotheses test the moderating effects of functional integration on the relationship between absorptive capacity and innovation performance:

Hypothesis 3a: *A higher level of absorptive capacity improves the financial criteria of a pharmaceutical firm's innovation performance, especially where firms integrate their functional units by creating cross-functional teams.*

Hypothesis 3b: *A higher level of absorptive capacity is associated with a higher number of new drugs that pharmaceutical firms introduce to the market, especially in firms where functional units are integrated by creating cross-functional teams.*

Hypothesis 3c: *A higher level of absorptive capacity improves the financial criteria of a pharmaceutical firm's innovation performance, especially where management supports functional integration.*

Hypothesis 3d: *A higher level of absorptive capacity is associated with a higher number of new drugs that pharmaceutical firms introduce to the market, especially in firms where management supports functional integration.*

In addition to improving a firm's innovation performance by building absorptive capacity through spending in R&D and SGA and the moderating effects of functional integration on this relationship, inter-organizational cooperative

arrangements are crucial ingredients of the corporate strategy in commercializing new technology. The literature provides evidence of the positive effects of vertical and horizontal integration (e.g., strategic take over and cooperative arrangement) on a firm's performance. Formal and informal integration are believed to have an impact on a firm's ability to commercialize its own innovation (Zahra and Nielsen, 2002). In addition, the resource-based view of the firm suggests that a company can achieve competitive advantage by having strong manufacturing and marketing capabilities (Stalk *et al.*, 1992; Narasimhan *et al.*, 2006; Dutta *et al.*, 1999). Cooperative arrangements enable firms to develop the skills, knowledge, processes, and equipment that they need to successfully commercialize their inventions.

Shan (1990) investigated the determinants of creating a cooperative relationship for commercializing new high-technology products in biotechnology firms and found that the competitive position of a firm has a significant impact on the firm's decision to cooperate with other firms in introducing their products to market. In other words, the further the firm is behind in competition with its rivals, the more likely it is to commercialize its products through a cooperative agreement such as complete merger, equity and contractual joint ventures, joint R&D agreements, licensing agreement, or manufacturing and marketing arrangements. The literature also suggests that firms cooperate at different stages of innovation depending on their size, the level of complementary assets they possess, and the strategy they formulate to improve performance. Smaller firms are believed to cooperate more with larger firms due to the lack of resources they need to commercialize their inventions.

Gans and Stern (2003) identified two main elements that shape the commercialization strategy (e.g., competition or cooperation) of a firm: excludability environment and complementary asset environment. An excludability environment is an environment in which a firm is capable of preventing its innovation from being imitated by other firms. One of the main appropriability mechanisms that innovators rely on to prevent their competitors from copying the new technology is the existence of a strong intellectual property protection mechanism (e.g., patent). A strong patent protection law, for example, guarantees that no other firm can produce or sell the innovator's new technology, as long as the patent for the new technology is not expired. Regulations, such as the existence of a strong patent protection law in the pharmaceutical industry, provide a bargaining power for drug inventors in their cooperation with other firms in developing and marketing the drug. This makes the complementary asset environment an important element in formulating a commercialization strategy for pharmaceutical firms. Depending on the level of control over complementary assets (e.g., production, marketing, distribution, business know-how), drug innovators usually cooperate with other firms by signing a cooperative agreement (e.g., licensing, co-marketing) at various stages of drug innovation (Hassanlou *et al.*, 2006) to commercialize their invention. In addition, Andrew and Sirkin (2003) identified three innovative approaches to guide executives in their decisions for successful launch of a new product in the market. However, these studies did not investigate the indirect impact of commercialization strategy on

the relationship among absorptive capacity and various dimensions of innovation performance of the pharmaceutical firms.

In this thesis, the commercialization strategy of a pharmaceutical firm is measured by items based on the approaches proposed by Andrew and Sirkin (2003) to classify innovation approaches, Gans and Stern (2003) to measure the excludability and complementary asset environment, and the willingness of a firm to enter into a cooperative agreement to develop a drug. Respondents have been asked to indicate the level of importance and the extent to which they agree or disagree with each of the following statements:

- 1- How important is each of the following items in generating revenue from your company's new drug projects?

Discovering a compound that could be developed to a drug

Developing the compound to an effective and safe drug

Manufacturing capabilities to produce the drug

Marketing and distributing capabilities to sell the drug

Business know-how to receive government approval

- 2- To what extent is your company capable of:

Discovering new compounds?

Developing the compound into a drug?

Manufacturing the drug?

Distributing and marketing the drug?

Post-marketing screening?

Receiving regulatory approval?

- 3- What level of control does your company have over the following resources?
  - Research and development
  - Manufacturing
  - Sales and marketing
  - Regulatory approval
- 4- How does your company protect its innovation from imitation by other firms?
  - Trade secrecy
  - Patent protection
  - Copyright protection
  - Other (please specify)
- 5- Patent protection law is very strong in the markets that our company operates in.
- 6- Our company enters into cooperative arrangements to:
  - Conduct R&D for other firms
  - Manufacture drugs developed by other firms
  - Market other firm's drugs
  - Provide business know-how to other firms
- 7- We hire other companies to:
  - Conduct R&D for us
  - Manufacture our drugs
  - Market our firm's drugs
  - Provide business know-how to us

The above questions are measured using a 7-point scale, where 1 = strongly disagree and 7 = strongly agree, except for the first three questions for which the level of importance of each item was measured using a 5-point scale (i.e., 1=low and 5=high).

The following two hypotheses will be tested to understand the moderating effects of commercialization strategy on the relationship between absorptive capacity and innovation performance:

Hypothesis 4a: The effect of absorptive capacity on a firm's innovation performance is significantly lower for integrator firms in the pharmaceutical industry.

Hypothesis 4b: The effect of absorptive capacity on a firm's innovation performance is significantly higher for licensor firms in the pharmaceutical industry.

The next chapter of the thesis explains the methodology applied to collect primary and secondary data to test the hypotheses and investigate the relationships among variables in the model.

Chapter 5: Research Methodology

This chapter explains the methodology applied to test the hypotheses and investigate the relationship among the variables in this study. First, a discussion of research design will be provided as a rationale for the adopted methodology. Second, the sampling frame for this research is explained. Third, information about the data collection procedures is provided.

5.1 Research Design

The purpose of research design is to develop a roadmap to guide in answering the research questions. According to Davis (2000), the design process is a series of decisions about what concepts are to be studied, how these concepts will be measured, what approaches will be used to study the problem, who will be studied, how the data will be collected and analyzed, and how the information that was collected will be used to solve the problem. Cooper and Emory (1995) suggest that research design spans a range of objectives from simple exploratory analysis to formal causal analysis. Exploratory analysis is a statistical practice that is concerned with reviewing, communicating, and using data where there is a low level of knowledge available about its cause system (Tukey, 1977). Causal analysis includes either prediction or explanation of variables, depending on the context of the question in the study (Davis, 1985).

Since the purpose of this study is to examine the impact of absorptive capacity on a firm's innovation performance, the study applies quantitative research methods to analyze, predict, and explain the relationships among variables. Wikipedia, the online encyclopedia, defines quantitative research as “the systematic scientific investigation of quantitative properties and phenomena and their relationships”. Quantitative research uses scientific methods – which include the generation of models, theories, and hypotheses; the development of instruments and methods for measurement; experimental control and manipulation of variables; collection of empirical data; modeling and analysis of the data; and evaluation of results. Quantitative research involves structured survey questioning of some type that is subsequently numerically and statistically analyzed (Davis, 2000).

According to Wikipedia, the objective of quantitative research is to develop and employ mathematical models, theories, and hypotheses pertaining to natural phenomena. The process of measurement is central to quantitative research because it provides the fundamental connection between empirical observation and mathematical expression of quantitative relationships. Therefore, quantitative research relies on numbers and statistical methods to investigate and describe all aspects of phenomena. An important element in quantitative research is the development of research instruments and measurement tools, including survey questions and test items that can effectively be used to collect data.

To test the hypotheses developed in the previous chapter, in addition to using secondary sources of data for some of the variables in the model, a survey instrument has been developed to collect primary data. Sorescu *et al.* (2003) list 17 data sources that provide reliable secondary data. One of the data sources mentioned in their study is the Standard and Poor's Compustat database that provides company-specific financial information for publicly traded firms. The author obtained secondary data from the Compustat for some of the variables in this thesis.

To operationalize the constructs in the framework of this study, the author used a number of empirical studies that have used similar constructs in their research. We either used the same measures or modified them to fit the framework under investigation. For example, Gans and Stern (2003) developed a model to investigate commercialization strategies adopted by firms. Many of the questions in their survey have been adopted and modified for this thesis to collect primary data. This is likely to be the most efficient and effective way to develop a survey instrument because the previous authors have already tested their survey instrument for reliability and lack of error⁶. The measurement of variables has already been discussed in the previous chapter. A copy of the survey that includes all the items designed to measure and study the constructs in this thesis is available in Appendix A1.

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⁶ As the questionnaire for the Gans and Stern (2003) study was not included in their article, we communicated directly with Gans and Stern and they generously provided a copy of their survey.

5.2 Sampling Frame

This study investigates the relationship between absorptive capacity and innovation performance in the U.S. and Canadian pharmaceutical companies. Therefore, the unit of analysis for this research is a pharmaceutical company. In specific, this thesis focuses on publicly traded companies that are included in the Standard Industrial Classification (SIC) system number 2834, which refers to pharmaceutical firms, and in the North American Industrial Classification System (NAICS) number 3254, which includes pharmaceutical and medicine manufacturing companies.

The sampling frame is comprised of the senior executives (e.g., CEOs, presidents, and vice-presidents) of the Canadian and U.S. pharmaceutical companies. We used Compustat to obtain a list of active and publicly traded pharmaceutical companies in the U.S. and Canada. The Standard and Poor's Compustat database provides financial information for all publicly traded companies. This database has general information and financial data for about 1,500 actively traded pharmaceutical companies across the world. The list contains information about the name of the companies; names and contact information of four of the senior managers in each company; mailing address; company SIC and NAICS codes; financial information on sales, assets, R&D; and SGA expenditure for 536 companies (i.e., 75 Canadian and 461 U.S. companies).

The very dynamic nature of the pharmaceutical industry reduces the accuracy of any database in a very short period of time. As will be explained later in the section on data collection, the list obtained from Compustat was not updated with recent changes in the company information. Six companies in the list have been taken over or have gone through mergers and acquisitions and did not exist anymore, which reduced the sample size of companies to 530. The author also noticed changes in the contact information, location, and names of the senior managers in a large number of companies in the Compustat list. As a result of inaccuracy in the list, the author looked at other sources, including company web sites, to find and update the list with correct information. The updated list was used to identify and contact survey recipients for this study.

Table 10 provides detailed information about the number and location of each company in the Compustat list. It also provides information about the number of usable responses that were received from companies in the two countries. As the table shows, companies in the U.S. are located in 32 states – the majority of them are in California, Massachusetts, New Jersey, and New York with 132, 55, 53, and 37 companies, respectively. Canadian pharmaceutical companies are mainly located in Quebec, Ontario, and British Columbia with 24, 23, and 15, respectively.

Table 10: Number and Location of pharmaceutical companies in the U.S. and Canada

Country	State/Province	No. of Companies	Number of Usable Responses Received
U.S.	Alabama	1	0
	Arizona	8	0
	California	132	13
	Colorado	13	0
	Connecticut	7	1
	Florida	21	2
	Georgia	5	0
	Hawaii	2	0
	Idaho	1	0
	Illinois	11	3
	Kentucky	1	0
	Maine	2	0
	Maryland	19	1
	Massachusetts	55	8
	Michigan	6	2
	Minnesota	6	0
	Missouri	3	0
	Nevada	3	0
	New Hampshire	1	0
	New Jersey	53	1
	New York	37	6
	North Carolina	9	2
	Ohio	3	0
	Oklahoma	2	0
	Oregon	2	0
	Pennsylvania	20	0
	Tennessee	5	0
	Texas	12	1
	Utah	7	0
	Virginia	2	1
	Washington	11	0
	Wisconsin	1	0
Total U.S. Companies		461	41
Canada	Alberta	10	3
	British Columbia	15	4
	Manitoba	1	0
	Newfoundland	1	0
	Nova Scotia	1	0
	Ontario	23	11
Quebec		24	6
Total Canadian Companies		75	24
Total Number of Companies		536	65

5.3 Data Collection

Primary data was collected through the use of an eight-page survey instrument designed for this study. The survey contained 127 items capturing general company information (51 items), financial criteria (13 items), customer criteria (five items), opportunity criteria (four items), functional integration (17 items), and commercialization strategy (37 items). Primary data collection posed a major challenge given the small number of publicly traded companies active in this industry and the industry's norms and standards for protecting company-specific information. In order to counteract this challenge, the following steps were taken to increase the response rate.

First, prior to sending the survey to the Canadian and U.S. pharmaceutical firms, the author contacted the survey recipients including, but not limited to, the presidents and vice presidents of R&D; business development; marketing; and commercialization, invited them to participate in this study, and obtained their agreement for sending them the questionnaire. Two of the people that we contacted refused participation and said that "... it is not our company policy to participate in research". Second, those who agreed to participate in this study received a personalized envelope containing an eight-page questionnaire and a highly personalized and signed cover letter that explained the nature of the research and its objectives, including the following paragraph about the confidentiality of information, and a professional return envelope with prepaid postage.

“Confidentiality will be insured by not disclosing the information in the questionnaire to outside parties, assigning a number to this questionnaire, and storing it in a locked location. Anonymity will be insured by combining the results of the individual questionnaire when reporting the research findings.”

Third, four weeks after the first contact and mailing the package, the author did a follow up with another phone call. In the call, potential participants were asked whether they had received the package and if they would like to receive more information to respond to the survey. The author sent another package to those who said that they had not received the package in the first mailing. At the time of the first contact, 48 senior managers in the dataset that had been contacted asked for a copy of the survey to be sent to them by email and provided their email address. This email address was used for future communication with the participants. Fourth, an email was sent to individuals who had agreed to participate but did not respond to the survey encouraging them to send us their response before a set deadline for data collection. Parallel to this email communication, we sent a second package to those who had not responded 6 weeks after the second mailing. Finally, we administered the same survey online to make it easier for participants to respond to the survey by answering the questions online. The link to the web site was provided in an email communication to the participants who provided their email address. However, there was no response using the online service.

Chapter 6: Descriptive Statistics

We received a total number of 67 responses (12.64 percent response rate), of which 24 were from Canadian companies, 41 from companies in the U.S. (Table 11), and two were unusable responses. These two responses were excluded from the analysis as the answers to the majority of questions were incomplete. The author used a coding system to be able to match the responses to the survey with the secondary data in the original database and, as a result, we were able to identify 64 companies that responded to the survey and match them to the original database obtained from Compustat. The author was unable to identify the respondent to one survey, although we know that it came from a Canadian company, as the respondent did not use the return envelope to mail the response. However, it was decided to include this response in the analysis. In addition, 18 survey envelopes were returned marked either as “undeliverable” or the sender included a note that she/he believed that the survey questions did not apply to her/his company.

Table 11: Distribution of usable responses by the U.S. and Canadian firms

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Canada	24	36.9	36.9	36.9
	U.S.	41	63.1	63.1	100.0
	Total	65	100.0	100.0	

To provide more information about the size of the companies that participated in this research, distributions of key variables in the study including sales revenue, R&D investment, SGA expenditure, number of employees and the number of new drugs are provided in Appendix D.

The average response time (i.e., the time elapsed from the first contact with the recipient to the time of receiving the response) for this research was 42 days, with a minimum of 1 day, a maximum of 111 days, and a median of 32 days. On average, it took 48.2 days to receive a response from a Canadian company compared to 38.12 days for receiving a response from the U.S. companies (Figure 13).

Figure 13: Boxplot of the response time by country

The difference in the average response time between companies in the two countries could be attributed to more support for university research by the U.S. firms, although other factors (e.g., the use of stamps on return envelopes for the U.S. firms

in place of pre-paid postage envelopes for the Canadian firms) might have an impact on the lower response time by the U.S. firms. However, we applied the independent samples t test to test the differences in the mean response time on key variables in the database (i.e., sales revenue, R&D spending, SGA expenditure, and number of employees) in this research and found no significant difference between companies in the two countries in their response time. The conclusion is that the difference between the Canadian and U.S. companies responding to the survey is purely random and due to chance. We checked the data to ensure that it meets the independent samples t test assumptions (i.e., equality of variance and independent observations) before the actual test. The independent samples t test is fairly robust to departures from normality but the data should be symmetric with no outliers. As the data was not symmetric (i.e., skewed to the right) for the variables under investigation, the variables were log-transformed to make the data symmetric and remove the outlier effects in the analysis. The Durbin-Watson test of independence fell in the acceptable range of 1.5-2.5 for all t tests (Bhargava *et al.*, 1982). Table 12 summarizes the independent samples t test to compare the two groups of the U.S. and Canadian cases on their response time.

Table 12: Summary output: Independent samples t test on country response time differences for selected variables

Assumptions=Equal variances

assumed

	Levene's Test for Equality of Variances		t-test for Equality of Means						
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
Log-Transformed number of employees	1.161	.285	.192	63	.848	.07941	.41364	-.74717	.90600
Log-Transformed Sales revenue	2.304	.134	.172	62	.864	.18729	1.08863	-1.98885	2.36344
Log-Transformed Average R&D spending	1.273	.263	-.858	62	.394	-.328	.382	-1.092	.436
Log-Transformed SGA Expenditure	1.067	.306	-.951	61	.345	-.391	.411	-1.214	.431
Response Time	.665	.418	1.351	63	.182	10.08638	7.46731	-4.83586	25.00862

The average number of employees working for the companies that participated in this research is 816, with a minimum of two employees in a small company and a maximum of 40,000 employees in a large multinational company. The average annual R&D spending for the sample is \$70 million compared to an average \$176 million for the SGA expenditure. On average, the companies in the sample generate more than \$330 million annual sales revenue (Table 13).

Table 13: Descriptive Statistics for selected variables

		Sales revenue	Average R&D spending in the past three years	SGA expenditure last year	Number of employees working for the company
N	Valid	64	64	63	65
	Missing	1	1	2	0
	Mean	3.32E8	70122367.96	1.7649E8	815.91
	Median	3068570.33	10742833.33	8.1720E6	50.00
	Std. Deviation	2.327E9	3.879E8	1.17647E9	4978.508
	Minimum	1000	171667	184000.00	2
	Maximum	18637000000	3108333333	9.35E9	40000

As illustrated in Table 14, Canadian pharmaceutical companies in our research sample generate average annual sales revenue of \$50.6 million compared to \$490 million for the U.S. companies. The average R&D spending in the past three years by the Canadian firms is lower than their U.S. counterparts, \$15.7 million compared to \$101 million. Further, the Canadian firms in the sample spent about 14 times less on SGA than the U.S. firms, \$19 million compared to \$260M. In addition, Canadian firms were smaller in size than the U.S. firms in terms of the number of employees working for the company (i.e., average 328 employees compared to 1,101).

Table 14: Descriptive statistics for selected variables

Variable	Country	Mean	Std. Error
Sales revenue	Canada	50658693.72	3.017E7
	U.S.	4.90E8	4.539E8
Average R&D spending in the past three years	Canada	15750603.62	3997623.311
	U.S.	1.01E8	7.557E7
SGA Expenditure last year	Canada	1.9013E7	6.60174E6
	U.S.	2.6099E8	2.27600E8
Number of employees working for the company	Canada	328.83	211.918
	U.S.	1101.02	972.944
Percentage of drug discoveries from in-house R&D in 3 years	Canada	.6239	.09088
	U.S.	.5539	.06776
Percentage of new drugs marketed in 3 years using internal sales resources	Canada	.1273	.07031
	U.S.	.2666	.06825

The U.S. pharmaceutical companies outsource more of their drug discovery projects and the Canadian firms use more in-house R&D resources to discover drugs. On average, more than 62 percent of the drug discoveries in the Canadian pharmaceutical companies were achieved using internal R&D resources, compared to 55 percent for the U.S. firms. On the other hand, Canadian firms outsource more of their drug sales and marketing activities. U.S. firms used their internal sales and marketing resources to market 26.7 percent of their drug discoveries compared to less than 13 percent for the Canadian firms (Table 14).

Table 15: Descriptive statistics – sources of cash in-flow

Variable	Country	Statistic	Std. Error
Percent of cash in-flow from the sales of new and existing drug	Canada	.1725	.07131
	U.S.	.2072	.05381
Percent of cash in-flow from licensing	Canada	.08263	.032658
	U.S.	.10474	.037555
Percent of cash in-flow from government research fund	Canada	.0315	.01783
	U.S.	.0167	.00695
Percent of cash in-flow from industry research fund	U.S.	.0026	.00256
Percent of cash in-flow from issuing company shares	Canada	.4070	.08576
	U.S.	.4046	.06602
Percent of cash in-flow from venture capital fund	Canada	.1320	.06823
	U.S.	.0962	.03793
Percent of cash in-flow from partnership	Canada	.09000	.038893
	U.S.	.09885	.029634
Percent of cash in-flow from long- and short-term loans	Canada	.0315	.02046
	U.S.	.0531	.02178
Percent of cash in-flow from interest income	Canada	.0410	.02994
	U.S.	.0136	.00431
Percent of cash in-flow spent on R&D	Canada	.5689	.07222
	U.S.	.5679	.05571
Percent of cash in-flow spent on sales and marketing	Canada	.0953	.02719
	U.S.	.1292	.03579

a. Cash in-flow from industry research fund % is constant when Country = Canada. It has been omitted.

In terms of cash-in-flow to run the operations, Canadian firms rely more on government research funds than do the U.S. companies (Table 15). On average, Canadian firms received 3.15 percent of their cash-in-flow from government compared to 1.67 percent for the U.S. firms. Cash-in-flow from the sales of new and

existing drugs is lower for the Canadian firms than for the U.S. firms (i.e., 17.2 percent compared to 20.7 percent). The U.S. firms received more cash in-flow from licensing activities than the Canadian firms (i.e., 10.4 percent compared to 8.2 percent). Venture capitals invested more in Canadian companies than in the U.S. pharmaceutical companies (i.e., 13.2 percent compared to 9.6 percent). Cash in-flow from interest income was three times higher for the Canadian firms than their U.S. counterparts (i.e., 4.1 percent compared to 1.3 percent) but the U.S. firms borrowed more than the Canadian companies (5.3 percent compared to 3.15 percent). Finally, about 40 percent of the needed cash in-flow in both Canadian and U.S. companies was obtained through issuing company shares.

While the U.S. and Canadian pharmaceutical companies in the sample spent about 57 percent of the generated cash-in-flow from various sources on R&D, the U.S. companies spent more on sales and marketing than did the Canadian pharmaceutical companies (i.e., 13 percent compared to 9.5 percent).

Chapter 7: Data Preparation and Analysis

This chapter of the thesis presents the methodology that we applied to prepare the data to meet various assumptions of statistical techniques used in hypotheses testing. First, a discussion of missing value analysis will be presented. Second, regression models (i.e., simple, multiple, and Poisson regression) that were applied as the main statistical techniques to test the proposed hypotheses in this study will be presented. Third, an examination of outliers, extreme points, and unusual cases will be discussed. Fourth, a discussion of non-response bias in this thesis will be presented. This will be followed by the reliability analysis that the author conducted to assess the reliability of the four constructs developed for this study. A discussion of factor analysis on each construct will also be provided in this section. Finally, the last section of this chapter will present hypothesis testing in this thesis.

7.1 Missing value Analysis

Out of the 65 responses that were received, 17 were complete with answers to all 127 questions. There are 48 responses that have missing values in at least one of the variables in the survey. Therefore, the author conducted a missing value analysis to understand if the missing is at random (MAR), missing completely at random (MCAR) or if there is a pattern in the missing values (i.e., missing not at random, MNAR). According to Karmaker and Kwek (2007), MCAR occurs when “the probability of a value being missing does not depend on observed or unobserved/missing

measurements”, and MAR happens when “the ‘missingness’ of a value does not depend on the unobserved data, given the observed data”. Rubin (1976) differentiated between MCAR, where there is independence between outcomes and the mechanism governing missingness, and MAR, where there is dependence between them, but only in the sense that missingness may depend on the observed, but not on the unobserved measurements. Finally, when there is a pattern in missing values (MNAR), the missing values depend on the unobserved outcomes, in addition to the observed outcomes.

The missing value procedure of the Statistical Package for the Social Sciences (SPSS) was used to find out if there is a pattern in the missing data, which variables have missing data and how big they are, what the extreme values are and for which variables, and whether the values are MAR or MCAR. This procedure can be used to obtain estimates of means, standard deviations, covariances, and correlations using different missing value techniques – such as listwise, pairwise, regression, or expectation-maximization (EM). In addition, this procedure can also be used to impute missing values with estimated values using mean, regression, or EM methods.

The univariate statistics of the missing value analysis output shows that the variables that measure customer criteria and opportunity criteria (i.e., five and four variables, respectively) have the highest percentage of the missing values ranging from 43.1 to 60 percent of the responses. In addition, the items measuring “percentage of cash in-

flow spent on sales and marketing” have the next highest percentage of missing values with 18.5 percent. This is followed by 16.9 percent of missing values for these variables: “R&D team provides input to train sales” and the “company will partner with another company if the new discovered drug does not fit in the company’s strategy”. On the other hand, a large number of variables have zero missing values. These variables include the “number of employees working for the company”, the company is involved in various drug development activities”, “ideas with the greatest scientific merit have the highest priority for drug research”, and “ideas with the greatest market value have the highest priority for drug research.” The variable for the “number of employees working in sales and marketing” has the greatest number of extreme values of 13.

The separate-variance t tests table of the missing value output identifies variables whose pattern of missing values may be influencing the quantitative variables. The author examined the separate-variance t tests table and noticed that companies that are more involved in drug research (i.e., those companies that spend more of their cash in-flow in R&D and have discovered more new drugs using internal R&D resources) are more likely to have missing values for the marketing variables. For example, cash in-flow spent in R&D has a higher mean missing value of 0.96 than the mean non-missing value of .5468 for the variable “drugs marketed in the past three years using internal marketing resources”. In addition, the mean missing values for all five customer criteria and four opportunity criteria variables are higher than the mean non-missing values for the two variables: “cash in-flow spent in R&D” and

the “new drugs discovered in the past three years using internal R&D resources”. The author obtained similar information by examining the cross-tabulation of categorical variables versus indicator variables tables, which is part of the output of the missing value analysis. One possible conclusion that could be made in the response sample is that respondents whose companies are more involved in drug discovery but less active in marketing drugs did not see the customer criteria and opportunity criteria questions as applicable to their situation, or the respondents were the head of the R&D department and did not know about the marketing function in their company to be able to respond to the customer criteria and opportunity criteria questions.

However, the Little MCAR test confirms that the missing data in this study may be missing completely at random (i.e., Chi-Square = 115.424, DF = 128, Sig. = .780). When the data are missing completely at random, one can safely use listwise or pairwise deletion to deal with missing values. However, listwise deletion results in loss of information and reduces the sample size, which diminishes the statistical power of the analysis and is not recommended for small sample sizes.

The literature is mixed on how to deal with the missing values. In general, there are three possible options to deal with missing values: 1) do nothing and leave the data as is (Rubin, 1976), 2) delete the cases with missing values (listwise or pairwise deletion), and 3) use imputation techniques to replace missing values (Graham and Hoffer, 2000). While each of the three options has advantages and disadvantages, it

seems that more researchers use imputation techniques in dealing with missing values. However, there is little agreement on what technique to use to impute the missing data. Some authors have replaced the missing values with the sample mean of the variable (Jordan, 2009), some have replaced the missing values with zero (Hersch *et al.*, 2008), and others have used regression method to impute the missing values (Barger and Gallo, 2008). The SPSS offers a number of techniques including series mean, median of nearby points, mean of nearby points, linear interpolation, and linear trend at a point to impute missing values.

Although mean substitution was the most common technique for imputation of missing values and some authors including Jordan (2009) have replaced the missing data with the sample mean, there is a concern about using this technique to impute missing values. Replacing missing values by the mean of the variable will reduce the variance in the variable (Stansbury and Victor, 2009), which can bias correlation downward (i.e., attenuation) or, if there are missing cases for two variables and means are substituted, correlation can be inflated. Following Barger and Gallo (2008), we used the regression method to replace missing values in the data with the predicted values resulting from regression before running statistical tests.

7.2 Regression Models

This section of the thesis explains the statistical techniques that were used to analyze the data. Depending on the type of data, we used different methods, including simple

linear regression, multiple regression, and Poisson regression models. A discussion of meeting the assumption of each statistical method is also provided.

7.2.1 Simple Linear Regression

In simple linear regression we are interested in predicting the value of a dependent variable from a single independent variable or predictor. The mathematical relationship between the dependent and independent variables can be shown as:

$$Y_i = a + bX_i + \varepsilon_i$$

Where Y_i is the dependent variable, a is the y intercept, b is the slope of the regression line, X_i is the predictor, and ε_i is the error term associated with observation i . The y intercept, a and coefficient b are the parameters of the model to be estimated using the least square criterion. The ε_i 's are the errors of prediction (i.e., residuals or the difference between the observed and predicted values) and are assumed to be independent, normally distributed with a mean of 0 and constant variance. We used simple linear regression to test some of the hypotheses in the research, including testing the relationship between financial criterion of innovation performance (i.e., sales revenue) with R&D and SGA expenditures.

7.2.2 Multiple Linear Regression

In multiple regression, we are interested in predicting a dependent variable from a set of independent variables or predictors. In general, in a multiple regression model the attempt is “to find the linear combination of independent variables which is maximally correlated with the dependent variable” (Stevens, 1992). In other words, the correlation between the observed and predicted y scores is maximized. The following equation is the mathematical representation of multiple regression:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_p X_{ip} + \epsilon_i, \quad i = 1, \dots, n$$

Where Y_i is the dependent variable, $\beta_0, \dots, \beta_p$ are model parameters to be estimated, $X_{i1}, \dots, X_{ip}$ are independent variables, and ϵ_i is the error term associated with observation i . In addition to the assumptions stated above for simple linear regression, the absence of multicollinearity is assumed in multiple regression. Multicollinearity poses a real problem in multiple regression for three reasons (Stevens, 1992); 1) it severely limits the size of multiple correlation because the predictors go after the same variance on y , 2) multicollinearity makes it difficult to determine the importance of a given predictor, and 3) multicollinearity increases the variance of the regression coefficient. We tested multicollinearity among predictors using Variance Inflation Factor (VIF) for each predictor and followed the method suggested by Stevens (1992) on combining the predictors if their VIF value exceeded 10. Another important concern in using multiple regression models for

prediction is the ratio of sample size to the number of predictors for the model to cross-validate. The literature suggests about 15 subjects per predictor for a reliable equation (Stevens, 1992).

We used multiple regression to test a number of hypotheses, including the test of moderating effects of functional integration and commercialization strategy, on the relationship between innovation performance and absorptive capacity.

7.2.3 Linear Regression Assumptions

Regression analysis is a linear procedure. This technique will underestimate the relationship between variables if the linearity assumption is violated. The linearity assumption was checked using partial regression plots, which graph each independent variable on the x axis against the dependent variable on the y axis and residual plots (i.e., plots of standardized residuals against standardized estimates of Y). The residual plot is a preferred method and it should show that there is no pattern in the graph and no signs of curvature or heteroscedasticity. The histogram of standardized residuals and normal probability plot were examined to test for the normally distributed error term assumption. For normally distributed residuals, the histogram of residuals should show a roughly normal curve and the residuals on P-P plot should lay on a 45-degree line. We tested the independent observation assumption using the Durbin-Watson statistics. Its value lies between 0 and 4 (Bhargava *et al.*, 1982). A Durbin-Watson test value of about two indicates that

observations are independent. All the regression tests that were performed in this study passed the Durbin-Watson test of independence. Finally, the equality of variance (i.e., homoscedasticity) assumption in the regression analysis was tested by looking at the plot of residuals on the Y axis against the predicted values on the X axis. A homoscedastic regression model should display a cloud of error terms, whereas a lack of homoscedasticity has a funnel shape pattern, indicating greater error as the dependent increases (Berry, 1993).

7.2.4 Poisson Regression

Considering the fact that the data obtained on the number of new drugs introduced to the market by the pharmaceutical firms is a count data for the dependent variable, the choice of ordinary least square models may not be the best estimation technique (Zou and Simpson, 2008). A number of hypotheses in this study investigate the relationship among a count response variable and some independent variables. In such cases, the Poisson regression was applied as the preferred sampling model to test the relationships. According to Hausman *et al.* (1984), “the Poisson distribution is often a reasonable description for events which occur both randomly and independently in time. It has a long history in the analysis of accidents data with the most famous example being Von Bortkiewicz’s 1898 study of accidental death by mule kick in the German army.” The Poisson distribution has a positive mean, and its mean and variance are equal. However, “count data often show greater variability in the response counts than one would expect if the distribution was Poisson”

(Agresti, 1996). This is called overdispersion in Poisson regression. We followed the methodology suggested by Agresti (1996) if overdispersion was present in the analysis.

The mathematical equation for the Poisson loglinear model can be shown as:

$$\text{Ln } \mu = \alpha + \beta X$$

$$\mu = \exp(\alpha + \beta X) = e^{\alpha} (e^{\beta})^x$$

where μ is the expected value for a Poisson variate, α and β are model parameters to be estimated and X is the predictor variable. In Poisson, one unit increase in X has a multiplicative effect of e^{β} on μ . In other words, the mean of the response Y at $x + 1$ equals the mean at x multiplied by e^{β} .

7.3 Outliers and Extreme Points

A number of companies in the sample for this thesis employ a higher number of employees than the rest of the group, spend more on R&D and SGA, and generate more revenue. A univariate analysis indicates that there are 10 extreme points for the “number of employees working for this company” variable. In addition, there are outliers and extreme points for other variables including sales revenue, R&D and SGA expenditure, and the “number of new drugs” that need to be examined.

The author screened the data for outliers using the technique recommended by Stevens (1992). Depending on the type of test, the Mahalanobis Distance, or Cook’s Distance and Leverage Points, were measured to identify cases with unusual

combinations of values for independent variables and cases that may have a large impact on the regression model. Mahalanobis Distance is most commonly used as a multivariate outlier statistic, and it is a measure of how far a case's values on independent variable differ from the centroid of all cases (Stevens, 1992). A large Mahalanobis distance identifies a case as an outlier (i.e., having extreme values on one or more of the independent variables). Cook's Distance is very useful in identifying influential data points (Stevens, 1992). It measures the combined influence of an observation being an outlier on Y and on the set of predictors (Stevens, 1992) and is a measure of how much the residuals of all cases would change if a particular case was excluded from the calculation of the regression coefficients. A large Cook's Distance indicates that excluding a case from computation of the regression statistics changes the coefficients substantially. According to Cook and Weisberg (1982), a Cook's Distance of greater than one is considered large.

Leverage measures the influence of a point on the fit of the regression. In addition to checking the individual Cook's Distance and Leverage values, the author graphically examined the plot of Cook's Distance against the Centered Leverage values in linear regression tests to identify influential data points. In addition, we tested the skewness and kurtosis on each variable and transformed the data if the data was skewed.

7.4 Non-Response Bias

The primary data was collected through mail survey. The mail survey has been criticized for non-response bias (Armstrong and Overton, 1997). One concern in using survey methodology is that a low response rate may prevent the generalizability of the research findings. If persons who respond differ substantially from those who do not, the results do not directly allow researchers to say how the entire sample would have responded, which is an important step before the sample is generalized to the population (Armstrong and Overton, 1997). Therefore, assessing non-response bias, which is the bias in the data caused by a lack of response to the survey, is an important aspect of the research. According to Armstrong and Overton (1997) “the most commonly recommended protection against non-response bias has been the reduction of non-response itself”.

The literature (Kish, 1965; Stephan and McCarthy, 1958) describes three methods for estimating non-response bias: comparisons with known values of the population, subjective estimates, and extrapolation.

In the first approach to measuring non-response bias, researchers measure the degree of bias by comparing survey respondents’ characteristics with known population parameters. Mott *et al.* (2001) raise two major concerns in using this approach. First, the time period in which the population parameters were collected is a major concern, as changes in the population characteristics over time may not be applicable at the time of the study. The second concern with this approach is how the

population parameters were collected. The use of different instruments in collecting population parameters may result in a different definition for variables or different values being reported. This approach is not applicable in this thesis because, as far as we know, there is no source of data that contains many of the variables in this study for the population.

In subjective estimates of non-response bias, Kirchner and Mousley (1963) and Vincent (1964) suggest determining socioeconomic differences, such as education level and personality differences, between respondents and non-respondents. Another widely recommended technique for subjective estimate is the "Interest Hypothesis" (Donald, 1960), which is based on the assumption that people who are more interested in the subject of the study will respond to it. Rosenthal (1965) reviews the literature and concludes that people are more likely to respond to a questionnaire if they would make a favorable impression upon anyone who reads the responses. However, as noted by Haddad (1998), subjective estimates are open to bias and error and, therefore, the author would prefer not to use this approach in this thesis.

The third approach in measuring non-response bias, extrapolation method, is based on the assumption that subjects who respond less readily are more like non-respondents (Armstrong and Overton, 1997). According to these authors, "Less readily" has been defined as late responses from participants, or responses from those who require more prodding to respond to the survey. The most common type

of extrapolation is carried over successive waves of a questionnaire. According to Armstrong and Overton, (1997), a "Wave" refers to a response following a stimulus, such as a follow-up postcard, second mailing, email communications, or phone call. Persons who respond in later waves are assumed to have responded because of the increased stimulus and are expected to be similar to non-respondents (Armstrong and Overton, 1997). Extrapolation is useful when a survey of non-respondents cannot be conducted because of a number of factors, including cost and time.

Israel (1992)⁷ identifies several strategies to deal with non-response and estimate of response bias. These strategies include: throw the data away, if the researcher feels that the data is invalid; generalize to the respondents only; assume there is no response bias and generalize to the population; call back non-respondents; compare data in hand on respondents and non-respondent; compare characteristics of early respondents with late respondents; and increase mailings or contact efforts.

To measure non-response bias in this research, the author compared early respondents with late respondents on key variables, which included sales revenue, R&D spending, SGA expenditure, the number of employees working for the company, and the number of new drugs introduced to the market in the past three years using the independent samples t test. Early respondents are defined as cases who responded in less than the mean response time of 42 days and late respondents

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⁷ <http://edis.ifas.ufl.edu/pdf/files/PD/PD00800.pdf> accessed on Dec. 07, 2008 at 17:05.

are defined as those whose responses came to us 42 days after the first contact. The following is the result of independent samples t-test for the above variables.

1) Sales revenue

The differences between early and late respondents on sale revenue were tested using the independent samples t test. The independent samples t test is fairly robust to departures from normality. However, the data was checked to ensure that there are no outliers in the variables. An initial screening of the sales revenue variable identified some outliers that were filtered in the analysis of independent samples t-tests. In addition, to test the assumption of independent observations, the Durbin-Watson test was used and no violation of this assumption was found (i.e., Durbin-Watson = 2.111). The Independent samples t-test procedure in SPSS produces two tests of the difference between the two groups. One test assumes that the variances of the two groups are equal. The Levene's statistic tests this assumption. The other is based on unequal variance assumption. In this case, the value of the Levene's statistic is 0.910, which is not significant and it can be assumed that the groups have equal variances. Since the significance value of the t test is greater than 0.05, (i.e., $P = 0.516$) a safe conclusion is that the mean difference of \$4.5 million more sales revenue in the early respondent's group is due to chance alone and there is no significant difference between the two groups of early and late respondents on this variable for responding to the survey.

2) Average R&D spending in the past three years

This test also assumes equality of variance (Levene's statistics $sig. = 0.232$) for the two groups. The t-test is not significant (i.e., $P = 0.426$), which confirms that the difference of more than \$4M spending in R&D by early respondents is due to chance and there is no significant difference between the two groups of early and late respondents in terms of their average R&D spending in the past three years.

3) SGA expenditure

The Levene's statistics for this test is not significant (i.e., $sig. = 0.125$), which assumes equality of variance. There is no difference between the early and late respondents ($t = .439$, $P = 0.663$) in terms of their average SGA expenditure. Therefore, the mean difference of about \$3.5 million more SGA expenditure by the early respondent group is due to chance only.

4) Number of employees

Levene's test is significant at $p = 0.045$, meaning that the assumption of equality of variance is not met. However, as this assumption is only marginally not met, at 5 percent, the author assumes that the homogeneity of variance in the two groups is not drastically violated. Under this assumption, there is no difference between early and late respondents in terms of the number of employees that they employ, and the mean difference of 40 more employees in early respondents is due to chance.

5) Number of New Drugs

The Levene's test of equality of variance is not significant at the 0.05 level (i.e., $sig. = .425$), confirming that the equality of variance assumption is met. The significance level of t statistics is $p = 0.756$, which allows the safe conclusion that there is no difference between early and late respondents on this variable. The difference, less than one new drug introduced in the market by late respondents, is purely due to chance.

The t test results (Appendix B) suggest no significant difference between early and late respondents on key variables, providing evidence that response bias is not a factor in this thesis.

7.5 Construct Reliability and Factor Analysis

Reliability refers to the consistency and stability of a score from a measurement scale (Davis, 1999). In order to demonstrate that the survey instrument is reliable for the four constructs (i.e., customer criteria, opportunity criteria, functional integration, and commercialization strategy) that were developed for this study, the author calculated the reliability of the scale using the internal consistency method (i.e., Cronbach's alpha). Mathematically, reliability is defined as the proportion of the variability in the responses to the survey that is the result of differences in the respondents. That is, answers to a reliable survey will differ because respondents have different opinions, not because the survey is confusing or has multiple

interpretations⁸. Cronbach's alpha can range from 0 to 1. When the alpha coefficient is 1 the scale is considered perfectly reliable, and a coefficient of 0 is a sign for a perfectly unreliable measure (Davis, 1999). For a scale to be reliable, a Cronbach's alpha of 0.7 or more is recommended in the literature (Bagozzi and Yi, 1988; Fornell and Larcker 1981). Davis (1999) recommends that a reliability coefficient of 0.7 be used for exploratory research, 0.8 used for basic research, and 0.9 used in applied settings where important decisions will be made with respect to test results. In this thesis, if the scale passes a cut-off point of a Cronbach's alpha of greater than or equal to 0.7, the author concludes that the scale is reliable and perform principal technique of factor analysis to test convergent and discriminant validity of the scale in addition to reducing the number of items in each scale.

Validity is a measure of the accuracy of a measurement scale and it shows whether the measurement scale measures what it is supposed to measure (Davis, 2000). There are two types of validity, which include content and construct validity in measurement that researchers must be concerned with. Content validity is defined as "the degree to which the scale items represent the domain or universe of the concept under study" (Davis, 2000). To assess the content validity of measurement scales in this thesis, the author conducted a comprehensive search of the literature for all possible items to be included in each scale. The author next solicited expert opinion to make changes to the developed scale. The measurement scales were then tested in

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⁸ Notes from SPSS 16 online help

terms of time and accuracy and were modified as necessary. Davis (2000) defines construct validity as “the degree to which the measurement scale represents and acts like the concept being measured”. There are two aspects involved in the assessment of construct validity; convergent and discriminant validity. Convergent validity calls for theoretical justification of the concept by searching the literature. Discriminant validity, which is purely statistical, measures how the measurement scale may be differentiated from other scales. The author tested convergent and discriminant aspects of construct validity by looking at the intercorrelation matrix that resulted from the principal component analysis. A measurement scale has construct validity if the component resulting from factor analysis has factor loading of greater than .5 and less than .3 (de Jang *et al.*, 2009).

The author tested the assumptions of factor analysis, including Bartlett’s test of sphericity, which tests whether the correlation is appropriate for factor analysis, and Kaiser-Meyer-Olkin (KMO), which is a measure of sampling adequacy. Bartlett’s test should be significant at $p < 0.05$ and KMO is recommended to be above .50 (Hair *et al.*, 1998; Chavadi and Kokatnur, 2008). The following section provides the results of the reliability and factor analysis for the four constructs in this thesis.

7.5.1 Construct Reliability: Customer Criteria

The customer criteria construct is introduced in the theoretical framework to measure the company’s executive opinion on the level of customer satisfaction with the drugs

that the company introduced to market in the past three years. The author used a 5-item scale to measure this construct. All five items in this scale employed a 7-point Likert scale that required the respondents to indicate the extent to which they agree or disagree with the statements. The higher score in each item is associated with higher agreement with the statement and, therefore, a higher management perception of customer satisfaction with the drugs introduced by the company. The univariate statistics of the missing data analysis show that many of the participating companies in this research are in the development stage and, therefore, responded either “not applicable” or did not answer the questions for measuring this construct. Therefore, two reliability analyses were run. First, the Cronbach’s alpha was calculated for the original data; the second test was performed with the missing data replaced with their predicted values using the linear regression method to see if the results will dramatically change after data imputation. The overall Cronbach’s alpha (i.e., internal consistency coefficient) for the first test is 0.743, which is higher than the cut-off point of 0.70 recommended in the literature (Bagozzi, 1981; Fornell and Larcker 1981) that was used for this research. The result of the second test is fairly close to the first test with an internal consistency alpha value of 0.726.

The item-total statistics output provides more information about changes in alpha if a specific item is deleted from the scale. This statistic shows that the Cronbach’s alpha can be increased if the last item in the scale (i.e., “number of customer complaints has increased recently because of the side effects of the drug that your company introduced in the market during the past three years”) is deleted. This is a reverse

coded variable that was included in the scale. The author examined the correlation matrix for the five items in this scale and found that all of the first four items in the scale are strongly, positively, and significantly correlated with each other, but they all have a weak correlation with the last item in the scale (Table 16).

Table 16: Correlations for the five customer criteria items

Variable	CCCSWYND	CCCINDYC3	CCNDONM3	CCCLOYB	CCCIBND
CCCSWYND	1.000	.598**	.513**	.662**	.082
CCCINDYC3		1.000	.653**	.486**	.000
CCNDONM3			1.000	.574**	.191
CCCLOYB				1.000	.250
CCCIBND					1.000

** . Correlation is significant at the 0.01 level (2-tailed).

Considering both correlation matrix and the item-total statistics of the reliability output, the last item was deleted from the scale. As a result of this deletion, the Cronbach's alpha for the test has increased to 0.835.

7.5.2 Factor Analysis: Customer Criteria

Principal Component Analysis (PCA) with varimax rotation and an eigenvalue greater than one (Stevens, 1992) extracts one component for this scale that explains about 65 percent of the variability in the original variables, and it has a high factor loading with all items (Table 17). This component will be called "Customer Satisfaction," and its scores have been saved as Fac1_4 in the original data file that will be used in place of the original variables for the statistical analysis. Bartlett's

test was significant at $p < 0.001$ and KMO was 0.714, higher than the recommended value of .50 for a satisfactory principal component analysis (Hair *et al.*, 1998; Chavadi and Kokatnur, 2008; Stevens, 1992).

Table 17: Principal Component Analysis of Customer Criteria Construct

	Component
	1
New drugs that your company introduced opened new markets outside the existing market	.820
Customers are loyal to your brand	.814
Customers increased significantly because of the new drugs that your company introduced in the past three years	.811
Compared to your competitors drugs, customers are more satisfied with your company's drugs	.747

Extraction Method: Principal Component Analysis.

7.5.3 Construct Reliability: Opportunity Criteria

The opportunity criteria construct is introduced in the theoretical framework with a 4- item scale to measure the opportunities gained in the market by introducing new drugs. All four items in this scale employed a 7-point Likert scale that required the respondents to indicate the extent to which they agreed or disagreed with the statements. The higher score in each item is associated with higher agreement with the statement. Similar to the customer criteria construct, some of the participating companies in this research either left the questions for this construct unanswered or answered as not applicable. We, therefore, obtained two reliability coefficients for

the original data with missing values and for the data with missing values replaced by their predicted values of regression analysis. The first test resulted in an overall Cronbach's alpha reliability coefficient of 0.730, which is higher than the cut-off point that was set for this research. The second test resulted in a Cronbach's alpha coefficient of 0.676, which is marginally lower than the acceptable cut-off point and therefore, we can assume that the scale is reliable (Challis *et al.*, 2005). Tukey's test of additivity is not significant ($P = 0.416$ for the first test and $P = 0.052$ for the second test), which means that there is no multiplicative interaction between items and observations.

7.5.4 Factor Analysis: Opportunity Criteria

A principal component analysis (PCA) with a varimax rotation and an eigenvalue higher than one was performed on this construct with missing values imputed. The PCA extracts two components that explain more than 80 percent of the variability in the original variables. The first component is highly correlated with two variables: "knowledge gained in developing new drugs in the past three years will help the company to introduce more drugs in the future" and "your company sets standards because of perceived quality of its drugs". However, the first variable is a better representative of component 1 because it is less correlated with the second component. Therefore, component 1 will be called the "Knowledge" variable in the hypothesis testing. The second component is highly correlated with the other two items in the scale: "your company introduced a new drug with negative side effects

that negatively affected the company” and “sales of the old drugs increased because of the effectiveness of the new drugs” (Table 18). Component 2 will be called “Safety and efficacy” in hypothesis testing. Bartlett’s test was significant at $p < 0.001$ and the KMO of 0.581 was higher than the recommended value of .50 for a satisfactory principal component analysis (Hair *et al.*, 1998; Chavadi and Kokatnur, 2008; Stevens, 1992).

Table 18: Principal Component Analysis of Opportunity Criteria Construct - Rotated Component Matrix^a

	Component	
	1	2
Knowledge gained in developing new drugs in the past three years will help the company to introduce more drugs in the future	.925	.087
Your company sets standards because of perceived quality of its drugs	.919	.115
Your company introduced a new drug with negative side effects that negatively affected the company	-.071	.903
Sales of the old drugs increased because of the effectiveness of the new drugs	.384	.739

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

The scores for these two components have been saved as FAC1_5 (i.e., knowledge) and FAC2_5 (safety and efficacy) in the original data file to be used in place of the original four variables for the statistical analysis.

7.5.5 Construct Reliability: Functional Integration

The functional integration construct is introduced in the theoretical framework with a set of items to test its moderating effects on the relationship between the absorptive capacity construct and the innovation performance of the pharmaceutical firms. We measured this construct using a 17- item scale. All 17 questions in this scale employed a 7-point Likert scale that required the respondents to indicate the extent to which they agreed or disagreed with each statement. The higher score in each item is associated with higher agreement with the statement. The three reverse-coded items in the scale were fixed and entered in the SPSS file before running the reliability test. There are 61 valid responses in this test, and the results show a very good Cronbach's alpha coefficient of 0.878, which is much higher than the cut-off point for this research. The individual summary statistics for each item indicate a high mean for the responses to the items. This indicates that the respondents seem to believe that functional integration is an important factor in their companies. However, one of the assumptions in calculating the reliability of a scale is that each item in the scale should be linearly related to the total score. The Tukey's test of additivity investigates the null hypothesis that there is no multiplicative interaction between items and observations. The Tukey's test is significant in this analysis, meaning that items and observations interact. SPSS also provides an estimate of power that observations must be raised to achieve additivity. In addition, item-total statistic output provides more information about changes in alpha if a specific item is

deleted from the scale. Examining this statistic, it is evident that Cronbach's alpha can be increased in this test by deleting one of the items (i.e., employee bonus and incentives are based on departmental performance) that has a low corrected item-total correlation coefficient of -.064. This variable was deleted from the analysis and a second reliability test was performed. The Cronbach's alpha coefficient increased to 0.898 and the Tukey's test of additivity was not significant at 0.05 (i.e., Friedman's Chi-Square = 0.406, $p = 0.524$). Therefore, with one item deleted from the scale, the author conclude that the functional integration scale is reliable.

7.5.6 Factor Analysis: Functional Integration

A PCA with varimax rotation and an eigenvalue higher than one extracts three components for this scale. The three components explain more than 65 percent of the variability in the original 16 variables. The first component is highly correlated with variables that measure the willingness of employees to share information with their co-workers. This component will be named "cross-functional information sharing" in the hypothesis testing. The second component is highly correlated with variables that measure top management's support for information sharing, and, therefore, it will be called "management support of information sharing" in further analysis. Finally, the third component has high factor loadings with two items that represent management support for cross-functional information exchange. This component will be called "management support of cross-functional information exchange" in the analysis (Table 19).

Table 19: Principal Component Analysis of Functional Integration Construct - Rotated Component Matrix^a

	Component		
	1	2	3
It is rare for employees in your company to share information to find solutions	.853	.060	.152
Employees in your company are willing to share information with their co-workers	.818	.333	.295
Employees in your company are not good in information exchange	.680	.051	-.197
Employees in your company are capable in sharing expertise to finish project	.675	.309	.386
Employees believe that information exchange helps in rapid drug development	.666	.426	.427
Employees see benefit from information exchange	.647	.360	.402
Employees in your company are proficient in information exchange to solve problems	.635	.506	.356
Employees believe that they learn from each other by information exchange	.633	.416	.478
Heads of departments meet with employees to share information on new drug projects	.605	.234	.348
Employee bonus and incentives are based on organizational performance	.341	.309	.101
Top management in your company encourages employees to share information while working on drug projects	.179	.913	.031
Top management in your company supports information exchange in all functional units	.208	.907	-.001
Communication is practically impossible	.362	.551	-.007
Top management in your company has incentives in place to encourage employees to share information while working on drug projects	.046	.517	.377
Top management asks the heads of departments to meet regularly to review drug projects	.074	.134	.776
Top management forms teams of all units to work on drug projects	.245	-.103	.670

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

As shown in Table 19, there are two components that each relates to some aspects of management support of functional integration. This might create some problems at the time of hypothesis testing as both management support components may not act

differently as moderators in investigating the relationships between absorptive capacity and firm performance. One possible way to overcome this problem is to force the principal component analysis to extract only two components. The author conducted this test and found that 1) the amount of variance in the original variables explained by the two components is reduced to 58% from the original 65% and 2) one item that measures management support of functional integration is grouped with cross-functional information sharing variable because of its high correlation with the first component. Although the reduction of variance explained creates problems as it illustrates the loss of information, the second factor is more problematic because it creates some conceptual problems. To avoid this problem, the author decided to use the original three components in hypothesis testing.

Bartlett's test was significant at $p < 0.001$ and the KMO of 0.872 was much higher than the recommended value of .50 for a satisfactory principal component analysis (Hair *et al.*, 1998; Chavadi and Kokatnur, 2008; Stevens, 1992). A component score is calculated for each case and each component. The resulting three component scores have been saved as FAC1_6, FAC2_6, and FAC3_6 in the original data file to be used in place of the original 16 variables for the statistical analysis and hypothesis testing.

Figure 14 shows that there are a number of outliers in the first two components that need to be considered (e.g., deleted or replaced) in the components at the time of statistical analysis and hypothesis testing. In addition, Shapiro-Wilks W test of

normality shows that components one and two are not normal but component three is normally distributed ($W = 0.925$, $df = 65$ and $p = .001$; $W = 0.932$, $df = 65$ and $p = 0.002$; $W = .969$, $df = 65$ and $p = .104$, respectively). However, the first two components changed to normal after filtering the outliers in these two components.

Figure 14: Scatter plot matrix for three components resulting from factor analysis of functional integration

7.5.7 Construct Reliability: Commercialization Strategy

Commercialization strategy is the last construct in the theoretical framework to test its moderating effects on the relationship between absorptive capacity and innovation performance of the pharmaceutical firms. The author used a 37-item scale

to capture information about marketing, manufacturing, regulatory approval, and R&D capabilities of the U.S. and Canadian pharmaceutical firms. Questions in this scale employed a 7-point Likert scale that required the respondents to indicate the extent to which they agreed or disagreed with each statement. Similar to the previous constructs, the higher score in each item is associated with a higher agreement with the statement. In addition, there are three sets of questions that measure the level of importance of developing internal capabilities for the company in generating revenue. An answer of 1 indicates low importance and 7 is an indication of the high importance of developing a specific capability for the company.

Reliability analysis on this construct resulted in obtaining an internal consistency coefficient of 0.735, higher than the recommended cut-off point. Tukey's test of additivity for the test is not significant ($p = 0.516$), confirming that there is no multiplicative interaction between items and observations.

7.5.8 Factor Analysis: Commercialization Strategy

A PCA with varimax rotation and an eigenvalue higher than one extracted 12 components for this scale. The 12 components explain almost 75 percent of the variability in the original 37 variables. On the relationship between sample size and reliable factors and the number of components to retain, Stevens (1992) states that "many of the popular rules suggests that sample size be determined as a function of the number of variables being analyzed, ranging anywhere from two subjects per

variable to 20 subjects per variable”. However, Stevens (1992) refers to a Monte Carlo study by Guadagnoli and Velicer (1988) who indicated that “contrary to the popular rules, that the most important factors are component saturation (i.e., the absolute magnitude of the loadings) and absolute sample size. Also, number of variable per component is somewhat important”. One of their recommendations is that components with four or more loadings above .60 in absolute value are reliable, regardless of sample size. The author examined the rotated component matrix of the factor analysis output and found that the first component has five factor loadings higher than .60 and the second component has four factor loadings greater than .60, which meet the criterion recommended above. These two components explain only about 25 percent of the total variance in the original 37 variables; if only these two components were retained, the result would be too much information loss. Components three and four, however, marginally meet the above criterion – each has three factor loadings higher than .60 and one loading close to this number (i.e., 0.574 and 0.536). The author decided to retain these two components in the analysis to increase the amount of variance in the original variables explained by the components. Therefore, the first four components that explain more than 41 percent of the variability in the original variables are retained.

The first component has the highest factor loadings with variables that measure some aspects of in-house drug discovery and development. This component represents “in-house drug development strategy” in hypothesis testing. The second component has high factor loadings with variables that measure some aspects of

building complementary asset capabilities. This component will be named “developing complementary asset strategy” variable in the hypothesis testing. The third component has the highest factor loadings with the variable that measure company strategy in creating joint venture and partnering with other firms. This component will be called “external integration strategy” (i.e., competition) in the future analysis. Finally, the fourth component has the highest factor loadings with items that measure many aspects of outsourcing and licensing drug development projects. This component will be called “licensing strategy” (i.e., cooperation) in the hypothesis testing (Table 20). Bartlett’s test was significant at $p < 0.001$ and the KMO of 0.461 was marginally lower than the recommended value of .50 for a satisfactory principal component analysis (Hair *et al.*, 1998; Chavadi and Kokatnur, 2008; Stevens, 1992). A component score is calculated for each case and each component; the resulting four component score variables have been saved as FAC1_7, FAC2_7, FAC3_7, and FAC4_7 in the original data file to be used in place of the original 37 variables for statistical analysis.

Table 20: Principal Component Analysis of Commercialization Strategy Construct -
Rotated Component Matrix^a

	Component			
	1	2	3	4
Importance of generating revenue from developing drug	.777	.039	.079	-.070
License out discovered compounds that do not fit in company strategy	.713	-.127	8.689E-6	.142
Drug development based on company strategy and portfolio of current and future drug development	.672	.265	.155	-.099
Importance of generating revenue from discovering a compound	.634	-.201	.117	.123
Develop the drug in-house if a newly discovered compound has promising commercial gain	.608	.086	.129	-.317
Patent protection law is very strong in your market	.576	.170	.010	.195
Difficulty in obtaining approval has forced you to limit R&D spending	-.546	.007	.342	-.012
Protect innovation from imitation by patent	.502	-.008	.272	.264
Hold the drug and do nothing if a newly discovered compound has promising commercial gain	-.432	.044	.155	-.092
Level of control over R&D	.321	-.122	.015	-.093
Other companies provide business know-how for your company	.310	-.215	.197	.253
Importance of generating revenue from developing sales and marketing capabilities	-.112	.765	.010	.093
Importance of generating revenue from developing manufacturing capabilities	.143	.659	.199	-.026
Importance of generating revenue from developing business know-how capabilities	.123	.642	.072	.040
Level of control over manufacturing	.035	.632	.021	-.145
Extend the business line for discovered compounds that do not fit in company strategy	-.017	.632	.236	.249
Your company has a strong regulatory affairs department	-.117	.560	-.133	-.124
Level of control over marketing and sales	-.394	.538	-.231	.095
Level of control over regulatory approval	-.246	.390	-.313	-.161
Your company sells drugs developed by others	-.156	.361	-.207	-.132

Table 20 Cont'd: Principal Component Analysis of Commercialization Strategy Construct -
Rotated Component Matrix^a

	Component			
	1	2	3	4
Difficulty in obtaining approval has forced you to partner with another company	-.242	-.220	.731	-.065
Difficulty in obtaining approval has forced you to apply for regulatory approval from other countries	-.139	-.179	.606	-.207
Form joint venture to develop the drug if a newly discovered compound has promising commercial gain	.139	.269	.599	.354
Difficulty in obtaining approval has forced you to license out the drug to another company	-.318	-.214	.590	.037
Your company conducts R&D for others	.167	.235	.553	-.131
Form joint venture for discovered compounds that do not fit in company strategy	.221	.349	.526	.108
Patent the discovered compounds that do not fit in company strategy to support current line of business	.282	.015	.476	.102
Your company provides business know-how for others	.133	.250	.379	-.115
Find a subcontractor to develop the drug if a newly discovered compound has promising commercial gain	-.087	.327	.135	.578
Other companies conduct R&D for your company	.170	.062	-.074	.564
Other companies manufacture your drugs	.097	-.248	-.209	.534
License out the drug development if a newly discovered compound has promising commercial gain	-.056	-.072	.338	.530
Your company manufactures drugs developed by others	-.033	.297	.198	-.507
Other companies sells and markets your drugs	.259	-.116	.335	.472
Protect innovation from imitation by trade secrecy	-.167	.063	-.011	.402
Protect innovation from imitation by copyright	-.384	.162	.133	.400
Regulatory approval is more difficult in the country that you operate	-.236	.136	.206	-.395

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 7 iterations.

An examination of the scatter plot matrix shows that there is an outlier in the first component that needs to be considered (e.g., deleted or replaced) at the time of statistical analysis of hypothesis testing. In addition, Shapiro-Wilks W test of normality confirms the visual examination that three of the components are normal and one of them (i.e., FAC1_7) is not normally distributed ($W = 0.924$, $df = 65$ and $P = .001$; $W = 0.965$, $df = 65$ and $P = 0.064$; $W = .975$, $df = 65$ and $P = .211$; $W = .965$, $df = 65$ and $P = .061$, respectively).

7.6 Hypothesis Testing

In this section of the thesis, the author statistically test the hypotheses that are developed in Chapter 4. The first hypothesis examines the relationship between R&D spending and financial performance of pharmaceutical firms.

***Hypothesis 1a:** A higher level of absorptive capacity achieved through investments in R&D will positively influence the financial criteria of a pharmaceutical firm's innovation performance.*

We tested this hypothesis by considering the relationship between two variables: sales revenue in 2007 and average R&D spending in the past three years. Following the work by Graves and Langowitz (1993), R&D efforts were measured with the amount of R&D expenditure reported by the firms. The two variables are positively and strongly correlated (i.e., $R = .996$, $p < .01$). The strong correlation between variables suggests that an increase in R&D spending will result in an increase in

sales revenue. However, the Pearson correlation coefficient works best when the variables are approximately normally distributed and have no outliers.

The data was screened for outliers, which can cause misleading results and evidence of a linear relationship. The author examined the scatter plot for the two variables and found that the one data point that is an outlier is changing the direction of the relationship between the two variables. One U.S. company reported sales revenue of more than \$18 billion in 2007, which is 30 times higher than the second highest sales revenue in the database. The author filtered this point and recalculated the Pearson correlation. The resulting Pearson correlation is positive and significant, but the correlation coefficient is reduced to 0.551 ($p < .01$). The scatter plot was examined with the outlier filtered and, as a result, new influential data points have emerged in both variables. Both variables were positively skewed, and, therefore, both the dependent and independent variables were log-transformed to remove the effect of outliers and to bring them to *close* to normal in the analysis. The scatterplot of the log-transformed sales revenue in 2007 and log-transformed average R&D spending in the past three years shows a linear relationship between the two variables ($R = .422, p < 0.01$).

We used simple linear regression to model the dependent variable, log-transformed sales revenue in 2007, based on its linear association with the predictor, log-transformed average R&D in the past three years. For the purpose of testing hypothesis 1a about the values of model parameters, the linear regression model

assumes that the error term has a normal distribution with a mean of 0, constant variance and independence (i.e., the value of the error term for a given case is independent of the values of the variables in the model and of the values of the error term for other cases). To test these assumptions the author looked at the plot of standardized residuals against predicted values in the regression model, histogram, and normal probability plot and found no major violation of these assumptions (Appendix B1A). The scatter plot of Cook's Distance and Centered Leverage value was also examined to check influential data points; no major point that affected the slope of the regression line was found. The following model was obtained for the relationship between the two variables. This model is significant ($p = 0.001$), which means that the variation explained by the model is not due to chance.

$$\text{Log-Transformed Sales in 2007} = 1.194 (\text{Log-Transformed R\&D in the past three years}) - 5.422$$

Although the ANOVA table in Appendix B1A shows a significant ability for the model to explain the variability in the dependent variable ($F=13.400$, $p = .001$), it does not address the strength of the relationship. The multiple correlation coefficient, R , shows a moderate relationship ($R = .422$). The coefficient of determination, R^2 , shows that about 18 percent of the variation in log-transformed sales is explained by the predictor. Therefore, hypothesis 1a is supported.

To deal with non-normality, outliers, and influential data points in the above model, both dependent and independent variables that were positively skewed have been log-transformed. According to Wooldridge (2003), "in instances where both the

dependent and independent variables are log-transformed variables, the relationship is commonly referred to in econometrics as elasticity. In a regression setting, elasticity is interpreted as the percent change in y (the dependent variable) while x (the independent variable) increases by one percent.” For this model, the author concludes that 1 percent increase in R&D spending would yield a 1.19 percent increase in sales revenue⁹. The literature provides inconsistent results for the effect of R&D on firm performance. While some authors, including Kamien and Schwartz (1982), observed a strong positive correlation between innovation output and R&D, others, including Lin *et al.* (2006), found no significant relationship between R&D and a firm’s financial performance. When controlled for the firm size (i.e., small < 100 employees and large ≥ 100), the author found that R&D spending does not have significant impact on a firm’s performance ($b = .474$, $p = .105$), but larger firms tend to generate higher financial performance than the smaller firms (Model 2 in Table 21). In addition, the author conducted sensitivity analysis on the size of the firm and considered companies with less than 75 as small and those with 75 or more employees as large and tested the relationship between the dependent and independent variables controlling for the firm size. The findings are similar to the previous test (Model 3 in Table 21).

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⁹ Introduction to SPSS. UCLA: Academic Technology Services, Statistical Consulting Group. from http://www.ats.ucla.edu/stat/spss/faq/spss_interpret_log.htm (accessed November 14, 2008).

Table 21: Ordinary least square regression results for testing *H1a*

Model and Variable	B	SE B	β	R ²	ANOVA F(Sig.)
Model 1:				.178***	13.4(.001)
Constant	-5.422	5.318			
Log-transformed average R&D spending	1.194***	.326	.422		
Model 2:				.479***	27.988(.000)
Constant	4.424	4.581			
Log-transformed average R&D spending	.474	.289	.167		
Number of employees (0 = small<100 and 1 = large≥100)	5.201***	.877	.604		
Model 3:				.496***	30.068(.000)
Constant	4.70	4.501			
Log-transformed average R&D spending	.446	.284	.157		
Number of employees (0 = small<75 and 1 = large≥75)	5.271***	.848	.623		

* $P < .05$, ** $P < .01$, and *** $P < .001$ Dependent variable = sales revenue

Hypothesis 1b: *A higher level of absorptive capacity achieved through investments in R&D will positively influence the customer criteria of a pharmaceutical firm's innovation performance.*

We tested this hypothesis using a simple linear regression method. The log-transformed R&D in the past three years was modeled with the customer satisfaction variable that was obtained from the principal component analysis; the result was a moderate linear relationship between the two variables ($R = .387$, $p = .002$). The regression model is significant ($F = 10.917$, $p = 0.002$) and the predictor explains about 15 percent of the variability in the response variable.

The regression analysis met all the assumptions for a reliable model (Appendix B1B) and the following model was obtained for relationship between the two variables:

$$\text{Customer satisfaction} = 0.198 (\text{Log-Transformed R\&D in the past three years}) - 3.219$$

This means that one percent increase in R&D spending would result in 0.00198 units increase in customer satisfaction. Hypothesis 1b is also supported. The literature does not provide a direct relationship between R&D and customer satisfaction. However, Westerman and Curley (2008) provide some insights about the increase in customer satisfaction through improvements in the quality of a product by conducting R&D.

The effect of firm size was controlled and the results showed that higher R&D spending is associated with increased customer satisfaction in both small and large firms. However, smaller firms tend to have more satisfied customers (Model 2 in Table 22). Model 3 in Table 22 shows similar results as model 2 when we considered small firms as firms with less than 75 employees and large firms as firms with 75 or more employees.

Table 22: Ordinary least squares regression results for testing *H1b*

Model and Variable	B	SE B	β	R ²	ANOVA F(Sig.)
Model 1:				.15**	10.917(.002)
Constant	-3.219**	.978			
Log-transformed average R&D spending	.198***	.060	.387		
Model 2:				.151	5.392(.007)
Constant	-3.292**	1.050			
Log-transformed average R&D spending	.204**	.067	.397		
Number of employees (0 = small<100 and 1 = large≥100)	-.039	.202	-.025		
Model 3:				.154	5.565(.006)
Constant	-3.438**	1.055			
Log-transformed average R&D spending	.214**	.067	.419		
Number of employees (0 = small<75 and 1 = large≥75)	-.114	.199	-.075		

* $P < .05$, ** $P < .01$, and *** $P < .001$ Dependent variable = customer satisfaction

Hypothesis 1c: *A higher level of absorptive capacity achieved through investments in R&D will positively influence the opportunities criteria of a pharmaceutical firm's innovation performance.*

Factor analysis of opportunities criteria extracted two components: “knowledge” and “safety and efficacy”. Two linear regression models were developed to test the following two equations:

$$\text{Knowledge} = a + b (\text{average R\&D spending})$$

$$\text{Safety and Efficacy} = a + b (\text{average R\&D spending})$$

The regression model for the first equation is significant ($F = 8.985$, $p = .004$) and β coefficient for the predictor is also significant ($p = .004$). A test for all the linear regression assumptions for this test showed no violations (Appendix B1C1). The author obtained the following equation for the first model:

$$\text{Knowledge} = -3.946 + .243 (\text{log-transformed R\&D in the past three years})$$

This means that one percent increase in R&D spending would result in .0024 units increase in knowledge. It is generally agreed in the literature that R&D results in creating knowledge and in improving growth and profitability (Brouwer *et al.*, 1993). According to Rammer and Schmiele (2009), R&D generates new knowledge and new applications of technologies, which is likely to generate a certain degree of innovation.

After controlling for firm size, R^2 did not change, suggesting that the added variable to the model did not explain more of the variability in the dependent variable. The regression model is significant ($F = 4.430$, $p = .016$), and the coefficient for R&D spending increased by a small value. This suggests that higher R&D spending is associated with increased knowledge in both small and large firms. However, smaller firms tend to generate more knowledge than larger firms (Model 2 in Table 23). Model 3 in Table 23 shows similar results as model 2 when we considered small firms as firms with less than 75 employees and large firms as firms with 75 or more employees. The previous three regression tests resulted in similar findings in terms of direction and significance when we controlled firm size under two assumptions for size of the firm. Therefore, to be consistent with the literature, we

will only consider companies with less than 100 employees as small and those with 100 or more employees as large in the future tests.

Table 23: Ordinary least squares regression results for testing H1c

Model and Variable	B	SE B	β	R ²	ANOVA F(Sig.)
Model 1:				.127**	8.985(.004)
Constant	-3.946**	1.332			
Log-transformed average R&D spending	.243**	.081	.356		
Model 2:				.127	4.430(.016)
Constant	-4.013**	1.430			
Log-transformed average R&D spending	.248**	.090	.363		
Number of employees (0 = small<100 and 1 = large≥100)	-.035	.274	-.017		
Model 3:				.131	4.603(.014)
Constant	-4.238**	1.4260			
Log-transformed average R&D spending	.265**	.090	.387		
Number of employees (0 = small<75 and 1 = large≥75)	-.152	.269	-.074		

* $P < .05$, ** $P < .01$, and *** $P < .001$ Dependent variable = knowledge

The second regression model that tests the relationship between safety and efficacy of drug and R&D spending is not significant ($F = .933$, $p = .338$), as there seems to be a very weak relationship between R&D spending and the safety and efficacy of drugs ($R = .122$). Further, R&D explains only 1.5 percent of the variability in the dependent variable. The scatter plot of the variables shows almost no sign of linear relationship between the two variables. This relationship did not change when the author controlled for firm size (Appendix B1C2). Therefore, the conclusion is that

increase in R&D does not improve the safety and efficacy of drugs after they are introduced to market.

Hypothesis 1d: *A higher level of absorptive capacity achieved through investments in R&D will positively influence the number of new drugs that a pharmaceutical firm develops and introduces to the market.*

Research participants were asked to report the number of new drugs that their companies developed and introduced to market in the past three years. As this dependent variable is count data, with values equal to or greater than zero, the hypothesis above was tested using a generalized linear regression model (i.e., Poisson regression). The data that was examined for outliers and influential data points showed that one company reported 150 new drugs during the past three years. To ensure that this large number and other extreme points do not negatively affect the analysis, the outliers were filtered before the Poisson test was run.

The Poisson regression model converged after six iterations with a likelihood ratio Chi Square value of 4.935 and significant ($p = 0.026$), which suggests a good model fit (Appendix B1D1). The Wald Chi-Square test of model effects equals 5.080 and it is significant at $p = .024$ for the independent variable. The fit of the Poisson loglinear model for this test is:

$$\ln \hat{\mu} = \hat{\alpha} + \hat{\beta} \chi$$

$$\hat{\mu} = \exp(\alpha + \beta\chi) = e^{-.071} + e^{.092X} = 0.931 + 1.096^x$$

In other words, the mean satisfies the exponential regression relationship in the model. This means that a one unit increase in R&D spending has a multiplicative impact of 1.096 on the mean predicted value of the number of new drugs. Hypothesis 1d is supported. The author also found that R&D spending does not have a significant impact on the number of new drugs after controlling for the firm size (Appendix B1D2). However, the results show that larger firms tend to introduce more new drugs (Model 2 in Table 24).

Table 24: Poisson regression results for testing *H1d*

Model and Variable	B	SE B	Likelihood Ratio χ^2	Log likelihood
Model 1:			4.935*	-234.948
Intercept	-.071	.6767		
Log-transformed average R&D spending	.092*	.0409		
Model 2:			39.681***	-217.575
Intercept	1.570*	.7025		
Log-transformed average R&D spending	-.031	.0442		
Number of employees (0 = small and 1 = large)	.850***	.1425		

* $P < .05$, ** $P < .01$, and *** $P < .001$ Dependent variable = number of new drugs

Hypothesis 2a: *A higher level of absorptive capacity achieved through investments in SGA will positively influence the financial criteria of a pharmaceutical firm's innovation performance.*

We applied simple linear regression to model the dependent variable, log-transformed sales revenue in 2007 based on its linear relationship with the predictor, log-transformed SGA expenditure. The assumption of linear regression in this test was examined and outliers in both variables were found; the variables were log-transformed to remove the effect of outliers in the data and make the data symmetric. The two log-transformed variables are positively and moderately correlated (i.e., $R = .495$, $p = .000$). The moderate positive correlation between variables suggests that an increase in SGA expenditure will result in an increase in sales revenue. The following model shows the relationship between the two variables. This model is significant ($F = 19.829$, $p = .000$), which means that the variation explained by the model is not due to chance (Appendix B2A).

$$\text{Log-Transformed Sales in 2007} = 1.321 (\text{Log-Transformed marketing expenditure}) - 7.558$$

The coefficient of determination, R^2 , shows that about 25 percent of the variation in log-transformed sales revenue is explained by the model. As the above equation shows, a one-percent increase in SGA expenditure will result in a 1.32 percent increase in sales revenue. Hypothesis 2a is supported. This is consistent with the

findings of Lin *et al.* (2006) that provide a strong positive relationship between SGA expenditure and firm performance. After controlling for firm size, the result also shows that the SGA expenditure does not have significant impact on financial performance, but larger firms tend to perform better than the smaller firms (Model 2 in Table 25).

Table 25: Ordinary least squares regression results for testing *H2a*

Model and Variable	B	SE B	β	R ²	ANOVA F(Sig.)
Model 1:				.245***	19.829(.000)
Constant	-7.558	4.856			
Log-transformed SGA expenditure	.1321***	.297	.495		
Model 2:				.47***	26.693(.000)
Constant	5.628	4.863			
Log-transformed SGA expenditure	.402	.310	.151		
Number of employees (0 = small and 1 = large)	5.044***	.999	.586		

* $P < .05$, ** $P < .01$, and *** $P < .001$ Dependent variable = sales revenue

Hypothesis 2b: *A higher level of absorptive capacity achieved through investments in SGA will positively influence the customer criteria of innovation performance of a pharmaceutical firm's innovation performance.*

This hypothesis tests the following mathematical relationship:

$$\text{Customer satisfaction} = a + b (\text{SGA expenditure})$$

The regression model for this test is significant ($F = 6.279$, $p = .015$). The independent variable explains only nine percent of the variability in the dependent variable and β coefficient is significant ($t = 2.506$, $p = .015$). The following model

is the result of this analysis, which shows that a one percent increase in marketing expenditure will increase customer satisfaction by 0.0014 units.

$$\text{Customer satisfaction} = 0.147 (\text{Log-Transformed marketing expenditure}) - 2.401$$

Although this result supports the hypothesis, the author expected a stronger relationship between these two variables as one would expect that higher customer satisfaction would result as marketing (i.e., SGA) expenditure increases. Hypothesis 2b is supported (Appendix B2B). Many researchers have also suggested that customer-based measures (e.g., satisfaction) are important to increase sales, profitability, and other measures of performance (Day and Wensley 1988). Heskett *et al.* (1994) provided evidence of the link between financial profitability in service organizations and customer satisfaction.

The result also shows that higher customer satisfaction is associated with higher SGA expenditure in both large and small firms. However, smaller firms tend to be more customer focused (Model 2 in Table 26).

Table 26: Ordinary least squares regression results for testing *H2b*

Model and Variable	B	SE B	β	R ²	ANOVA F(Sig.)
Model 1:				.093*	6.279(.015)
Constant	-2.401*	.963			
Log-transformed SGA expenditure	.147*	.059	.305		
Model 2:				.095	3.166(.049)
Constant	-2.633*	1.149			
Log-transformed SGA expenditure	.163*	.073	.339		
Number of employees (0 = small and 1 = large)	-.089	.236	-.057		

* $P < .05$, ** $P < .01$, and *** $P < .001$ Dependent variable = customer satisfaction

Hypothesis 2c: *A higher level of absorptive capacity achieved through investments in SGA will positively influence the opportunities criteria of a pharmaceutical firm's innovation performance.*

Similar to testing hypothesis 1c, a linear regression model was developed for each of the following equations:

$$\text{Knowledge} = a + b (\text{SGA expenditure})$$

$$\text{Safety and Efficacy} = a + b (\text{SGA expenditure})$$

The analysis for the first equation shows a weak association between the two variables ($R = .258$, $p = .041$), which means that SGA expenditure explains only seven percent of the variability in knowledge. The regression model is significant ($F = 4.351$, $p = .041$), which suggests a good fit model. The data meets the assumptions for running a reliable regression analysis (Appendix B2C1). The following equation explains the relationship among variables, meaning that a one percent increase in SGA expenditure will result in 0.0016 units increase in knowledge:

$$\text{Knowledge} = 0.166 (\text{Log-Transformed SGA expenditure}) - 2.704$$

When the effect of firm size (i.e., small or large) was controlled, the result was that the SGA expenditure has significant impact on knowledge at the 10 percent level.

However, the result also shows that smaller firms tend to create more knowledge than do the larger firms (Model 2 in Table 27).

Table 27: Ordinary least squares regression results for testing *H2c*

Model and Variable	B	SE B	β	R ²	ANOVA F(Sig.)
Model 1:				.067*	4.351(.041)
Constant	-2.704*	1.302			
Log-transformed SGA expenditure	.166*	.080	.258		
Model 2:				.067	2.153(.125)
Constant	-2.838*	1.556			
Log-transformed SGA expenditure	.175*	.099	.272		
Number of employees (0 = small and 1 = large)	-.051	.320	-.025		

+*p*<.10, *P<.05, **P<.01, and ***P<.001 Dependent variable =knowledge

There seems to be no relationship between the safety and efficacy variable and the SGA expenditure. The regression model for the second equation is not significant ($F = .048$, $p = .826$). The second equation in hypothesis 2c is not supported, as it reveals that SGA expenditure has a weak association with the safety and efficacy of drugs (Appendix B2C2).

Hypothesis 2d: *A higher level of absorptive capacity achieved through investments SGA will positively influence the number of new drugs that a pharmaceutical firms introduce to the market.*

Similar to hypothesis 1d, a Poisson regression was used to test the relationship between SGA expenditure and the number of new drugs that pharmaceutical firms develop and introduce to the market (Appendix B2D1). The Poisson regression

model fits the data well, with a likelihood ratio Chi-Square value of 13.971, and it is significant ($p = 0.000$). The Wald Chi-Square test of model effects is significant at $p = .000$ for the predicting variable. The fit of the Poisson loglinear model for this test is:

$$\ln \hat{\mu} = \hat{\alpha} + \hat{\beta} \chi$$

$$\hat{\mu} = \exp(\alpha + \beta \chi) = e^{-0.813} + e^{0.136X} = 0.4435 + 1.146^x$$

This means that a one-unit increase in x has a multiplicative impact of 1.146 on the mean predicted value of the new drugs, μ . Hypothesis 2d is supported. After controlling for the firm size, the result shows that SGA expenditure does not have a significant impact on the number of number of new drugs (Appendix B2D2). However, larger firms tend to have a higher number of new drugs (Model 2 in Table 28).

Table 28: Poisson regression results for testing *H2d*

Model and Variable	B	SE B	Likelihood Ratio χ^2	Log likelihood
Model 1:			13.971***	-230.430
Intercept	-.813	.5804		
Log-transformed SGA expenditure	.136***	.0345		
Model 2:			39.194***	-217.819
Intercept	1.031	.7170		
Log-transformed SGA expenditure	.003	.0454		
Number of employees (0 = small and 1 = large)	.800***	.1576		

* $P < .05$, ** $P < .01$, and *** $P < .001$ Dependent variable = number of new drugs

Hypothesis 3a: *A higher level of absorptive capacity improves the financial criteria of a pharmaceutical firm's innovation performance especially where firms integrate their functional units by forming cross-functional teams.*

The following mathematical relationship was tested to investigate the above hypothesis:

$$\text{Sales Revenue} = a + b_1 (\text{average R\&D spending}) + b_2 (\text{SGA expenditure}) + b_3 (\text{cross-functional information sharing}) + b_4 (\text{R\&D} * \text{CF}^{10}) + b_5 (\text{SGA} * \text{CF})$$

Frazier *et al.* (2004) explain that predictors should be standardized or centered when one tests the moderating effects (i.e., interactions). Based on their recommendation, variables were standardized before running the regression test. The moderating variable for the cross-functional information sharing component is the result of the PCA. Its mean is very close to zero and it has a standard deviation close to one; therefore, there was no need to standardize it. Interaction terms have been created by multiplying standardized variables by the moderating variable (e.g., ZLNAVGRD * FAC1_6), to create an interaction term between R&D spending and cross-functional information sharing variables. A hierarchical Multiple Regression was applied to test the moderating effect of cross-functional information sharing on the relationship between absorptive capacity and the financial criteria of innovation performance. In step one of the hierarchical regression model, both standardized

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¹⁰ Cross functional information sharing

R&D and SGA variables (i.e., absorptive capacity) were entered; in step 2 the moderator and the interaction terms (Z-log-transformed R&D * CF and Z-log-transformed SGA * CF) were entered. R^2 changes from .248 to .259 (i.e., one percent increase) although not significant ($P = .809$), meaning that the added moderating and interaction variables do not contribute to explaining more of the variance in the dependent variable over and above the main effect (Appendix B3A). The coefficient for the standardized log-transformed SGA expenditure is the only variable that is significant in the model at 0.05 level ($b = 1.753$, $p = .038$). Hypothesis 3a is not supported (Model 2 in Table 29). This finding is different from the result of the study by Luo *et al.* (2006), who show that cross-functional cooperation has a positive effect on a firm's customer and financial performance because of increased market learning. Once controlled for firm size, SGA does not have a significant impact on financial performance, and there is no significant interaction effect between SGA and cross-functional information sharing on financial performance. However, after controlling for firm size, the results show that larger firms tend to have better performance (Model 3 in Table 29).

Table 29: Hierarchical multiple Regression Results for testing *H3a*

Model and Variable	B	SE B	β	R ²	ANOVA F(Sig.)
Model 1:				.246***	9.803 (.000)
Constant	13.968***	.461			
Z-Log-transformed average R&D spending	.222	.801	.054		
Z-Log-transformed SGA expenditure	1.873*	.801	.452		
Model 2:				.259	3.982(.004)
Constant	13.881***	.485			
Z-Log-transformed average R&D spending	.330	.826	.080		
Z-Log-transformed SGA expenditure	1.753*	.826	.423		
Cross-functional information sharing	.428	.602	.103		
Z-Log-transformed average R&D * CF	.136	.921	.041		
Z-Log-transformed SGA expenditure * CF	.328	1.217	.082		
Model 3:				.498***	9.258(.000)
Constant	12.086***	.532			
Z-Log-transformed average R&D spending	.783	.692	.189		
Z-Log-transformed SGA expenditure	-.089	.773	-.022		
Cross-functional information sharing	.103	.503	.025		
Z-Log-transformed average R&D * CF	1.032	.784	.314		
Z-Log-transformed SGA expenditure * CF	-1.065	1.046	-.267		
Number of employees (0 = small and 1 = large)	5.426***	1.051	.631		

* $P < .05$, ** $P < .01$, and *** $P < .001$ Dependent variable = sales revenue

Hypothesis 3b: *A higher level of absorptive capacity is associated with a higher number of new drugs that pharmaceutical firms introduce to the market especially in firms where functional units are integrated by forming cross-functional teams.*

Poisson regression model was used to test this hypothesis. The mathematical model to test this hypothesis can be shown as:

$$\ln \hat{\mu} = \hat{\alpha} + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3 + \hat{\beta}_4 x_4 + \hat{\beta}_5 x_5$$

Where X_1 is the standardized log-transform R&D spending in the past three years, X_2 is the standardized log-transformed SGA expenditure, X_3 is the cross-functional information sharing, X_4 is the interaction between standardized log-transform R&D spending in the past three years and cross-functional information sharing, and X_5 is the interaction between standardized log-transformed SGA expenditure and cross-functional information sharing variable.

Expected No. of New Drugs = $\exp (a + b_1 * \text{R\&D} + b_2 * \text{SGA} + b_3 * \text{CF} + b_4 * \text{RD*CF} + b_5 * \text{SGA*CF})$

The Poisson regression fits the data well with a likelihood ratio Chi Square value of 37.756 and it is significant ($p=.000$), which suggests a good model fit. The Wald Chi-Square test of parameter estimate is significant at $p < .01$ for three variables (Model 2 in Table 30 and Appendix B3B2). The fit of the Poisson loglinear model for this test is:

$$\ln \hat{\mu} = 1.420 + .393(ZLN\text{MAREXP}) + .505(IN\text{TRDCF}) - .747(INT\text{GSGACF})$$

$$\hat{\mu} = \exp[1.420 + .393(ZLN\text{MAREXP}) + .505(IN\text{TRDCF}) - .747(INT\text{GSGACF})]$$

$$\hat{\mu} = 4.137 + 1.481^{ZLN\text{MAREXP}} + 1.657^{IN\text{TRDCF}} + 0.4738^{INT\text{GSGACF}}$$

This shows that cross-functional information sharing has a positive impact on the relationship between absorptive capacity and the number of new drugs in the pharmaceutical industry, and it supports Hypothesis 3b (Appendices B3B1-B3B3). The results show that the interaction of R&D and cross-functional information sharing variables significantly improves the number of new drugs that firms introduce to the market (Model 2 in Table 30). This suggests that firms that have mechanisms in place to encourage information sharing among the functional units should invest in R&D to increase the number of new drugs. On the other hand, the number of new drugs is not sensitive to the changes in the interaction between SGA and cross-functional information sharing; this means that a change in the company policy in improving information sharing among employees produces a smaller change in the number of new drugs. In addition, a higher level of R&D spending in large and small companies that encourage cross-functional information sharing has more positive impact on the performance of firms, but larger firms generate more new drugs than the smaller firms. On the other hand, the impact is negative for those small and large firms with higher SGA expenditure but less cross-functional information sharing. In general, there seems to be an agreement in the

literature that some form of cross-functional integration (i.e., degree of interaction, communication, and information sharing) has a positive impact on new product development (Troy *et al.*, 2008). The result of this study is consistent with the literature by illustrating that cross-functional information sharing has a positive impact on the relationship between absorptive capacity and the number of new drugs that pharmaceutical companies introduce to market.

Table 30: Poisson regression results for testing *H3b*

Model and Variable	B	SE B	Likelihood Ratio χ^2	Log Likelihood
Model 1:			16.970***	-228.931
Intercept	1.398***	.0663		
Z-Log-transformed average R&D spending	-.189 ⁺	.1084		
Z-Log-transformed SGA expenditure	.370***	.1059		
Model 2:			37.756***	-218.538
Intercept	1.420	.0679		
Z-Log-transformed average R&D spending	-.185 ⁺	.1119		
Z-Log-transformed SGA expenditure	.393***	.1073		
Cross-functional information sharing	-.096	.0812		
Z-Log-transformed average R&D * CF	.505***	.1302		
Z-Log-transformed SGA expenditure * CF	-.747***	.1674		
Model 3:			70.268***	-202.282
Intercept	1.071***	.0990		
Z-Log-transformed average R&D spending	-.073	.1014		
Z-Log-transformed SGA expenditure	.074	.1109		
Cross-functional information sharing	-.212**	.0830		
Z-Log-transformed average R&D * CF	.519***	.1148		
Z-Log-transformed SGA expenditure * CF	-.855***	.1614		
Number of employees (0 = small and 1 = large)	.926***	.1588		

⁺ $P < .10$, * $P < .05$, ** $P < .01$, and *** $P < .001$ Dependent variable = number of new drugs

***Hypothesis 3c:** A higher level of absorptive capacity improves the financial criteria of a pharmaceutical firm's innovation performance especially where management supports functional integration.*

The following mathematical relationship is tested to investigate the above hypothesis:

$$\text{Sales Revenue} = a + b_1 (\text{average R\&D spending}) + b_2 (\text{SGA expenditure}) + b_3 (\text{MSIS}^{11}) + b_4 (\text{R\&D} * \text{MSIS}) + b_5 (\text{SGA} * \text{MSIS})$$

Similar to testing hypothesis 3a, a hierarchical linear regression test was used to test this hypothesis (Appendix B3C1). As shown in Table 31, the added management support of the information-sharing variable and the interaction terms in the model adds 0.1 percent in explaining more of the variance in the dependent variable and only the coefficient for one variable (i.e., standardized log-transformed SGA expenditure) is significant. This finding is consistent with the findings of Rapp *et al.* (2008) that suggest a firm's market orientation leads to innovativeness and positive performance. However, Rapp *et al.* (2008) state that "having top management champion the technology innovation initiatives is crucial for successful results."

Model 3 in Table 31 shows the result of hierarchical regression analysis for controlling firm size on the above relationship. When controlled for firm size, SGA and R&D did not have any significant impact on a firm's financial performance. However, larger firms tend to perform better than the smaller firms. Although not significant at the 5 percent level, the result shows that the interaction between

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¹¹ Management support of information sharing

management support of information sharing and SGA expenditure variables increases performance. The relationship is the opposite for the interaction between management support of information sharing and R&D spending.

Table 31: Hierarchical multiple regression results for testing *H3c*

Model and Variable	B	SE B	β	R ²	ANOVA F(Sig.)
Model 1:				.246***	9.803 (.000)
Constant	13.968***	.461			
Z-Log-transformed average R&D spending	.222	.809	.053		
Z-Log-transformed SGA expenditure	1.873*	.817	.454		
Model 2:				.247	3.733(.005)
Constant	13.965***	.483			
Z-Log-transformed average R&D spending	.205	.830	.049		
Z-Log-transformed SGA expenditure	1.885*	.832	.455		
Management support of information sharing	.021	.505	.005		
Z-Log-transformed average R&D * MSIS [^]	.171	1.061	.033		
Z-Log-transformed SGA expenditure * MSIS	-.130	.923	-.029		
Model 3:				.481***	8.654(.000)
Constant	12.100***	.549			
Z-Log-transformed average R&D spending	.709	.702	.171		
Z-Log-transformed SGA expenditure	.013	.790	.003		
Management support of information sharing	.050	.423	.012		
Z-Log-transformed average R&D * MSIS	-.437	.896	-.085		
Z-Log-transformed SGA expenditure * MSIS	.223	.776	.049		
Number of employees (0 = small and 1 = large)	5.241***	1.042	.609		

* $P < .05$, ** $P < .01$, and *** $P < .001$ ^ Management support of information sharing Dependent variable = sales revenue

Table 32 presents the results of the tests of the moderating effect of management support of cross-functional information exchange variable (i.e., the third component

that resulted from the PCA on functional integration construct) on the relationship between absorptive capacity and a pharmaceutical firm's financial performance.

Table 32: Hierarchical multiple regression results for testing the moderating effect of management support of cross functional information exchange

Model and Variable	B	SE B	β	R ²	ANOVA F(Sig.)
Model 1:				.246***	9.803(.000)
Constant	13.968***	.461			
Z-Log-transformed average R&D spending	.222	.801	.054		
Z-Log-transformed SGA expenditure	1.873*	.801	.452		
Model 2:				.250	3.806(.005)
Constant	13.927***	.478			
Z-Log-transformed average R&D spending	.260	.824	.063		
Z-Log-transformed SGA expenditure	1.823*	.833	.440		
Management support of CFIX	-.002	.518	.000		
Z-Log-transformed average R&D * MSCFIX [^]	.091	.830	.025		
Z-Log-transformed SGA expenditure * MSCFIX	.161	.944	.041		
Model 3:				.486***	8.836(.000)
Constant	12.065***	.542			
Z-Log-transformed average R&D spending	.708	.694	.171		
Z-Log-transformed SGA expenditure	-.048	.787	-.012		
Management support of CFIX	.072	.432	.017		
Z-Log-transformed average R&D * MSCFIX	.11	.693	.003		
Z-Log-transformed SGA expenditure * MSCFIX	.354	.789	.089		
Number of employees (0 = small and 1 = large)	5.217***	1.028	.606		

* $P < .05$, ** $P < .01$, and *** $P < .001$ ^ Management support of cross functional information Exchange

Dependent variable = sales revenue

The result is very similar to the previous test in showing that management support of cross-functional information exchange improves a firm's financial performance (Appendix B3C2). As shown in model 2 in Table 32, an increase in SGA expenditure is the most important variable in this model in improving a firm's financial performance and none of the interaction terms are significant.

***Hypothesis 3d:** A higher level of absorptive capacity is associated with a higher number of new drugs that pharmaceutical firms introduce to the market especially in firms where management supports functional integration.*

Poisson regression was used to test this hypothesis. The mathematical model that was tested for this hypothesis can be shown as:

$$\ln \hat{\mu} = \hat{\alpha} + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3 + \hat{\beta}_4 x_4 + \hat{\beta}_5 x_5$$

Where X_1 is the standardized log-transform R&D spending in the past three years, X_2 is the standardized log-transformed SGA expenditure, X_3 is management support of information sharing (MSIS), X_4 is the interaction between standardized log-transform R&D spending in the past three years and management support of information sharing, and X_5 is the interaction between standardized log-transformed SGA expenditure and management support of information sharing variables.

$$\text{Expected No. of New Drugs} = \exp(a + b_1 * \text{R\&D} + b_2 * \text{SGA} + b_3 * \text{MSIS} + b_4 * \text{RD*MSIS} + b_5 * \text{SGA*MSIS})$$

The Poisson regression fits the data well with a likelihood ratio Chi Square value of 24.616 and it is significant ($p=.000$). The Wald Chi-Square test of model effects is significant at 0.05 for three variables (Model 2 in Table 33 and Appendix B3D1).

The fit of the Poisson loglinear model for this test is as follows:

$$\ln \hat{\mu} = 1.382 - .215(\text{ZLNAVGRD}) + .404(\text{ZLNMAREXP}) + .317(\text{INTRDMSIS})$$

$$\hat{\mu} = \exp[1.382 - .215(\text{ZLNAVGRD}) + .404(\text{ZLNMAREXP}) + .317(\text{INTRDMSIS})]$$

$$\hat{\mu} = 4.1369 + .8065^{\text{ZLNAVGRD}} + 1.4978^{\text{ZLNMAREXP}} + 1.373^{\text{INTRDMSIS}}$$

As could be seen in the above equation, the interaction between R&D and management support of information sharing (i.e., INTRDMSIS) has a multiplicative effect on the predicted value of the number of new drugs that pharmaceutical companies introduce to the market. Interaction between management support of information sharing and SGA expenditure, on the other hand, is negative but not significant (Model 2 in Table 33). The result suggests that to increase the number of new drugs to market, management should increase marketing expenditure and encourage R&D teams to interact with other functional units to share information and develop drugs. Model 3 in Table 33 shows that none of the variables in this model is significant except the coefficient for the number of employees, which suggests that larger firms introduce more new drugs than do smaller firms.

Table 33: Poisson regression results for testing the moderating effect of management support of information sharing

Model and Variable	B	SE B	Likelihood Ratio χ^2	Log likelihood
Model 1:			16.970***	-228.931
Intercept	1.398***	.0663		
Z-Log-transformed average R&D spending	-.189 ⁺	.1084		
Z-Log-transformed SGA expenditure	.370***	.1059		
Model 2:			24.616***	-225.108
Intercept	1.382***	.0687		
Z-Log-transformed average R&D spending	-.215 ⁺	.1053		
Z-Log-transformed SGA expenditure	.404***	.1042		
Management support of information sharing	.080	.0721		
Z-Log-transformed average R&D * MSIS [^]	.317*	.1402		
Z-Log-transformed SGA expenditure * MSIS	-.198	.1208		
Model 3:			44.875***	-214.978
Intercept	1.085***	.1019		
Z-Log-transformed average R&D spending	-.141	.983		
Z-Log-transformed SGA expenditure	.143	.1125		
Management support of information sharing	.098	.0726		
Z-Log-transformed average R&D * MSIS	.171	.1346		
Z-Log-transformed SGA expenditure * MSIS	-.127	.1140		
Number of employees (0 = small and 1 = large)	.754***	.1656		

+ $P < .10$, * $P < .05$, ** $P < .01$, and *** $P < .001$ [^] Management support of information Sharing

Dependent variable = number of new drugs

We also tested the effect of management support of cross-functional information exchange (MSCFIX) variable on the relationship between absorptive capacity and the number of new drugs. A Poisson regression test showed that the model fits well with a likelihood ratio Chi-Square value of 24.037 and significant at $p = .000$.

However, the coefficients for the three main effect variables are significant at 0.05 level and none of the two interaction terms were significant (Appendix B3D2).

The following equation shows the result of the second Poisson regression test for this hypothesis. Hypothesis 3d is supported for management support of functional integration.

Expected No. of New Drugs = $\exp (a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ MSCFIX} + b_4 \text{ RD* MSCFIX} + b_5 \text{ SGA* MSCFIX})$

$$\hat{\mu} = \exp[1.388 - .222(ZLNAVGRD) + .386(ZLNMAREXP) + .175(MSCFIX)]$$

$$\hat{\mu} = 4.007 + .80^{ZLNAVGRD} + 1.471^{ZLNMAREXP} + 1.191^{MSCFIX}$$

Hypothesis 4a: The effect of absorptive capacity on a firm's innovation performance is significantly lower for integrator firms in the pharmaceutical industry.

To test this hypothesis, a multiple regression model was developed for each of the first four following equations and a Poisson regression test for the fifth equation.

- 1- Sales revenue = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC3\_7}^{12} + b_4 \text{ R\&D} * \text{FAC3\_7} + b_5 \text{ SGA} * \text{FAC3\_7}$
- 2- Customer satisfaction = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC3\_7} + b_4 \text{ R\&D} * \text{FAC3\_7} + b_5 \text{ SGA} * \text{FAC3\_7}$
- 3- Knowledge = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC3\_7} + b_4 \text{ R\&D} * \text{FAC3\_7} + b_5 \text{ SGA} * \text{FAC3\_7}$
- 4- Safety and efficacy = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC3\_7} + b_4 \text{ R\&D} * \text{FAC3\_7} + b_5 \text{ SGA} * \text{FAC3\_7}$
- 5- Number of new drug = $\exp(a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC3\_7} + b_4 \text{ R\&D} * \text{FAC3\_7} + b_5 \text{ SGA} * \text{FAC3\_7})$

Table 34 summarizes the result of four multiple regressions for the significant models that resulted from applying hierarchical regression method to investigate the effect of external integration strategy for the first four mathematical equations. The SPSS output for all four tests is provided in Appendices B4A1-B4A4. The summary results for these tests are provided in Table 34 and show that the interaction between R&D and the external integration strategy of a firm has a negative impact on the customer satisfaction variable. For those firms with higher R&D spending, external integration has a negative impact on the management perception of customer satisfaction than it does for firms with a lower level of R&D spending.

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¹² External integration strategy component that resulted from principal component analysis on commercialization strategy

Interaction between SGA and integration strategy has no significant impact on innovation performance.

Pharmaceutical companies that follow an external integration strategy are strong in R&D and business know-how. In cases of difficulties in obtaining regulatory approval to market their drug discoveries, they usually partner with other companies; apply for regulatory approval from other countries that have less stringent regulations for drug approval; or license-out their discoveries. In many cases, they form a joint venture to develop the drug if a newly discovered compound does not fit in their company's strategy but has promising commercial gains. They apply for patents for their discoveries and use this intellectual property protection mechanism to protect their innovation from imitation and to support their current line of business.

Table 34: Summary statistics on testing moderating effects of integration strategy on firm performance

Dependent Variable	Model and Variable	B	SE B	β	R ²	ANOVA F (Sig.)
Sales Revenue	Model 1: (main effect)				0.246***	9.803 (.000)
	Constant	13.968***	.461			
	Z-Log-transformed	1.873*	.801	.452		
	SGA expenditure					
	Z- Log-transformed	.222	.801	.054		
	Average R&D					
	Model 2: (main and interaction effect)				0.260	4.003(.004)
	Constant	13.860***	.482			
	Z-Log-transformed	1.677*	.850	.405		
	SGA expenditure					
	Z- Log-transformed	.263	.823	.063		
	Average R&D					
	FAC3_7	-.015	.508	-.004		
	INTRD37	.365	.667	.097		
	INTSGA37	-.749	.75	-.176		

Table 34 Cont'd.

Customer	<i>Model 1: (main effect)</i>				.150**	5.2941(.000)
Satisfaction	Constant	-3.932E-16	.089			
	Z-Log-transformed SGA expenditure	-.022	.154	-.029		
	Z- Log-transformed R&D	.308*	.154	.411		
	<i>Model 2: (main and interaction effect)</i>				.341**	5.897(.000)
	Constant	-.053	.082			
	Z-Log-transformed SGA expenditure	-.126	.145	-.169		
	Z- Log-transformed R&D	.265*	.140	.353		
	FAC3_7	-.107	.087	-.141		
	INTRD37	-.246*	.114	-.362		
	INTSGA37	-.110	.129	-.142		
Knowledge	<i>Model 1: (main effect)</i>				.13*	4.467(.016)
	Constant	-1.252E-16	.119			
	Z-Log-transformed SGA expenditure	-.095	.208	-.095		
	Z= Log-transformed R&D	.433*	.208	.433		
	<i>Model 2: (main and interaction effect)</i>				.214	3.109(.015)
	Constant	-.050	.120			
	Z-Log-transformed SGA expenditure	-.178	.211	-.178		
	Z- Log-transformed R&D	.392*	.204	.392		
	FAC3_7	-.037	.126	-.037		
	INTRD37	-.019	.166	-.209		
	INTSGA37	-.134	.188	-.130		

Table 34 Contd.

Safety and Efficacy	Model 1: (main effect)				0.030	.922(.403)
	Constant	-9.353E-16	.126			
	Z-Log-transformed SGA expenditure	-.221	.219	-.211		
	Z- Log-transformed R&D	.294	.219	.294		
	Model 2: (main and interaction effect)				.074	.905(.484)
	Constant					
	Z-Log-transformed SGA expenditure	.041	.130			
	Z- Log-transformed R&D	-.131	.229	-.131		
	FAC3_7	.265	.222	.265		
	INTRD37					
	INTSGA37	.012	.137	.012		
		-.212	.180	-.234		
		.329	.204	.319		

+p<.10, *p<.05, **p<.01, and ***p<.001

In addition, the author tested the moderating effect of external integration strategy on the number of new drugs (the fifth mathematical equation above) using Poisson regression (Table 35 and Appendices B4A5-1 and B4A5-2). The data fits the Poisson model with a likelihood ratio Chi-square value of 26.743 and significant at $p=.000$. The coefficients for log-transformed SGA expenditure and interaction between external integration strategy and log-transformed SGA expenditure are significant ($b = .450, p = .000$ and $b = .296, p = .006$). The coefficient for the log-transformed R&D spending is marginally significant at 5 percent ($b = -.222, P = .055$). The results show that the interaction of SGA with the external integration strategy variable has a positive multiplicative impact on the mean predicted value of

the number of drugs introduced to the market (Table 35), suggesting that firms that follow an external integration strategy should increase their marketing activities to be able to introduce more new drugs to the market. This result is very encouraging as we previously found that firms with internal integration (i.e., cross-functional information sharing) need to invest more in R&D to bring more drugs to market but in firms with external integration strategy higher SGA will result in higher number of new drugs.

Table 35: Moderating effect of integration strategy on the relationship between absorptive capacity and number of new drugs

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.412	.0670	1.280	1.543	443.989	1	.000
ZLNAVGRD	-.222	.1157	-.449	.005	3.686	1	.055
ZLNMAREXP	.450	.1137	.227	.672	15.651	1	.000
FAC3_7	-.092	.0749	-.239	.054	1.520	1	.218
intrd37	-.132	.0973	-.323	.058	1.851	1	.174
intsga37	.296	.1086	.083	.509	7.422	1	.006
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC3_7, intrd37, intsga37

a. Fixed at the displayed value.

Hypothesis 4b: The effect of absorptive capacity on a firm's innovation performance is significantly higher for licensor firms in the pharmaceutical industry.

Similar to the previous section on testing hypothesis 4a, four hierarchical regression models and one Poisson regression were developed to test the following five mathematical equations:

$$1\text{- Sales revenue} = a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC4\_7}^{13} + b_4 \text{ R\&D} * \text{FAC4\_7} + b_5 \text{ SGA} * \text{FAC4\_7}$$

$$2\text{- Customer satisfaction} = a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC4\_7} + b_4 \text{ R\&D} * \text{FAC4\_7} + b_5 \text{ SGA} * \text{FAC4\_7}$$

$$3\text{- Knowledge} = a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC4\_7} + b_4 \text{ R\&D} * \text{FAC4\_7} + b_5 \text{ SGA} * \text{FAC4\_7}$$

$$4\text{- Safety and efficacy} = a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC4\_7} + b_4 \text{ R\&D} * \text{FAC4\_7} + b_5 \text{ SGA} * \text{FAC4\_7}$$

$$5\text{- Number of new drug} = \exp(a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC4\_7} + b_4 \text{ R\&D} * \text{FAC4\_7} + b_5 \text{ SGA} * \text{FAC4\_7})$$

Table 36 summarizes the result of the four multiple regression models that were applied to investigate the effect of licensing strategy on the relationship between absorptive capacity and firm performance (i.e., tests for the first four mathematical equations). The results (Appendices B4B1-B4B4) show that the interaction between SGA expenditure and licensing strategy of a firm has a negative impact on the customer satisfaction variable.

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¹³ Licensing strategy component that resulted from principal component analysis on commercialization strategy

Table 36: Summary statistics on testing moderating effects of licensing strategy on firm performance

Dependent Variable	Model and Variable	B	SE B	β	R ²	ANOVA F (Sig.)
Sales Revenue	Model 1: (main effect)				0.246***	9.803 (.000)
	Constant	13.968***	.461			
	Z- Log-transformed R&D	.222	.801	.054		
	Z-Log-transformed SGA	1.873*	.801	.452		
	Model 2: (main and interaction effect)				.267	4.157(.003)
	Constant	13.882***	.474	.016		
	Z- Log-transformed R&D	.067	.827	.453		
	Z-Log-transformed SGA	1.880*	.823			
	expenditure			-.061		
	FAC4_7	-.253	.498	.014		
	INTRD47	.067	.728	-.144		
	INTSGA47	-.748	.751			
Customer Satisfaction	Model 1: (main effect)				.15**	5.294(.008)
	Constant	-3.932E-16	.089			
	Z- Log-transformed R&D	.308*	.154	.411		
	Z-Log-transformed SGA	-.022	.154	-.029		
	expenditure					
	Model 2: (main and interaction effect)				.346**	6.031(.000)
	Constant	-.051	.081			
	Z- Log-transformed R&D	.232	.141	.309		
	Z-Log-transformed SGA	-.029	.141	-.309		
	expenditure					
	FAC4_7	-.118	.085	-.156		
	INTRD47	-.027	.124	-.030		
	INTSGA47	-.380**	.128	-.406		

Table 36 Cont'd.: Summary statistics on testing moderating effects of licensing strategy on firm performance

Knowledge	Model 1: (main effect)				.130*	4.467(.016)
	Constant	-1.252E-16	.119			
	Z- Log-transformed R&D	.433*	.208	.433		
	Z-Log-transformed SGA expenditure	-.095	.208	-.095		
	Model 2: (main and interaction effect)				.179	2.487(.042)
	Constant	-.035	.121			
	Z- Log-transformed R&D	.392+	.211	.392		
	Z-Log-transformed SGA expenditure	-.112	.21	-.112		
	FAC4_7	-.093	.127	-.092		
	INTRD47	-.072	.186	-.061		
	INTSGA47	-.201	.192	-.161		
Safety and efficacy	Model 1: (main effect)				.030	.922(.403)
	Constant	-9.353E-16	.126			
	Z- Log-transformed R&D	.294	.219	.294		
	Z-Log-transformed SGA expenditure	-.211	.219	-.211		
	Model 2: (main and interaction effect)				.078	.969(.444)
	Constant	.037	.128			
	Z- Log-transformed R&D	.329	.224	.329		
	Z-Log-transformed SGA expenditure	-.192	.223	-.192		
	FAC4_7	.050	.135	.049		
	INTRD47	.100	.197	.085		
	INTSGA47	.194	.203	.155		

+ $p < .10$, * $p < .05$, ** $p < .01$, and *** $p < .001$

SGA expenditure has a strong positive impact on sales revenue, and R&D expenditure has a positive impact on knowledge opportunity of a firm. There is no impact on the safety and efficacy performance variable in the model. In addition, the author developed a Poisson regression model to test the moderating effect of licensing strategy (LS) on the number of new drugs using. The following mathematical relationship was tested:

$$\text{Expected No. of New Drugs} = \exp(a + b_1 \text{R\&D} + b_2 \text{SGA} + b_3 \text{LS} + b_4 \text{RD*LS} + b_5 \text{SGA*LS})$$

The Poisson model that was developed in this test fits the data well with a likelihood ratio Chi-square value of 41.377 ($p = .000$). All the variables that were entered in the Poisson model are significant and contribute to explaining part of the variability in the dependent variable (Appendix B4B5-1). Table 37 provides more information on the significance of the coefficients resulted from Poisson regression. The result shows that interactions between licensing strategy and both R&D spending and SGA expenditure variables are significant. For those firms with high R&D spending, licensing strategy increases the number of new drugs. On the other hand, for firms that have a higher SGA expenditure, licensing strategy reduces the number of new drugs that a pharmaceutical company introduces to market. The following equation shows the relationship among variables.

$$\hat{\mu} = \exp[1.362 - .226(ZLNAVGRD) + .364(ZLNMAREXP) - .285(FAC4\_7) + .230(INTRD47) - .230(INTMAREXP47)]$$

$$\hat{\mu} = 3.904 + .798^{LNAVGRD} + 1.439^{LNMAREXP} + .752^{FAC4\_7} + 1.258^{INTRD47} + .794^{INTMAREXP47}$$

Table 37: Poisson regression result for moderating effect of licensing strategy on the relationship between absorptive capacity and number of new drugs

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.362	.0687	1.228	1.497	393.559	1	.000
ZLNAVGRD	-.226	.1148	-.451	.000	3.866	1	.049
ZLNMAREXP	.364	.1121	.144	.584	10.532	1	.001
FAC4_7	-.285	.0672	-.417	-.153	18.011	1	.000
intrd47	.230	.1056	.023	.437	4.763	1	.029
intmarexp47	-.230	.0979	-.422	-.038	5.524	1	.019
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC4_7, intrd47, intmarexp47

a. Fixed at the displayed value.

Some of the characteristics of companies that follow a licensing strategy include licensing their R&D, production, and marketing drug projects to other companies. They usually work with subcontractors in developing a drug or license-out a newly discovered compound that has a promising commercial gain.

In addition to testing hypothesis 4a and 4b and investigating the moderating effect of external integration and licensing strategy on the relationship between absorptive capacity and firm's innovation performance, the author tested the moderating effect of the other two components that resulted from the principal component analysis on the commercialization strategy construct (i.e., in-house drug development strategy and developing complementary asset strategy). Tables 38 and 39 summarize the result of four multiple regression models and one Poisson regression test that were applied to investigate the following five mathematical relationships for testing the first component of commercialization strategy (i.e., in-house drug development strategy) on the relationship between absorptive capacity and firm performance.

- 1- Sales revenue = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC1\_7}^{14} + b_4 \text{ R\&D} * \text{FAC1\_7} + b_5 \text{ SGA} * \text{FAC1\_7}$
- 2- Customer satisfaction = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC1\_7} + b_4 \text{ R\&D} * \text{FAC1\_7} + b_5 \text{ SGA} * \text{FAC1\_7}$
- 3- Knowledge = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC1\_7} + b_4 \text{ R\&D} * \text{FAC1\_7} + b_5 \text{ SGA} * \text{FAC1\_7}$
- 4- Safety and efficacy = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC1\_7} + b_4 \text{ R\&D} * \text{FAC1\_7} + b_5 \text{ SGA} * \text{FAC1\_7}$

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¹⁴ In-house drug development strategy component that resulted from principal component analysis on commercialization strategy

$$5- \text{ Number of new drug} = \exp(a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC1\_7} + b_4 \text{ R\&D} * \\ \text{FAC1\_7} + b_5 \text{ SGA} * \text{ FAC1\_7})$$

The results (Appendix BF171) of the statistical analysis show that in-house drug development strategy is a significant moderator on the relationship among absorptive capacity and two dimensions of innovation performance (i.e., customer satisfaction and the number of new drugs).

Generating revenue from drug discovery and development is very important for the survival and profitability of the companies that follow the in-house drug development strategy. These companies usually direct their resources toward discovering and developing a drug that fits in the company's portfolio of current and future drug development. They use patents extensively to protect their innovation from imitation. If the discovered compound does not fit in the company's line of business but has the potential for commercial gain, they license out the compound. Difficulties in obtaining regulatory approval for their drugs does not result in limiting their R&D budget, and they hire other companies who have experience in working with the regulatory agencies to apply and receive marketing approval for their drugs.

Table 38: Summary statistics for testing moderating effects of in-house drug development strategy
on firm performance

Dependent Variable	Model and Variable	B	SE B	β	R ²	ANOVA F (Sig.)
Sales Revenue	Model 1: (main effect)				0.246***	9.803 (.000)
	Constant	13.968***	.461			
	Z-Log-transformed SGA expenditure	1.873*	.801	.452		
	Z- Log-transformed average R&D	.222	.801	.054		
	Model 2: (main and interaction effect)				0.278	4.390(.002)
	Constant	13.729***	.499			
	Z-Log-transformed SGA expenditure	1.441	.884	.348		
	Z- Log-transformed average R&D	.751	.898	.181		
	FAC1_7	-.498	.560	-.119		
	INTRD17	1.029	.799	.348		
	INTSGA17	-1.017	.875	-.319		

Table 38 Cont'd.

Customer	<i>Model 1: (main effect)</i>				.150**	5.2941(.000)
Satisfaction	Constant	-3.932E-16	.089			
	Z-Log-transformed SGA expenditure	-.022	.154	-.029		
	Z- Log-transformed R&D	.308*	.154	.411		
	<i>Model 2: (main and interaction effect)</i>				.371***	6.719(.000)
	Constant	.021	.084			
	Z-Log-transformed SGA expenditure	.228	.149	.304		
	Z- Log-transformed R&D	.018	.152	.024		
	FAC1_7	.403***	.094	.534		
	INTRD17	-.089	.135	-.166		
	INTSGA17	.124	.148	.215		
Knowledge	<i>Model 1: (main effect)</i>				.13*	4.467(.016)
	Constant	-1.252E-16	.119			
	Z-Log-transformed SGA expenditure	-.095	.208	-.095		
	Z= Log-transformed R&D	.433*	.208	.433		
	<i>Model 2: (main and interaction effect)</i>				.185	2.586(.035)
	Constant	.028	.128			
	Z-Log-transformed SGA expenditure	.009	.227	.009		
	Z- Log-Transformed R&D	.278	.230	.278		
	FAC1_7	.172	.143	.171		
	INTRD17	-.123	.205	-.173		
	INTSGA17	.032	.224	.041		

Table 38 Contd.

Safety and	Model 1: (main effect)				0.030	.922(.403)
Efficacy	Constant	-9.353E-16	.126			
	Z-Log-transformed SGA	-.221	.219	-.211		
	expenditure					
	Z- Log-transformed R&D	.294	.219	.294		
	Model 2: (main and interaction effect)				.081	1.006(.423)
	Constant					
	Z-Log-transformed SGA	-.056	.136			
	expenditure	-.324	.241	-.324		
	Z- Log-transformed R&D					
	FAC1_7	.385	.244	.385		
	INTRD17					
	INTSGA17	-.103	.152	-.102		
		.234	.217	.328		
		-.382	.238	-.496		

+p<.10, *p<.05, **p<.01, and ***p<.001

Table 39: Parameter Estimates – Poisson regression for testing moderating effects of in-house drug development strategy on firm performance

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.298	.0768	1.147	1.448	285.291	1	.000
ZLNAVGRD	-.201	.1282	-.453	.050	2.464	1	.116
ZLNMAREXP	.394	.1206	.157	.630	10.644	1	.001
FAC1_7	.127	.0815	-.033	.287	2.428	1	.119
intrd17	.292	.1009	.094	.490	8.384	1	.004
intsga17	-.288	.1040	-.492	-.084	7.673	1	.006
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_7, intrd17, intsga17

a. Fixed at the displayed value.

Finally, by testing the following five mathematical equations, the author tested the moderating effects of the second component of commercialization strategy (i.e., developing a complementary asset strategy) on the relationship between absorptive capacity and firm performance. The results show that this strategy is a significant moderator on the relationship between absorptive capacity and two dimensions of performance; customer satisfaction and the number of new drugs (Appendices BF271-BF275). Tables 40 and 41 summarize the result of four multiple regression and one Poisson regression for testing this relationship.

- 1- Sales revenue = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC2\_7}^{15} + b_4 \text{ R\&D} * \text{FAC2\_7} + b_5 \text{ SGA} * \text{FAC2\_7}$
- 2- Customer satisfaction = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC2\_7} + b_4 \text{ R\&D} * \text{FAC2\_7} + b_5 \text{ SGA} * \text{FAC2\_7}$
- 3- Knowledge = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC2\_7} + b_4 \text{ R\&D} * \text{FAC2\_7} + b_5 \text{ SGA} * \text{FAC2\_7}$
- 4- Safety and efficacy = $a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC2\_7} + b_4 \text{ R\&D} * \text{FAC2\_7} + b_5 \text{ SGA} * \text{FAC2\_7}$
- 5- Number of new drug = $\exp(a + b_1 \text{ R\&D} + b_2 \text{ SGA} + b_3 \text{ FAC2\_7} + b_4 \text{ R\&D} * \text{FAC2\_7} + b_5 \text{ SGA} * \text{FAC2\_7})$

Generating revenue from developing complementary assets such as manufacturing, sales, marketing, and business know-how is very important for the survival and profitability of the companies that follow this strategy. These companies maintain maximum control over all complementary assets. They use this advantage to not only develop and market their own drugs but also license-in drugs developed by others for the purpose of marketing. If a discovered compound does not fit in their strategy and portfolio of current business, they extend the business line to develop the compound to a drug and market it to generate additional revenue.

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¹⁵ Developing complementary asset strategy component that resulted from principal component analysis on commercialization strategy construct

Table 40: Summary statistics for testing moderating effects of developing complementary asset strategy on firm performance

Dependent Variable	Model and Variable	B	SE B	β	R ²	ANOVA F (Sig.)
Sales Revenue	Model 1: (main effect)				0.246***	9.803 (.000)
	Constant	13.968***	.461			
	Z-Log-transformed	1.873*	.801	.452		
	SGA expenditure					
	Z- Log-transformed	.222	.801	.054		
	Average R&D					
	Model 2: (main and interaction effect)				0.308	5.064(.001)
	Constant	13.600***	.486			
	Z-Log-transformed	.901	.928	.217		
	SGA expenditure					
	Z- Log-transformed	1.058	.881	.255		
	Average R&D					
	FAC2_7	.185	.495	.044		
	INTRD27	-1.552 ⁺	.897	-.351		
	INTSGA27	2.267*	1.016	.469		

Table 40 Cont'd.

Customer	Model 1: (main effect)				.150**	5.2941(.000)
Satisfaction	Constant	-3.932E-16	.089			
	Z-Log-transformed SGA expenditure	-.022	.154	-.029		
	Z- Log-transformed R&D	.308*	.154	.411		
	Model 2: (main and interaction effect)				.204	2.913(.021)
	Constant	-.005	.094			
	Z-Log-transformed SGA expenditure	-.139	.180	-.186		
	Z- Log-transformed R&D	.381*	.171	.508		
	FAC2_7	.168 ⁺	.096	.222		
	INTRD27	-.134	.174	-.168		
	INTSGA27	.100	.197	.115		
Knowledge	Model 1: (main effect)				.13*	4.467(.016)
	Constant	-1.252E-16	.119			
	Z-Log-transformed SGA expenditure	-.095	.208	-.095		
	Z= Log-transformed R&D	.433*	.208	.433		
	Model 2: (main and interaction effect)				.189	2.657(.032)
	Constant	-.012	.127			
	Z-Log-transformed SGA expenditure	-.281	.242	-.281		
	Z- Log-transformed R&D	.564	.230	.564		
	FAC2_7	.196	.129	.194		
	INTRD27	-.299	.234	-.281		
	INTSGA27	.223	.265	.191		

Table 40 Cont'd.

Safety and	Model 1: (main effect)				0.030	.922(.403)
Efficacy	Constant	-9.353E-16	.126			
	Z-Log-transformed SGA	-.221	.219	-.211		
	expenditure					
	Z- Log-transformed R&D	.294	.219	.294		
	Model 2: (main and					
	interaction effect)				.082	1.021(.414)
	Constant	.045	.135			
	Z-Log-transformed SGA	-.193	.258	-.193		
	expenditure					
	Z- Log-transformed R&D	.242	.245	.242		
	FAC2_7	.179	.138	.177		
	INTRD27	.136	.249	.128		
	INTSGA27	-.247	.282	-.212		

+ $p < .10$, * $p < .05$, ** $p < .01$, and *** $p < .001$

Table 41: Parameter Estimates – Poisson regression for testing moderating effects of developing complementary asset strategy on firm performance

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	.759	.1070	.549	.969	50.299	1	.000
ZLNAVGRD	.797	.1422	.519	1.076	31.450	1	.000
ZLNMAREXP	-.883	.1630	-1.202	-.563	29.331	1	.000
FAC2_7	.569	.0894	.394	.745	40.600	1	.000
intrd27	-1.444	.1386	-1.716	-1.173	108.661	1	.000
intsga27	1.841	.1677	1.513	2.170	120.590	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC2_7, intrd27, intsga27

a. Fixed at the displayed value.

As shown in Table 41, developing complementary asset strategy emerged as a strong moderator on the relationship between absorptive capacity and the number of new drugs that pharmaceutical companies develop and introduce to market. All variables in the model are significant contributor in the model. The results show that firms that follow this strategy invest heavily in sales to be able to bring higher number of drugs to market. The next chapter of the thesis discusses the results and findings of this research.

Chapter 8: Results and Discussion

This thesis examines the relationship between absorptive capacity (i.e., identification, assimilation, transformation, and exploitation of new knowledge), financial and non-financial dimensions of innovation performance of U.S. and Canadian pharmaceutical firms and provides answers to the following questions:

- How important is absorptive capacity in the performance of pharmaceutical firms?
- What are the factors that pharmaceutical firms should consider to achieve the benefits of investments in building absorptive capacity?
- Does R&D improve a firm's innovation performance or is it the expenditure on sales, general and administration (SGA) that is more important in improving performance, or both?
- What factors moderate the relationship between absorptive capacity and firm's innovation performance?

To answer these questions, a theoretical framework was developed and 14 hypotheses have been developed and tested. This study showed that absorptive capacity, as measured by R&D and SGA expenditures, has a positive impact on the financial and some of the non-financial dimensions of innovation performance. Some researchers, including Cohen and Levinthal, (1990) and Stock *et al.* (2001) operationalized absorptive capacity by measuring R&D, but others, including Zahra

and George (2000), criticized this and argued that R&D expenditure alone does not measure all aspects of absorptive capacity. However, the thesis operationalized absorptive capacity by measuring both R&D and SGA expenditure. Zahra and George (2000) argue that investments in transforming and exploiting the new knowledge (i.e., SGA expenditure) is as important as investments in identifying and assimilating knowledge through spending in R&D. Lin *et al.* (2006) developed and tested a model to investigate the relationship between R&D and commercialization orientation, measured by SGA expenditure, on firm performance; their study found that R&D spending does not have a significant impact on their dependent variable. However, the results of the study show that there is a positive and significant relationship between SGA expenditure and their dependent variable. The author suggests that sales and marketing expenditure is as important as R&D expenditure in affecting the company's bottom line. This seems to be reasonable as spending in both R&D and SGA should improve a firm's financial performance. Investments in R&D and SGA should also allow the firm to proactively search for sources of new knowledge, acquire the new knowledge, and commercialize the newly acquired knowledge to gain competitive advantage.

From a theoretical standpoint, the methodology used in this thesis for measuring absorptive capacity is superior because investments in building absorptive capacity should not only result in identifying and assimilating new knowledge, but they should also result in the firm's increased ability in transforming and exploiting the

newly acquired knowledge into products or services that satisfy market needs and improve the firm's performance.

8.1 Impact of Absorptive capacity on firm performance

The results of separate regression models for the relationship between R&D and SGA expenditures and financial performance were discussed in Chapter 7, and they are provided in the Appendices B1A-BF275. The results show that there is a moderate positive and significant relationship between R&D and financial performance ($R = .422$). This result is intuitive, as one would expect that one main reason for spending in R&D is to invent new products that could be commercialized to improve financial performance. However, the author found a stronger positive and significant relationship between SGA expenditure and financial performance ($R = .495$) in the sample of pharmaceutical firms; this means that SGA expenditure contributes more to improvements in the financial performance of pharmaceutical firms. This result suggests that although R&D is important in discovering new drugs, more resources should be devoted to SGA to be able to bring the discoveries to market to benefit from the scientific work, which was argued by Zahra and George (2000).

Based on the support for hypotheses 1a and 2a, it is safe to say that absorptive capacity is an important contributor to a firm's financial performance, and building higher levels of absorptive capacity through investments in both R&D and SGA

improve the financial performance of pharmaceutical companies. Although R&D is fundamental in nature for the growth of firms, marketing activities – such as advertising and direct communication with physicians, pharmacists, and patients – would benefit pharmaceutical firms in improving their financial performance. The thesis also shows that the relationship among R&D and SGA interaction and financial performance is positive and significant ($R = .507$, $b = .043$, $t = 4.590$, $p = .000$). Consistent with the literature (Lin *et al.*, 2006), this suggests that R&D and SGA complement each other in generating revenue for high technology pharmaceutical firms. Both investments are important in innovation and in generating wealth and they contribute significantly to the success of these firms.

The findings of this thesis also support that increases in R&D and SGA expenditures improve customer satisfaction (i.e., hypotheses 1b and 2b are supported). As explained in Chapter 7, a one-percent increase in R&D spending would result in 0.00198 units increase in customer satisfaction. Similarly, a one-percent increase in SGA expenditure results in 0.00147 units increase in customer satisfaction. This is a substantive finding, as one would expect that higher customer satisfaction would result because of higher marketing expenditure compared to R&D spending. However, one factor to consider in interpreting these numbers is that the information on the customer criteria construct was captured through a survey of senior executives of pharmaceutical companies. The results, thus, reflect their opinion about how their innovation impacts customers and how they believe

customers (e.g., patients, physicians, and pharmacists) perceive their innovative drugs. In other words, this thesis did not capture customer opinion about a particular drug, and, therefore, it might be misleading to interpret these numbers without considering this fact. Eleven of the participating companies in this research are in the development stage with sales revenues close to zero. Therefore, they did not have any product in the market and did not have complete information about customer opinion on their drugs. However, those eleven cases were filtered from the database, and the relationships among R&D, SGA, and customer satisfaction were retested. The results showed a similar association and the findings were consistent with the previous tests in terms of sign and significance (i.e., $b = .212$, $p = .003$ for R&D and $b = .154$, $p = .025$ for SGA). Therefore, it is safe to conclude that higher investments in R&D and SGA are positively associated with a higher management perception of customer loyalty and satisfaction with company drugs.

The author also found support for hypotheses 1c and 2c that measured the association between R&D and SGA expenditures with the first component of the principal component analysis of opportunity criteria construct. This component was called “knowledge” and it was found to have a positive and significant relationship with both R&D and SGA expenditure. However, as shown in Chapter 7 and in Appendix B1C1, the relationship between R&D and knowledge is stronger than the relationship between SGA and knowledge (i.e., $b = .243$, $p < .001$ compared to $b = .166$, $p < .05$). Basic R&D helps companies to acquire and assimilate new

knowledge that they need to invent compounds that could be further developed into new drugs. Every research project that a company undertakes helps its scientists and marketers to gain new knowledge that builds on the pool of existing knowledge, which is necessary to be more efficient and productive in their drug development projects. To be highly productive and successful in drug development and marketing, it is important for pharmaceutical companies to have a positive working relationship between their marketing and R&D functions. During each drug development project, the marketing team can provide the scientific team with valuable information about the market for a disease or a therapeutic area. Information about the detailed description of the market for a disease, actual and potential trends, patient prevalence, current and projected sales data, available marketed drugs in the same therapeutic area, prescribing patterns, and competitive products (Spilker, 1989) could help the scientific staff to have a better understanding of the market and, accordingly, allocate the resources they need to pursue a drug development project.

The second component that resulted from principal component analysis of the opportunity criteria construct, safety and efficacy, did not have a significant relationship with R&D or SGA expenditures. Safety and efficacy is screened during the post marketing research and after the drug has been approved for marketing by the regulatory agencies. Although the industry is highly regulated and drug companies are obliged to comply with the regulations, there is a high temptation to

introduce a drug to the market as soon as possible to help the patients and receive the financial benefit of the drug's introduction. While drug companies take the invented drug through all the necessary steps to make sure that no negative side effect will result from prescribing the drug, mistakes happen and lawsuits follow. For example, consider Merck's Vioxx super aspirin drug that was promoted to safely relieve pain in patients with osteoarthritis. However, it was recalled after the company received complaints about the increased risk of stroke and heart attacks from drug use. Vioxx was approved by the FDA on May 20, 1999; after seven years of research and development by Merck the compound was found to have no unusual expected toxicity. The clinical trial of Vioxx included more than 5,000 patients, and it was approved by the FDA for diminishing pain. However, there were many reports of death from use of the drug. Merck agreed to pay about \$5 billion to settle the 27,000 lawsuits from people who were injured or died after consuming the drug¹⁶. Cases such as Vioxx can damage the brand and reputation of a drug company and negatively affect other drugs introduced by the company. For example, the news reported in March 2008 that Merck had received requests from the FDA to provide more information and data on its blockbuster drug, Singulair, because of allegations that the drug is linked to suicide¹⁷.

The author's analysis of the data also supports hypotheses 1d and 2d that there is a positive association among R&D and SGA expenditures and the number of new

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¹⁶ http://www.weitzlux.com/vioxx/lawsuit_1051.html accessed on Feb. 15, 2009

¹⁷ <http://psychcentral.com/blog/archives/2008/03/27/asthma-singulair-suicide/> visited on Feb. 15, 2009.

drugs introduced to the market. The Poisson regression results show that a one unit increase in R&D spending has a multiplicative impact of 1.096 on the mean predicted value of the number of new drugs. This result is consistent with the findings in the literature (Graves and Langowitz, 1993). Graves and Langowitz (1993) investigated the relationship between R&D expenditure and the number of New Chemical Entities (NCE) and found that increased R&D expenditure has a positive effect on the rate of NCE introduction. In addition, this study found support for a positive association between SGA and the number of new drugs. The Poisson analysis also shows that each unit increase in SGA expenditure has a multiplicative impact of 1.146 on the mean predicted value of the number of new drugs, which is higher than the R&D impact. This finding that SGA expenditure is more important than R&D spending in introducing new drugs to the market is very important. This research result is consistent with the findings of Lin *et al.* (2006), in that commercialization orientation (i.e., sales and marketing expenditure) of a firm positively affects firm performance. As stated by Lin *et al.* (2006) "...these results highlight the critical role of commercialization efforts in the innovation process. The increase in R&D expense alone cannot be a source of value creation. Technology-based firms need to devote more resources to technology commercialization and marketing."

When the number of employees who work for the firms was entered in the Poisson regression model as a control variable, the study showed that R&D spending did not

have a significant impact on the number of new drugs. However, it showed that larger firms tend to introduce more new drugs to market. This is in part due to the fact that larger firms have more resources to employ to discover drugs. Larger firms have the financial, technical, and market-related resources that put them in a better position to manage innovation and bring more new drugs to the market. They enjoy economies of scale and economies of scope in all aspects of innovation from discovery through development to manufacturing and marketing. Economies of scope and economies of scale in research and development make the firm more efficient in allocating their research budget to a larger number of projects, which in turn increases the possibility of discovering new products. This will also help the firm to generate additional new ideas, which has an impact on a firm's absorptive capacity through the identification and assimilation of new knowledge.

A large number of leads must be pursued to generate a new drug (Graves and Langowitz, 1993). According to the authors and by referring to the Pharmaceutical Manufacturing Association (1989), only five percent of the compounds that entered the clinical stage of the innovation process received FDA approval. According to Spilker (1989), out of 10,000 synthesized compounds only 10 reach the stage of human testing in the U.S. In Japan, 7,000 compounds are investigated to develop one promising drug (Yoshikawa, 1989), and the estimate for Europe ranges as high as 10,000 to one. Larger firms with resources in many therapeutic areas have an advantage in discovering more new leads that could be developed into life saving

drugs. However, Graves and Langowitz (1989) found a negative estimated coefficient of the size term in their study, suggesting that expected number of NCEs decrease with firm size. The coefficient for the size term in their study, however, is not statistically significant.

This thesis also found that SGA expenditure does not have a significant impact on the number of new drugs after controlling for the firm size. However, similar to the R&D impact, the study found that larger firms tend to introduce more new drugs.

Smaller companies in this research tend to place more emphasis on the commercial value of a drug or therapeutic area in decisions about which drugs to study. More than 90 percent of small companies (i.e., 59 percent of all firms) in this study somewhat to strongly agreed that they consider the commercial value of a drug or therapeutic area as the main criterion to pursue a drug project. On the other hand, 85 percent of small firms in this study (56 percent of all firms studied) somewhat to strongly agreed that they would consider the medical value of a drug as a criterion for their decisions on which drug to study.

According to Spilker (1989), “balancing the influence of research and development and marketing forces in developing drugs and driving the corporate business is a major challenge at most companies. One group or the other is usually more influential in decisions made about drug development.” The tradition of a company in defining success based on financial terms or the medical value of a drug plays an important role in the pharmaceutical industry. Spilker (1989) believes that

commercial consideration of drug development should always dominate the decisions on drug development. This research also finds that more than 84 percent of the senior executives of both U.S. and Canadian pharmaceutical companies somewhat to strongly agree that the criteria used in their companies to pursue a specific drug or a therapeutic area are based on the commercial value of the drug or therapeutic area.

8.2 Moderating effects of cross-functional integration

This thesis also tested the moderating effect of functional integration on the relationship between absorptive capacity and pharmaceutical firm performance. The principal component analysis of the functional integration construct extracted three components: “cross-functional information sharing”, “management support of information sharing”, and “management support of cross functional information exchange”. The results of the regression analysis (Table 29) show that the cross-functional information sharing variable and its interaction with R&D and SGA have a positive but insignificant impact on the relationship between absorptive capacity and a firm’s financial performance. On the other hand, the interaction between cross-functional information sharing and R&D showed to be positive and significant when the relationship between absorptive capacity and the number of new drugs was tested. This supports the moderating effects of the functional integration variable on the relationship between absorptive capacity and a firm’s innovation performance. The Poisson loglinear model shows that each unit increase

in SGA expenditure has a multiplicative impact of 1.481 on the mean predicted value of the number of new drugs. In addition, each unit increase in the interaction between R&D and cross-functional information sharing has a multiplicative impact of 1.657 on the mean predicted value of the number of new drugs. Similarly, each unit increase in the interaction between SGA and cross-functional information sharing has a multiplicative impact of 0.4738 on the mean predicted value of the number of drugs that pharmaceutical companies introduce to the market (Table 30). The author can safely conclude that to introduce more new drugs to market, firms need to invest more in R&D and create a culture of sharing information that encourages employees of all functional units of the company to share information on various drug projects. However, in an environment that encourages employees to share information, an increase in SGA investment will result in a smaller change in the number of new drugs that pharmaceutical companies introduce to market. This relationship became stronger in absolute *b* values when the firm size was entered in the model as a control variable. The results show that larger firms introduce more new drugs and that a higher level of interaction between R&D and cross-functional information sharing has a positive impact on performance for both large and small firms. On the other hand, the impact is more negative for both small and large firms with higher SGA and cross-functional information sharing interaction. This means that for firms with a culture of information sharing where employees can easily discuss and share information with their colleagues, higher SGA investments result

in smaller positive changes in the mean number of new drugs introduced to market (i.e., b changes from 0.4738 to 0.425).

In general, the literature supports the positive impact of functional integration on firm performance (Droge *et al.*, 2000 and McDonough, 2000), and the finding of this study is parallel to and consistent with the literature.

The cross-functional information sharing variable in this research emerged as a strong and significant moderator on the relationship between absorptive capacity and the number of new drugs. The creation of cross-functional teams composed of members of R&D, manufacturing, marketing, and regulatory approval, allow employees of a pharmaceutical company to share information with their colleagues in other functional units to achieve higher efficiency, effectiveness and productivity in drug development projects.

Tables 31 and 32 summarize the regression results for testing the moderating effects of “management support of information sharing” and “management support of cross-functional information exchange” on the relationship between the absorptive capacity and financial performance of pharmaceutical firms. There is only one main effect variable, SGA expenditure, that is highly positive and significant. None of the interaction terms in these two models were found to be significant. However, the author found that management support of information sharing has a strong and positive impact on the relationship between absorptive capacity and the number of new drugs. Model 2 of Table 33 shows a positive and significant relationship

among the absorptive capacity variables and R&D interaction with management support of information sharing with firm performance (i.e., number of new drugs). Interaction between SGA expenditure and management support of information sharing is negative but not significant at the 5 percent level, and, therefore, this variable was excluded in the resulting mathematical equation for this test.

The key message from the test of the moderating effect of functional integration on the relationship between absorptive capacity and firm performance is that management needs to support information sharing across all functional units of the organization to be more efficient and productive in drug development. The company executives should encourage employees in marketing, manufacturing, and R&D who work on different drug projects to meet regularly and share information. Management also can put incentives in place that encourage employees to work closely in sharing information. By creating a team of staff in all functional units early in the life of a project, management increases the chances of success in a drug project and could be assured that drug projects will successfully move through various steps of drug development. As explained earlier in section 3.4 of this thesis, Pelz and Andrew (1966) found a positive correlation between the amount of interaction and a firm's new product development performance. Cooper (1984) suggests that management strategies that balance R&D and marketing have a greater percentage of success in new product development projects. To achieve success, it is also necessary for the management team to remove barriers to

information sharing in integrating functional units. Griffin and Hauser (1996) suggest a number of barriers in integration. These barriers include personality differences; cultural differences; language differences; organizational differences on priorities, responsibilities, and reward systems; and physical barriers in achieving optimum cooperation. Boyle *et al.* (2005) also identify some of the organizational factors that create or hamper support for cross-functional interactions. According to the authors, the extent and quality of communication and collaboration among the functional areas of an organization is the best indicator of organizational support for cross-functional teams. In this thesis, the results are consistent with the literature in that both cross-functional information sharing and management support of information sharing have a positive impact on a pharmaceutical company's new drug performance.

On the importance of R&D and marketing interface in the success of new drug projects, Spilker (1989) states "... it is critically important for companies to have a positive relationship between research and development and marketing. The complexity of the tasks in each functional unit may not be known to the staff in another division. For example, the research team may not understand that the success of a drug depends on timely registration and drug differentiation. Others may not believe that the marketing team is doing a good job on selling the company's products effectively. In such situations the relationships will be strained and the R&D team will not seek input from the marketing unit." In similar cases,

the management team should be involved to clarify the importance of each unit to other units and help in improving the communication between employees.

8.3 Moderating effects of commercialization strategy

The commercialization strategy that a pharmaceutical firm formulates has an impact on its performance. This thesis tested the moderating effects of external integration strategy (i.e., competition) and licensing strategy (i.e., cooperation) on the relationship between absorptive capacity and a firm's financial performance. Table 34 provides information on the first test and shows that the coefficient for SGA expenditure, which is the only significant variable in this relationship, drops from $b = 1.873, p = .023$ to $b = 1.667, p = .053$, when interaction terms between R&D and SGA with external integration strategy were entered in the model. When the interaction terms were entered in the model, the coefficient of determination, R^2 , increased from .246 to .260, and the regression model fitted the data well ($F = 4.003, p = .004$). This result supports hypothesis 4a that the external integration strategy makes financial performance worse. Firms that dictate an external integration strategy invest heavily in building complementary assets. These firms also invest heavily in searching the world for sources of new knowledge (i.e., smaller biotechnology firms that have a good number of new drugs in their pipeline) and take over these firms. They also search for sources of manufacturing and marketing assets and invest heavily in building their internal capabilities to gain a competitive advantage.

In the second regression test in Table 34, we tested the moderating effects of external integration strategy on the relationship between absorptive capacity and customer satisfaction. The only significant variable in the model is the interaction between R&D and external integration strategy with a negative impact. In the first model of this test, when only the main effect variables were entered, the coefficient for R&D was significant and negative (i.e., $b = -.308$, $p = .50$). The absolute b value of this variable becomes smaller when the interaction and main effect terms were entered in the model (i.e., $b = -.246$, $p = .035$), suggesting a lack of support for hypothesis 4a on the customer satisfaction performance variable. This suggests that an external integration strategy makes it possible for a firm to become larger and stronger in providing services to its customers with stronger R&D, sales, and marketing capabilities.

The results of the analysis of the moderating effect of external integration strategy on the relationship between absorptive capacity and knowledge are also given Table 34. The results show that R&D expenditure is the only significant contributor in creating knowledge. This result is consistent with Rammer and Schmiele (2009), who suggest that R&D generates new knowledge and new applications of technologies, both of which will likely generate a certain degree of innovation. None of the interaction terms in this test were found to be significant.

External integration strategy was also found to have no impact on the relationship between the safety and efficacy of a drug and the absorptive capacity. Finally, the

author tested the moderating effect of external integration strategy on the relationship between absorptive capacity and the number of new drugs introduced by a firm. The result showed that both SGA expenditure and interaction between SGA and external integration strategy have a positive and significant impact on this relationship. This result suggests that pharmaceutical companies that formulate an external integration strategy to develop the complementary assets that they need to discover and develop drugs use a very strong sales team to proactively visit physicians, pharmacists, and patients to promote their company's new drugs. The management of these companies is highly involved in "search and development" instead of "research and development". They actively search for and take over smaller biotechnology companies that have the potential for making the next blockbuster drugs.

The thesis shows that a licensing strategy positively impacts the financial performance of the firms that choose to follow this strategy. The results from the first test in table 36 suggest that the effect of absorptive capacity on sales revenue is higher when the licensing strategy variable and its interactions with R&D and SGA were entered in the model. The coefficients of the SGA variable in both model 1 (i.e., main effect) and model 2 (main effect and interactions) are positive and significant ($b = 1.873$, $p = .023$ and $b = 1.880$, $p = .026$). According to Spilker (1989) "...the simplest licensing strategy is to license drugs or technologies that are going to earn [the] greatest profit for the company". Companies that formulate and follow this strategy are open to all proposals that come to them from outside

sources including other companies, universities, and government laboratories. Spilker (1989) identifies a number of important elements in licensing strategies including stage of development, commercial potential, R&D staff to develop the drug, corporate comfort size, production capabilities, therapeutic category of the licensed drug, business terms and arrangements, and the risk of licensing. These elements should be thoroughly investigated before a licensing contract is signed. Another aspect of licensing strategy occurs when a company licenses its developed drug to a company in another country where the original company is not actively selling its drugs. This strategy will help the company to open new markets for its drugs while giving away part of the profit from its innovation. Licensing the drug or forming a joint venture is a business practice that increases revenue for the original developer of the drug.

The second test in Table 36 investigates the moderating effects of licensing strategy on the relationship between absorptive capacity and customer satisfaction. The only significant variable in this model is the interaction between SGA and licensing strategy with a negative value ($b = -.380$, $p = .004$), suggesting that customer satisfaction will be lower with the moderating effect of the licensing strategy variable. The results also show that licensing strategy has a strong and significant impact on the relationship between absorptive capacity and the number of new drugs. All the main effect and interaction terms are significant and contribute to the model (Table 37). While two of the variables in the Poisson model (i.e., SGA

expenditure, and interaction between R&D and licensing strategy) are positively associated with the number of new drugs, the other three variables (i.e., R&D spending, licensing strategy, and interaction between SGA and licensing strategy) are negatively associated with the number of new drugs. This result suggests that companies that follow licensing strategy spend more on SGA to be able to introduce more new drugs to the market. In other words, those firms that license-in new drugs from other companies will be able to introduce more drugs to the market should they spend more on SGA. However, a change in R&D spending, licensing strategy, and interaction between licensing strategy and SGA expenditure will produce a smaller change in the number of new drugs. After controlling for firm size, the results show that licensing strategy and the interaction between licensing strategy and SGA expenditure negatively affect the number of new drugs. However, the interaction between R&D spending and licensing strategy positively and significantly affect the number of new drugs. This test also shows that larger firms introduce more drugs than do smaller firms. The partial support for hypothesis 4b is due to the fact that licensing strategy has some risk elements embedded in it. There is a possibility that a company that licenses the drug will not be able to develop the drug as it hoped it will. The risks involved in the safety and efficacy of a drug, the cost of moving the drug through the development process, the possibility of liability suits, and the probability that the drug will not be marketed in time to obtain minimally accepted returns are some other factors that Spilker (1989) points out that need to be considered before signing a licensing agreement. Table 38

summarizes the 14 hypotheses developed for this research and provides information on whether they are supported or not.

Table 42: Supported and Non-supported hypotheses

Hypothesis	Support
<i>Hypothesis 1a: A higher level of absorptive capacity achieved through investments in R&D will positively influence the financial criteria of a pharmaceutical firm's innovation performance.</i>	Yes
<i>Hypothesis 1b: A higher level of absorptive capacity achieved through investments in R&D will positively influence customer criteria of a pharmaceutical firm's innovation performance.</i>	Yes
<i>Hypothesis 1c: A higher level of absorptive capacity achieved through investments in R&D will positively influence opportunities criteria of a pharmaceutical firm's innovation performance.</i>	Yes
<i>Hypothesis 1d: A higher level of absorptive capacity achieved through investments in R&D will positively influence the number of new drugs that a pharmaceutical firm develops and introduces to the market.</i>	Yes
<i>Hypothesis 2a: A higher level of absorptive capacity achieved through investments in SGA will positively influence the financial criteria of a pharmaceutical firm's innovation performance.</i>	Yes
<i>Hypothesis 2b: A higher level of absorptive capacity achieved through investments in SGA will positively influence customer criteria of innovation performance of a pharmaceutical firm's innovation performance.</i>	Yes
<i>Hypothesis 2c: A higher level of absorptive capacity achieved through investments in SGA will positively influence the opportunities criteria of a pharmaceutical firm's innovation performance.</i>	Yes
<i>Hypothesis 2d: A higher level of absorptive capacity achieved through investments SGA will positively influence the number of new drugs that pharmaceutical firms introduce to the market.</i>	Yes
<i>Hypothesis 3a: A higher level of absorptive capacity improves the financial criteria of a pharmaceutical firm's innovation performance especially where firms integrate their functional units by forming cross-functional teams.</i>	No
<i>Hypothesis 3b: A higher level of absorptive capacity is associated with a higher number of new drugs that pharmaceutical firms introduce to the market especially in firms where functional units are integrated by forming cross-functional teams.</i>	Yes
<i>Hypothesis 3c: A higher level of absorptive capacity improves the financial criteria of a pharmaceutical firm's innovation performance especially where management supports functional integration.</i>	No
<i>Hypothesis 3d: A higher level of absorptive capacity is associated with a higher number of new drugs that pharmaceutical firms introduce to the market especially in firms where management supports functional integration.</i>	Yes
<i>Hypothesis 4a: The effect of absorptive capacity on a firm's innovation performance is significantly lower for integrator firms in the pharmaceutical industry.</i>	Partial support
<i>Hypothesis 4b: The effect of absorptive capacity on a firm's innovation performance is significantly higher for licensor firms in the pharmaceutical industry.</i>	Partial support

Chapter 9: Conclusion

Innovation is the life blood of pharmaceutical companies. It encompasses both the discovery of a compound that could be developed to become a safe and effective drug and the commercialization of the drug. To discover and commercialize new drugs, pharmaceutical companies invest heavily in R&D and in sales and marketing. Investments in R&D help a firm to identify and assimilate new knowledge but do not guarantee that the firm can benefit from its investment if the newly acquired knowledge is not transformed into a safe and marketable drug. To benefit from R&D investments, firms have to commercialize their drugs by investing in sales and marketing so that they can take R&D results to the market. Therefore, commercialization of new drug products has become an important factor in the innovation process of pharmaceutical firms.

Absorptive capacity (Cohen and Levinthal, 1990) is defined as the ability of a firm to identify, assimilate, transform, and exploit knowledge. Absorptive capacity is a function of a firm's prior related knowledge, and it is crucial to the firms' innovative capabilities. The literature provides evidence that absorptive capacity has an impact on New Product Development (NPD) performance. The literature also suggests that NPD performance would improve if firms build higher levels of absorptive capacity through the identification and assimilation of external sources of knowledge. However, despite the vast theoretical and empirical studies

investigating the impact of absorptive capacity on firm performance, there is no systematic empirical evidence which confirms that absorptive capacity improves the innovation performance of pharmaceutical firms. There is also conflicting opinion in the literature on what factors should be measured to operationalize absorptive capacity. Therefore, the questions under investigation in this thesis were:

- ✓ How important is absorptive capacity in the innovation performance of pharmaceutical firms?
- ✓ What are the factors that pharmaceutical firms should consider to achieve the benefits of building absorptive capacity?
- ✓ Does R&D expenditure improve a firm's innovation performance, is it the expenditure on SGA that is more important in improving performance, or are both necessary to improve performance?
- ✓ What factors moderate the relationship between absorptive capacity and a firm's innovation performance?

This thesis reviewed the theoretical and empirical studies in the literature; and it developed a comprehensive framework that outlines the relationship between absorptive capacity, innovation performance, functional integration, and commercialization strategy that a pharmaceutical firm formulates to achieve maximum benefits from its innovation. The thesis also collected data from senior executives of Canadian and U.S. pharmaceutical companies and statistically

analyzed the data to test the hypotheses developed in this thesis. The process provided an answer to each of the questions above.

Innovation performance in this thesis is considered to be a multidimensional construct, which includes the most important factors that researchers recommend to be included in studying performance. Financial criteria, customer criteria, opportunity criteria, and the number of new drugs that a pharmaceutical company develops and introduces to the market were dimensions of the performance that were considered in this thesis.

The author operationalized absorptive capacity by measuring both R&D and SGA expenditures to investigate their association with the dimensions of innovation performance. The moderating effects of functional integration and commercialization strategy of a firm on the relationship between absorptive capacity and a firm's financial and non-financial performance were also tested.

Functional integration, through forming cross-functional teams, is one of the most effective techniques that help a company to achieve efficiency in its operations and improve NPD performance. The commercialization strategy that a firm formulates will also have an impact on its performance. An excludability environment and a complementary asset environment are two important factors that determine the type of commercialization strategy (i.e., integration or licensing) that a firm uses to bring its new drugs to the market.

To identify potential respondents to the survey in this thesis, Standard and Poor's Compustat was used to obtain a list of active and publicly traded companies in the U.S. and Canada. The list contains information about 735 companies currently listed in this database. An eight-page questionnaire with a personalized covering letter was mailed to the senior executives of these companies asking them to participate in this research. A total number of 65 usable responses have been received and analyzed.

The (SPSS) was used to analyze the data and test the 14 hypotheses developed in this thesis. The responses have been examined for missing values, outliers, extreme points, non-response bias, and reliability of constructs. Missing values were found to be missing completely at random (MCAR). Outliers have been filtered or the variables that included outliers and were right skewed have been log-transformed to ensure that they will not drastically change the direction of the regression line. Regression methods (i.e., simple, multiple, and Poisson) were used to test the hypotheses. To test the hypotheses in this thesis 36 separate regression tests were applied; the results showed that both R&D and SGA have a positive impact on the firm's financial performance. In fact, they complement each other in improving the performance. Results also showed that the SGA has a higher impact than R&D on the financial performance of pharmaceutical firms. This suggests that firms need to increase their sales and marketing activities to realize the benefits of their R&D activities. In addition, the results of the analysis show that

R&D spending positively affects the number of new drugs that a company introduces to the market but SGA expenditure has a negative impact on this variable. In terms of the measures of performance for sales revenue and the number of new drugs, in general, larger firms performed better than the smaller firms in this sample.

This thesis also tested the moderating effects of a functional integration and commercialization strategy of a pharmaceutical firm on the relationship between absorptive capacity and firm performance. This thesis found that functional integration does not improve sales performance but has a positive impact on the number of new drugs that a company introduces to the market. Management support of functional integration was found to have a mixed impact on the relationship between absorptive capacity and a firm's financial performance. However, the interaction between R&D and management support of information sharing has a positive and significant impact on the relationship between absorptive capacity and the number of new drugs that a company introduces to the market.

The moderating effects of commercialization strategy on the relationship between absorptive capacity and innovation performance were also tested using multiple linear regression and Poisson regression techniques. The results provide partial support for the relationships because integration and licensing strategies moderate

the relationship between absorptive capacity and four dimensions of the performance differently.

This thesis contributes to the literature in a number of ways. First, it synthesizes and extends the previous theoretical and empirical studies and develops a framework to investigate the importance of absorptive capacity in a pharmaceutical firm. Second, it empirically tests the direct effects of absorptive capacity on innovation performance of a pharmaceutical firm. Third, the study investigates and tests the importance and indirect effects of functional integration and commercialization strategy on the relationship between absorptive capacity and a firms' innovation performance. Fourth, this thesis contributes to the strategic management literature by identifying four commercialization strategies (i.e., in-house drug development strategy, developing complementary asset strategy, external integration strategy, and licensing strategy) that pharmaceutical companies can formulate to commercialize their innovation. In addition, the study contributes to the literature by investigating the effects of firm size on the innovation performance of pharmaceutical firms.

9.1 Limitations and Future Research Direction

The findings of this research support the majority of the proposed hypotheses. However, the study has the following limitations that suggest possibilities for further theoretical and empirical studies.

- The empirical investigation in this research is based on the use of quantitative measurement of R&D and SGA expenditures as proxies for absorptive capacity. However, when firms use a specific commercialization strategy, differences in the quality and level of skills in their employees, who are involved in the drug discovery and development, emerge that need to be investigated. This thesis did not capture the qualitative aspects of absorptive capacity, which is an important limitation for the research. Future research should focus on measuring the quality of the workforce in identifying, assimilating, transforming and exploiting new knowledge. Qualitative measures of absorptive capacity should be added to the quantitative measures that were identified in this thesis to estimate the impact of absorptive capacity on a firm's innovation performance.
- The second limitation of the study is the sample size, which consists of 65 pharmaceutical companies. This small sample size prevents the use of more comprehensive statistical tools, such as Structural Equation Modeling in hypothesis testing. This limitation resulted in conducting more than 36 separate tests to be able to analyze the data and test the 14 proposed hypotheses. Future research should be designed in such a way that provides the possibility of obtaining a minimum of 100 responses.

- This study focused on one very sensitive industry. Therefore, the findings of the research may not be generalized to other industries. Further research is needed to investigate the relationship among the variables of interest in this study in other sectors of the economy.
- Cohen and Levinthal, (1990) state that absorptive capacity is history and path dependent. No attempt has been made to investigate these factors in this research. Future research should focus on determining the history of a pharmaceutical firm and the level (i.e., depth and breadth) of new knowledge that old and young firms can identify, acquire, assimilate, transform, and exploit. In addition, the line of business and involvement of a pharmaceutical firm in a specific therapeutic area may have an impact on the level and type of knowledge that it can assimilate, which will affect its performance. This also needs to be investigated in the future research.
- This study was designed to capture information from one respondent in each company. The use of a single respondent may influence the accuracy of the measurement scale. Many of the respondents to the survey were responsible for a specific functional unit of their companies and, therefore, did not know much about the details of other functional units. More research is needed to design a study to capture multiple

responses per company and compare the responses to obtain higher accuracy in the results.

- This study investigated the relationships among different variables by focusing on the U.S. and Canadian pharmaceutical firms. The author's previous research (Hassanlou *et al.* 2006 and 2007) shows that pharmaceutical companies in other countries, such as the U.K. and Switzerland, are more successful than the Canadian firms. Further research is necessary to determine the effect of absorptive capacity on firm performance for the best practice firms in other countries.

Despite these limitations, this thesis significantly contributes to the body of knowledge in the innovation and technology management literature.

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Appendix A

Letter of Invitation to Participate in the Study

Dear Sir/Madam:

My name is Ali R Hassanlou. I am a Ph.D. Candidate at the Sprott School of Business, Carleton University, Ottawa, Canada. I am currently working on my thesis research, which examines the relationship between absorptive capacity (i.e., the ability of a firm to identify, assimilate, transform, and exploit knowledge) and innovation performance of pharmaceutical and biotechnology companies. In addition, the research considers functional integration and commercialization strategy of a pharmaceutical/ biotechnology firm as moderating variables.

The specific questions my Ph.D. thesis explores are: how important is absorptive capacity in the innovation performance of pharmaceutical/ biotechnology firms? What are the factors that pharmaceutical/ biotechnology firms should consider to achieve the benefits of building absorptive capacity? Does R&D expenditure improve a firm's innovation performance or is it the expenditure on Sales, General and Administration (SGA) that is more important in improving performance, or both? What factors moderate the relationship between absorptive capacity and firm's innovation performance?

I would like to kindly request to please participate in this study by completing the enclosed questionnaire and returning it in the provided self-addressed stamped return envelop. I do understand that your time is very valuable. However, by taking **30 minutes** of your time to complete this questionnaire, you will directly and significantly enhance my ability to complete my Ph.D. thesis, for which I would be very grateful. As a way of saying thank you for assisting me with this research project, you will receive a copy of the research findings summarizing how organizations such as yours will benefit from building absorptive capacity.

I ensure you that the results of individual questionnaire are confidential and will not be disclosed to any outside parties. Anonymity will be ensured by assigning numbers to individual questionnaire and combining the results of individual questionnaires when reporting the research findings. **Please return the completed survey using the enclosed self-addressed stamped envelop that ensures anonymity of data. The information that you provide will be used for this research project and will be stored indefinitely and future publications.** There is no risk involved in participating in this study as no information will be disclosed about you or your company.

Thank you very much for your time and input.

Ali R Hassanlou
Ph.D. Candidate

Appendix A1: Survey of Pharmaceutical Company Performance

The goal of this research project is to investigate the impact of R&D and marketing intensity (i.e., absorptive capacity) on the innovation performance of pharmaceutical firms. In addition, the study explores indirect effect of different commercialization strategies and functional integration of a pharmaceutical firm on the relationship between absorptive capacity and innovation performance. The following is the definition of the terms that we use in our research.

Research and Development (R&D) in this study refers to all the steps that companies take to study a subject or market in order to acquire and assimilate new ideas and new knowledge. This includes scientific research for discovering a compound and preclinical/clinical tests to investigate the safety and effectiveness of the compound on animals and human.

Drug commercialization refers to the process of transforming and exploiting the new ideas and knowledge to a safe and effective drug and making it available to customers (e.g., physicians, patients, pharmacists, etc.) in different markets.

Drug development refers to the technical (i.e., chemical, pharmaceutical, and analytical) aspects of the entire process that includes pre-clinical and clinical studies to take a discovered drug (compound) through the regulatory approval to test the safety and efficacy of the drug and to the market.

Thank you for completing this questionnaire, your input is very much appreciated.

Results of individual questionnaire are confidential and will not be disclosed to any outside parties. Anonymity will be ensured by assigning numbers to individual questionnaire and combining results of individual responses when reporting the research findings.

Please provide your mailing address if you wish to receive a copy of the research findings. Your contact information will be placed in a separate envelop after the data is analyzed so that your answers can not be associated to you or your company.

Name _____ Title _____

Company _____ Phone _____

Address _____

City _____ Province/State _____

Postal Code/Zip _____ Country _____

Email address _____

Part I: General Company Information

1- Please indicate whether your company is involved in the following activities and at what level:

		Low					High	
Drug Discovery (Basic R&D)	☐ Yes ☐ No	1	2	3	4	5	6	7
Pre-Clinical and Clinical Tests	☐ Yes ☐ No	1	2	3	4	5	6	7
Drug Approval	☐ Yes ☐ No	1	2	3	4	5	6	7
Drug Manufacturing	☐ Yes ☐ No	1	2	3	4	5	6	7
Drug Sales and Marketing	☐ Yes ☐ No	1	2	3	4	5	6	7
Others (please specify)		1	2	3	4	5	6	7

2- Please indicate the approximate number of employees working for your company

_____

3- Please indicate the approximate number of employees working in the following business units:

_____ R&D	_____ Pre-Clinical and Clinical test
_____ Manufacturing	_____ Sales and Marketing
_____ Regulatory Affairs	_____ Others (please specify)

4- Where does your company obtain new drug compounds?

	Strongly disagree					Strongly agree	
Company In-house research	1	2	3	4	5	6	7
Licensing-in from other companies	1	2	3	4	5	6	7
Licensing-in from government labs and universities	1	2	3	4	5	6	7
Joint venture	1	2	3	4	5	6	7
Others (please specify).....	1	2	3	4	5	6	7

5- What percentage of new drug discoveries in your company during the past three years is achieved using your company's internal R&D resources? _____

6- What percentage of new drugs developed by your company during the past three was marketed using your company's sales and marketing resources? _____

7- Please indicate the approximate number of new drugs developed by your company during the past three years that fall into the following categories:

----- New to the world	----- New to the firm
----- New to the country	----- Major revisions to an existing drug
	----- Minor revisions to an existing drug

8- How does your company decide to study a specific disease? Please indicate your level of agreement with each of the following statements:

	Strongly disagree					Strongly agree	
A team that includes people from all functional units in your company decides on this issue	1	2	3	4	5	6	7
The head of the Research & development department decides on this issue	1	2	3	4	5	6	7
The head of the sales and marketing department decides on this issue	1	2	3	4	5	6	7
Top management decides on this issue	1	2	3	4	5	6	7
Science Advisory Board decides on this issue	1	2	3	4	5	6	7
Board of Directors decides on this issue	1	2	3	4	5	6	7
Others (please specify).....	1	2	3	4	5	6	7

9- The criteria used in your company to pursue a therapeutic area or disease are:

	Strongly disagree					Strongly agree	
The commercial value of therapeutic area or disease	1	2	3	4	5	6	7
The medical value therapeutic area or disease	1	2	3	4	5	6	7
The skills and expertise available in the company	1	2	3	4	5	6	7
Interest of top management	1	2	3	4	5	6	7
Availability of the drug in the therapeutic area	1	2	3	4	5	6	7
Tradition of the company in emphasizing a therapeutic area	1	2	3	4	5	6	7
Others (please specify).....	1	2	3	4	5	6	7

10- Usually drug companies have many new ideas on drug research. Which ideas in your company receive a higher priority?

	Strongly disagree					Strongly agree	
The ideas with the greatest scientific merit	1	2	3	4	5	6	7
The ideas with the greatest market value	1	2	3	4	5	6	7
Guesswork at an early stages	1	2	3	4	5	6	7
The ideas that have support of top management	1	2	3	4	5	6	7
Others (Please specify)	1	2	3	4	5	6	7

11- The R&D unit in your company:

	Strongly disagree				Strongly agree		
Provides input to the training of sales representatives	1	2	3	4	5	6	7
Supports marketing, medical, legal, production, and other business units with information	1	2	3	4	5	6	7
Participates in writing and reviewing promotional material	1	2	3	4	5	6	7
Participates in writing and reviewing technical material	1	2	3	4	5	6	7
Answers telephone calls and written requests from customers for relevant information	1	2	3	4	5	6	7
Sets the criteria (medical, technical, and commercial) for development of a drug (go-no-go decisions)	1	2	3	4	5	6	7
Works with manufacturing and marketing units at every stage of drug development	1	2	3	4	5	6	7

Part II: Performance

This study considers four dimensions of performance including financial (i.e., annual sales revenue from the new and existing drugs), customer (e.g., how customers feel about the drugs developed by a company), opportunity (i.e, how new drugs bring opportunities for a company), and the number of new drugs developed by a company to measure innovation performance of a pharmaceutical firm.

Financial Criteria:

1- Please indicate the approximate annual sales of your company (circle one that applies):

- 1 = Less than \$100 US Million   2 = \$100 US million to less than \$1 US billion
 3 = \$1 US billion to less than \$5 US billion   4 = \$5 US billion to less than \$10 US billion
 5 = \$10 US billion and more

2- What percentage of the stated annual sales revenue comes from the sales of new drugs that your company developed and introduced to the market during the past three years?

- 1 = Less than 20%   2 = 20% to less than 40%
 3 = 40% to less than 60%   4 = 60% to less than 80%
 5 = 80% and more

3- Please indicate approximate percentage of each of the following items as a source of cash in-flow to your company (please complete as many items as apply):

-----Sales of new and existing drugs	----- Venture capital fund
-----Licensing revenue	-----Partnership
-----Government research fund	----- Long and short term loan
-----Industry research fund	----- Interest income
-----Issue of additional company shares	----- Other (please identify)

4- What percentage of the total revenue in all the above categories does your company spend in R&D? _____

5- What percentage of the total revenue in all the above categories does your company spend in sales and marketing? _____

Please note that customers for a pharmaceutical company include patients, physicians, pharmacists, and drug distributors.

Customer Criteria	Strongly agree							Strongly disagree						
3- Comparing to your main competitor's drug, customers are more satisfied with the new drugs that your company introduces to the market .	1	2	3	4	5	6	7							
4- New drugs that your company introduced to the market during the past three years increased the number of new customers significantly.	1	2	3	4	5	6	7							
5- New drugs that your company introduced to the market during the past three years opened up new markets outside the existing market.	1	2	3	4	5	6	7							
6- Customers are loyal to your company's brand and buy new drugs that it introduces to market.	1	2	3	4	5	6	7							
7- Number of customer complaints has increased recently because of the side effects of the drugs that your company introduced to the market during the past three years.	1	2	3	4	5	6	7							
Opportunity Criteria														
8- Your company's revenue for selling its old products increased because of the effectiveness of the new drugs that you developed during the past three years.	1	2	3	4	5	6	7							

9- Your company sets industry standards in introducing new drugs because of its perceived drug quality (e.g., safety and efficacy) by customers.	1	2	3	4	5	6	7
10- The knowledge gained in developing and introducing new drugs to market during the past three years will help the company develop more new drugs in the future.	1	2	3	4	5	6	7
11- Your company introduced a new drug to market during the past three years that had negative side effects. This problem has negatively affected its brand and sales revenue.	1	2	3	4	5	6	7

Part III: Functional Integration and Commercialization Strategy

Functional integration by forming cross-functional teams is considered to have an impact on the performance of new drug projects. A cross-functional team is a team comprised of members of R&D, manufacturing, marketing, and customers working together in a new drug project. Please indicate your level of agreement with each of the following statements.

III-I. Functional Integration	Strongly agree				Strongly disagree		
1- Employees in all functional units of your company including R&D, manufacturing, marketing and regulatory approval see benefits from exchanging and combining ideas with one another.	1	2	3	4	5	6	7
2- Employees in all functional units believe that by exchanging and combining ideas and knowledge they can move new drug development projects forward more quickly than by working alone.	1	2	3	4	5	6	7
3- At the end of the day, your employees feel that they have learnt from each other by exchanging and combining ideas.	1	2	3	4	5	6	7
4- Employees in your company are proficient at combining and exchanging ideas to solve problems or create new opportunities.	1	2	3	4	5	6	7
5- Employees in your company do not do a good job of sharing information to come up with new ideas, products or services.	1	2	3	4	5	6	7
6- Employees are capable of sharing their expertise to bring new projects to completion.	1	2	3	4	5	6	7

7- The employees in your company are willing to exchange and combine information with their co-workers.	1	2	3	4	5	6	7
8- It is rare for employees to exchange information to find solution to problems.	1	2	3	4	5	6	7
9- The management team in your company supports information sharing among employees in all functional units.	1	2	3	4	5	6	7
10- The management team in your company encourages employees of all functional units to share information while working on various drug development projects.	1	2	3	4	5	6	7
11- The management has incentives in place that encourage employees of all functional units to work closely together and share information on various drug development projects.	1	2	3	4	5	6	7
12- Employee bonuses and incentive plans in your company are based primarily on the performance of the organization.	1	2	3	4	5	6	7
13- Incentive plans in your company are based primarily on departmental performance.	1	2	3	4	5	6	7
14- The management teams forms a team of R&D, marketing, manufacturing, and regulatory approval units every time a drug project is initiated.	1	2	3	4	5	6	7
15- Communication of new ideas from one department to another is practically impossible.	1	2	3	4	5	6	7
16- The management team asks the head of all departments meet regularly to review drug development projects.	1	2	3	4	5	6	7
17- The head of each department in your company regularly meets with the employees of her/his department to share information and review drug project within the department.	1	2	3	4	5	6	7

III.II. Commercialization Strategy

This study defines commercialization as "... the process of bringing science and technology capabilities or R&D results to the market". Many pharmaceutical companies formulate a commercialization strategy based on the excludability environment (e.g., intellectual property protection law) and availability of complementary assets (e.g., manufacturing and marketing capabilities). Considering these elements, please answer to the following questions.

- 1- Please indicate the level of importance of each of the following items in generating revenue from your company's new drug projects:

	Low				High		
Discovering a compound that could be developed to a drug	1	2	3	4	5	6	7
Developing the compound to an effective and safe drug	1	2	3	4	5	6	7
Manufacturing capabilities to produce the drug	1	2	3	4	5	6	7
Marketing and distributing capabilities to sell the drug	1	2	3	4	5	6	7
Business know-how to receive government approval	1	2	3	4	5	6	7

- 2- What level of control does your company have over the following resources:

	Low				High		
Research and development	1	2	3	4	5	6	7
Manufacturing	1	2	3	4	5	6	7
Sales and marketing	1	2	3	4	5	6	7
Regulatory approval	1	2	3	4	5	6	7
Others (please specify)	1	2	3	4	5	6	7

- 3- How does your company protect its innovation from imitation by other firms:

	Strongly disagree				Strongly agree		
Trade secrecy	1	2	3	4	5	6	7
Patent protection	1	2	3	4	5	6	7
Copyright protection	1	2	3	4	5	6	7
Other (please specify)	1	2	3	4	5	6	7

- 4- Please indicate your opinion about the following statement:

Patent protection law is very strong in the markets that your company operates

Strongly disagree				Strongly agree		
1	2	3	4	5	6	7

- 5- In decisions on which drugs to develop, your company pays attention to whether the drug fits into company's strategy and portfolio for current and future drug development.

Strongly disagree				Strongly agree		
1	2	3	4	5	6	7

- 6- If a newly discovered compound does not fit in your company's strategy and portfolio of drug development, you:

	Strongly disagree				Strongly agree		
License-out the compound	1	2	3	4	5	6	7
Extend the business into a new product line	1	2	3	4	5	6	7
Form a Joint venture	1	2	3	4	5	6	7
Patent the compound and use it in support of the current line of business	1	2	3	4	5	6	7
Others (please specify)	1	2	3	4	5	6	7

- 7- If a newly discovered compound has promising commercial gains, your company:

	Strongly disagree				Strongly agree		
Develops the drug in-house	1	2	3	4	5	6	7
Finds a subcontractor to develop the drug	1	2	3	4	5	6	7
Prefers to license-out the compound	1	2	3	4	5	6	7
Forms joint venture	1	2	3	4	5	6	7
Hold it and do nothing	1	2	3	4	5	6	7
Others (please specify)	1	2	3	4	5	6	7

- 8- Your company has a strong regulatory affairs unit that can work with the regulatory agencies to approve a drug for marketing?

Strongly disagree	Strongly agree						
1	2	3	4	5	6	7	

- 9- The path to regulatory approval is more difficult in the country that your company operates than in other countries?

Strongly disagree	Strongly agree						
1	2	3	4	5	6	7	

10- The difficulty in obtaining regulatory approval in the country that your company operates has forced you to:

	Strongly disagree				Strongly agree			
License the drug to another company	1	2	3	4	5	6	7	
Partner with another company	1	2	3	4	5	6	7	
Get regulatory approval from other countries	1	2	3	4	5	6	7	
Limit the development projects (reduce R&D spending on various development projects)	1	2	3	4	5	6	7	
Others (Please specify)	1	2	3	4	5	6	7	

11- Your company enters into cooperative arrangements to:

	Strongly disagree				Strongly agree			
Conduct R&D for other firms	1	2	3	4	5	6	7	
Manufacture drugs developed by other firms	1	2	3	4	5	6	7	
Market and sell other firms' drugs	1	2	3	4	5	6	7	
Provide business know-how to other firms	1	2	3	4	5	6	7	
Others (please specify).....	1	2	3	4	5	6	7	

12- Your company hires other firms to:

	Strongly disagree				Strongly agree			
Conduct R&D for you	1	2	3	4	5	6	7	
Manufacture your drugs	1	2	3	4	5	6	7	
Market your firm's drugs	1	2	3	4	5	6	7	
Provide you business know-how	1	2	3	4	5	6	7	
Others (please specify).....	1	2	3	4	5	6	7	

Appendix B

Independent Samples t-test for non-response bias

1) Sales revenue

Group Statistics					
Response Category		N	Mean	Std. Deviation	Std. Error Mean
Sales in \$\$	Less than 42 days	36	15198612.93	2.615E7	4358472.650
	Greater than or equal to 42 days	23	10701519.19	2.514E7	5241529.130

Independent Samples Test

Assumptions=Equal variances assumed

	Levene's Test for Equality of Variances		t-test for Equality of Means						
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
Sales in \$\$	.013	.910	.654	57	.516	4497093.738	6877515.905	-9274894.307	1.827E7

2) Average R&D spending in the past three years

Group Statistics					
Response Category		N	Mean	Std. Deviation	Std. Error Mean
Average R&D spending in the past three years	Less than 42 days	36	18104588.72	2.047E7	3411745.139
	Greater than or equal to 42 days	23	14081856.06	1.573E7	3280308.346

Independent Samples Test

Assumptions=Equal variances
assumed

	Levene's Test for Equality of Variances		t-test for Equality of Means						
	F	Sig.	t	df	Sig. (2- tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
Average R&D spending in the past three years	1.457	.232	.802	57	.426	4022732.658	5014090.721	-6017810.820	1.406E7

1) SGA expenditure

Group Statistics

Response Category		N	Mean	Std. Deviation	Std. Error Mean
\$\$ Marketing Expenditure last year	Less than 42 days	36	2.0522E7	3.53310E7	5.88849E6
	Greater than or equal to 42 days	23	1.7054E7	1.69737E7	3.53927E6

Independent Samples Test

Assumptions=Equal variances
assumed

	Levene's Test for Equality of Variances		t-test for Equality of Means						
	F	Sig.	t	df	Sig. (2- tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
\$\$ Marketing Expenditure last year	2.421	.125	.439	57	.663	3.46805E6	7.90825E6	-1.23679E7	1.93040E7

4) Number of employees

Group Statistics

Response Category		N	Mean	Std. Deviation	Std. Error Mean
Number of employees working for the company	Less than 42 days	36	100.47	120.01542	20.002
	Greater than or equal to 42 days	23	60.30	65.164	13.588

Independent Samples Test

Assumptions		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Number of employees working for the company	Equal variances assumed	4.218	.045	1.472	57	.147	40.168	27.331	-14.562	94.898
	Equal variances not assumed			1.661	55.838	.102	40.168	24.181	-8.276	88.612

5) Number of new drugs

Group Statistics

Response Category		N	Mean	Std. Deviation	Std. Error Mean
Number of New Drugs	Less than 42 days	34	3.97	4.982	.854
	Greater than or equal to 42 days	24	4.54	8.900	1.817

Independent Samples Test

Assumptions=Equal variances

assumed

	Levene's Test for Equality of Variances		t-test for Equality of Means						
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
Number of New Drugs	.646	.425	-.312	56	.756	-.571	1.831	-4.239	3.097

Appendix B1A

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.422 ^a	.178	.164	3.79018	.178	13.400	1	62	.001	
2	.692 ^b	.479	.461	3.04297	.301	35.187	1	61	.000	1.813

a. Predictors: (Constant), Log-Transformed Average R&D

b. Predictors: (Constant), Log-Transformed Average R&D, Number of employees category

c. Dependent Variable: Log-Transformed Sales

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	192.503	1	192.503	13.400	.001 ^a
	Residual	890.661	62	14.365		
	Total	1083.163	63			
2	Regression	518.323	2	259.161	27.988	.000 ^b
	Residual	564.841	61	9.260		
	Total	1083.163	63			

a. Predictors: (Constant), Log-Transformed Average R&D

b. Predictors: (Constant), Log-Transformed Average R&D, Number of employees category

c. Dependent Variable: Log-Transformed Sales

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-5.422	5.318		-1.020	.312		
	Log-Transformed Average R&D	1.194	.326	.422	3.661	.001	1.000	1.000
2	(Constant)	4.424	4.581		.966	.338		
	Log-Transformed Average R&D	.474	.289	.167	1.644	.105	.823	1.215
	Number of employees category	5.201	.877	.604	5.932	.000	.823	1.215

a. Dependent Variable: Log-Transformed Sales

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B1B

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.387 ^a	.150	.136	.69713384	.150	10.917	1	62	.002	
2	.388 ^b	.150	.122	.70261438	.001	.037	1	61	.849	2.048

a. Predictors: (Constant), Log-Transformed Average R&D

b. Predictors: (Constant), Log-Transformed Average R&D, Number of employees category

c. Dependent Variable: REGR factor score 1 for analysis 4

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.306	1	5.306	10.917	.002 ^a
	Residual	30.132	62	.486		
	Total	35.438	63			
2	Regression	5.324	2	2.662	5.392	.007 ^b
	Residual	30.114	61	.494		
	Total	35.438	63			

a. Predictors: (Constant), Log-Transformed Average R&D

b. Predictors: (Constant), Log-Transformed Average R&D, Number of employees category

c. Dependent Variable: REGR factor score 1 for analysis 4

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-3.219	.978		-3.291	.002		
	Log-Transformed Average R&D	.198	.060	.387	3.304	.002	1.000	1.000
2	(Constant)	-3.292	1.058		-3.113	.003		
	Log-Transformed Average R&D	.204	.067	.397	3.055	.003	.823	1.215
	Number of employees category	-.039	.202	-.025	-.191	.849	.823	1.215

a. Dependent Variable: REGR factor score 1 for analysis 4

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B1C1

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.356 ^a	.127	.112	.94207537	.127	8.985	1	62	.004	
2	.356 ^b	.127	.098	.94963613	.000	.017	1	61	.898	2.155

a. Predictors: (Constant), Log-Transformed Average R&D in \$\$

b. Predictors: (Constant), Log-Transformed Average R&D, Number of employees category

c. Dependent Variable: REGR factor score 1 for analysis 5

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.975	1	7.975	8.985	.004 ^a
	Residual	55.025	62	.888		
	Total	63.000	63			
2	Regression	7.990	2	3.995	4.430	.016 ^b
	Residual	55.010	61	.902		
	Total	63.000	63			

a. Predictors: (Constant), Log-Transformed Average R&D

b. Predictors: (Constant), Log-Transformed Average R&D, Number of employees category

c. Dependent Variable: REGR factor score 1 for analysis 5

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-3.946	1.322		-2.986	.004		
	Log-Transformed Average R&D	.243	.081	.356	2.998	.004	1.000	1.000
2	(Constant)	-4.013	1.430		-2.807	.007		
	Log-Transformed Average R&D	.248	.090	.363	2.753	.008	.823	1.215
	Number of employees category	-.035	.274	-.017	-.129	.898	.823	1.215

a. Dependent Variable: REGR factor score 1 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B1C2

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.122 ^a	.015	-.001	1.00053416	.015	.933	1	62	.338	
2	.137 ^b	.019	-.013	1.00667730	.004	.246	1	61	.622	2.000

a. Predictors: (Constant), Log-Transformed Average R&D

b. Predictors: (Constant), Log-Transformed Average R&D, Number of employees category

c. Dependent Variable: REGR factor score 2
for analysis 5

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.934	1	.934	.933	.338 ^a
	Residual	62.066	62	1.001		
	Total	63.000	63			
2	Regression	1.183	2	.591	.584	.561 ^b
	Residual	61.817	61	1.013		
	Total	63.000	63			

a. Predictors: (Constant), Log-Transformed Average R&D

b. Predictors: (Constant), Log-Transformed Average R&D, Number of employees category

c. Dependent Variable: REGR factor score 2 for analysis 5

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-1.350	1.404		-.962	.340		
	Log-Transformed Average R&D	.083	.086	.122	.966	.338	1.000	1.000
2	(Constant)	-1.078	1.515		-.712	.479		
	Log-Transformed Average R&D	.063	.095	.093	.663	.510	.823	1.215
	Number of employees category	.144	.290	.069	.496	.622	.823	1.215

a. Dependent Variable: REGR factor score 2 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B1D1

Goodness of Fit^b

	Value	df	Value/df
Deviance	308.136	56	5.502
Scaled Deviance	308.136	56	
Pearson Chi-Square	631.461	56	11.276
Scaled Pearson Chi-Square	631.461	56	
Log Likelihood ^a	-234.948		
Akaike's Information Criterion (AIC)	473.896		
Finite Sample Corrected AIC (AICC)	474.115		
Bayesian Information Criterion (BIC)	478.017		
Consistent AIC (CAIC)	480.017		

Dependent Variable: Number of New Drugs

Model: (Intercept), LNAVGRD

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio		
Chi-Square	df	Sig.
4.935	1	.026

Dependent Variable: Number of New Drugs

Model: (Intercept), LNAVGRD

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	.011	1	.916
LNAVGRD	5.080	1	.024

Dependent Variable: Number of New Drugs

Model: (Intercept), LNAVGRD

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.071	.6767	-1.398	1.255	.011	1	.916
LNAVGRD	.092	.0409	.012	.172	5.080	1	.024
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), LNAVGRD

a. Fixed at the displayed value.

Appendix B1D2

Goodness of Fit^b

	Value	df	Value/df
Deviance	273.390	55	4.971
Scaled Deviance	273.390	55	
Pearson Chi-Square	471.944	55	8.581
Scaled Pearson Chi-Square	471.944	55	
Log Likelihood ^a	-217.575		
Akaike's Information Criterion (AIC)	441.150		
Finite Sample Corrected AIC (AICC)	441.594		
Bayesian Information Criterion (BIC)	447.331		
Consistent AIC (CAIC)	450.331		

Dependent Variable: Number of New Drugs

Model: (Intercept), LNAVGRD, CATNOEMP

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio Chi-Square	df	Sig.
39.681	2	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), LNAVGRD, CATNOEMP

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	4.992	1	.025
LNAVGRD	.492	1	.483
CATNOEMP	35.581	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), LNAVGRD, CATNOEMP

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.570	.7025	.193	2.947	4.992	1	.025
LNAVGRD	-.031	.0442	-.118	.056	.492	1	.483
CATNOEMP	.850	.1425	.571	1.129	35.581	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), LNAVGRD, CATNOEMP

a. Fixed at the displayed value.

Appendix B2A

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.495 ^a	.245	.233	3.63151	.245	19.829	1	61	.000	
2	.686 ^b	.470	.453	3.06761	.225	25.488	1	60	.000	1.808

a. Predictors: (Constant), Log-Transformed SGA Expenditure

b. Predictors: (Constant), Log-Transformed SGA Expenditure, Number of employees category

c. Dependent Variable: Log-Transformed Sales

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	261.509	1	261.509	19.829	.000 ^a
	Residual	804.462	61	13.188		
	Total	1065.970	62			
2	Regression	501.355	2	250.677	26.639	.000 ^b
	Residual	564.616	60	9.410		
	Total	1065.970	62			

a. Predictors: (Constant), Log-Transformed Marketing Expenditure in \$\$

b. Predictors: (Constant), Log-Transformed Marketing Expenditure in \$\$, Number of employees category

c. Dependent Variable: Log-Transformed Sales

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-7.558	4.856		-1.557	.125		
	Log-Transformed SGA Expenditure	1.321	.297	.495	4.453	.000	1.000	1.000
2	(Constant)	5.628	4.863		1.157	.252		
	Log-Transformed SGA Expenditure	.402	.310	.151	1.299	.199	.655	1.527
	Number of employees category	5.044	.999	.586	5.049	.000	.655	1.527

a. Dependent Variable: Log-Transformed Sales

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B2B

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.305 ^a	.093	.078	.71997624	.093	6.279	1	61	.015	
2	.309 ^b	.095	.065	.72509876	.002	.141	1	60	.708	2.102

a. Predictors: (Constant), Log-Transformed SGA Expenditure

b. Predictors: (Constant), Log-Transformed SGA Expenditure, Number of employees category

c. Dependent Variable: REGR factor score 1 for analysis 4

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.255	1	3.255	6.279	.015 ^a
	Residual	31.620	61	.518		
	Total	34.875	62			
2	Regression	3.329	2	1.664	3.166	.049 ^b
	Residual	31.546	60	.526		
	Total	34.875	62			

a. Predictors: (Constant), Log-Transformed Marketing Expenditure in \$\$

b. Predictors: (Constant), Log-Transformed Marketing Expenditure in \$\$, Number of employees category

c. Dependent Variable: REGR factor score 1 for analysis 4

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-2.401	.963		-2.495	.015		
	Log-Transformed Marketing Expenditure in \$\$	.147	.059	.305	2.506	.015	1.000	1.000
2	(Constant)	-2.633	1.149		-2.291	.025		
	Log-Transformed Marketing Expenditure in \$\$	.163	.073	.339	2.234	.029	.655	1.527
	Number of employees category	-.089	.236	-.057	-.376	.708	.655	1.527

a. Dependent Variable: REGR factor score 1 for analysis 4

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B2C1

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.258 ^a	.067	.051	.97402664	.067	4.351	1	61	.041	
2	.259 ^b	.067	.036	.98190231	.000	.025	1	60	.874	2.218

a. Predictors: (Constant), Log-Transformed SGA Expenditure

b. Predictors: (Constant), Log-Transformed SGA Expenditure, Number of employees category

c. Dependent Variable: REGR factor score 1 for analysis 5

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.128	1	4.128	4.351	.041 ^a
	Residual	57.872	61	.949		
	Total	62.000	62			
2	Regression	4.152	2	2.076	2.153	.125 ^b
	Residual	57.848	60	.964		
	Total	62.000	62			

a. Predictors: (Constant), Log-Transformed Marketing Expenditure in \$\$

b. Predictors: (Constant), Log-Transformed Marketing Expenditure in \$\$, Number of employees category

c. Dependent Variable: REGR factor score 1 for analysis 5

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-2.704	1.302		-2.077	.042		
	Log-Transformed SGA Expenditure	.166	.080	.258	2.086	.041	1.000	1.000
2	(Constant)	-2.838	1.556		-1.823	.073		
	Log-Transformed SGA Expenditure	.175	.099	.272	1.768	.082	.655	1.527
	Number of employees category	-.051	.320	-.025	-.159	.874	.655	1.527

a. Dependent Variable: REGR factor score 1 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B2C2

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.028 ^a	.001	-.016	1.00776287	.001	.048	1	61	.826	
2	.117 ^b	.014	-.019	1.00958237	.013	.780	1	60	.381	2.102

a. Predictors: (Constant), Log-Transformed SGA Expenditure

b. Predictors: (Constant), Log-Transformed SGA Expenditure, Number of employees category

c. Dependent Variable: REGR factor score 2 for analysis 5

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.049	1	.049	.048	.826 ^a
	Residual	61.951	61	1.016		
	Total	62.000	62			
2	Regression	.845	2	.422	.414	.663 ^b
	Residual	61.155	60	1.019		
	Total	62.000	62			

a. Predictors: (Constant), Log-Transformed SGA Expenditure

b. Predictors: (Constant), Log-Transformed SGA Expenditure, Number of employees category

c. Dependent Variable: REGR factor score 2 for analysis 5

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.295	1.347		-.219	.827		
	Log-Transformed SGA Expenditure	.018	.082	.028	.220	.826	1.000	1.000
2	(Constant)	.464	1.600		.290	.773		
	Log-Transformed SGA Expenditure	-.035	.102	-.054	-.341	.734	.655	1.527
	Number of employees category	.290	.329	.140	.883	.381	.655	1.527

a. Dependent Variable: REGR factor score 2 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B2D1

Goodness of Fit^b

	Value	df	Value/df
Deviance	299.101	56	5.341
Scaled Deviance	299.101	56	
Pearson Chi-Square	584.913	56	10.445
Scaled Pearson Chi-Square	584.913	56	
Log Likelihood ^a	-230.430		
Akaike's Information Criterion (AIC)	464.861		
Finite Sample Corrected AIC (AICC)	465.079		
Bayesian Information Criterion (BIC)	468.982		
Consistent AIC (CAIC)	470.982		

Dependent Variable: Number of New Drugs

Model: (Intercept), LNMAREXP

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio		
Chi-Square	df	Sig.
13.971	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), LNMAREXP

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	1.963	1	.161
LNMAEXP	15.602	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), LNMAEXP

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.813	.5804	-1.951	.324	1.963	1	.161
LNMAEXP	.136	.0345	.069	.204	15.602	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), LNMAEXP

a. Fixed at the displayed value.

Appendix B2D2

Goodness of Fit^b

	Value	df	Value/df
Deviance	273.878	55	4.980
Scaled Deviance	273.878	55	
Pearson Chi-Square	475.310	55	8.642
Scaled Pearson Chi-Square	475.310	55	
Log Likelihood ^a	-217.819		
Akaike's Information Criterion (AIC)	441.638		
Finite Sample Corrected AIC (AICC)	442.082		
Bayesian Information Criterion (BIC)	447.819		
Consistent AIC (CAIC)	450.819		

Dependent Variable: Number of New Drugs

Model: (Intercept), LNMAREXP, CATNOEMP

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio Chi-Square	df	Sig.
39.194	2	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), LNMAREXP, CATNOEMP

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	2.070	1	.150
LNMAEXP	.005	1	.945
CATNOEMP	25.746	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), LNMAEXP, CATNOEMP

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.031	.7170	-.374	2.437	2.070	1	.150
LNMAEXP	.003	.0454	-.086	.092	.005	1	.945
CATNOEMP	.800	.1576	.491	1.109	25.746	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), LNMAEXP, CATNOEMP

a. Fixed at the displayed value.

Appendix B3A

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.496 ^a	.246	.221	3.65930	.246	9.803	2	60	.000	
2	.509 ^b	.259	.194	3.72286	.013	.323	3	57	.809	
3	.706 ^c	.498	.444	3.09130	.239	26.670	1	56	.000	1.864

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, Interaction between SGA and Cross-functional team, REGR factor score 1 for analysis 6, Interaction between R&D and Cross-functional team

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, Interaction between SGA and Cross-functional team, REGR factor score 1 for analysis 6, Interaction between R&D and Cross-functional team, Number of employees category

d. Dependent Variable: Log-Transformed Sales

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	262.540	2	131.270	9.803	.000 ^a
	Residual	803.431	60	13.391		
	Total	1065.970	62			
2	Regression	275.967	5	55.193	3.982	.004 ^b
	Residual	790.004	57	13.860		
	Total	1065.970	62			
3	Regression	530.827	6	88.471	9.258	.000 ^c
	Residual	535.143	56	9.556		
	Total	1065.970	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, Interaction between SGA and Cross-functional team, REGR factor score 1 for analysis 6, Interaction between R&D and Cross-functional team

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, Interaction between SGA and Cross-functional team, REGR factor score 1 for analysis 6, Interaction between R&D and Cross-functional team, Number of employees category

d. Dependent Variable: Log-Transformed Sales

Coefficients ^a							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	13.968	.461		30.297	.000		
Zscore: Log-Transformed Average R&D	.222	.801	.054	.277	.782	.336	2.974
Zscore: Log-Transformed SGA Expenditure	1.873	.801	.452	2.336	.023	.336	2.974
2 (Constant)	13.881	.485		28.634	.000		
Zscore: Log-Transformed Average R&D	.330	.826	.080	.399	.691	.328	3.053
Zscore: Log-Transformed SGA Expenditure	1.753	.826	.423	2.123	.038	.328	3.052
REGR factor score 1 for analysis 6	.428	.602	.103	.712	.479	.628	1.593
Interaction between R&D and Cross-functional team	.136	.921	.041	.148	.883	.166	6.037
Interaction between SGA and Cross-functional team	.328	1.217	.082	.269	.789	.139	7.170
3 (Constant)	12.086	.532		22.722	.000		
Zscore: Log-Transformed Average R&D	.783	.692	.189	1.132	.263	.322	3.103
Zscore: Log-Transformed SGA Expenditure	-.089	.773	-.022	-.116	.908	.258	3.878
REGR factor score 1 for analysis 6	.103	.503	.025	.205	.838	.618	1.619
Interaction between R&D and Cross-functional team	1.032	.784	.314	1.316	.194	.158	6.347
Interaction between SGA and Cross-functional team	-1.065	1.046	-.267	-1.018	.313	.130	7.680
Number of employees category	5.426	1.051	.631	5.164	.000	.601	1.663

a. Dependent Variable: Log-Transformed Sales

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B3B1

Goodness of Fit^b

	Value	df	Value/df
Deviance	296.101	55	5.384
Scaled Deviance	296.101	55	
Pearson Chi-Square	562.055	55	10.219
Scaled Pearson Chi-Square	562.055	55	
Log Likelihood ^a	-228.931		
Akaike's Information Criterion (AIC)	463.861		
Finite Sample Corrected AIC (AICC)	464.306		
Bayesian Information Criterion (BIC)	470.043		
Consistent AIC (CAIC)	473.043		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio		
Chi-Square	df	Sig.
16.970	2	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	444.478	1	.000
ZLNAVGRD	3.044	1	.081
ZLNMAREXP	12.189	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.398	.0663	1.268	1.528	444.478	1	.000
ZLNAVGRD	-.189	.1084	-.402	.023	3.044	1	.081
ZLNMAREXP	.370	.1059	.162	.577	12.189	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP

a. Fixed at the displayed value.

Appendix B3B2

Goodness of Fit^b

	Value	df	Value/df
Deviance	275.316	52	5.295
Scaled Deviance	275.316	52	
Pearson Chi-Square	464.780	52	8.938
Scaled Pearson Chi-Square	464.780	52	
Log Likelihood ^a	-218.538		
Akaike's Information Criterion (AIC)	449.076		
Finite Sample Corrected AIC (AICC)	450.723		
Bayesian Information Criterion (BIC)	461.439		
Consistent AIC (CAIC)	467.439		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_6, INTRDCF, INTSGACF

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio		
Chi-Square	df	Sig.
37.756	5	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_6, INTRDCF, INTSGACF

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	437.070	1	.000
ZLNAVGRD	2.746	1	.098
ZLNMAREXP	13.448	1	.000
FAC1_6	1.409	1	.235
INTRDCF	15.056	1	.000
INTSGACF	19.925	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_6,
INTRDCF, INTSGACF

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.420	.0679	1.286	1.553	437.070	1	.000
ZLNAVGRD	-.185	.1119	-.405	.034	2.746	1	.098
ZLNMAREXP	.393	.1073	.183	.604	13.448	1	.000
FAC1_6	-.096	.0812	-.255	.063	1.409	1	.235
INTRDCF	.505	.1302	.250	.760	15.056	1	.000
INTSGACF	-.747	.1674	-1.075	-.419	19.925	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_6, INTRDCF, INTSGACF

a. Fixed at the displayed value.

Appendix B3B3

Goodness of Fit^b

	Value	df	Value/df
Deviance	242.804	51	4.761
Scaled Deviance	242.804	51	
Pearson Chi-Square	382.522	51	7.500
Scaled Pearson Chi-Square	382.522	51	
Log Likelihood ^a	-202.282		
Akaike's Information Criterion (AIC)	418.564		
Finite Sample Corrected AIC (AICC)	420.804		
Bayesian Information Criterion (BIC)	432.987		
Consistent AIC (CAIC)	439.987		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_6, INTRDCF, INTSGACF, CATNOEMP

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio Chi-Square	df	Sig.
70.268	6	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_6, INTRDCF, INTSGACF, CATNOEMP

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	116.877	1	.000
ZLNAVGRD	.511	1	.475
ZLNMAREXP	.447	1	.504
FAC1_6	6.548	1	.010
INTRDCF	20.414	1	.000
INTSGACF	28.075	1	.000
CATNOEMP	34.027	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_6,
INTRDCF, INTSGACF, CATNOEMP

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.071	.0990	.876	1.265	116.877	1	.000
ZLNAVGRD	-.073	.1014	-.271	.126	.511	1	.475
ZLNMAREXP	.074	.1109	-.143	.291	.447	1	.504
FAC1_6	-.212	.0830	-.375	-.050	6.548	1	.010
INTRDCF	.519	.1148	.294	.744	20.414	1	.000
INTSGACF	-.855	.1614	-1.172	-.539	28.075	1	.000
CATNOEMP	.926	.1588	.615	1.237	34.027	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_6, INTRDCF, INTSGACF, CATNOEMP

a. Fixed at the displayed value.

Appendix B3C1

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.496 ^a	.246	.221	3.65930	.246	9.803	2	60	.000	
2	.497 ^b	.247	.181	3.75335	.000	.010	3	57	.999	
3	.694 ^c	.481	.426	3.14275	.234	25.301	1	56	.000	1.818

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, Interaction between SGA and Management Support, REGR factor score 2 for analysis 6, Interaction between R&D and Management Support

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, Interaction between SGA and Management Support, REGR factor score 2 for analysis 6, Interaction between R&D and Management Support, Number of employees category

d. Dependent Variable: Log-Transformed Sales

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	262.540	2	131.270	9.803	.000 ^a
	Residual	803.431	60	13.391		
	Total	1065.970	62			
2	Regression	262.977	5	52.595	3.733	.005 ^b
	Residual	802.994	57	14.088		
	Total	1065.970	62			
3	Regression	512.866	6	85.478	8.654	.000 ^c
	Residual	553.104	56	9.877		
	Total	1065.970	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, Interaction between SGA and Management Support, REGR factor score 2 for analysis 6, Interaction between R&D and Management Support

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, Interaction between SGA and Management Support, REGR factor score 2 for analysis 6, Interaction between R&D and Management Support, Number of employees category

d. Dependent Variable: Log-Transformed Sales

Coefficients ^a							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	13.968	.461		30.297	.000		
Zscore: Log-Transformed Average R&D	.222	.801	.054	.277	.782	.336	2.974
Zscore: Log-Transformed SGA Expenditure	1.873	.801	.452	2.336	.023	.336	2.974
2 (Constant)	13.965	.483		28.914	.000		
Zscore: Log-Transformed Average R&D	.205	.830	.049	.247	.806	.330	3.033
Zscore: Log-Transformed SGA Expenditure	1.885	.832	.455	2.265	.027	.328	3.049
REGR factor score 2 for analysis 6	.021	.505	.005	.041	.967	.905	1.105
Interaction between R&D and Management Support	.171	1.061	.033	.161	.873	.309	3.233
Interaction between SGA and Management Support	-.130	.923	-.029	-.141	.888	.322	3.105
3 (Constant)	12.100	.549		22.052	.000		
Zscore: Log-Transformed Average R&D	.709	.702	.171	1.010	.317	.323	3.096
Zscore: Log-Transformed SGA Expenditure	.013	.790	.003	.016	.987	.255	3.918
REGR factor score 2 for analysis 6	.050	.423	.012	.119	.906	.905	1.105
Interaction between R&D and Management Support	-.437	.896	-.085	-.488	.628	.304	3.293
Interaction between SGA and Management Support	.223	.776	.049	.288	.774	.319	3.131
Number of employees category	5.241	1.042	.609	5.030	.000	.632	1.582

a. Dependent Variable: Log-Transformed Sales

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B3C2

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.496 ^a	.246	.221	3.65930	.246	9.803	2	60	.000	
2	.500 ^b	.250	.185	3.74439	.004	.101	3	57	.959	
3	.697 ^c	.486	.431	3.12698	.236	25.731	1	56	.000	1.808

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, INTRD36, REGR factor score 3 for analysis 6, INTSGA36

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, INTRD36, REGR factor score 3 for analysis 6, INTSGA36, Number of employees category

d. Dependent Variable: Log-Transformed Sales

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	262.540	2	131.270	9.803	.000 ^a
	Residual	803.431	60	13.391		
	Total	1065.970	62			
2	Regression	266.804	5	53.361	3.806	.005 ^b
	Residual	799.166	57	14.020		
	Total	1065.970	62			
3	Regression	518.404	6	86.401	8.836	.000 ^c
	Residual	547.567	56	9.778		
	Total	1065.970	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, INTRD36, REGR factor score 3 for analysis 6, INTSGA36

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, INTRD36, REGR factor score 3 for analysis 6, INTSGA36, Number of employees category

d. Dependent Variable: Log-Transformed Sales

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	13.968	.461		30.297	.000		
Zscore: Log-Transformed Average R&D	.222	.801	.054	.277	.782	.336	2.974
Zscore: Log-Transformed SGA Expenditure	1.873	.801	.452	2.336	.023	.336	2.974
2 (Constant)	13.927	.478		29.154	.000		
Zscore: Log-Transformed Average R&D	.260	.824	.063	.316	.753	.333	3.006
Zscore: Log-Transformed SGA Expenditure	1.823	.833	.440	2.188	.033	.326	3.068
REGR factor score 3 for analysis 6	-.002	.518	.000	-.004	.997	.857	1.166
INTRD36	.091	.830	.025	.109	.913	.249	4.012
INTSGA36	.161	.944	.041	.171	.865	.232	4.315
3 (Constant)	12.065	.542		22.249	.000		
Zscore: Log-Transformed Average R&D	.708	.694	.171	1.020	.312	.327	3.055
Zscore: Log-Transformed SGA Expenditure	-.048	.787	-.012	-.061	.951	.254	3.931
REGR factor score 3 for analysis 6	.072	.432	.017	.166	.869	.857	1.168
INTRD36	.011	.693	.003	.017	.987	.249	4.014
INTSGA36	.354	.789	.089	.448	.656	.231	4.325
Number of employees category	5.217	1.028	.606	5.073	.000	.642	1.557

a. Dependent Variable: Log-Transformed Sales

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B3D1

Goodness of Fit^b

	Value	df	Value/df
Deviance	296.101	55	5.384
Scaled Deviance	296.101	55	
Pearson Chi-Square	562.055	55	10.219
Scaled Pearson Chi-Square	562.055	55	
Log Likelihood ^a	-228.931		
Akaike's Information Criterion (AIC)	463.861		
Finite Sample Corrected AIC (AICC)	464.306		
Bayesian Information Criterion (BIC)	470.043		
Consistent AIC (CAIC)	473.043		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio		
Chi-Square	df	Sig.
16.970	2	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	444.478	1	.000
ZLNAVGRD	3.044	1	.081
ZLNMAREXP	12.189	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.398	.0663	1.268	1.528	444.478	1	.000
ZLNAVGRD	-.189	.1084	-.402	.023	3.044	1	.081
ZLNMAREXP	.370	.1059	.162	.577	12.189	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP

a. Fixed at the displayed value.

Appendix B3D2

Goodness of Fit^b

	Value	df	Value/df
Deviance	288.455	52	5.547
Scaled Deviance	288.455	52	
Pearson Chi-Square	538.137	52	10.349
Scaled Pearson Chi-Square	538.137	52	
Log Likelihood ^a	-225.108		
Akaike's Information Criterion (AIC)	462.215		
Finite Sample Corrected AIC (AICC)	463.862		
Bayesian Information Criterion (BIC)	474.578		
Consistent AIC (CAIC)	480.578		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC2_6, INTRD26, INTSGA26

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio		
Chi-Square	df	Sig.
24.616	5	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD,
ZLNMAREXP, FAC2_6, INTRD26, INTSGA26

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	404.682	1	.000
ZLNAVGRD	4.188	1	.041
ZLNMAREXP	15.014	1	.000
FAC2_6	1.232	1	.267
INTRD26	5.108	1	.024
INTSGA26	2.686	1	.101

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC2_6,
INTRD26, INTSGA26

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.382	.0687	1.247	1.517	404.682	1	.000
ZLNAVGRD	-.215	.1053	-.422	-.009	4.188	1	.041
ZLNMAREXP	.404	.1042	.200	.608	15.014	1	.000
FAC2_6	.080	.0721	-.061	.221	1.232	1	.267
INTRD26	.317	.1402	.042	.592	5.108	1	.024
INTSGA26	-.198	.1208	-.435	.039	2.686	1	.101
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC2_6, INTRD26, INTSGA26

a. Fixed at the displayed value.

Appendix B3D3

Goodness of Fit^b

	Value	df	Value/df
Deviance	268.197	51	5.259
Scaled Deviance	268.197	51	
Pearson Chi-Square	466.980	51	9.156
Scaled Pearson Chi-Square	466.980	51	
Log Likelihood ^a	-214.978		
Akaike's Information Criterion (AIC)	443.957		
Finite Sample Corrected AIC (AICC)	446.197		
Bayesian Information Criterion (BIC)	458.380		
Consistent AIC (CAIC)	465.380		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC2_6, INTRD26, INTSGA26, CATNOEMP

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio Chi-Square	df	Sig.
44.875	6	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC2_6, INTRD26, INTSGA26, CATNOEMP

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	113.308	1	.000
ZLNAVGRD	2.062	1	.151
ZLNMAREXP	1.628	1	.202
FAC2_6	1.842	1	.175
INTRD26	1.615	1	.204
INTSGA26	1.245	1	.264
CATNOEMP	20.730	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC2_6,
INTRD26, INTSGA26, CATNOEMP

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.085	.1019	.885	1.285	113.308	1	.000
ZLNAVGRD	-.141	.0983	-.334	.051	2.062	1	.151
ZLNMAREXP	.143	.1125	-.077	.364	1.628	1	.202
FAC2_6	.098	.0726	-.044	.241	1.842	1	.175
INTRD26	.171	.1346	-.093	.435	1.615	1	.204
INTSGA26	-.127	.1140	-.351	.096	1.245	1	.264
CATNOEMP	.754	.1656	.429	1.079	20.730	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC2_6, INTRD26, INTSGA26, CATNOEMP

a. Fixed at the displayed value.

Appendix B4A1

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.496 ^a	.246	.221	3.65930	.246	9.803	2	60	.000	
2	.510 ^b	.260	.195	3.72041	.014	.348	3	57	.790	
3	.696 ^c	.484	.428	3.13484	.224	24.283	1	56	.000	1.796

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37, Number of employees category

d. Dependent Variable: Log-Transformed Sales

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	262.540	2	131.270	9.803	.000 ^a
	Residual	803.431	60	13.391		
	Total	1065.970	62			
2	Regression	277.007	5	55.401	4.003	.004 ^b
	Residual	788.963	57	13.841		
	Total	1065.970	62			
3	Regression	515.645	6	85.941	8.745	.000 ^c
	Residual	550.326	56	9.827		
	Total	1065.970	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37, Number of employees category

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.496 ^a	.246	.221	3.65930	.246	9.803	2	60	.000	
2	.510 ^b	.260	.195	3.72041	.014	.348	3	57	.790	
3	.696 ^c	.484	.428	3.13484	.224	24.283	1	56	.000	1.796

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37, Number of employees category

d. Dependent Variable: Log-Transformed Sales

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	13.968	.461		30.297	.000		
Zscore: Log-Transformed Average R&D	.222	.801	.054	.277	.782	.336	2.974
Zscore: Log-Transformed SGA Expenditure	1.873	.801	.452	2.336	.023	.336	2.974
2 (Constant)	13.860	.482		28.777	.000		
Zscore: Log-Transformed Average R&D	.263	.823	.063	.320	.750	.330	3.033
Zscore: Log-Transformed SGA Expenditure	1.677	.850	.405	1.972	.053	.309	3.239
REGR factor score 3 for analysis 7	-.015	.508	-.004	-.030	.976	.877	1.140
intsga37	-.749	.755	-.176	-.992	.325	.415	2.409
intrd37	.365	.667	.097	.547	.586	.414	2.415
3 (Constant)	12.097	.541		22.357	.000		
Zscore: Log-Transformed Average R&D	.680	.699	.164	.973	.335	.325	3.078
Zscore: Log-Transformed SGA Expenditure	-.091	.801	-.022	-.113	.910	.247	4.052
REGR factor score 3 for analysis 7	-.260	.431	-.062	-.602	.550	.866	1.155
intsga37	-.218	.645	-.051	-.338	.737	.403	2.478
intrd37	.017	.566	.004	.030	.976	.408	2.453
Number of employees category	5.168	1.049	.601	4.928	.000	.621	1.611

a. Dependent Variable: Log-Transformed Sales

Appendix B4A2

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.387 ^a	.150	.122	.70289357	.150	5.294	2	60	.008	2.259
2	.584 ^b	.341	.283	.63502471	.191	5.503	3	57	.002	
3	.584 ^c	.342	.271	.64033576	.001	.058	1	56	.810	

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37, Number of employees category

d. Dependent Variable: REGR factor score 1 for analysis 4

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.231	2	2.616	5.294	.008 ^a
	Residual	29.644	60	.494		
	Total	34.875	62			
2	Regression	11.889	5	2.378	5.897	.000 ^b
	Residual	22.986	57	.403		
	Total	34.875	62			
3	Regression	11.913	6	1.986	4.842	.000 ^c
	Residual	22.962	56	.410		
	Total	34.875	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37, Number of employees category

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.387 ^a	.150	.122	.70289357	.150	5.294	2	60	.008	
2	.584 ^b	.341	.283	.63502471	.191	5.503	3	57	.002	
3	.584 ^c	.342	.271	.64033576	.001	.058	1	56	.810	2.259

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37, Number of employees category

d. Dependent Variable: REGR factor score 1 for analysis 4

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-3.932E-16	.089		.000	1.000		
Zscore: Log-Transformed Average R&D	.308	.154	.411	2.000	.050	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.022	.154	-.029	-.141	.888	.336	2.974
2 (Constant)	-.053	.082		-.640	.525		
Zscore: Log-Transformed Average R&D	.265	.140	.353	1.884	.065	.330	3.033
Zscore: Log-Transformed SGA Expenditure	-.126	.145	-.169	-.871	.388	.309	3.239
REGR factor score 3 for analysis 7	-.107	.087	-.141	-1.227	.225	.877	1.140
intsga37	-.110	.129	-.142	-.852	.398	.415	2.409
intrd37	-.246	.114	-.362	-2.164	.035	.414	2.415
3 (Constant)	-.035	.111		-.316	.753		
Zscore: Log-Transformed Average R&D	.261	.143	.347	1.826	.073	.325	3.078
Zscore: Log-Transformed SGA Expenditure	-.109	.164	-.145	-.664	.509	.247	4.052
REGR factor score 3 for analysis 7	-.104	.088	-.138	-1.181	.242	.866	1.155
intsga37	-.115	.132	-.149	-.873	.386	.403	2.478
intrd37	-.243	.116	-.356	-2.099	.040	.408	2.453
Number of employees category	-.052	.214	-.033	-.242	.810	.621	1.611

a. Dependent Variable: REGR factor score 1 for analysis 4

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B4A3

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.360 ^a	.130	.101	.94837509	.130	4.467	2	60	.016	2.273
2	.463 ^b	.214	.145	.92445358	.085	2.048	3	57	.117	
3	.463 ^c	.214	.130	.93266420	.000	.001	1	56	.977	

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37, Number of employees category

d. Dependent Variable: REGR factor score 1 for analysis 5

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.035	2	4.018	4.467	.016 ^a
	Residual	53.965	60	.899		
	Total	62.000	62			
2	Regression	13.287	5	2.657	3.109	.015 ^b
	Residual	48.713	57	.855		
	Total	62.000	62			
3	Regression	13.288	6	2.215	2.546	.030 ^c
	Residual	48.712	56	.870		
	Total	62.000	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37, Number of employees category

d. Dependent Variable: REGR factor score 1 for analysis 5

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-1.252E-16	.119		.000	1.000		
Zscore: Log-Transformed Average R&D	.433	.208	.433	2.084	.041	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.095	.208	-.095	-.456	.650	.336	2.974
2 (Constant)	-.050	.120		-.422	.675		
Zscore: Log-Transformed Average R&D	.392	.204	.392	1.915	.060	.330	3.033
Zscore: Log-Transformed SGA Expenditure	-.178	.211	-.178	-.841	.404	.309	3.239
REGR factor score 3 for analysis 7	-.037	.126	-.037	-.295	.769	.877	1.140
intsga37	-.134	.188	-.130	-.713	.479	.415	2.409
intrd37	-.190	.166	-.209	-1.144	.257	.414	2.415
3 (Constant)	-.047	.161		-.295	.769		
Zscore: Log-Transformed Average R&D	.391	.208	.391	1.881	.065	.325	3.078
Zscore: Log-Transformed SGA Expenditure	-.175	.238	-.175	-.732	.467	.247	4.052
REGR factor score 3 for analysis 7	-.037	.128	-.037	-.287	.775	.866	1.155
intsga37	-.135	.192	-.131	-.702	.486	.403	2.478
intrd37	-.189	.168	-.208	-1.122	.267	.408	2.453
Number of employees category	-.009	.312	-.004	-.029	.977	.621	1.611

a. Dependent Variable: REGR factor score 1 for analysis 5

Coefficients ^a							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-1.252E-16	.119		.000	1.000		
Zscore: Log-Transformed Average R&D	.433	.208	.433	2.084	.041	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.095	.208	-.095	-.456	.650	.336	2.974
2 (Constant)	-.050	.120		-.422	.675		
Zscore: Log-Transformed Average R&D	.392	.204	.392	1.915	.060	.330	3.033
Zscore: Log-Transformed SGA Expenditure	-.178	.211	-.178	-.841	.404	.309	3.239
REGR factor score 3 for analysis 7	-.037	.126	-.037	-.295	.769	.877	1.140
intsga37	-.134	.188	-.130	-.713	.479	.415	2.409
intrd37	-.190	.166	-.209	-1.144	.257	.414	2.415
3 (Constant)	-.047	.161		-.295	.769		
Zscore: Log-Transformed Average R&D	.391	.208	.391	1.881	.065	.325	3.078
Zscore: Log-Transformed SGA Expenditure	-.175	.238	-.175	-.732	.467	.247	4.052
REGR factor score 3 for analysis 7	-.037	.128	-.037	-.287	.775	.866	1.155
intsga37	-.135	.192	-.131	-.702	.486	.403	2.478
intrd37	-.189	.168	-.208	-1.122	.267	.408	2.453
Number of employees category	-.009	.312	-.004	-.029	.977	.621	1.611

a. Dependent Variable: REGR factor score 1 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B4A4

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.173 ^a	.030	-.003	1.00126107	.030	.922	2	60	.403	
2	.271 ^b	.074	-.008	1.00384560	.044	.897	3	57	.448	
3	.320 ^c	.102	.006	.99698392	.029	1.787	1	56	.187	2.119

a. Predictors: (Constant), Zscore: Log-Transformed Marketing Expenditure in \$\$, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37, Number of employees category

d. Dependent Variable: REGR factor score 2 for analysis 5

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.849	2	.924	.922	.403 ^a
	Residual	60.151	60	1.003		
	Total	62.000	62			
2	Regression	4.561	5	.912	.905	.484 ^b
	Residual	57.439	57	1.008		
	Total	62.000	62			
3	Regression	6.337	6	1.056	1.063	.396 ^c
	Residual	55.663	56	.994		
	Total	62.000	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 3 for analysis 7, intsga37, intrd37, Number of employees category

d. Dependent Variable: REGR factor score 2 for analysis 5

Coefficients ^a							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-9.353E-16	.126		.000	1.000		
Zscore: Log-Transformed Average R&D	.294	.219	.294	1.340	.185	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.211	.219	-.211	-.963	.339	.336	2.974
2 (Constant)	.041	.130		.313	.755		
Zscore: Log-Transformed Average R&D	.265	.222	.265	1.191	.238	.330	3.033
Zscore: Log-Transformed SGA Expenditure	-.131	.229	-.131	-.573	.569	.309	3.239
REGR factor score 3 for analysis 7	.012	.137	.012	.089	.929	.877	1.140
intsga37	.329	.204	.319	1.613	.112	.415	2.409
intrd37	-.212	.180	-.234	-1.179	.243	.414	2.415
3 (Constant)	-.111	.172		-.648	.520		
Zscore: Log-Transformed Average R&D	.300	.222	.300	1.353	.182	.325	3.078
Zscore: Log-Transformed SGA Expenditure	-.284	.255	-.284	-1.114	.270	.247	4.052
REGR factor score 3 for analysis 7	-.009	.137	-.009	-.064	.949	.866	1.155
intsga37	.374	.205	.364	1.825	.073	.403	2.478
intrd37	-.242	.180	-.267	-1.345	.184	.408	2.453
Number of employees category	.446	.334	.215	1.337	.187	.621	1.611

a. Dependent Variable: REGR factor score 2 for analysis 5

Coefficients ^a							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-9.353E-16	.126		.000	1.000		
Zscore: Log-Transformed Average R&D	.294	.219	.294	1.340	.185	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.211	.219	-.211	-.963	.339	.336	2.974
2 (Constant)	.041	.130		.313	.755		
Zscore: Log-Transformed Average R&D	.265	.222	.265	1.191	.238	.330	3.033
Zscore: Log-Transformed SGA Expenditure	-.131	.229	-.131	-.573	.569	.309	3.239
REGR factor score 3 for analysis 7	.012	.137	.012	.089	.929	.877	1.140
intsga37	.329	.204	.319	1.613	.112	.415	2.409
intrd37	-.212	.180	-.234	-1.179	.243	.414	2.415
3 (Constant)	-.111	.172		-.648	.520		
Zscore: Log-Transformed Average R&D	.300	.222	.300	1.353	.182	.325	3.078
Zscore: Log-Transformed SGA Expenditure	-.284	.255	-.284	-1.114	.270	.247	4.052
REGR factor score 3 for analysis 7	-.009	.137	-.009	-.064	.949	.866	1.155
intsga37	.374	.205	.364	1.825	.073	.403	2.478
intrd37	-.242	.180	-.267	-1.345	.184	.408	2.453
Number of employees category	.446	.334	.215	1.337	.187	.621	1.611

a. Dependent Variable: REGR factor score 2 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B4A5-1

Goodness of Fit^b

	Value	df	Value/df
Deviance	286.328	52	5.506
Scaled Deviance	286.328	52	
Pearson Chi-Square	524.537	52	10.087
Scaled Pearson Chi-Square	524.537	52	
Log Likelihood ^a	-224.044		
Akaike's Information Criterion (AIC)	460.088		
Finite Sample Corrected AIC (AICC)	461.735		
Bayesian Information Criterion (BIC)	472.451		
Consistent AIC (CAIC)	478.451		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC3_7, intrd37, intsga37

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio		
Chi-Square	df	Sig.
26.743	5	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC3_7, intrd37, intsga37

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	443.989	1	.000
ZLNAVGRD	3.686	1	.055
ZLNMAREXP	15.651	1	.000
FAC3_7	1.520	1	.218
intrd37	1.851	1	.174
intsga37	7.422	1	.006

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC3_7, intrd37, intsga37

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.412	.0670	1.280	1.543	443.989	1	.000
ZLNAVGRD	-.222	.1157	-.449	.005	3.686	1	.055
ZLNMAREXP	.450	.1137	.227	.672	15.651	1	.000
FAC3_7	-.092	.0749	-.239	.054	1.520	1	.218
intrd37	-.132	.0973	-.323	.058	1.851	1	.174
intsga37	.296	.1086	.083	.509	7.422	1	.006
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC3_7, intrd37, intsga37

a. Fixed at the displayed value.

Appendix B4A5-2

Goodness of Fit^b

	Value	df	Value/df
Deviance	257.899	51	5.057
Scaled Deviance	257.899	51	
Pearson Chi-Square	439.688	51	8.621
Scaled Pearson Chi-Square	439.688	51	
Log Likelihood ^a	-209.829		
Akaike's Information Criterion (AIC)	433.659		
Finite Sample Corrected AIC (AICC)	435.899		
Bayesian Information Criterion (BIC)	448.082		
Consistent AIC (CAIC)	455.082		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC3_7, intrd37, intsga37, CATNOEMP

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio Chi-Square	df	Sig.
55.173	6	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC3_7, intrd37, intsga37, CATNOEMP

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	108.789	1	.000
ZLNAVGRD	1.689	1	.194
ZLNMAREXP	1.748	1	.186
FAC3_7	3.307	1	.069
intrd37	2.683	1	.101
intsga37	11.244	1	.001
CATNOEMP	28.731	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC3_7, intrd37, intsga37, CATNOEMP

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.062	.1018	.862	1.261	108.789	1	.000
ZLNAVGRD	-.136	.1049	-.342	.069	1.689	1	.194
ZLNMAREXP	.156	.1181	-.075	.388	1.748	1	.186
FAC3_7	-.135	.0742	-.280	.010	3.307	1	.069
intrd37	-.142	.0864	-.311	.028	2.683	1	.101
intsga37	.333	.0994	.139	.528	11.244	1	.001
CATNOEMP	.880	.1641	.558	1.201	28.731	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC3_7, intrd37, intsga37, CATNOEMP

a. Fixed at the displayed value.

Appendix B4B1

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.496 ^a	.246	.221	3.65930	.246	9.803	2	60	.000	
2	.517 ^b	.267	.203	3.70191	.021	.542	3	57	.655	
3	.706 ^c	.498	.444	3.09048	.231	25.785	1	56	.000	1.707

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47, Number of employees category

d. Dependent Variable: Log-Transformed Sales

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	262.540	2	131.270	9.803	.000 ^a
	Residual	803.431	60	13.391		
	Total	1065.970	62			
2	Regression	284.834	5	56.967	4.157	.003 ^b
	Residual	781.136	57	13.704		
	Total	1065.970	62			
3	Regression	531.111	6	88.518	9.268	.000 ^c
	Residual	534.859	56	9.551		
	Total	1065.970	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47, Number of employees category

d. Dependent Variable: Log-Transformed Sales

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	13.968	.461		30.297	.000		
Zscore: Log-Transformed Average R&D	.222	.801	.054	.277	.782	.336	2.974
Zscore: Log-Transformed SGA Expenditure	1.873	.801	.452	2.336	.023	.336	2.974
2 (Constant)	13.882	.474		29.293	.000		
Zscore: Log-Transformed Average R&D	.067	.827	.016	.082	.935	.324	3.091
Zscore: Log-Transformed SGA Expenditure	1.880	.823	.453	2.285	.026	.326	3.063
REGR factor score 4 for analysis 7	-.253	.498	-.061	-.509	.613	.907	1.103
intrd47	.067	.728	.014	.092	.927	.587	1.704
intmarexp47	-.748	.751	-.144	-.997	.323	.612	1.633
3 (Constant)	12.045	.536		22.469	.000		
Zscore: Log-Transformed Average R&D	.494	.695	.119	.711	.480	.319	3.136
Zscore: Log-Transformed SGA Expenditure	.121	.769	.029	.157	.876	.260	3.842
REGR factor score 4 for analysis 7	.041	.419	.010	.098	.923	.889	1.124
intrd47	.457	.612	.093	.746	.459	.578	1.731
intmarexp47	-.902	.627	-.174	-1.438	.156	.611	1.637
Number of employees category	5.278	1.039	.613	5.078	.000	.614	1.629

a. Dependent Variable: Log-Transformed Sales

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B4B2

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.387 ^a	.150	.122	.70289357	.150	5.294	2	60	.008	
2	.588 ^b	.346	.289	.63257365	.196	5.694	3	57	.002	
3	.591 ^c	.350	.280	.63631930	.004	.331	1	56	.567	2.133

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47, Number of employees category

d. Dependent Variable: REGR factor score 1 for analysis 4

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.231	2	2.616	5.294	.008 ^a
	Residual	29.644	60	.494		
	Total	34.875	62			
2	Regression	12.066	5	2.413	6.031	.000 ^b
	Residual	22.809	57	.400		
	Total	34.875	62			
3	Regression	12.200	6	2.033	5.022	.000 ^c
	Residual	22.675	56	.405		
	Total	34.875	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47, Number of employees category

d. Dependent Variable: REGR factor score 1 for analysis 4

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-3.932E-16	.089		.000	1.000		
Zscore: Log-Transformed Average R&D	.308	.154	.411	2.000	.050	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.022	.154	-.029	-.141	.888	.336	2.974
2 (Constant)	-.051	.081		-.634	.529		
Zscore: Log-Transformed Average R&D	.232	.141	.309	1.641	.106	.324	3.091
Zscore: Log-Transformed SGA Expenditure	-.029	.141	-.039	-.206	.837	.326	3.063
REGR factor score 4 for analysis 7	-.118	.085	-.156	-1.387	.171	.907	1.103
intrd47	-.027	.124	-.030	-.214	.831	.587	1.704
intmarexp47	-.380	.128	-.406	-2.967	.004	.612	1.633
3 (Constant)	-.008	.110		-.077	.939		
Zscore: Log-Transformed Average R&D	.222	.143	.296	1.550	.127	.319	3.136
Zscore: Log-Transformed SGA Expenditure	.012	.158	.016	.076	.940	.260	3.842
REGR factor score 4 for analysis 7	-.125	.086	-.165	-1.445	.154	.889	1.124
intrd47	-.036	.126	-.040	-.284	.778	.578	1.731
intmarexp47	-.377	.129	-.402	-2.918	.005	.611	1.637
Number of employees category	-.123	.214	-.079	-.575	.567	.614	1.629

a. Dependent Variable: REGR factor score 1 for analysis 4

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-3.932E-16	.089		.000	1.000		
	Zscore: Log-Transformed Average R&D	.308	.154	.411	2.000	.050	.336	2.974
	Zscore: Log-Transformed SGA Expenditure	-.022	.154	-.029	-.141	.888	.336	2.974
2	(Constant)	-.051	.081		-.634	.529		
	Zscore: Log-Transformed Average R&D	.232	.141	.309	1.641	.106	.324	3.091
	Zscore: Log-Transformed SGA Expenditure	-.029	.141	-.039	-.206	.837	.326	3.063
	REGR factor score 4 for analysis 7	-.118	.085	-.156	-1.387	.171	.907	1.103
	intrd47	-.027	.124	-.030	-.214	.831	.587	1.704
	intmarexp47	-.380	.128	-.406	-2.967	.004	.612	1.633
3	(Constant)	-.008	.110		-.077	.939		
	Zscore: Log-Transformed Average R&D	.222	.143	.296	1.550	.127	.319	3.136
	Zscore: Log-Transformed SGA Expenditure	.012	.158	.016	.076	.940	.260	3.842
	REGR factor score 4 for analysis 7	-.125	.086	-.165	-1.445	.154	.889	1.124
	intrd47	-.036	.126	-.040	-.284	.778	.578	1.731
	intmarexp47	-.377	.129	-.402	-2.918	.005	.611	1.637
	Number of employees category	-.123	.214	-.079	-.575	.567	.614	1.629

a. Dependent Variable: REGR factor score 1 for analysis 4

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B4B3

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.360 ^a	.130	.101	.94837509	.130	4.467	2	60	.016	
2	.423 ^b	.179	.107	.94495067	.049	1.145	3	57	.339	
3	.424 ^c	.179	.092	.95314082	.000	.025	1	56	.876	2.163

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47, Number of employees category

d. Dependent Variable: REGR factor score 1 for analysis 5

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.035	2	4.018	4.467	.016 ^a
	Residual	53.965	60	.899		
	Total	62.000	62			
2	Regression	11.103	5	2.221	2.487	.042 ^b
	Residual	50.897	57	.893		
	Total	62.000	62			
3	Regression	11.125	6	1.854	2.041	.075 ^c
	Residual	50.875	56	.908		
	Total	62.000	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47, Number of employees category

d. Dependent Variable: REGR factor score 1 for analysis 5

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-1.252E-16	.119		.000	1.000		
Zscore: Log-Transformed Average R&D	.433	.208	.433	2.084	.041	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.095	.208	-.095	-.456	.650	.336	2.974
2 (Constant)	-.035	.121		-.286	.776		
Zscore: Log-Transformed Average R&D	.392	.211	.392	1.858	.068	.324	3.091
Zscore: Log-Transformed SGA Expenditure	-.112	.210	-.112	-.531	.597	.326	3.063
REGR factor score 4 for analysis 7	-.093	.127	-.092	-.729	.469	.907	1.103
intrd47	-.072	.186	-.061	-.389	.699	.587	1.704
intmarexp47	-.201	.192	-.161	-1.051	.298	.612	1.633
3 (Constant)	-.017	.165		-.103	.918		
Zscore: Log-Transformed Average R&D	.388	.214	.388	1.810	.076	.319	3.136
Zscore: Log-Transformed SGA Expenditure	-.095	.237	-.095	-.399	.691	.260	3.842
REGR factor score 4 for analysis 7	-.095	.129	-.095	-.737	.464	.889	1.124
intrd47	-.076	.189	-.064	-.402	.689	.578	1.731
intmarexp47	-.200	.193	-.160	-1.033	.306	.611	1.637
Number of employees category	-.050	.321	-.024	-.157	.876	.614	1.629

a. Dependent Variable: REGR factor score 1 for analysis 5

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-1.252E-16	.119		.000	1.000		
Zscore: Log-Transformed Average R&D	.433	.208	.433	2.084	.041	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.095	.208	-.095	-.456	.650	.336	2.974
2 (Constant)	-.035	.121		-.286	.776		
Zscore: Log-Transformed Average R&D	.392	.211	.392	1.858	.068	.324	3.091
Zscore: Log-Transformed SGA Expenditure	-.112	.210	-.112	-.531	.597	.326	3.063
REGR factor score 4 for analysis 7	-.093	.127	-.092	-.729	.469	.907	1.103
intrd47	-.072	.186	-.061	-.389	.699	.587	1.704
intmarexp47	-.201	.192	-.161	-1.051	.298	.612	1.633
3 (Constant)	-.017	.165		-.103	.918		
Zscore: Log-Transformed Average R&D	.388	.214	.388	1.810	.076	.319	3.136
Zscore: Log-Transformed SGA Expenditure	-.095	.237	-.095	-.399	.691	.260	3.842
REGR factor score 4 for analysis 7	-.095	.129	-.095	-.737	.464	.889	1.124
intrd47	-.076	.189	-.064	-.402	.689	.578	1.731
intmarexp47	-.200	.193	-.160	-1.033	.306	.611	1.637
Number of employees category	-.050	.321	-.024	-.157	.876	.614	1.629

a. Dependent Variable: REGR factor score 1 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B4B4

Model Summary^d

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.173 ^a	.030	-.003	1.00126107	.030	.922	2	60	.403	
2	.280 ^b	.078	-.002	1.00124282	.049	1.001	3	57	.399	
3	.325 ^c	.106	.010	.99502159	.027	1.715	1	56	.196	1.974

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47, Number of employees category

d. Dependent Variable: REGR factor score 2 for analysis 5

ANOVA^d

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.849	2	.924	.922	.403 ^a
	Residual	60.151	60	1.003		
	Total	62.000	62			
2	Regression	4.858	5	.972	.969	.444 ^b
	Residual	57.142	57	1.002		
	Total	62.000	62			
3	Regression	6.556	6	1.093	1.104	.372 ^c
	Residual	55.444	56	.990		
	Total	62.000	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47

c. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, REGR factor score 4 for analysis 7, intmarexp47, intrd47, Number of employees category

d. Dependent Variable: REGR factor score 2 for analysis 5

Coefficients ^a							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-9.353E-16	.126		.000	1.000		
Zscore: Log-Transformed Average R&D	.294	.219	.294	1.340	.185	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.211	.219	-.211	-.963	.339	.336	2.974
2 (Constant)	.037	.128		.291	.772		
Zscore: Log-Transformed Average R&D	.329	.224	.329	1.472	.146	.324	3.091
Zscore: Log-Transformed SGA Expenditure	-.192	.223	-.192	-.861	.393	.326	3.063
REGR factor score 4 for analysis 7	.050	.135	.049	.370	.713	.907	1.103
intrd47	.100	.197	.085	.510	.612	.587	1.704
intmarexp47	.194	.203	.155	.956	.343	.612	1.633
3 (Constant)	-.115	.173		-.667	.507		
Zscore: Log-Transformed Average R&D	.365	.224	.365	1.629	.109	.319	3.136
Zscore: Log-Transformed SGA Expenditure	-.338	.248	-.338	-1.363	.178	.260	3.842
REGR factor score 4 for analysis 7	.074	.135	.074	.549	.585	.889	1.124
intrd47	.133	.197	.112	.674	.503	.578	1.731
intmarexp47	.181	.202	.145	.898	.373	.611	1.637
Number of employees category	.438	.335	.211	1.310	.196	.614	1.629

a. Dependent Variable: REGR factor score 2 for analysis 5

Coefficients ^a							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-9.353E-16	.126		.000	1.000		
Zscore: Log-Transformed Average R&D	.294	.219	.294	1.340	.185	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.211	.219	-.211	-.963	.339	.336	2.974
2 (Constant)	.037	.128		.291	.772		
Zscore: Log-Transformed Average R&D	.329	.224	.329	1.472	.146	.324	3.091
Zscore: Log-Transformed SGA Expenditure	-.192	.223	-.192	-.861	.393	.326	3.063
REGR factor score 4 for analysis 7	.050	.135	.049	.370	.713	.907	1.103
intrd47	.100	.197	.085	.510	.612	.587	1.704
intmarexp47	.194	.203	.155	.956	.343	.612	1.633
3 (Constant)	-.115	.173		-.667	.507		
Zscore: Log-Transformed Average R&D	.365	.224	.365	1.629	.109	.319	3.136
Zscore: Log-Transformed SGA Expenditure	-.338	.248	-.338	-1.363	.178	.260	3.842
REGR factor score 4 for analysis 7	.074	.135	.074	.549	.585	.889	1.124
intrd47	.133	.197	.112	.674	.503	.578	1.731
intmarexp47	.181	.202	.145	.898	.373	.611	1.637
Number of employees category	.438	.335	.211	1.310	.196	.614	1.629

a. Dependent Variable: REGR factor score 2 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix B4B5-1

Goodness of Fit^b

	Value	df	Value/df
Deviance	271.695	52	5.225
Scaled Deviance	271.695	52	
Pearson Chi-Square	436.194	52	8.388
Scaled Pearson Chi-Square	436.194	52	
Log Likelihood ^a	-216.727		
Akaike's Information Criterion (AIC)	445.455		
Finite Sample Corrected AIC (AICC)	447.102		
Bayesian Information Criterion (BIC)	457.818		
Consistent AIC (CAIC)	463.818		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC4_7, intrd47, intmarexp47

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio		
Chi-Square	df	Sig.
41.377	5	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD,
ZLNMAREXP, FAC4_7, intrd47, intmarexp47

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	393.559	1	.000
ZLNAVGRD	3.866	1	.049
ZLNMAREXP	10.532	1	.001
FAC4_7	18.011	1	.000
intrd47	4.763	1	.029
intmarexp47	5.524	1	.019

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC4_7, intrd47, intmarexp47

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.362	.0687	1.228	1.497	393.559	1	.000
ZLNAVGRD	-.226	.1148	-.451	.000	3.866	1	.049
ZLNMAREXP	.364	.1121	.144	.584	10.532	1	.001
FAC4_7	-.285	.0672	-.417	-.153	18.011	1	.000
intrd47	.230	.1056	.023	.437	4.763	1	.029
intmarexp47	-.230	.0979	-.422	-.038	5.524	1	.019
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC4_7, intrd47, intmarexp47

a. Fixed at the displayed value.

Appendix B4B5-2

Goodness of Fit^b

	Value	df	Value/df
Deviance	253.379	51	4.968
Scaled Deviance	253.379	51	
Pearson Chi-Square	395.765	51	7.760
Scaled Pearson Chi-Square	395.765	51	
Log Likelihood ^a	-207.570		
Akaike's Information Criterion (AIC)	429.139		
Finite Sample Corrected AIC (AICC)	431.379		
Bayesian Information Criterion (BIC)	443.562		
Consistent AIC (CAIC)	450.562		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC4_7, intrd47, intmarexp47, CATNOEMP

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio Chi-Square	df	Sig.
59.692	6	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC4_7, intrd47, intmarexp47, CATNOEMP

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	117.363	1	.000
ZLNAVGRD	1.802	1	.179
ZLNMAREXP	.957	1	.328
FAC4_7	10.819	1	.001
intrd47	7.315	1	.007
intmarexp47	6.752	1	.009
CATNOEMP	18.924	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC4_7, intrd47, intmarexp47, CATNOEMP

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.086	.1002	.889	1.282	117.363	1	.000
ZLNAVGRD	-.143	.1067	-.352	.066	1.802	1	.179
ZLNMAREXP	.116	.1183	-.116	.348	.957	1	.328
FAC4_7	-.224	.0680	-.357	-.090	10.819	1	.001
intrd47	.264	.0976	.073	.455	7.315	1	.007
intmarexp47	-.236	.0908	-.414	-.058	6.752	1	.009
CATNOEMP	.728	.1672	.400	1.055	18.924	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC4_7, intrd47, intmarexp47, CATNOEMP

a. Fixed at the displayed value.

Appendix BF171

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.496 ^a	.246	.221	3.65930	.246	9.803	2	60	.000	
2	.527 ^b	.278	.215	3.67444	.032	.836	3	57	.480	2.016

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intsga17, REGR factor score 1 for analysis 7, intrd17

c. Dependent Variable: Log-Transformed Sales

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	262.540	2	131.270	9.803	.000 ^a
	Residual	803.431	60	13.391		
	Total	1065.970	62			
2	Regression	296.385	5	59.277	4.390	.002 ^b
	Residual	769.585	57	13.501		
	Total	1065.970	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intsga17, REGR factor score 1 for analysis 7, intrd17

c. Dependent Variable: Log-Transformed Sales

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	13.968	.461		30.297	.000		
Zscore: Log-Transformed Average R&D	.222	.801	.054	.277	.782	.336	2.974
Zscore: Log-Transformed SGA Expenditure	1.873	.801	.452	2.336	.023	.336	2.974
2 (Constant)	13.729	.499		27.538	.000		
Zscore: Log-Transformed Average R&D	.751	.898	.181	.835	.407	.270	3.706
Zscore: Log-Transformed SGA Expenditure	1.441	.884	.348	1.630	.109	.278	3.592
REGR factor score 1 for analysis 7	-.498	.560	-.119	-.889	.378	.706	1.416
intrd17	1.029	.799	.348	1.288	.203	.174	5.753
intsgal7	-1.017	.875	-.319	-1.163	.250	.169	5.934

a. Dependent Variable: Log-Transformed Sales

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix BF172

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.387 ^a	.150	.122	.70289357	.150	5.294	2	60	.008	
2	.609 ^b	.371	.316	.62044852	.221	6.668	3	57	.001	1.895

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intsga17, REGR factor score 1 for analysis 7, intrd17

c. Dependent Variable: REGR factor score 1 for analysis

4

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.231	2	2.616	5.294	.008 ^a
	Residual	29.644	60	.494		
	Total	34.875	62			
2	Regression	12.932	5	2.586	6.719	.000 ^b
	Residual	21.943	57	.385		
	Total	34.875	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intsga17, REGR factor score 1 for analysis 7, intrd17

c. Dependent Variable: REGR factor score 1 for analysis 4

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-3.932E-16	.089		.000	1.000		
Zscore: Log-Transformed Average R&D	.308	.154	.411	2.000	.050	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.022	.154	-.029	-.141	.888	.336	2.974
2 (Constant)	.021	.084		.249	.804		
Zscore: Log-Transformed Average R&D	.018	.152	.024	.117	.907	.270	3.706
Zscore: Log-Transformed SGA Expenditure	.228	.149	.304	1.526	.132	.278	3.592
REGR factor score 1 for analysis 7	.403	.094	.534	4.268	.000	.706	1.416
intrd17	-.089	.135	-.166	-.659	.513	.174	5.753
intsga17	.124	.148	.215	.839	.405	.169	5.934

a. Dependent Variable: REGR factor score 1 for analysis 4

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix BF173

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.360 ^a	.130	.101	.94837509	.130	4.467	2	60	.016	
2	.430 ^b	.185	.113	.94158243	.055	1.290	3	57	.287	2.119

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intsga17, REGR factor score 1 for analysis 7, intrd17

c. Dependent Variable: REGR factor score 1 for analysis

5

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.035	2	4.018	4.467	.016 ^a
	Residual	53.965	60	.899		
	Total	62.000	62			
2	Regression	11.465	5	2.293	2.586	.035 ^b
	Residual	50.535	57	.887		
	Total	62.000	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intsga17, REGR factor score 1 for analysis 7, intrd17

c. Dependent Variable: REGR factor score 1 for analysis 5

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-1.252E-16	.119		.000	1.000		
	Zscore: Log-Transformed Average R&D	.433	.208	.433	2.084	.041	.336	2.974
	Zscore: Log-Transformed SGA Expenditure	-.095	.208	-.095	-.456	.650	.336	2.974
2	(Constant)	.028	.128		.216	.830		
	Zscore: Log-Transformed Average R&D	.278	.230	.278	1.210	.231	.270	3.706
	Zscore: Log-Transformed SGA Expenditure	.009	.227	.009	.041	.967	.278	3.592
	REGR factor score 1 for analysis 7	.172	.143	.171	1.199	.235	.706	1.416
	intrd17	-.123	.205	-.173	-.603	.549	.174	5.753
	intsga17	.032	.224	.041	.141	.888	.169	5.934

a. Dependent Variable: REGR factor score 1 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix BF174

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.173 ^a	.030	-.003	1.00126107	.030	.922	2	60	.403	
2	.285 ^b	.081	.000	.99976615	.051	1.060	3	57	.373	1.937

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intsga17, REGR factor score 1 for analysis 7, intrd17

c. Dependent Variable: REGR factor score 2 for analysis

5

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.849	2	.924	.922	.403 ^a
	Residual	60.151	60	1.003		
	Total	62.000	62			
2	Regression	5.027	5	1.005	1.006	.423 ^b
	Residual	56.973	57	1.000		
	Total	62.000	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intsga17, REGR factor score 1 for analysis 7, intrd17

c. Dependent Variable: REGR factor score 2 for analysis 5

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-9.353E-16	.126		.000	1.000		
	Zscore: Log-Transformed Average R&D	.294	.219	.294	1.340	.185	.336	2.974
	Zscore: Log-Transformed SGA Expenditure	-.211	.219	-.211	-.963	.339	.336	2.974
2	(Constant)	-.056	.136		-.412	.682		
	Zscore: Log-Transformed Average R&D	.385	.244	.385	1.574	.121	.270	3.706
	Zscore: Log-Transformed SGA Expenditure	-.324	.241	-.324	-1.346	.184	.278	3.592
	REGR factor score 1 for analysis 7	-.103	.152	-.102	-.677	.501	.706	1.416
	intrd17	.234	.217	.328	1.077	.286	.174	5.753
	intsga17	-.382	.238	-.496	-1.605	.114	.169	5.934

a. Dependent Variable: REGR factor score 2 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix BF175

Goodness of Fit^b

	Value	df	Value/df
Deviance	285.615	52	5.493
Scaled Deviance	285.615	52	
Pearson Chi-Square	543.744	52	10.457
Scaled Pearson Chi-Square	543.744	52	
Log Likelihood ^a	-223.687		
Akaike's Information Criterion (AIC)	459.375		
Finite Sample Corrected AIC (AICC)	461.022		
Bayesian Information Criterion (BIC)	471.737		
Consistent AIC (CAIC)	477.737		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_7, intrd17, intsga17

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio		
Chi-Square	df	Sig.
27.457	5	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD,
ZLNMAREXP, FAC1_7, intrd17, intsga17

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	285.291	1	.000
ZLNAVGRD	2.464	1	.116
ZLNMAREXP	10.644	1	.001
FAC1_7	2.428	1	.119
intrd17	8.384	1	.004
intsga17	7.673	1	.006

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_7, intrd17, intsga17

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	1.298	.0768	1.147	1.448	285.291	1	.000
ZLNAVGRD	-.201	.1282	-.453	.050	2.464	1	.116
ZLNMAREXP	.394	.1206	.157	.630	10.644	1	.001
FAC1_7	.127	.0815	-.033	.287	2.428	1	.119
intrd17	.292	.1009	.094	.490	8.384	1	.004
intsga17	-.288	.1040	-.492	-.084	7.673	1	.006
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC1_7, intrd17, intsga17

a. Fixed at the displayed value.

Appendix BF271

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.496 ^a	.246	.221	3.65930	.246	9.803	2	60	.000	
2	.555 ^b	.308	.247	3.59847	.061	1.682	3	57	.181	2.065

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intrd27, REGR factor score 2 for analysis 7, intsga27

c. Dependent Variable: Log-Transformed Sales

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	262.540	2	131.270	9.803	.000 ^a
	Residual	803.431	60	13.391		
	Total	1065.970	62			
2	Regression	327.878	5	65.576	5.064	.001 ^b
	Residual	738.093	57	12.949		
	Total	1065.970	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intrd27, REGR factor score 2 for analysis 7, intsga27

c. Dependent Variable: Log-Transformed Sales

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	13.968	.461		30.297	.000		
Zscore: Log-Transformed Average R&D	.222	.801	.054	.277	.782	.336	2.974
Zscore: Log-Transformed SGA Expenditure	1.873	.801	.452	2.336	.023	.336	2.974
2 (Constant)	13.600	.486		27.965	.000		
Zscore: Log-Transformed Average R&D	1.058	.881	.255	1.201	.235	.269	3.720
Zscore: Log-Transformed SGA Expenditure	.901	.928	.217	.971	.336	.243	4.121
REGR factor score 2 for analysis 7	.185	.495	.044	.373	.711	.865	1.157
intrd27	-1.552	.897	-.351	-1.730	.089	.295	3.391
intsga27	2.267	1.016	.469	2.232	.030	.275	3.638

a. Dependent Variable: Log-Transformed Sales

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix BF272

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.387 ^a	.150	.122	.70289357	.150	5.294	2	60	.008	
2	.451 ^b	.204	.134	.69807926	.054	1.277	3	57	.291	2.226

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intrd27, REGR factor score 2 for analysis 7, intsga27

c. Dependent Variable: REGR factor score 1 for analysis 4

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.231	2	2.616	5.294	.008 ^a
	Residual	29.644	60	.494		
	Total	34.875	62			
2	Regression	7.098	5	1.420	2.913	.021 ^b
	Residual	27.777	57	.487		
	Total	34.875	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intrd27, REGR factor score 2 for analysis 7, intsga27

c. Dependent Variable: REGR factor score 1 for analysis 4

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-3.932E-16	.089		.000	1.000		
Zscore: Log-Transformed Average R&D	.308	.154	.411	2.000	.050	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.022	.154	-.029	-.141	.888	.336	2.974
2 (Constant)	-.005	.094		-.058	.954		
Zscore: Log-Transformed Average R&D	.381	.171	.508	2.227	.030	.269	3.720
Zscore: Log-Transformed SGA Expenditure	-.139	.180	-.186	-.773	.443	.243	4.121
REGR factor score 2 for analysis 7	.168	.096	.222	1.747	.086	.865	1.157
intrd27	-.134	.174	-.168	-.771	.444	.295	3.391
intsga27	.100	.197	.115	.509	.613	.275	3.638

a. Dependent Variable: REGR factor score 1 for analysis 4

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix BF273

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.360 ^a	.130	.101	.94837509	.130	4.467	2	60	.016	
2	.435 ^b	.189	.118	.93922051	.059	1.392	3	57	.255	2.270

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intrd27, REGR factor score 2 for analysis 7, intsga27

c. Dependent Variable: REGR factor score 1 for analysis 5

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.035	2	4.018	4.467	.016 ^a
	Residual	53.965	60	.899		
	Total	62.000	62			
2	Regression	11.718	5	2.344	2.657	.032 ^b
	Residual	50.282	57	.882		
	Total	62.000	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intrd27, REGR factor score 2 for analysis 7, intsga27

c. Dependent Variable: REGR factor score 1 for analysis 5

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-1.252E-16	.119		.000	1.000		
Zscore: Log-Transformed Average R&D	.433	.208	.433	2.084	.041	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.095	.208	-.095	-.456	.650	.336	2.974
2 (Constant)	-.012	.127		-.094	.926		
Zscore: Log-Transformed Average R&D	.564	.230	.564	2.452	.017	.269	3.720
Zscore: Log-Transformed SGA Expenditure	-.281	.242	-.281	-1.159	.251	.243	4.121
REGR factor score 2 for analysis 7	.196	.129	.194	1.515	.135	.865	1.157
intrd27	-.299	.234	-.281	-1.279	.206	.295	3.391
intsga27	.223	.265	.191	.840	.404	.275	3.638

a. Dependent Variable: REGR factor score 1 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix BF274

Model Summary^c

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.173 ^a	.030	-.003	1.00126107	.030	.922	2	60	.403	
2	.287 ^b	.082	.002	.99916260	.052	1.084	3	57	.363	2.031

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intrd27, REGR factor score 2 for analysis 7, intsga27

c. Dependent Variable: REGR factor score 2 for analysis 5

ANOVA^c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.849	2	.924	.922	.403 ^a
	Residual	60.151	60	1.003		
	Total	62.000	62			
2	Regression	5.095	5	1.019	1.021	.414 ^b
	Residual	56.905	57	.998		
	Total	62.000	62			

a. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D

b. Predictors: (Constant), Zscore: Log-Transformed SGA Expenditure, Zscore: Log-Transformed Average R&D, intrd27, REGR factor score 2 for analysis 7, intsga27

c. Dependent Variable: REGR factor score 2 for analysis 5

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-9.353E-16	.126		.000	1.000		
Zscore: Log-Transformed Average R&D	.294	.219	.294	1.340	.185	.336	2.974
Zscore: Log-Transformed SGA Expenditure	-.211	.219	-.211	-.963	.339	.336	2.974
2 (Constant)	.045	.135		.337	.737		
Zscore: Log-Transformed Average R&D	.242	.245	.242	.987	.328	.269	3.720
Zscore: Log-Transformed SGA Expenditure	-.193	.258	-.193	-.748	.457	.243	4.121
REGR factor score 2 for analysis 7	.179	.138	.177	1.299	.199	.865	1.157
intrd27	.136	.249	.128	.547	.586	.295	3.391
intsga27	-.247	.282	-.212	-.875	.385	.275	3.638

a. Dependent Variable: REGR factor score 2 for analysis 5

Histogram

Normal P-P Plot of Regression Standardized Residual

Appendix BF275

Goodness of Fit^b

	Value	df	Value/df
Deviance	138.548	52	2.664
Scaled Deviance	138.548	52	
Pearson Chi-Square	153.019	52	2.943
Scaled Pearson Chi-Square	153.019	52	
Log Likelihood ^a	-150.154		
Akaike's Information Criterion (AIC)	312.308		
Finite Sample Corrected AIC (AICC)	313.955		
Bayesian Information Criterion (BIC)	324.671		
Consistent AIC (CAIC)	330.671		

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC2_7, intrd27, intsga27

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Omnibus Test^a

Likelihood Ratio		
Chi-Square	df	Sig.
174.524	5	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD,
ZLNMAREXP, FAC2_7, intrd27, intsga27

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	50.299	1	.000
ZLNAVGRD	31.450	1	.000
ZLNMAREXP	29.331	1	.000
FAC2_7	40.600	1	.000
intrd27	108.661	1	.000
intsga27	120.590	1	.000

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC2_7, intrd27, intsga27

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	.759	.1070	.549	.969	50.299	1	.000
ZLNAVGRD	.797	.1422	.519	1.076	31.450	1	.000
ZLNMAREXP	-.883	.1630	-1.202	-.563	29.331	1	.000
FAC2_7	.569	.0894	.394	.745	40.600	1	.000
intrd27	-1.444	.1386	-1.716	-1.173	108.661	1	.000
intsga27	1.841	.1677	1.513	2.170	120.590	1	.000
(Scale)	1 ^a						

Dependent Variable: Number of New Drugs

Model: (Intercept), ZLNAVGRD, ZLNMAREXP, FAC2_7, intrd27, intsga27

a. Fixed at the displayed value.

Appendix C: Variable Names and Labels

Variable Name	Variable Label
General Company Information Items	
FIRMID	Company ID
Country	Country
RESTIME	Response Time
RESCAT	Response Category
SALES07	Sales Revenue in 2007
SALES	Sales
LNSALES	Log-Transformed Sales
AVGASSET	Average Asset in three years
CATAVGRD	Classes of R&D
AVGRD	Average R&D spending in the past three years
AVGRD3Y	Average R&D in the past 3 years
LNAVGRD	Log-Transformed Average R&D
RDINT2	R&D intensity = R&D/sales
RDINT	R&D Intensity
CATMAREX	Classes of Marketing expenditure
MAREXP	Marketing Expenditure last year
MAREXP1Y	Marketing Expenditure last year
LNMAREXP	Log-Transformed Marketing Expenditure
LNINTRDM	Interaction LogRD and LogSGA
SGAINT2	SGA intensity = SGA/Sales
SGAINT	SGA Intensity
INVDD	Is the company involved in drug discover (basic R&D)
LEVINVDD	Level of involvement in drug discovery
INVPC	Is the company involved in preclinical and clinical test
LEVINVPC	Level of involvement in preclinical and clinical test
INVDA	Is the company involved in drug approval
LEVINVDA	Level of involvement in preclinical and clinical test
INVDM	Is the company involved in drug manufacturing
LEVINVDM	Level of involvement in drug manufacturing
INVDS	Is the company involved in drug sales and marketing
LEVINVDS	Level of involvement in drug sales and marketing
LNNUMEM	Log-Transformed number of employees
CATEMP2	Number of employees category (small<75 and large≥75)
CATNOEMP	Number of employees category (small<100 and large≥100)
NUMEMP	Number of employees working for the company
NOEMPRD	Number of employees working in R&D
NOEMPPC	Number of employees working in preclinical and clinical test
NOEMPM	Number of employees working in manufacturing
NOEMPSM	Number of employees working in sales and marketing
NOEMPRA	Number of employees working in regulatory approval
NOEMPO	Number of employees in other departments including support staff
NDFIHRD	New drug from in-house R&D
NDFLIOC	New drug by licensing from other company
NDFLIGU	New drug by licensing from government or university
NDFJV	New drug by forming joint venture
DDFIRD3Y	Percentage of drug discoveries from in-house R&D in 3 years
NDMISM3Y	Percentage of new drugs marketed in 3 years using internal sales resources

NOND	Number of New Drugs
NONDNW	Number of new drugs - new to the world
NONDNF	Number of new drugs - new to the firm
NONDNC	Number of new drugs - new to the country
NONDMAJR	Number of new drugs - major revision
NONDMINR	Number of new drugs - minor revision
AFUDSSD	All functional units decide to study a scientific disease
HRDDSSD	Head of R&D decides to study a scientific disease
HSMDDSD	Head of sales and marketing decides to study a scientific disease
TMDSSD	Top management decides to study a scientific disease
SABDSSD	Science advisory board decides to study a scientific disease
BDDSSD	Board of directors decides to study a scientific disease
CVCFS	Commercial value is the criterion to study a disease
MVCFS	Medical value is the criterion to study a disease
SACFS	Skill available is the criterion to study a disease
TMICFS	Top management interest is the criterion to study a disease
DACFS	Drug availability in a therapeutic area is the criterion to study a disease
CTCFS	Company tradition is the criterion to study a disease
IGSMHPDR	Ideas with the greatest scientific merit have the highest priority for drug research
IGMVHPDR	Ideas with the greatest market value have the highest priority for drug research
ESGHPDR	Early stage guess has the highest priority for drug research
ISTMHPDR	Ideas with top management support have the highest priority for drug research
RDPITS	R&D provides input to train sales people
RDPIAFU	R&D provides information to all functional units
RDPWPM	R&D participates in writing promotional material
RDPWTM	R&D participates in writing technical material
RDRTC	R&D responds to customers
RDSGNOGC	R&D sets go no go criteria
RDWWM	R&D works with mfg and marketing at every stage of drug development
ASR	Annual sales revenue
ASRFND	Percentage of annual sales revenue from new drugs
CIFFSNED	Cash in-flow from the sales of new and existing drug
CIFFLIC	Cash in-flow from licensing
CIFFGRF	Cash in-flow from government research fund
CIFFIRF	Cash in-flow from industry research fund
CIFFICS	Cash in-flow from issuing company shares
CIFFVCF	Cash in-flow from venture capital fund
CIFFP	Cash in-flow from partnership
CIFFLSL	Cash in-flow from long and short term loan
CIFFII	Cash in-flow from interest income
CIFSRD	Percent of cash in-flow spent on R&D
CIFSS	Percent of cash in-flow spent on sales and marketing
Customer Criteria Items	
CCCSWYND	Compared to your competitors drugs, customers are more satisfied with your company's drug
CCCINDYC3	Customers increased significantly because of the new drugs that your company introduced in the past 3 years
CCNDONM3	New drugs your company introduced opened new markets outside the existing market
CCCLOYB	Customers are loyal to your brand
CCCIBND3	Customer companies increased because of the side effects of the drugs your company introduced in the market in the past 3 years

Opportunities Criteria Items	
OCSOIEND	Sales of the old drugs increased because of the effectiveness of the new drugs
OCYCSSBQ	Your company sets standards because of perceived quality of its drugs
OCKGHDMD	Knowledge gained in developing new drugs in the past three years will help the company to introduce more drugs in the future
OCNDSENB	Your company introduced a new drug with negative side effects that negatively affected the company
Functional Integration Items	
FIEPBFX	Employees see benefit from information exchange
FIEPBXHR	Employees believe that information exchange helps in rapid drug development
FIEPLFEX	Employees believe that they learn from each other by information exchange
FIEPPXS	Employees in your company are proficient in information exchange to solve problems
FIEPNOGX	Employees in your company are not good in information exchange
FIEPCXED	Employees in your company are capable in sharing expertise to finish project
FIEPWX	Employees in your company are willing to share information with their co-workers
FIEPRX	It is rare for employees in your company share information to find solutions
FITMSXA	Top management in your company supports information exchange in all functional units
FITMEEXPX	Top management in your company encourages employees to share information while working on drug projects
FITMHIPX	Top management in your company has incentives in place to encourages employees to share information while working on drug projects
FIBIORG	Employee bonus and incentives are based on organizational performance
FIBIDEPP	Employee bonus and incentives are based on departmental performance
FITMFTW	Top management forms teams of all units to work on drug projects
FICOMIMP	Communication is practically impossible
FITMDEPM	Top management asks the head of departments to meet regularly to review drug projects
FIHDMEX	Head of departments meets with employees to share information on new drug projects
Commercialization Strategy Items	
CSIOGRDC	Importance of generating revenue from discovering a compound
CSIOGRD	Importance of generating revenue from developing drug
CSIOGRDM	Importance of generating revenue from developing manufacturing capabilities
CSIOGRDS	Importance of generating revenue from developing sales and marketing capabilities
CSIOGRDB	Importance of generating revenue from developing business know-how capabilities
CSCOVRD	Level of control over R&D
CSCOVMF	Level of control over manufacturing
CSCOVMS	Level of control over marketing and sales
CSCOVRA	Level of control over regulatory approval
CSPIFIBT	Protect innovation from imitation by trade secrecy
CSPIFIBP	Protect innovation from imitation by patent
CSPIFIBC	Protect innovation from imitation by copyright
CSPPLVSM	Patent protection law is very strong in your market
CSDDDBOS	Drug development based on company strategy and portfolio of current and future drug development
CSNDNFSL	License out discovered compounds that do not fit in company strategy
CSNDNFSE	Extend the business line for discovered compounds that do not fit in company

	strategy
CSNDNFSJ	Form joint venture for discovered compounds that do not fit in company strategy
CSNDNFSP	Patent the discovered compounds that do not fit in company strategy to support current line of business
CSNDGDIH	Develop the drug in-house if a newly discovered compound has promising commercial gain
CSNDGFS	Find a subcontractor to develop the drug if a newly discovered compound has promising commercial gain
CSNDGLO	License out the drug development if a newly discovered compound has promising commercial gain
CSNDGFJ	Form joint venture to develop the drug if a newly discovered compound has promising commercial gain
CSNDGH	Hold the drug and do nothing if a newly discovered compound has promising commercial gain
CSSREGA	Your company has a strong regulatory affair department
CSREGAD	Regulatory approval is more difficult in the country that you operate
CSREGADL	Difficulty in obtaining approval has forced you to license out the drug to another company
CSREGADP	Difficulty in obtaining approval has forced you to partner with another company
CSREGADO	Difficulty in obtaining approval has forced you to apply for regulatory approval from other countries
CSRGADLR	Difficulty in obtaining approval has forced you to limit R&D spending
CSYCRDFO	Your company conducts R&D for others
CSYCMDBO	Your company manufactures drugs developed by others
CSYCSDBO	Your company sells drugs developed by others
CSYCBKO	Your company provides business know-how for others
CSOCRDFY	Other companies conduct R&D for your company
CSOCMYD	Other companies manufacture your drugs
CSOCSMYD	Other companies sells and markets your drugs
CSOCBKY	Other companies provides business know-hoe for your company

Appendix D

Distribution of key variables in the study