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A PATENT BASED STUDY OF THE RELATIONSHIP BETWEEN
INDUSTRY RESEARCH STRUCTURE AND
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A PATENT BASED STUDY OF THE RELATIONSHIP BETWEEN INDUSTRY RESEARCH STRUCTURE AND RESEARCH ACTIVITY

By

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ABSTRACT

A PATENT BASED STUDY OF THE RELATIONSHIP BETWEEN INDUSTRY RESEARCH STRUCTURE AND RESEARCH ACTIVITY

By

William Wallace Keep

New products and the technological changes that make them possible are increasingly important to both marketing academics and practitioners. Yet most research has failed to focus exclusively on the technological change process. In addition, there are few managerially useful models for monitoring technological change in a competitive environment.

Using the industrial organization (IO) approach from economics, the current research develop and tests a model of five variables hypothesized to influence the technological change process. The variables modeled are: the number of competing firms, the level of research concentration, competitor lead time, technological focus, and technological complexity. Technological change is measured as the amount of research activity observed in specific technological areas.

The data used to test the model is the electronic patent data base available from the U.S. Patent and Trademark Office. Patent data is historical, objective, systematically collected, and readily available. As a result, patent based research is appealing to both

academicians and managers. The nature of the patent classification scheme allows the model to be tested within narrowly defined technological areas, thereby avoiding some of the weaknesses of earlier research.

The model was tested using multiple regression with ordinary least squares (OLS) estimation. The regression confirmed that the number of competing firms, the level of research concentration, the degree of technological complexity, and the interaction between technological complexity and technological focus all significantly influenced the amount of research activity observed in a technological area.

DEDICATION

This dissertation and all that it implies, in terms of the work involved and the opportunities it holds, is dedicated to my loving wife, Susan and our sons, Andy and Ben.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

RESEARCHING TECHNOLOGICAL CHANGE

Research into the nature of technological change has increased with the growing appreciation for technology's role in creating market opportunities. At the macro level, technology based innovations have been related to changes in economic growth and dramatic social changes (Kondratieff 1926; Schumpeter 1939; Kuznets 1953; Solow 1957; Rostow 1975). From 1929 until 1969, forty five percent of the growth in the gross national product (GNP) in the United States was due to technological innovation and fifty percent of corporate sales are derived from products introduced during the preceding ten year period (Sach and Benson 1981). Increasingly, corporate and national competitive advantage are being linked to technological success (Porter 1990).

Tracking technological change and the new innovations that follow have long been of interest (see Ayres 1990 for an historical review). While the research described above examined the general relationship between technological change and economic growth, more recent studies explored the specific conditions that contribute to technological change and innovation. Attempts to move from a macro to a micro level of understanding include studies of the characteristics of innovative firms, (da Rocha, Christensen and Paim 1990; Schoonhoven, Eisenhardt and Lyman 1990, Romano 1990), the R&D/marketing interface (Berenson 1968; Brownlie 1987, Calantone and di Benedetto 1988; Hise, O'Neal, Parasuraman and McNeal 1990), the timing of new market entries (Fetke and Birch 1982; Green and Ryans 1990; Lilien and Yoon 1990), and factors contributing to the success of new products (Cooper 1985; Johne and Snelson 1988).

Further contributions have been made by economists studying industry innovations. With the help of simulation models these researchers have clearly demonstrated the importance of including complex competitive relationships in order to obtain results that correspond to real business experiences (Rosenbloom and Cusumano 1987; Sah and Stiglitz 1987; Grossman and Shapiro 1987).

Taken as a whole, these studies have made important progress in furthering the understanding of technological change and the innovations that follow. They have demonstrated the importance of viewing technological change as a dynamic, ongoing process, rather than episodic and unpredictable. Firm specific studies, including case analysis, have identified factors that directly affect the speed with which innovations are brought about. And industry-based research has shown competitive interactions to be important in facilitating the flow of new technologies and innovations.

MOTIVATION FOR CURRENT RESEARCH

The current research is motivated by both the achievements and weaknesses of earlier research on the innovation process. Previous studies provide evidence suggesting reasons one firm or a group of firms is successful in bringing an innovation to market. Some studies looked at the evolution of successful products, while others examined the characteristics of innovative firms. But these approaches have often resulted in mixing factors that influence the technological change process with those that affect the product introduction process. As a result, these studies failed to identify factors that specifically influence the technological change process versus the product introduction process. Identifying factors that affect the technological change process is important because it is change at this level that makes future product introductions possible.

Previous studies also established the importance of including competitive relationships in any model of innovation or technological change. However, researchers studying competitive influences report inconsistent findings. One reason for inconsistent findings is the lack of agreement of what constitutes the relevant industry.

Some researchers have defined the relevant industry according to Standard Industrial Classification (SIC) codes while others have used a more product specific definition. Different definitions of the relevant industry can affect the outcome of a study because the more general the industry definition, the more likely irrelevant and unwanted firms will be included in the analysis. Thus far, only a handful of researchers looking at competitive influences have defined the relevant industry to be only those firms researching in a specific technological area.

The current research is motivated by the need to identify factors that influence the technological change process. The need for such a model exists because previous research either failed to focus exclusively on the technological change process or produced inconsistent results based on inconsistent definitions of the relevant industry. The current research addresses these deficiencies by first, presenting a model of factors that affect technological change prior to the launch of a new product or innovation and, second, by defining the relevant industry to be only those firms actively researching in a specific technological area.

In addition, the current research for the first time provides the opportunity to combine previously disparate findings. Economic models using conventional measures of industry structure and competition are difficult to reconcile with product specific and firm specific models of innovation found in marketing. However, each approach has helped identify factors important to the technological change process. By focusing on specific technological areas, the current research can measure both firm and industry characteristics.

PURPOSE OF CURRENT RESEARCH

The purpose of the current research is to present and test a model of factors that affect technological change prior to the launch of a new product or innovation. In order to accomplish this, and avoid the weaknesses of earlier research, the current study addresses the following research question: "Can an industrial organizational (IO) approach to modeling firm and industry technological activities explain technological change?"

Much of the research on the impact of competitive relationships on technological change has been done by industrial organization (IO) economists. The IO approach of relating industry structure to industry performance has achieved some success. The current research adopts this approach by relating the industry research structure to the total amount of research activity observed. Though differing in their approach, marketing studies can complement the work in economics because they identify firm characteristics important to the technological change process that can be generalized across all firms researching in a specific technological area. The current model draws from these two literatures.

CONCEPTUAL MODEL

As indicated earlier, the approach taken in previous studies varies a great deal, with very few looking at the technology change process per se. The current research studies the technological change process by relating industry structure variables to the amount of technological change observed in the form of research activity. In order to focus specifically on the technological change process, the present research uses studies in which innovations presumably flowed from earlier research activity. In some cases the number of innovations served as a measure of the underlying research activity, while in others research activity was measured directly. But in each case factors were identified that have an effect on research activity.

The model (Figure 1 - 1) brings together those factors that have been identified to have an effect on the amount of research activity that takes place in an industry during a specific time period. The inclusion of each variable in the model is supported by multiple studies. The following paragraphs briefly describe each variable in the model and its hypothesized effect on research activity.

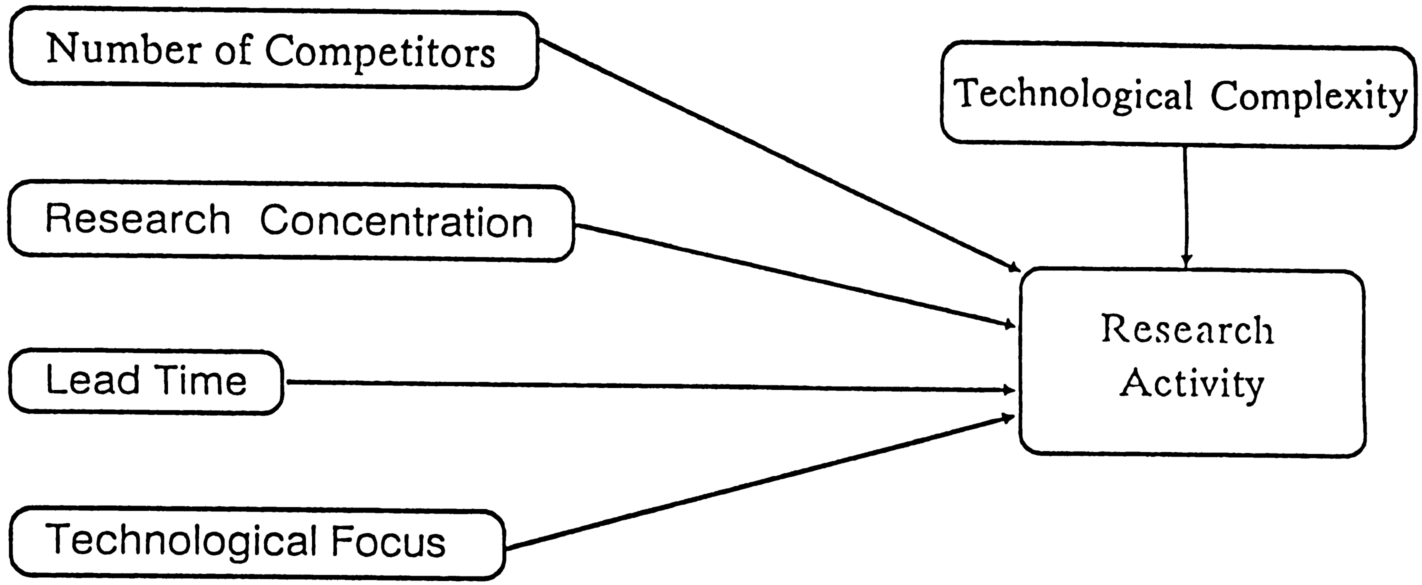

Figure 1 - 1

Conceptual Model

The number of firms competing in an industry and the degree of industry concentration are two variables frequently included in an IO analysis. Generally, the number of competing firms has been found to be positively related to the total number of innovations observed (Sah and Stiglitz 1987; Reinganum 1984).

Industry concentration has also been found to have a positive effect on the number of industry innovations but only if the degree of concentration is moderate. Extremely high or extremely low levels of industry concentration tend to inhibit innovations (Dasgupta 1986; Scherer 1967; Levin, Cohen, and Mowery 1985; Scott 1984). As a result, the relationship between industry concentration and research activity is hypothesized to be that of an inverted "U".

A third variable that is suggested to be positively related to the amount of research activity observed is the extent to which firms focus their research in a specific research area. Research focus at the firm level is difficult to measure, but marketing researchers have demonstrated its importance in facilitating the flow of research activity (Rosenbloom and Cusumano 1987).

Marketing researchers have also demonstrated the impact of the timing of competitor entry on the number of innovations introduced in an industry. As the length of time decreases between when a pioneering firm enters a product area and when the first competing firm enters, the total number of innovations increases (Urban, et al. 1986; Robinson 1988). Again, assuming that innovations at least in part flow from research activity, this finding suggests that the shorter the time period between when a pioneer enters a research area and when the first competing firm enters the area, the greater the total research activity.

A final consideration is the degree of complexity in the technological area. Technological complexity is not part of the industry research structure but rather an inherent part of the technology. It is also another variable that has proven difficult to measure. However, a number of studies, each using different measures, found that the more complex the technology, the lower the research activity observed during a specified time period (Roberts and Hauptman 1987; Schoonhoven, Eisenhardt and Lyman 1990).

Thus, the model includes the following independent variables: the number of competitors in a technological area, the level of research concentration among competing firms, the degree to which competing firms have focused their research, the amount of lead time between when the first firm enters a technological area and when a competing firm enters, and the degree of complexity inherent in the technological area. The dependent variable is the amount of research activity in a technological area during a specified time period.

As described above, each variable is measured according to the activity observed in a specific technological area. For example, the number of competitors is measured as the number of firms researching in a specific technological area. While a large number of firms may compete in a broadly defined industry, some firms may choose to research in only selected technological areas. The current model focuses on only those firms competing within each specific technological area. By taking this approach the model redefines the industry to be narrower and more technologically specific, avoiding some of the weaknesses of earlier research.

USING A PATENT BASED APPROACH

A secondary consideration in developing the current research is the issue of managerial relevance. Given the economic importance of technology-based innovations discussed in the introductory paragraph, it comes as no surprise that product managers are increasingly looking to technological change and the new innovations that follow as a way of increasing sales and improving their market position. However, there are few managerially useful mechanisms for monitoring technological change in a competitive environment.

Measuring the effects of competition on research activity has always been difficult and virtually all measures are indirect. Patent based research relating various measures of R&D effort and industry structure to the number of patents generated by an industry was an early attempt to do accomplish this goal (Schmookler 1966; Scherer 1965; Comanor and Scherer 1969; Lunn 1987).

These early studies used conventional measures of R&D effort and industry structure, such as the percentage of sales dedicated to R&D and the market share-based four firm concentration ratio. The number of patents was a measure of industry-wide research output. The weaknesses of these traditional approaches are well known, particularly the use of patents as a measure of industry-wide research output (Mansfield 1971; Scherer and Ross 1990).

Recently published patent based research focuses on the technological change process within a specific technological area, as opposed to a more general, industry-wide approach. Results suggest that this approach is usable for both academic researchers and managers. Patent data provide a resource that is historical, objective, systematically collected, readily available and, perhaps most importantly, captures at least some of the research activities of competing firms (Ashton and Sen 1988; Narin, Noma and Perry 1987).

These recent studies limit research to firms actually participating in a technological area rather than measuring the efforts of all firms across the many technologies that can comprise the broader industry. The success of these studies rests in the patent classification and citation schemes. Patent information is classified according to technology rather than the industry (e.g., SIC code). Related technological changes are grouped into technological areas called "patent subclasses." This classification scheme makes it possible to study only those firms that participate in the changes that take place in a specific technological area.

The results of these studies have contributed to understanding competitive relationships and tracking specific innovation processes. Researchers have successfully used patent data to test how the actions of competing firms influence research activity (Van Vianen, Moed and Van Raan 1990; Achilladelis, Schwarzkopf and Cines 1990; Wheale and McNally 1986). And, long patent histories are proving helpful in understanding ongoing technology-based competition (Basberg 1987). Patent data has even been correlated to the "quality" of technological changes (Narin, Carpenter and Woolf 1984; Albert, Avery, McAllister and Narin 1990).

PATENT BASED MODEL

In spite of the recent progress, no research currently exists that specifically relates patent activity within a patent subclass to the apparent industry research structure in that subclass. Figure 1 - 2 shows the conceptual model transformed into a patent based research model. On the left side of the model are the four industry structure variables and on the right side the dependent variable, the amount of research activity. Technological complexity has an impact on research activity but is not part of the industry research structure. Each variable is then defined according to the patent classification scheme (see APPENDIX A for a list of term definitions).

The number of competitors in a technological area is defined as the number of firms patenting in a patent subclass. Research concentration measures the extent to which research in a patent subclass is concentrated in the hands of the top four firms in that subclass. The degree of technological focus is indicated by the degree to which firms patenting in a patent subclass focus their research in that technological area (or, conversely, the degree to which competing firms spread their research across many technological areas). Competitor lead time considers the time between when the initial innovating firm enters a patent subclass and when the first competing firm enters. And technological complexity is seen as the degree to which

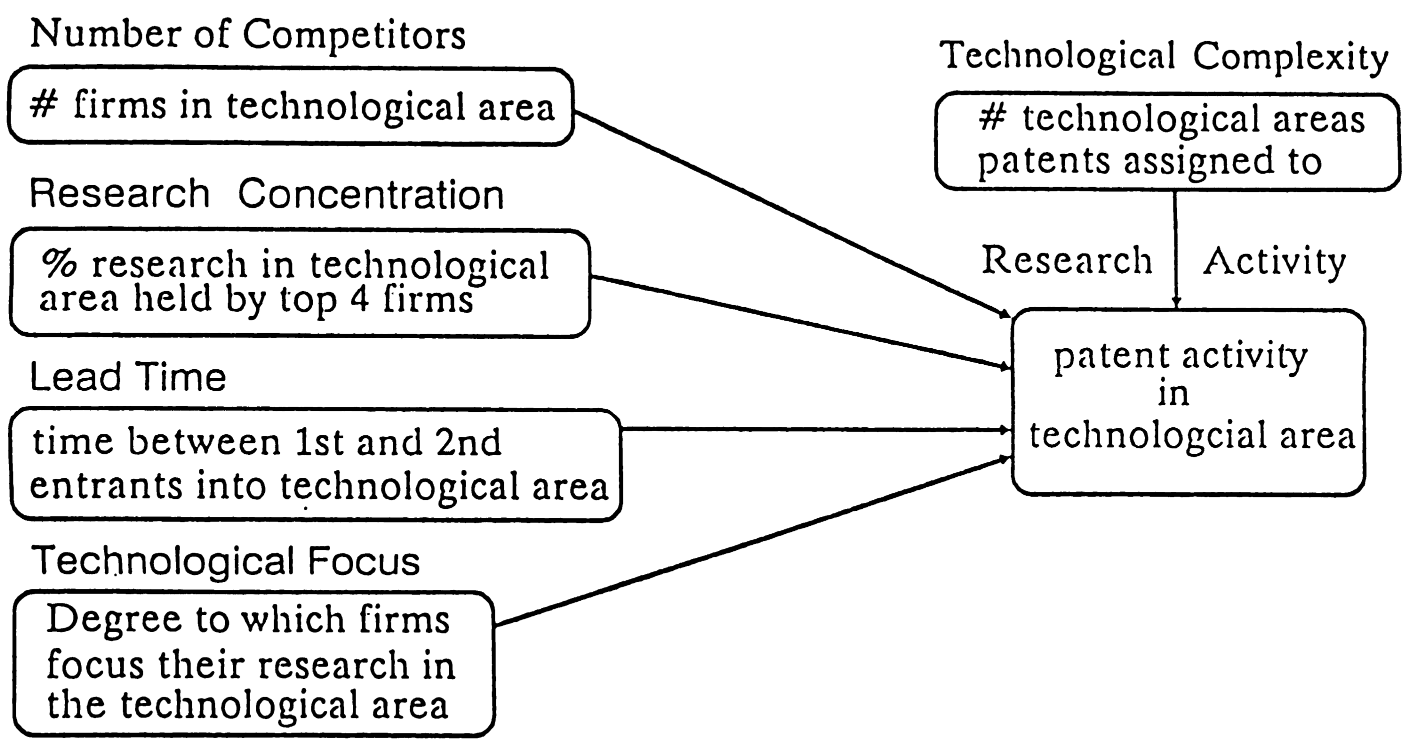

Figure 1 - 2

Patent Based Model

patents in a subclass are also assigned to additional patent subclasses.

SCOPE OF STUDY

Understanding research activities that lead to new product developments has long been of interest to marketers (Wind 1982). The growing interest in the innovation process has caused marketing researchers to be increasingly interested in the role of marketing in the new product development process (Hise et al. 1990). Figure 1 - 3 places the current study in the context of a new product development process. The period between concept/product development and final product evaluation is considered to be the period during which technologies are formalized into actual product innovations. During this time patents are obtained to protect these technologies. Patent activity is treated as a surrogate measure of research activity during this stage of the product innovation process.

The current study does not look at products or markets, per se. Instead, it focuses on that part of the innovation process that precedes the generation and evaluation of the final product. Ideally, the model will be able to identify which industry factors and interactions among factors are most important in explaining the amount of research activity observed.

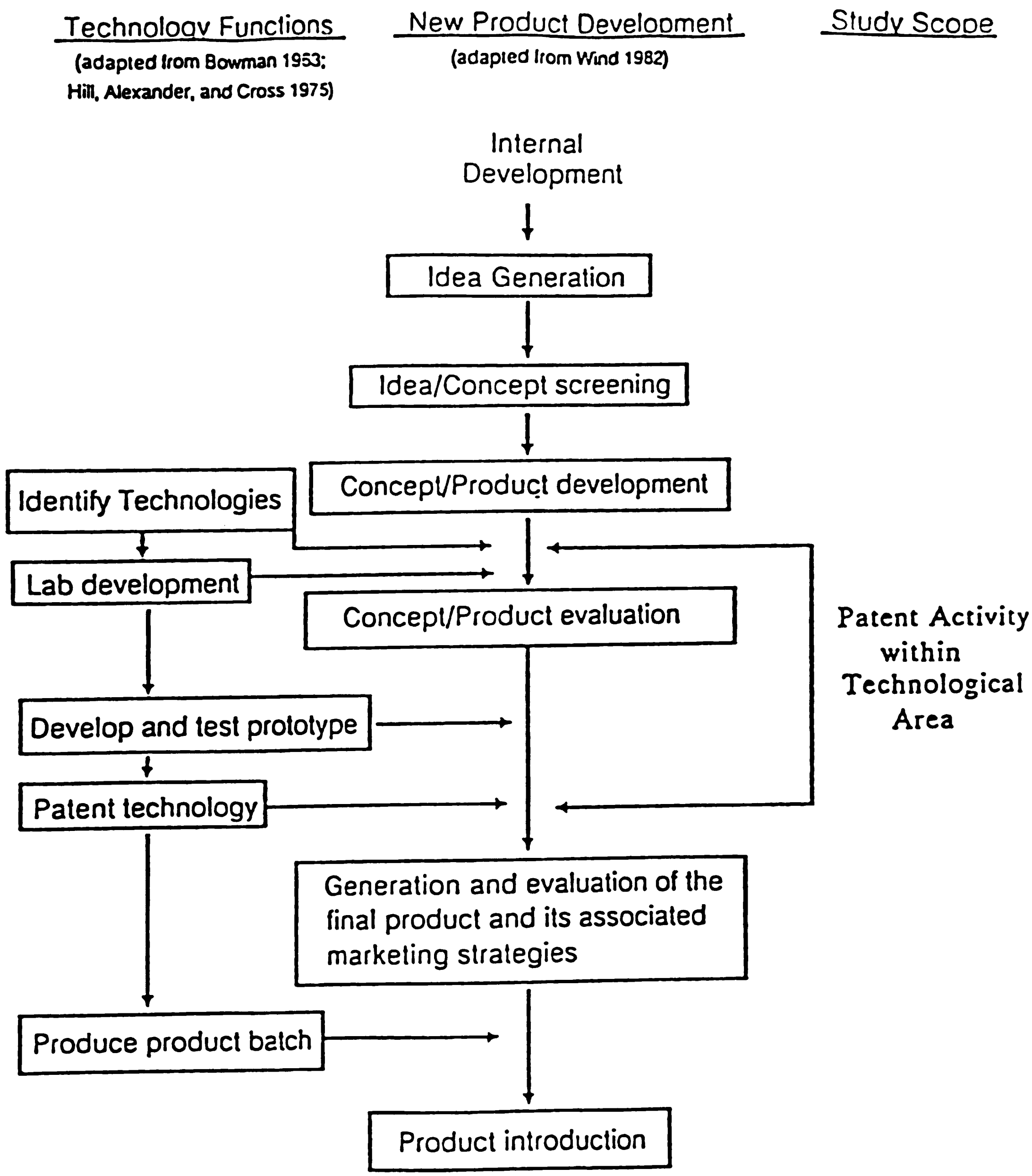

Figure 1 - 3

Scope of the Study in a
New Product Development Context

CHAPTER TWO

LITERATURE REVIEW

INTRODUCTION

Chapter One introduced a conceptual model that relates the industry research structure to the amount of research activity observed. The model differs from previous research because it explores the research process at a more technologically specific level, it combines measures of the industry research structure in a manner not previously combined and, third, it uses a patent based approach. This chapter provides support for the current research model.

The first section of this chapter begins with a general discussion of early efforts to understand technological change and the innovation process. Particular emphasis is placed on research that studies the relationship between the structure of the industry and the industry's research effort. The results of this research are discussed and an argument is made for conducting the current research at a technologically specific level, as opposed to a broader industry level.

Next, economics and marketing literature is cited that supports the inclusion of each variable as a measure of the industry research structure. After justifying each variable in the model, a proposition is presented that relates each variable to the dependent variable. Since the actual model being tested is the patent based model, each proposition is written in terms of the amount of patent activity observed.

Because the current study seeks to further demonstrate the viability of using a patent based approach, it is necessary to review the patent research literature. The second section of this chapter reviews the patent based approach. Particular emphasis is placed on recent patent based research which studies patent activity within specific technological areas.

NOTE ON RESEARCH TERMINOLOGY

Before relating previous research to the current study it is necessary to discuss similarities and differences in some of the terminology used. Two terms that frequently appear in the literature are "research effort" and "innovations".

Some studies have measured research effort as output (e.g. number of new products or patents generated), relating it to the structure of the industry. Others have measured research effort as inputs into the innovative process (e.g. amount of dollars or number of people), with innovations as a measure of research output (e.g. number of new products or number of patents). In short, some studies were conducted that distinguish between research effort and innovations while others treat them as essentially synonymous.

Most of the literature used to support the independent variables in the current model measure output as research effort (or alternatively "research and development effort"). Therefore, in order to maintain the integrity of previous literature, the term "research effort" appears frequently. In a few instances, a study is cited where innovations are the measure of output. Except in the initial discussion of the relationship between research effort and innovations, these studies use innovations in a manner that is synonymous with research effort.

The current model uses the term "research activity" as a measure of research output. The primary difference between it and the research output labelled as research effort or innovations in previous studies is that research activity is measured within a specific technological area, rather than at the broader industry level. Throughout the discussion no references are made to any study that involves "research activity". The term is used exclusively to refer to the dependent variable of the current model.

TECHNOLOGICAL CHANGE AND THE INNOVATION PROCESS

A long history of empirical and theoretical work has consistently found a strong positive relationship between industry research and development effort and the rate of industry innovation. Mansfield (1971), a leading economic theorist in the area of technological change, argues that the rate of innovation is influenced by the same kind of factors that determine the output of any good or service. That is, an increase in the inputs to the technological system (i.e., R&D effort) will lead to a faster rate of output (i.e., innovations).

Traditional measures of R&D effort have included the ratio of R&D spending to sales, the number of R&D employees as a percentage of the total work force, and the number of professional employees as a percentage of the total work force. Innovation output measures have included sales volume from new products, total number of patents, total number of inventions, and the probability of innovation success (Comanor and Scherer 1969; Pavitt and Wald 1971; Schmookler 1966; Mansfield 1968; Comanor 1965; Mclean and Round 1978; Cooper 1985). Studies measuring related aspects of R&D effort, such as the degree of R&D coordination and the presence and use of technical expertise within the company, have also found R&D effort to be an important indicator of successful innovations (Romano 1990; Calantone and di Benedetto 1988). In every case a positive relationship was found between research and development effort and innovation output.

While establishing an important and fundamental relationship, these studies offer little insight into the dynamic nature of industry research effort, particularly as it pertains to specific technological areas. Mansfield and others (Kamien and Schwartz 1982) recognize that there is "considerable uncertainty" in the process linking research inputs to outputs. It is uncertainty regarding the factors that contribute to overall industry research effort that led contemporary researchers to focus more closely on the industry research structure.

In attempting to understand how industry research efforts vary, industrial organization economists have related the amount of research effort to the industry research structure. The evidence suggests that the degree to which a firm pursues research opportunities, and therefore the total amount of industry-wide research effort, is to some extent determined by the number of competing firms and the amount of industry concentration (Stiglitz 1986; Lunn 1987). These studies typically measured research effort in terms of the number of innovations introduced during a specific period of time.

For marketers, research efforts are reflected in the firm's overall market strategy. Alderson (1965), Porter (1985) and others have long recognized the desire of competing firms to gain a competitive advantage through technological innovation. Firms use research innovations to reduce their costs, improve their current products, or develop new products (Grabowski and Vernon 1987). A large number of studies have examined the degree to which successful research and development strategies translate into sales, market share, and profits (Parasuraman and Zeren 1983; Morbey 1988; Franko 1989). Firms may also, of course, spread their resources over multiple research areas or pursue other marketing strategy options. The degree to which a firm focuses on a particular research area and the timing of new product entry, which implies an underlying research strategy, have both proven to be significant to the firm's success (Rosenbloom and Cusumano 1987; Urban, et al. 1986).

The four factors that either directly affect the firm's research effort, or relate to the firm's success in the market place based on a particular research strategy are: the number of competing firms, the amount of industry concentration, the extent to which firms focus on a particular research area, and the timing of competitor entry.

The current model builds on the previous literature in two ways. First, instead of measuring overall industry research effort, the current model measures the amount of research activity within a specific technological area. By doing so the model more closely focuses on the factors that affect specific technological changes. The primary objective of the model is to explain how research activity is affected by these variables.

Second, the current model combines variables demonstrated to have an impact on research effort but that, until now, have not been combined in a single model. Previous models that included the number of competitors and degree of concentration measured these variables at an industry-wide level, while those using entry time and degree of focus often measured the effect of these variables on a specific product or commercial innovation. The current model is made possible because all four variables are measured within the same technological area.

The model also includes a measure of technological complexity, which relates to the requisite amount of research and development activity needed to bring about a change. While technological complexity is exogenous to the firm, and therefore not part of the industry structure, it is included as a confounding variable that interacts with the other four independent variables. Support for the inclusion of technological complexity is found generally throughout the technology literature.

NUMBER OF COMPETITORS

Changes in industry technology have the potential to restructure the industry. With a winning technology, current followers can leap to leadership positions and current leaders can quickly become followers (Porter 1985). If, however, the industry could not be restructured because there were no followers, no leaders, or firms lacked the ability to change positions, the pursuit of technological superiority would be less compelling. Thus, it is competition in conjunction with technological opportunities that give the innovative process its dynamic, societally positive role.

Under the simplest economic assumptions, the greater the number of competitors the greater the industry competition. Therefore, as the number of competitors in an industry increases so will the industry's total research effort (with a corresponding increase in societal benefits). However, not all theorists agree with the above argument.

Some economists argue that as the number of competing firms increases, the amount of profits available for each firm decreases. Lower profits mean fewer resources available to use for research and development which, in turn, reduces the firm's research effort. As profits continue to fall each firm reduces their research effort until eventually the industry's total research effort declines (Schumpeter 1942; Galbraith 1952).

Other theorists argue that a large number of competitors means numerous alternatives available to customers. The large number of alternatives serves to delay customers' willingness to purchase. According to this argument delayed purchases cause firms to delay the introduction of new products which, in turn, inhibits the firms overall investment in new research opportunities

(Nelson and Winter 1977; Schoonhoven, Eisenhardt and Lyman 1990).

Both of these arguments were used in a recent study in an attempt to relate a high number of competitors with slow product innovations and fewer market introductions. However, empirical support was lacking. In fact, though not statistically significant, the research showed that a larger number of competitors reduced the time between product introductions, increasing the total number of introductions in a given time period (Schoonhoven, Eisenhardt and Lyman 1990).

There are theorists who support the original argument, that the number of competing firms leads to greater industry research effort. This position rests on two main points: first, that an increase in the number of competitors increases the risks associated with research and, second, that firms must continue to pursue research opportunities even in the face of greater risk.

As long as the first firm to market can find some mechanism to appropriate the returns from its R&D efforts, firms in a competitive environment that are late with their innovation risk not recovering their research investment. Thus, as the number of firms competing in the same area increases, the probability of any one firm benefiting from its own research effort decreases (Stiglitz 1986). The decreasing probability is simply a function of the increased number of opportunities for success.

The decreasing probability of success could have the effect of discouraging firms from conducting research. However, in a competitive industry firms that do not successfully innovate will have difficulty maintaining or improving their position in the market. Thus, as the number of competitors increases, firms are forced to strive harder just to stay even with their innovating competitors. The net effect is that the increasing number of competitors increases total industry research.

Economists have modeled competitive R&D situations in order to test the above proposition. As might be expected, the outcome varies depending on the assumptions of the model. Important variables are: whether or not it is a "winner-takes-all" competition, whether or not firms can invest in more than one research project, and whether or not competition extends beyond one time period (Kamien and Schwartz 1982). If the model assumes a winner-takes-all competition, that firms invest in only one project, and that competition is for only one time period, then the actions of competing firms appear to have a negligible affect on any one firm's research effort (Sah and Stiglitz 1987). But when the model contains a more realistic scenario, where firms conduct research in a technological area on an ongoing basis and the market provides future opportunities yet to be tapped, one firm's research efforts are affected by the actions of competing firms.

Additional research has also shown that as long as firms can appropriate benefits of their R&D efforts, the rate of research investment (i.e. effort) by an individual firm and the aggregate industry rate of research investment increases as the number of firms engaging in R&D increases (Reinganum 1984). In a dynamic competitive model that allows for multi-stage investment in R&D under changing competitive conditions, it was found that "When a lagging firm draws even with a rival that was formerly ahead in the race, both competitors respond by increasing their research efforts (Grossman and Shapiro 1987). In order to increase their chances of benefiting from their research both firms strive harder to get their innovations developed.

The outcome under these more realistic conditions suggests that the number of competitors increases the aggregate research effort within the industry. The effect on patent activity is suggested by the following proposition:

> **Proposition 1:** The greater the number of competitors the higher the patent activity in a technological area.

RESEARCH CONCENTRATION

A great number of economic studies have also looked at the effect industry concentration has on industry innovation. Concentration is usually measured as the amount of market share held by the largest firms in the industry (e.g., CR4).

Some theorists concluded that an increasing number of competing firms decreases the total amount of industry research. These same theorists also hypothesized that R&D effort increases with firm size (Galbraith 1952; Scherer 1965). Their conclusions are based on the presumption that an industry with more competitors is more competitive and therefore has fewer overall profits. Lower profits and more firms means both fewer profits per firm and fewer total industry profits to invest in research. Alternatively, an industry made up of a few large firms would be less competitive, providing greater opportunity for firms to extract profits. These profits would, in turn, be spread across fewer firms. Thus, in industries dominated by a few large firms total industry research and per firm research would be higher. As a result, according to these theorists, as industry concentration increases so would the industry's overall research effort.

Others have suggested that dominant firms are less innovative because they have the ability to maintain rent streams from current products (Williamson 1975; Conner 1988). Both arguments concede the presence of greater profits in more concentrated industries. But, contrary to the first argument, the second suggests that greater profits from current products reduce the need to conduct research on new innovations.

Recent studies based on a large number of industries indicate that a greater rate of innovation occurs at moderate levels of industry concentration, decreasing when concentration is extremely low or high (Dasgupta 1986; Levin, Cohen and Mowery 1985; Scott 1984). Some of these same studies also found, however, that the "inverted-U" relationship between industry concentration and innovation could become statistically insignificant with the addition of multiple variables reflecting a variety of diverse inter and intra industry factors. At this point it is unclear whether the effects of the added variables influenced concentration or are affected by it. Scherer and Ross (1990) conclude that given the underlying theory and consistent finding of the "inverted-U" under repeated statistical analysis, the suggested relationship cannot be dismissed.

To summarize the above arguments, the relative concentration of industry power is seen to affect the incentive to innovate. Empirical findings suggest that at moderate levels of concentration individual firms are the most innovative. When industry concentration is low individual firms either may not feel threatened, given the absence of dominant firms in the industry, or may be uncertain regarding market conditions and their ability to appropriate the returns from their research and development efforts. At high concentration levels, aggregate industry innovation decreases as dominant firms attempt to gain the most from their current product offerings.

The relevance of this economic research is important to understanding patent activity. If industry patent activity is a reflection of R&D effort and the desire to get new products to market (or improve processes) as quickly as possible, then R&D effort should be greatest and patent activity highest at a moderate level of industry concentration. Furthermore, if the concentration of technological power equates to a concentration of industry power, then the relationship between research concentration and patent activity should follow a pattern similar to that between industry concentration and industry innovativeness. That is, patent activity will be highest at a moderate level of research concentration. In the current model research concentration is conceived as the research concentration ratio (RCR4) - the share of research in an technological area held by the four most active firms in the technological area. The current research extends previous economic studies by suggesting the following proposition:

> **Proposition 2:** Patent activity in a technological area will be highest at a moderate level of research concentration, decreasing as research concentration approaches extremely low or high levels.

COMPETITOR LEAD TIME

Measuring the number of competitors and the degree of research concentration within a specified time period assumes that these measures are consistent throughout the time period. While both reflect aspects of the competitive relationships that are present, neither provide an indication of the importance of the timing of a competitive threat. By including a measure of lead time the current model allows the initial competitive threat to vary. Lead time looks at how quickly the second firm enters a technological area initiated by a pioneering firm.

An early study of 40 industrial products using the PIMS data base showed that even though the market share of pioneering firms decreased significantly when competitors entered the market, market shares did not equalize among competing firms (Biggadike 1976). Dillon, Calantone, and Worthing (1979) found pioneering to be a major determinant of long-term success in industrial products. In a study also based on PIMS data, Robinson and Fornell (1985) confirmed the earlier findings that pioneers tend to maintain market leadership. They also found that pioneers in the market have higher product quality and broader product lines, while charging essentially the same price as late entrants. These same results were confirmed in an expanded PIMS study three years later (Robinson 1988).

An empirical study of consumer products conducted in 1983 by Urban, Carter, Gaskin and Mucha (1986) also established a positive relationship between order of market entry and market share. The market share of the pioneering firm dropped from 100 percent to 27.3 percent as six competing firms entered the market but this lower market share represented a significant long term premium nonetheless. Green and Ryan (1990) found a similar positive effect using a simulation model but the success of the pioneer was indirect, attributed more to improved competitive positioning than to early entry time alone.

In a study of new industrial products introduced by French firms Lilien and Yoon (1990) considered order of entry, stage of the product life cycle, and the product development time prior to market entry. Their findings disconfirmed the advantage of early entry, showing a higher success rate for third and fourth entrants than for firms entering first or second. However, the findings also showed product success to be higher when the time lag between development and market entry was longer. This second result suggests that the first firm in a research area may choose to spend time developing an innovation in order to enter the market with a superior product.

When a firm obtains a monopoly position (albeit a limited monopoly) in a research area, two strategy alternatives are possible. First, the pioneering firm may see the absence of competitor activity as an opportunity to fully explore the research possibilities in the technological area. Additional patented research will strengthen the firm's monopoly position and is therefore pursued. The entry of a competitor may inhibit the pioneering firm's research efforts since the quicker the competitor enters the greater the pressure to commercialize preexisting technology and the lower the probability of obtaining monopoly benefits from future research efforts. This logic leads to the conclusion that the longer the competitor lead time, the greater the patent activity in the technological area.

A second view suggests that the pioneering firm may be inclined to exploit its early monopoly position before generating additional patentable research. When threatened by competitor activity, the pioneer will respond with increased research activity; otherwise, not. The logic of this position assumes that the benefits of an early patent(s) can be exploited and that the absence of competition observed in a patent subclass represents a low threat of competitor activity in general. Under this scenario the shorter the period between pioneer activity and the entry of another firm, the higher the number of patents in the technological area.

This second argument has some empirical support. Research has shown that greater incentive for innovation exists when the intensity of rivalry increases over time (Kamien and Schwartz 1972; Fethke and Birch 1982). An increased incentive for the pioneer to respond in the face of early competition is also supported by studies showing the earlier the entry of a market follower, the better the performance of the follower's product (Lilien and Yoon 1990; Urban et al. 1986).

The research evidence suggests that the longer the period between the first and second entrant the lower the relative R&D effort and the fewer patents granted. This leads to the third proposition:

> **Proposition 3:** The longer the competitor lead time the lower the patent activity in a technological area.

TECHNOLOGICAL FOCUS

Do more technologically diversified firms obtain synergies from their diversity? The answer may be "yes" if firms can transfer the results from one field of research to another. To the extent that common resources and researchers can be utilized, additional synergies may also be possible. However, economic studies have failed to establish the link. While some have found a positive relationship between research diversity and innovation, the coefficients were small and statistically insignificant

(Scherer 1984; Cohen, Levin and Mowery 1987). One economic study actually showed the opposite effect, with the ratio of R&D to sales lower in product lines from firms having a history of diversification mergers but again the result were not statistically significant (Ravenscraft and Scherer 1987).

Researchers who study the innovation process increasingly point to the need for establishing core areas of expertise (Lauglaug 1987), formal product development procedures (Moore 1987), and critical skill levels (Johne and Snelson 1988; Calantone and di Benedetto 1988). While research diversification does not prevent a firm from accomplishing these goals per se, it does increase the likelihood that researchers will be asked to wear too many hats and that any gains from synergistic relationships may be offset by disruptions in individual research programs. One study of "technological pioneering" found that success is more likely to flow from a focused, though flexible, management of technology (Rosenbloom and Cusumano 1987). The current research adopts the focus oriented philosophy and proposes the following:

> **Proposal 4**: The greater the industry's technological focus the higher the patent activity in a technological area.

An important caveat in the argument for a focused research approach is that products and processes are increasingly drawn from a diverse set of technologies (Clark

1989). To the extent that this is true firms will find a broad technological base necessary. The trend toward increasing technological complexity suggests a corollary to proposition 4:

> **Proposal 4.1:** When technological complexity is high, and the industry's technological focus is high, patent activity in the technological area will be low; otherwise, the greater the industry's technological focus the higher the patent activity in a technological area.

This issue extends beyond the current study's focus on the amount of research activity observed. The above argument suggests that under a condition of increasing technological complexity firms and possibly whole industries that are too technologically focused will no perform at an acceptable level. Thus, the impact will not only be felt in terms of the amount of research activity observed, but also qualitatively, in the overall performance of the industry.

TECHNOLOGICAL COMPLEXITY

The process of technological change "does not usually move in a straight line, according to plan, but takes unexpected twists and turns" (Schon 1967). Products containing a greater number of technologies face a greater number of unexpected twists and turns. The impact of this result is felt in two ways. First, risk aversive managers will be inclined to see products containing multiple technologies as research areas posing greater uncertainty (Sachs and Benson 1981). The greater risk associated with this uncertainty will require a larger expected return before R&D dollars are committed.

Second, in the words of Mansfield (1971), "It takes more resources to redesign a big product with a large number of components, because there are more drawings to be made, more analysis to be done, and more tests to perform." Mansfield refers to unpublished empirical research on the development of military airframes conducted by Glennan and the RAND Corporation to support his claim. Further research has shown that complex innovations require more new information and greater R&D effort (Galbraith 1977; Schoonhoven 1981). Similarly, the amount of knowledge created for a new innovation and the amount of existing knowledge synthesized are both positively related to longer waiting times for product introductions and first product shipments (Roberts and Hauptman 1987; Schoonhoven, Eisenhardt and Lyman 1990).

The net effect is that technologically complex products require greater research effort, producing fewer patented innovation per R&D dollar spent. Hence, the fifth proposition reads as follows:

> **Proposition 5:** The greater the technological complexity the lower the patent activity in a technological area.

The proposed model contains five variables which, at various times, have been found to significantly affect total industry research effort. In the current model these relationships are measured and tested within the context of patent data. Figure 2 - 1 lists the constructs in the current research and how they will be measured using patent information. The main propositions and their testable hypotheses are presented in Figures 2 - 2 and 2 - 3. The methodological approach adopted in the current model is based on the unique nature of patent data. The following section elaborates on the patent based approach.

	Variable	Construct Being Measured
X_1	number of firms patenting in the subclass	Number of competitors in the technological area.
X_2	share of patents in subclass held by four top firms	Degree of research concentration within the technological area.
X_3	time period between when initial firm is granted a patent in subclass and when second firm is granted a patent in the same subclass	Competitor lead time in technological area.
X_4	average of each firm's percent of total patents filed in subclass	Level of technological focus of firms conducting R&D in the technological area.
X_5	the average number of subclasses each patent in the subclass is assigned to	Degree of product complexity.
Y_1	number of patents filed in a subclass during a specific period of time	Amount of research and development activity corresponding in technological area.

Definitions:

"Technological area" refers to a specific patent subclass.

"Subclass" refers to the particular patent subclass under investigation.

FIGURE 2 - 1

PATENT SUBCLASS LEVEL OF ANALYSIS

P_1 The greater the number of competitors the higher the patent activity in a technological area.

P_2 Patent activity in a technological area will be highest at a moderate level of research concentration, decreasing as research concentration approaches extremely low or high levels.

P_3 The longer the competitor lead time the lower the patent activity in a technological area.

P_4 The greater the industry's technological focus the higher the patent activity in a technological area.

$P_{4.1}$: When technological complexity is high, and the industry's technological focus is high, patent activity in the technological area will be low; otherwise, the greater the industry's technological focus the higher the patent activity in a technological area.

P_5 The greater the product complexity the lower the patent activity in a technological area.

FIGURE 2 - 2

PROPOSITIONS

H_1 The greater the number of firms granted patents in a patent subclass (X_1) the higher the number of patents granted in the subclass (Y).

H_2 The number of patents granted in a patent subclass (Y) will be highest when the share of patents in the patent subclass held by the top four firms (X_2) is moderate.

H_3 The longer the time period between when the first firm is granted a patent in a patent subclass and when a competing firm is granted a patent in the same subclass (X_3), the lower the number of patents in the subclass (Y).

H_{4a} The greater the average of each company's percent of patents filed in a patent subclass (X_4) the higher the number of patents in the subclass (Y).

H_{4b} As technological complexity (i.e. the total number of subclasses the average patent in a patent subclass is assigned to - X_5) increases, the greater the technological focus (i.e. the average of each company's percent of patents filed in a patent subclass - X_4), the lower the number of patents in the subclass (Y).

H_5 The greater the number of subclasses assigned to the average patent in the subclass (X_5) the lower the number of patents in the subclass (Y).

FIGURE 2 - 3

TESTABLE HYPOTHESIS

PATENT BASED RESEARCH

The literature on patent based research is almost as old as the patent system itself. Studies that use patent statistics can be broadly grouped into three categories: those that attempt to measure the relationship between technological change and economic development, those that use patents to monitor the diffusion of technology from one country to the next, and those that focus on the innovation process itself (Basberg 1987). The current study falls into the latter category.

The first part of this section examines the nature of patent data and why it can be useful for understanding technological change and the innovation process. The second part reviews current patent based research that has focused on specific technological areas. And, the third part looks at the weaknesses associated with a patent based approach. The focus of the discussion is on the general applicability of a patent based approach. A description of how patent data is used to measure variables in the current study is provided in Chapter Three.

THE NATURE OF PATENT DATA

The justification for using patent data as a means of analyzing the innovative process stems from the function patents play in safeguarding proprietary information. In an effort to stimulate innovations, most nations of the world provide firms and individuals with limited monopolies through patent protection (Scherer and Ross 1990). In the United States the protection period is seventeen years. By achieving patent protection for this period, and the monopoly it implies, innovating firms can more quickly recover their research costs.

In order to be granted a patent, an applicant must describe the product/process under consideration in great detail and also any relevant historical scientific information. Some of the information included on a patent application is the name of the inventor, the name of the company filing the patent, the company's country of origin, and citations referencing previously published research, such as might appear in scholarly journals. In addition, the patent examiner provides citations of previously granted patents that are relevant to the patent under review and, upon granting the patent, assigns the patent to the patent classes and subclasses to which the patent might apply (Narin and Olivastro 1988).

The results of this process include a chronological history of patents, grouped according to technological area; scientific citations relating patents to published scientific research; patent citations which allow for the tracking of patents both forward and backward in time, and across competing firms; and measures of patent activity by firm, inventor, and company.

Patent histories, available in many countries, are unique in their ability to provide complete case histories of technological development back to the eighteenth century (Basberg 1987; Wheale and McNally 1986). Historical information on technological change is interesting in its own right plus, it provides an opportunity to test theories of research activity. Over the past decade a number of firms in the United States began offering customized data bases and competitor analysis information using both U.S. and international patent data.

Information that is of particular interest to those who study technological change include the historical nature of the data grouped by technological area, patent and scientific citations, and company information. From these data sources researchers have tracked the evolution of specific technologies, areas of technological emphasis to individual firms, and the relevant technological strengths of competing firms.

While patent data has always been accessible to the public, the recent computerization of patent information greatly facilitates its use. As a result, since the early 1980s the number of studies using patent data to examine the innovative process has grown dramatically.

CURRENT PATENT BASED RESEARCH

The increased accessibility of the patent data base is only one reason for the flurry of patent based research conducted during the past decade. Other important reasons are the speed with which technological changes are occurring, and the absence of reliable information on evolving technologies among managers and planners (Ashton and Sen 1988). These latter two reasons have increased the managerial urgency of finding reliable technological information. Patent information is beginning to fill that void by providing insights into the innovative process through patent trend analysis.

Ashton and Sen (1988) suggest five business applications for patent trend analysis: technology competition analysis, allowing for the comparison of the relative technological strengths of competing firms; new venture evaluation, for assessing acquisition and joint venture opportunities; patent portfolio management, helping to classify patents based on value and potential; R&D management, for analyzing the pace of R&D in evolving technologies; and product area surveillance, to bridge the gap between technological development and marketable innovations.

Ashton and Sen (1989) demonstrated three of these applications when they used patent data to identify firms who were well positioned to be market leaders in the battery industry, which technological areas provided the best licensing opportunities, and how technological activity can be used to anticipate commercial applications.

Other recent research by Narin, Noma and Perry (1987) found a significant correlation between overall corporate technological strength, as perceived by industry experts, and the number of U.S. patents granted to companies; and between increases in company profits and sales on the one hand, and patent citation frequency and the degree to which firms focus research within a few patent classes on the other. Achilladelis, Schwarzkopf and Cines (1990) suggest a four stage technological evolutionary process based on their analysis of patents and innovations. And Wheale and McNally (1986) used patent trend analysis to forecast the future market value of selected micro-genetically engineered products.

Additional patent based research has been conducted which studies the relationship between technological change and economic development, and, through international patenting, monitors the diffusion of technology from one country to another. These studies have confirmed the importance of government sponsored protection for innovations (Harris and Vickers 1985; Grossman and Shapiro 1987), the growing internationalization of research (Pavitt 1980; Soete and Wyatt 1983), the highly centralized nature of research among multinational corporations (Etemad and Dulude 1987), and the shifting relative technological advantage of nations (Van Vianen, Moed and Van Raan 1990; Frame and Narin 1990; Andrews 1989).

The effect of these recent patent based studies on the current research is two-fold. First, these studies demonstrate the relevance of using patent data to track technological change. And, second, they provide clues to new methods of measuring competitive relationships.

WEAKNESSES OF PATENT RESEARCH

Like all measures of technological change, patent data is only an indirect measure of technological change and the innovation process (Mansfield 1971; Basberg 1987). Studies have shown patents to be only one way firms appropriate the benefits of research and development (Scherer et al. 1959; Taylor and Silberston 1973; Levin et al. 1987). Therefore, patents can only be considered as representative of the research being done; and the degree to which patents are representative varies across firms and industries (Mansfield 1968, 1986).

Some researchers have even hypothesized that firms are increasingly less likely to patent their research results (Milnamow 1982; Shapley 1978). However, in a recent study Mansfield (1986) found that the tendency to patent had not decreased over time, concluding:

> Moreover, despite the frequent assertions that firms are making less use of the patent system than in the past, the evidence does not seem to bear this out. ...On the contrary, even in those industries where

> practically all inventions would be introduced without patent protection, the bulk of the patentable inventions are patented.

Another significant weakness is that the importance and costs associated with each patent differs considerably (Kuznets 1962; Mansfield 1968). This weakness is particularly relevant for those patent based studies that use patents as a measure of output. Though significant correlations were found in this research (Griliches and Schmookler 1963; Schmookler 1966), care must be taken in interpreting the results.

The current study avoids the weaknesses inherent in the traditional uses of patent data while building on more recent patent based research. First, though the current study uses patent activity as the dependent variable, no cost is associated with the independent variables and no importance or value is given to the dependent variable, as had been the case in earlier studies. Thus, unlike the studies mentioned in the preceding paragraph, no attempt is made in the current study to relate R&D costs with the value of products or innovations that flow from patent activity. Instead, the current study uses patent activity and its relationship to the independent variables to provide information on the structure of the technological change process.

Second, the current study confines the research to those firms active in a patent subclass, rather than at a broader industry level. By using a narrowly defined industry the current study includes only those firms that are relevant competitors and avoids generalizing results across broad, multi-product and/or multi-technology industries. This approach has been implied by recent patent research but has not yet been tested.

CONCLUSION

The current study proposes a research model that utilizes variables demonstrated to have an influence on total industry research effort. The study is unique because it combines and tests these variables in a single model, and because it uses patent data. The combination is made possible because the industry is narrowly defined and each variable is measured from a single data set.

Previous studies measuring industry-wide research defined the industry very broadly, for example, the ethical drug industry or the VCR industry. In doing so the number of competing firms and the amount of industry concentration was aggregated across multiple products and technologies. To the extent that firms researched in a limited number of technologies within the industry, this aggregation masked the true number of competitors and the exact degree of concentration. In order to include the degree of research focus and the timing of competitor entry along with these variables a research methodology would be required that emphasized distinct product innovations or technologies underlying innovations, rather than multiple products and technologies.

A patent based approach allows the industry to be defined as a specific technological area. As a result, only those firms researching in the area are counted as relevant competitors. Patent data has the additional benefits of providing a means for measuring each variable and being accessible to academics and managers.

CHAPTER THREE

METHODOLOGY

The purpose of the current research is to present and test a model of those factors that affect technological change prior to the launching of a new product or innovation. Chapter Two discussed each component of the model used in the current research and its competitive implications. Support was also provided for a patent based research approach. This chapter explains the methodology used in the research. The topics covered include a description of the patent data base, the sample selection, operationalization of variables, and data analysis.

SECTION ONE: DESCRIPTION OF PATENT DATA BASE

Before describing the United States patent data base, it is first necessary to explain why it continues to be one of the most important sources of information pertaining to patentable inventions in the world. As mentioned in Chapter Two, the bulk of all patentable inventions in the United States are patented, with the average number of patents granted annually in the United States from 1975 to 1988 exceeding 60,000 (Andrews 1989).

In addition, competing firms from outside of the United States continue to view the U.S. market as one of the world's richest. As a result, many firms based outside of the United States pursue U.S. patents in order to access the U.S. market. An indication of this phenomenon is the percentage of U.S. patents granted annually to Japanese firms, which has gone from 8.9 percent in 1975 to 17.9 percent in 1985 (Narin and Frame 1989). The continued propensity of U.S. firms to patent and the interest of foreign based firms in obtaining U.S. patents combine to make the U.S. patent data base a valuable resource.

Every patent granted in the United States is assigned to at least one patent class and one subclass within that class. If the patent has implications for more than one technological area it is assigned to more than one class and subclass. The assignment of the patent to the class(es) and subclass(es) is made by the patent examiner and reflects the examiner's decision regarding the technological area(s) most affected by the patent under consideration.

It is important to note that the classification is based on technological area, not industry. For example, the rolling mechanism for a ball point pen would be found in the same patent class as the mechanism used to apply roll-on deodorant. In terms of classification, the technology is the primary consideration; the industry within which the patent is being used is, for the most part, incidental. Because patents are grouped by technology it is possible to study the innovative process within a technological area.

It is this classification scheme that provides the structure of distinct technological areas necessary for the current research. The following sections describe the classification scheme and the manner in which the U.S. patent data was obtained.

U.S. PATENT CLASSIFICATION SCHEME

The United States patent classification scheme consists of approximately 360 classes, with up to 100,000 subclasses (Narin and Olivastro 1988). The actual numbers change as new classes and subclasses are added. Understanding the nuances of the classification scheme is important to understanding why a subclass level of analysis was chosen for the current study.

Each patent class represents a group of related technologies. The class is then further divided into subclasses representing greater levels of technological specificity. For example, **class 354 - Photography** contains major subclass areas (nominally labelled "main lines"), such as **subclass 400 - automatic camera focusing**, and **subclass 410 - automatic exposure control system or device**. These main lines are then further divided into more technologically specific areas. For example, under subclass 410 are **subclasses 425 - automatic exposure control system or device having a log transformation circuit**, and **426 -**

automatic exposure control system or device having a log transformation circuit that is digital (Figure 3-1).

A number of important observations can be made from the above example. First, some patent classes, such as class 354 - Photography, appear to correspond to identifiable industries. While other classes, such as class 116 - Signals and Indicators, appear to be more closely associated with a technological function. The reason for the apparent difference between these types of patent classes is that some technologies are more industry specific while others are of a more general nature.

It would be incorrect, however, to consider a patent class such as class 354 to truly represent an industry. To take such a research approach would be to assume that technological changes affecting the industry only comes from technological areas already present in the class. This is clearly not the case. For example, electronic still camera technology competes with traditional photography but patents unique to electronic still cameras are assigned to class 358 - Pictorial Communication; Television, not class 354 - Photography.

Identifying a patent class as an industry also assumes that all of the technologies within the class are relevant to one specific industry. This is also not the case. Consider a main line subclass within class 354, subclass 297 - fluid-treating apparatus. Patents in this subclass are

Patent Class - 354 **Title - Photography**

Patent Class/Subclass	Definition
354/400	AUTOMATIC CAMERA FOCUSING
354/401	● Using sound
354/402	● Having photoelectric focusing system of device
354/403	●● Using active ranging
.	
.	
.	
354/410	AUTOMATIC EXPOSURE CONTROL SYSTEM OR DEVICE
354/411	● Nonphotoelectric exposure control type
354/412	● For controlling entire photographic operation
354/413	● Including artificial illumination system or device
354/414	●● For fill-in illumination
354/415	●● With pre-exposure flashing
354/416	●● With flash termination control
354/417	●●● Quench type
354/418	●● Charge level or power supply responsive
354/419	●● Automatically activated under low light condition
354/420	●● Controlling exposure without controlling flash
354/421	●●● With follow focus control of exposure
354/422	●●● With single circuit controlling the shutter and diaphragm
354/423	●●● With means for controlling only the diaphragm
354/423	●● With photocell used as flashed trigger
354/425	● Having log transformation circuit
354/426	●● Digital
354/427	●● With log expansion
.	
.	

FIGURE 3 - 1

STRUCTURE OF U.S. PATENT CLASSIFICATION SCHEME directed to the film treating and development processes, rather than the picture taking processes involved in the camera itself. While both are part of the patent class Photography, they represent different, although overlapping industries and different competing firms.

A second observation pertaining to the classification scheme is the horizontal relationship present among subclasses within the same class. The horizontal relationship refers to the many distinctly different subclasses present within a class that, in sum, comprise the broader group of related technologies. In the case of Photography, the technological problems of automatic camera focusing (subclass 400) are different from those of automatic exposure control (subclass 410). Yet, both technological areas contribute to the broader field of Photography. It is possible that a manufacturer of cameras or camera parts may pursue a competitive advantage through enhanced camera focusing while another concentrates on improved exposure control. Even if competing cameras contain both technologies, the suppliers of the respective technologies, the firms actually holding the patents, may not be direct competitors.

A third observation with regard to the classification scheme is the vertical relationship between some subclasses within a class. The vertical relationship refers to the hierarchical nature of some subclasses. The relationship between subclasses 410, 425, and 426, mentioned above, illustrates the point (see Figure 3 -1). Subclass 410 contains patents that relate to the camera's automatic exposure control system or device. This is considered a main line technology within the patent class. However, a patent pertaining to an automatic exposure control system or device is assigned to subclass 410 only if it cannot be assigned to a more specific subclass within the same main line. Thus, a patent pertaining to an automatic exposure control system having a log transformation circuit would be assigned to subclass 425, while one having a log transformation circuit that is digital would be assigned to subclass 426.

Multiple subclasses within the same main line indicate the growing technological sophistication of the technology. Therefore, while the subclasses within the main line are related technologically, they vary in terms of the approach taken within each technological area. With reference to the above example, if only one technological approach was taken in solving the problem of automatic exposure control all patents would be assigned to subclass 410. However, as multiple approaches are discovered subclasses are created and patents are assigned to the new subclasses within the main line that correspond to the technological approach taken.

In summary, although some patent classes resemble identifiable industries, analysis at the patent class level would incorrectly group competing and noncompeting firms. Second, main line subclasses within a patent class are technologically distinct enough to be considered unique. And third, though there is a hierarchical relationship among subclasses within the same main line, each subclass represents a uniquely different approach. For these reasons the current research defines the relevant industry to be only those firms operating within a particular subclass.

A Caveat - The decision to define the relevant industry at the subclass level is based on the many arguments presented above. Since each subclass constitutes an industry, it is possible to test the model with any subclass sample of sufficient size. However, part of the motivation for a patent based approach is to develop a model useful to managers and other decision makers. While a competitive threat can come from any class and subclass, managers are most likely to be concerned with technological developments known to be relevant to their overall industry. Therefore, while testing the model with totally unrelated subclasses is theoretically defensible, to do so would leave the question of managerial relevance still unanswered.

To maintain managerial relevance the current study uses subclasses drawn from one patent class, class 354 - Photography. Each subclass has some relationship with the overall industry of Photography but, as stated earlier, the technological problems of automatic camera focusing (subclass 400) are different from those of automatic exposure control (subclass 410). Yet, both technological areas contribute to the broader field of Photography.

The Photography class is interesting for a variety of reasons. First, photography ranks 5th among all U.S. industries in the percent of net sales spent on R&D activities (Scherer and Ross 1990). Second, researchers in photography show a propensity to patent their technological innovations. The Eastman Kodak Company is a leader among U.S. firms in the filing of patents applications and has helped pioneer recent patent-citation research (Albert et al. 1990). And, third, research in Photography has important international implications, with 57.6% of all U.S. patents assigned to the Photography class held by Japanese firms (Narin and Frame 1989).

CASSIS - A U.S. PATENT DATA BASE

An advantage to using United States patent data is its increasing availability. Microfilm copies of patents have been available at the United States Patent and Trademark Office (USPTO) in Washington D.C. and at patent depositories located throughout the country. However, in the early 1970s the USPTO began computerizing patent information. One form of computerized patent data is the

Classification and Search Support Information System (CASSIS).

The CASSIS system provides patent data in a computer-readable form using a CD-ROM. CASSIS provides access to current patent classification information, the primary focus of the current study. It also allows patents to be searched according to patent number, issue year, submitting company (based on an assignee code), the state and country from which the patent originated, the patent class and subclass, and key words in the title or abstract. However, this information is available only from 1969 forward. In addition, other patent information, such as the previous patents and scientific journals cited on the front page of a patent, is not available through this system. The CASSIS disc used in the current study provided patent data from 1969 to August 1990.

Patent numbers indicate the type of patent and are assigned according to filing date with the first patent number issued in 1836. Currently "utility" patents, the name given to an original product or process patent, are assigned a seven digit number. Additional patent types are identified according to the following alpha prefix: A (additional improvement); T (defensive publication, a conditional patent waiver); D (design patent, for ornamental designs); PP (plant patent, for asexually reproduced plants), H (formerly used for defensive publications); X (approximately 1,000 of the 10,000 "Name and Date Patents" granted before 1836); RD (reissued design patent); RE (reissued utility patent); RX (reissued X number) (USPTO 1990). These additional patent types were removed from the data since the current study focuses on original research activity, which is represented by utility patents.

SECTION TWO: SAMPLE SELECTION

The earlier caveat explained the reasons for choosing only those subclasses that are in the class 354 - Photography. Currently, class 354 contains 405 subclasses. These subclasses, in turn, contain over 30,000 patent assignments, the first of which was granted in 1842.

Subclasses that contain patents granted prior to 1969 create somewhat of a problem for testing the current model since information pertaining to these patents is not available on the CASSIS system. In some subclasses no patent information is available because all patent activity took place prior to 1969. Conversely, in twenty two instances the subclass itself was created sometime after 1969 and all of the patent activity can be measured.

An evaluation of each subclass was conducted to determine the percentage of patents assigned to the subclass that were granted after 1969. The decision was made to choose only those subclasses where at least 50 percent of the patent activity could be measured. By choosing subclasses where at least 50 percent of the activity could be measured the overall percentage of patents available for analysis was kept high (78.3 percent), and the sample size was sufficient to test the model (N=181).

The use of the above selection criteria implies that those subclasses where at least 50 percent of the patents can be measured are similar to those subclasses where 100 percent of the patent activity can be measured. It also implies that subclasses where less than 50 percent of the patent activity can be measured are somehow different. This assumption will be tested as part of the data analysis.

From a managerial perspective the removal of subclasses that lack recent patent activity is of little importance. A review of the sample shows that those subclasses where at least 50 percent of the patents were granted since 1969 are the technological areas that have generated the most significant recent innovation in photography.

SECTION THREE: OPERATIONALIZATION OF THE VARIABLES

The operationalization of all variables with the exception of Lead Time was accomplished using the CASSIS CD-ROM data base. The measurement period, again with the exception of Lead Time, is from 1969 to August 1990. Patents in a subclass held by firms identified as noncompeting firms, according to the process described earlier, were removed before final measurement.

Since the model is a study of patent activity at the subclass level and each subclass contains data for every patent assigned to that subclass, it is the assignment of the patent to the subclass that allows the variables to be measured. Thus, the actual unit of measurement in the study is the assignment of a patent to a subclass.

The model includes five independent variables: the number of competitors researching in a technological area (X_1), the level of research concentration among competing firms (X_2), the amount of lead time between when the first firm enters a technological area and when a competing firm enters (X_3), the degree to which competing firms have focused their research in a technological area (X_4), and the degree of complexity inherent in the technological area (X_5). The model also contains an interaction between the degree to which firms have focused their research in a technological area (X_4) and the degree of technological complexity present in the area (X_5). The dependent variable is the amount of research activity in a technological area (Y_1).

Number of Competitors (X_1) measures one aspect of the structure of the research industry. The variable was measured by counting the number of different assignee codes in each patent subclass. Each assignee code represents a different competing firm. Patents without an assignee code are held by individual inventors. These patents are generally considered to be relatively unimportant (Narin and Olivastro 1988) and were removed.

$$X_1 = C_{is}$$

where C is the number of firms i in subclass s.

Research Concentration (X_2) is a second characteristic of industry structure. The variable was measured by first computing the percentage of patents held by each firm patenting in the subclass. The four firm Research Concentration Ratio (RCR4) was then computed as the total percentage of patents held by the four most active firms in the subclass. This method of measuring concentration is comparable to the four firm concentration ratio (CR4) commonly used by economists. An alternative measure of industry concentration is the Herfindahl-Hirschman Index (HHI). This method combines both the number of firms and the degree to which inequality exist within the industry by squaring the industry share held by each firm. A sample comparison was made between the two measures using 49 subclasses with various degrees of research concentration. No significant difference between the two methods was detected. Indeed, Scherer and Ross (1990) report a correlation between the two methods of .954. As a result, the four firm method, the one most commonly used and reported, was utilized.

$$X_2 = \sum_{i=1}^{4} S_{is}$$

where S_{is} is the research share (S) held by firm i in subclass s and i = 1, 2, 3 or 4 when S_{is} is among the four highest research shares held by all firms in subclass s.

$$S_{is} = \frac{P_{jis}}{\sum_{i}^{n} P_{jis}}$$

where P_{jis} is the sum of all patents j held by firm i in subclass s and $\sum_{i}^{n} P_{jis}$ is the sum of all patents j held by all firms i in subclass s.

Lead Time (X_3) measures the length of time the pioneer firm in the subclass conducts R&D without the threat of direct competition. The variable was measured as the length of time in months between the month and year the initial patent in the subclass was issued and the month and year the first competing firm entered the subclass. This information was not available on the CASSIS system and was obtained from microfilm at the patent depository in the public library in Detroit, Michigan.

$$X_3 = D_{i1,s} - D_{i2,s}$$

where D_{i1s} is the issue date (D) for firm i1s, the first firm i issued a patent in subclass s, and D_{i2s} is the issue date for firm i2s, the second firm i to be issued a patent in subclass s.

Technological Focus (X_4) measures the degree to which firms active in the subclass focus their research in that specific subclass. The variable was measured by first computing a ratio of the number of patents issued to the firm in the subclass divided by the total number of patents issued to the firm in all subclasses. This ratio was then averaged across all firms patenting in the subclass.

$$X_4 = \frac{\sum_{i}^{n} F_{is}}{n}$$

where F_{is} is the subclass focus (F) of firm i in subclass s and n is the number of firms in subclass s.

$$F_{is} = \frac{P_{jis}}{\sum_{s}^{n} P_{jis}}$$

where P_{jis} is the sum of all patents j held by firm i in subclass s and $\sum_{s}^{n} P_{jis}$ is the sum of all patents j held by firm i in all subclasses.

Product Complexity (X_5) measures the number of technological areas the patent applies to. The variable was measured as the number of patent subclasses each patent in the subclass was assigned to, divided by the number of patents in the subclass.

$$X_5 = \frac{\sum_{j}^{n} A_{js}}{P_{js}}$$

where $\sum_{j}^{n} A_{js}$ is the sum of all subclass assignments (A) for all patents j in subclass s and P_{js} is the sum of all patents j in subclass s.

Research Activity (Y_1) was measured by counting the number of patents in a patent subclass.

$$Y_1 = P_s$$

where P_s is the sum of all patents in subclass s.

SECTION FOUR: MODEL DEVELOPMENT AND TESTING

The model is founded on two premises: first, that variables have been identified that relate the level of industry research activity to specific aspects of the innovation process in a competitive environment and, second, that comparable variables can be identified and measured in the classification scheme of the U.S. patent data.

The proposed model is a multivariate regression model with five independent variables and one two-way interaction. Mathematically the model reads as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 (55 - X_2)^{-2} - \beta_3 X_3 + \beta_4 X_4 - \beta_5 X_5 - \beta_6 X_4 X_5 + \epsilon$$

where Y is the number of patents in the subclass, β_0 is the intercept, + $\beta_1 X_1$ is the positive relationship between Y and the number of competitors in the subclass, + $\beta_2 (55 - X_2)^{-2}$ is the nonlinear relationship between Y and research concentration, - $\beta_3 X_3$ is the negative relationship between Y and lead time, + $\beta_4 X_4$, is the positive relationship between Y and research focus, - $\beta_5 X_5$ is the negative relationship between Y and product complexity, - $\beta_6 X_4 X_5$ is the negative relationship between Y and research focus when product complexity is high, and ϵ is the error term.

The transformation term $(55 - X_2)^{-2}$, the only term in the model not explained in earlier chapters, is derived from research conducted by economists studying industry structure and R&D/sales ratios. At various times economists have found R&D/sales ratios, a measure of research effort, to peak when four seller concentration reached 50 to 55 percent (Scherer 1967), 52 percent (Levin et al. 1985), and 64 percent (Scott 1984). Since there have been no previous studies using patent assignment to a subclass as a unit of measure and the percentage of patents held as a measure of concentration it is unclear at what concentration level research activity will be maximized. The 55 percent is suggested as a supportable starting point.

The test of the model will essentially be a test of the proposed theory, not a search for the best overall model or for predictive validity. The goal is to test the statistical significance of each independent variable and the overall R^2.

No previous model has combined and measured these four variables using patent data. Therefore, it is difficult to estimate the size of the coefficients and the R^2. One study relating industry structure, including industry concentration, to industry research activity achieved R^2s of between .5 and .6. Another obtained an R^2 of .40 when relating technical skills and resources, and market intelligence, two variables that in combination reflect at least to some degree the firm's focus on a problem, to technical activities (Calantone and di Benedetto 1988). Recent patent based research has not used regression analysis. However, the above model should provide R_2s comparable to previous industry structure and innovative process based research.

CHAPTER FOUR

MODEL ANALYSIS AND RESULTS

Chapter Four discusses the data sample and presents the results of the model analysis. The chapter begins with a description of the sample data. A comparison is made between subclasses included in the analysis and those that were excluded. As explained in Chapter Three, a subclass was excluded from the analysis if less than 50 percent of the patent activity was measurable. A subsample from the sample used is compared to a subsample of subclasses that were excluded from the analysis to check for this potential sampling bias.

Each hypothesis is then tested based on the full regression model and the corresponding correlation matrix. A univariate analysis of each variable is also presented to further explain the regression results. Support is provided for altering the measurement of the research concentration variable. And, finally, a second model with an alternative hypothesis is tested and the regression results discussed.

THE SAMPLE DATA

The sample data was selected from the CASSIS system available from the U.S. Patent and Trademark Office. All variables were measured using the CASSIS system with the exception of the lead time variable, which was measured using hard-copy patent records.

The selection of the sample is based on the criteria outlined in Chapter Three. The first criterion is that all subclasses be drawn from within patent class 354 - Photography. This criterion helps ensure the managerial relevance of the current model by confining the data to a single group of related technologies.

The second criterion requires that at least 50 percent of the patent activity within a subclass be measurable. Without this criterion subclasses would be included in the sample that contained few measurable data points, effectively reducing the variation in the dependent and independent variables. By choosing subclasses with at least 50 percent measurable patent activity, the overall percentage of patents available for analysis was kept high (78.3 percent) and the sample size was sufficient to test the model.

The resulting sample consists of 181 subclasses. The subclasses are from 23 of 41 possible "main line" areas within the Photography class (Table 4 - 1). As described in Chapter Three, a "main line" represents a major subclass area. The number of subclasses per "main line" serves as an indicator of the degree of technological specificity in the area. Though the selected sample contains only 44.7 percent of all possible subclasses, these subclasses represent 56.1

percent of all "main line" areas and the "main lines" represented are some of the most technologically specific in the class.

TABLE 4 - 1

COMPARISON OF SELECTED AND NONSELECTED SUBCLASSES

	Original	Selected	Not Selected
Mainlines	41	23	18
Subclasses	405	181	224
Subclasses/Mainline	9.9	15.1	3.2
Patent Assignments (from 1969 to 1990)	22,273	14,938[1]	5,480
Patent Assignments/ Subclass	55	82.5	24.5
% of measurable Patent Activity	49.4	78.3	26.0

[1] Originally the selected subclasses contained a total of 16,793 patent assignments. However, 1,855 patent assignments were excluded from the analysis because they represented patents held by individuals (see Chapter Three).

The unit of analysis is the assignment of a patent to a subclass. In the selected sample 14,938 patent assignments were made, with an average of 82.5 patent assignments per subclass. Even with the removal of patents held by individual inventors, the selected subclasses contained 67.1 percent of all patent assignments made since 1969.

The percent of measurable patent activity is the number of patents assigned to the subclass since 1969 divided by the total number of patents assigned to the subclass. In the selected subclasses an average of 78.3 percent of all patents assigned to the subclasses were assigned since 1969. This percentage is considerably higher than the measurable patent activity for the nonselected subclasses as well as for the entire original data base.

COMPARING SAMPLE AND NONSAMPLE SUBCLASSES

Based on the 50 percent measurability criterion, 224 subclasses were excluded from the analysis. In seven of these subclasses all patent assignments were made prior to 1969, making the percent of measurable patent activity for these subclasses zero. The measurable patent activity for the remaining 217 ranged from less than 1 percent to 49 percent. On average, the measurable patent activity in the 224 subclasses that were not selected was 26 percent (Table 4 - 1). From Table 4 - 1 and the preceding discussion it is clear that the excluded subclasses represent technological areas that have, in general, not been as active as those in the selected sample during the past twenty years.

However, the inability to measure at least 50 percent of the patent activity does not necessarily preclude using the current model. The 50 percent criterion simply helps to ensur

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ensure that the model is not rejected on the basis of inadequate measurement alone.

The purpose of comparing subsamples of the subclasses used to those from the excluded subclasses is to see if screening on the basis of the percentage of measurable patent activity biases the sample. Four data subsamples were taken. The average measurable patent activity in the subclasses in each subsample was 20, 40, 60 and 80 percent, respectively. Thus, two subsamples came from subclasses excluded from the original sample and two were from the original sample. Each of the four data subsamples had a sample size of 22.

Unfortunately, measures of some independent variables in nonsample subclasses were not available. It was possible, however, to obtain Pearson correlations for three independent variables and the dependent variable. The three independent variables that could be measured were the number of competitors (X_1), research concentration prior to transformation (X_2), and technological complexity (X_5). Table 4 - 2 compares the four Pearson correlation matrixes.

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TABLE 4 - 2

SUBSAMPLES OF SUBCLASSES HAVING 20, 40, 60, AND 80 PERCENT MEASURABLE PATENT ACTIVITY

PATENT ACTIVITY MEASURED EQUALS 20%

	X_1	X_2	X_5
Y_1	.853****	-.610***	-.183
X_1		-.889****	.027
X_2			-.187

PATENT ACTIVITY MEASURED EQUALS 40%

	X_1	X_2	X_5
Y_1	.867****	-.324	-.234
X_1		-.685****	-.206
X_2			-.125

PATENT ACTIVITY MEASURED EQUALS 60%

	X_1	X_2	X_5
Y_1	.689****	-.016	-.179
X_1		-.591***	.227
X_2			-.377*

PATENT ACTIVITY MEASURED EQUALS 80%

	X_1	X_2	X_5
Y_1	.630***	.296	-.188
X_1		-.422*	.173
X_2			-.426*

*p = .10; **p = .05; ***p = .01; ****p = .001

There are few apparent differences when comparing the four subsamples. All subsamples show a strong relationship between the number of competitors in a subclasses and the number of patents in each subclass. And in each case the number of competitors is negatively and significantly correlated with research concentration. The finding of no difference suggests that testing the model with subclasses where the measurable patent activity is less than 50 percent does not create a sampling bias.

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MODEL ANALYSIS AND HYPOTHESIS TESTING

Table 4 - 3 provides the regression results for the full model and Table 4 - 4 provides the Pearson correlation matrix. These tables are based on results obtained via the PROC REG and CORR procedures in the SAS statistical software package (SAS 1985).

In the full model all of the coefficients are in the directions hypothesized but only three independent variables are significant. The model has an unadjusted R^2 of .6017, with an adjusted R^2 of .588. The correlation matrix shows four of six correlations between the dependent and independent variables to be significant. There is also significant correlation among independent variables, some of which will be examined in the current analysis.

TABLE 4 - 3

MULTIPLE REGRESSION RESULTS: FULL MODEL

Variable	Coefficient (Std. Error)	Significance
X_1 Number of competitors	3.55 (.2616)	.0001
X_2 Research concentration (RCR4 transformed)	.0496 (.0165)	.0031
X_3 Lead time	-.2175 (1.69)	.8978
X_4 Technological focus	102.37 (244.63)	.6761
X_5 Technological complexity	-24.60 (9.63)	.0115
X_6 Interaction between X_4 and X_5	-69.31 (67.47)	.3057
Intercept	93.73 (33.50)	.0057
R^2	.6017	
F value	43.81	.0001
d.f.	6	
N	181	

TABLE 4 - 4

PEARSON CORRELATIONS OF ALL VARIABLES

	Number of Patents Y_1	Number of Competitors X_1	Research Concentration X_2	Lead Time X_3	Technological Focus X_4	Technological Complexity X_5	Interaction X_4 and X_5 X_6
Y_1		.654****	.271****	-.290****	.116	-.146**	.065
X_1			.144*	-.429****	.495****	.277****	.503****
X_2				-.100	.070	-.051	.042
X_3					-.252***	-.117*	-.237***
X_4						.293****	.975****
X_5							.461****
X_2	-.104	-.644****		.440****	-.469****	-.312****	-.488****

(Research Concentration before transformation; transformation = $(55\text{-RCR4})^{-2}$)

*p = .10; **p = .05; ***p = .01; ****p = .001

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TEST OF HYPOTHESES

H_1 The greater the number of firms granted patents in a patent subclass (X_1) the higher the number of patents granted in the subclass (Y).

The regression results show a significant, positive coefficient for X_1 of 3.55. Thus, the greater the number of firms granted patents in a patent subclass, the higher the number of patents granted in the subclass. The first hypothesis is therefore accepted.

Two aspects of the innovation process are evident with this finding. The first is the competition-driven nature of the process. Under basic economic assumptions, as the number of firms in an industry increases, the probability of success (in terms of profitability or market position) for any one firm decreases. This expected result is particularly true when the industry is narrowly defined, encompassing those competitors that compete most directly. The current model is tested using industries that are narrowly defined.

An increasing number of competitors increases the risk to firms in the industry, thereby increasing the need to pursue greater competitive advantage. Innovation is one means of obtaining a competitive advantage (e.g. Alderson 1965; Porter 1985). As the need to obtain a competitive advantage increases, so does the firm's tendency to innovate. This theoretical argument is strongly supported by the regression results.

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The firm's ability to appropriate the benefits of its innovations is the second aspect of the innovation process underlying the regression results. It is important to note that by using patent data the model assumes a competitive environment that provides protection for innovating firms. The positive relationship between the number of competitors and the number of patents holds, given the presence of this protection.

Innovation models in the economics literature show similar results as long as the model allows for the appropriation of innovation benefits. In models that do not allow for the appropriation of benefits, firms are less likely to innovate. A similar result may be found with the current model if it is tested using variables operationalized in an environment that does not allow for the appropriations of innovation benefits.

H_2 The number of patents granted in a patent subclass (Y) will be highest when the share of patents in the patent subclass held by the top four firms (X_2) is moderate.

The regression result for X_2 indicates that after transformation, the RCR4 variable has a positive and significant affect on the dependent variable. Thus, H_2 is initially accepted. As with X_1, this result is also consistent with recent (non-patent) empirical studies in the economics literature.

However, a more complete examination of the transformed variable showed a potential problem. The univariate analysis showed a skewed distribution, large variance and an inappropriately high maximum value of 2500. This value resulted from the transformation of a single data point. The inappropriately high value was removed by reducing the number of decimal points read into the transformation equation. However, when the high value was removed, the variable's coefficient was no longer statistically significant.

The loss of significance with the removal of a single data point represents an instability in the variable when tested in the full model. As a result, the acceptance of X_2 is questionable. Later in this chapter an attempt is made to resolve the instability of the measurement and to more firmly establish the relationship between X_2 and the dependent variable.

H_3 **The longer the time period between when the first firm is granted a patent in a patent subclass and when a competing firm is granted a patent in the same subclass (X_3), the lower the number of patents in the subclass (Y).**

Though in the anticipated direction, the coefficient for the lead time variable is not statistically significant; therefore, H_3 is rejected. Based on the analysis, a shorter time between the pioneering firm and the first competing firm does not necessarily lead to a greater number of pat

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patents in the subclass. However, this result may be more a function of the way the variable is measured than a true test of the hypothesized relationship.

The initial univariate analysis of the variable indicated an extremely skewed distribution. The square root of the measure was used in an attempt to minimize the effect of skewness, with only marginal improvement in the distribution. The highly skewed distribution may be preventing a true test of the null hypothesis. In the future an alternative measure of the variable may prove more fruitful in testing the hypothesized relationship.

The issue of a poor measure notwithstanding, the lack of significance may also call into question the assumption that new firms entering a patent subclass (i.e. a technological area) are perceived by the initial firm in the subclass as competitors. It is possible that a new firm may introduce technology that is complementary to previous patents. As a result, a pioneering firm may wait to see the developments patented by subsequent firms, a reaction that would detract from the positive relationship hypothesized. Thus, in addition to developing a new measure for the variable, added work needs to be done regarding the pioneer/follower relationship in a patent subclass.

H_{4a} The greater the average of each company's percent of patents filed in a patent subclass (X_4) the higher the number of patents in the subclass (Y).

The technological focus variable has a positive coefficient (102.37) in the regression model and is positively correlated with the dependent variable (correlation = .11564) but the regression coefficient is not significant. Therefore, H_{4a} is rejected. Further discussion of this result will come with the discussion of the interaction term tested in H_{4b}. The test of the H_{4b} hypothesis is reserved until after the discussion of H_5 since the complexity variable (H_5) is part of the interaction tested in H_{4b}.

H_5 The greater the number of subclasses assigned to the average patent in the subclass (X_5) the lower the number of patents in the subclass (Y).

Hypothesis H_5 is accepted. The observed relationship between technological complexity and the dependent variable is negative (-24.60) and statistically significant.

The assignment of a patent to multiple subclasses is a measure of the patent's technological complexity. The negative relationship supports the argument that technologically complex innovations require more time. In the patent data environment this means the number of patents granted in patent subclasses that contain technologically complex patents will increase more slowly over time.

H_{4b} As technological complexity (i.e. the total number of subclasses the average patent in a patent subclass is assigned to - X_5) increases, the greater the technological focus (i.e. the average

of each company's percent of patents filed in a patent subclass - X_4), the lower the number of patents in the subclass (Y).

The interaction term (X_6) used to test hypothesis H_{4b} was in the direction hypothesized but was not statistically significant. As a result, H_{4b} was initially rejected.

However, inconsistencies in the analysis indicated a need to further examine the variable. While the regression coefficient was negative (though not statistically significant), the Pearson correlation between the interaction term and the dependent variable was positive but not significantly different from zero (Table 4 - 3). The switch in the sign indicates high multicollinearity in the full regression model.

Certainly correlation between the interaction term and the independent variables that comprise it is expected. However, the correlation between technological complexity (X_5) and the interaction term (X_6) was .461, while the correlation between technological focus (X_4) and the interaction term (X_6) was .975.

The ordinary least squares (OLS) estimation procedure uses only variation unique to each regressor when estimating each coefficient. For the purpose of coefficient estimation (as opposed to the determination of the model's R^2), variation that is common to two or more regressors is discarded (Kennedy 1985). A correlation of .975 means that very little variation in the dependent variable can be attr

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attributed to either the technological focus variable alone or the interaction term alone. As a result, the coefficients for both were not significant. The technological complexity coefficient, on the other hand, was significant.

Given the extremely high correlation between X_4 and X_6, the model was rerun with the technological focus variable removed. Dropping technological focus rather than the interaction term allows the impact of technological focus to be included while still providing the opportunity to test the hypothesized interaction. The results (Table 4 - 4) show that by dropping technological focus, the interaction term becomes highly significant in the direction anticipated. Based on the revised model, hypothesis H_{4b} is accepted.

With the omission of the technological focus variable, the regression results show four of six hypotheses being accepted. The model has an R^2 of .6013, essentially the same as the R^2 for the full model. The F value tests against a null model where each variable coefficient is equal to zero. The F test indicates the hypothesized model is significant at the .0001 level.

TABLE 4 - 5

MULTIPLE REGRESSION RESULTS:
FULL MODEL & MODEL MINUS TECHNOLOGICAL FOCUS

Variable	Full Model Coefficient (Std. Error)	Minus Focus Coefficient (Std. Error)
X_1 Number of competitors	3.55**** (.2616)	3.56**** (.2606)
X_2 Research concentration (RCR4 transformed)	.0496*** (.0165)	.0502*** (.0164)
X_3 Lead time	-.2175 (1.69)	-.3119 (1.67)
X_4 Technological focus	102.37 (244.63)	
X_5 Technological complexity	-24.60** (9.63)	-27.80**** (5.82)
X_6 Interaction between X_4 and X_5	-69.31 (67.47)	-41.43**** (10.52)
Intercept	93.73*** (33.50)	105.03**** (19.78)
R^2	.6017	.6013
F value	43.81	52.79
d.f.	6	5
N	181	181
Model significance	P<.0001	P<.0001

**p = .05; ***p = .01; ****p = .001

UNIVARIATE ANALYSIS

A univariate analysis is presented for the purpose of describing the statistical characteristics of each variable. These characteristics (i.e. mean, standard deviation, skewness, etc.) provide important information regarding why the hypothesized relationships may or may not be present.

Number of Competitors (X_1)

The number of competitors measures one aspect of the competitive environment within which firms innovate. The measure simply counts the number of firms patenting in a patent subclass. The regression result supports the hypothesized positive relationship between the number of competing firms and the number of patents granted in a patent subclass.

The measurement presumes that each firm patenting in a subclass is a competitor or a potential competitor. It is conceivable that a subsequent patent may in fact complement rather than compete with a preexisting patent. Therefore, the firm holding the complementary patent would not be a true competitor. However, even in a complementary situation the presence of the complementary innovation threatens the first firm's technological hegemony. Therefore, each patenting firm is considered a competitor in the subclass.

The analysis shows a mean number of competitors of 24, with a range from 3 to 80 (Table 4 - 6). The positive skewness indicates the sample mean may not be centered over the true mean (i.e. a biased estimator) but given the regression results, the variance is apparently small enough to allow a test of the relationship hypothesized.

TABLE 4 - 6

NUMBER OF COMPETITORS (X_1)

mean	24.0031	median	20	minimum	3
std. dev.	14.4676	mode	19	maximum	80
skewness	1.3981	D:normal	.14804	(prob.	<.01)
N 181					

Research Concentration (X_2)

The research concentration variable is another aspect of the competitive structure of the industry. In the current research the variable is measured in terms of the amount of research held by the top four firms in each subclass. The initial regression result supports the hypothesized inverted "U" relationship but as indicated in the following discussion, this result is highly suspect.

Table 4 - 7 describes the four firm research concentration ratio (RCR4) before transformation. The analysis shows RCR4 to be normally distributed with a mean of 59 and a standard deviation of 16.

TABLE 4 - 7

RESEARCH CONCENTRATION (X_2)

mean	59.0808	median	58.13	minimum	22.44
std. dev.	16.7374	mode	50.00	maximum	100.00
skewness	.1612	D:normal	.07394	(prob. >.017)	
N 181					

The original variable was transformed before testing the model. As presented in Chapter Three, the transformation equation is, "RCR4 transformed = $(55 - \text{RCR4})^{-2}$". The transformation equation takes the hypothesized nonlinear inverted "U" relationship and converts it to a linear relationship. The impact of the transformed variable is greatest when the difference between 55 and the research concentration ratio is between 1 and -1 (i.e. when the research concentration ratio falls between 54 and 56 inclusive). The impact decreases at concentration levels below and above these percentages. No RCR4 measurement of exactly 55 percent is transformed because the resulting transformation would be zero.

A skewed distribution was expected after transformation since all values below 54 and above 56 are converted to a positive number less than 1. However, the transformed variable showed extreme skewness and large variance, both of which can be attributed to the extreme maximum value (Table 4 - 8). As discussed earlier, alterations to the maximum value resulted in a loss of significance. The following section in this chapter discusses the resolution of this problem.

TABLE 4 - 8

RESEARCH CONCENTRATION (X_2) - transformed

mean 14.1103	median .013	minimum .0005	
std. dev. 185.808	mode .04	maximum 2500	
skewness 13.452	D:normal .503	(prob. <.01)	
N 181			

Lead Time (X_3)

Lead time measures the length of time a pioneer firm operates within a patent subclass without the threat or assistance of direct competition. The measurement is the time, in terms of months, between the granting of the initial patent in a subclass and the granting of a patent to the first competing firm to enter the subclass. The hypothesized relationship was not supported by the regression result though the coefficient was in the direction anticipated.

Analysis (Table 4 - 9) shows the variable to be positively skewed, with the median and mode values considerably less than the mean value. In fact, the analysis shows 75 percent of the lead time values to be 12.5 months or less. It is clear that far more than half of the data points are less than the mean value of 11 months.

TABLE 4 - 9

LEAD TIME (X_3)

mean (months)	11.0884	median	5	minimum	0
std. dev.	18.7905	mode	2	maximum	145
skewness	4.2827	D:normal	.27756 (prob. <.01)		
N 181					

To reduce the effects of the highly skewed distribution, the square root of the lead time measure was taken before introducing the variable into the regression model. The square root transformation shifts the mean, median, and mode by significantly reducing large outlying values. As lead time values approach one the effects of the transformation are less noticeable.

The univariate analysis of the square root of the measure is presented in Table 4 - 10. The transformation has improved the distribution with the median value now nearly equal to the mean. However, even with the improved distribution, the variable's coefficient was still not statistically significant.

TABLE 4 - 10

LEAD TIME (X_3) - Square Root

mean	2.675	median	2.24	minimum	0
std. dev.	1.989	mode	1.41	maximum	12.0
skewness	1.678	D:normal	.14322 (prob. <.01)		
N 181					

Technological Focus (X_4)

The purpose of including a measure of technological focus in the model was to see if the degree to which a firm concentrated its research effort in a particular technological area affected the number of patents granted in that area. Though the regression coefficient was positive and in the direction anticipated, the coefficient was not significant and the hypothesis was rejected.

The variable has a broad range of values, .00058 to .39476 and, as has been the case with the other measures, the distribution is skewed (Table 4 - 11). However, the skewed distribution is not nearly as extreme as in the original lead time variable or the transformed research concentration measure. In fact, the distribution of the technological focus measure is the second least skewed of all independent variables.

However, high correlation between X_4 and X_6 and the use of OLS estimation may account for the lack of significance. As explained earlier, OLS uses only that variance unique to an individual variable when testing the variable's significance. With a correlation of .975 between X_4 and X_6, very little nonoverlapping information could be attributed to either of these variables.

TABLE 4 - 11

TECHNOLOGICAL FOCUS (X_4)

mean	.09973	median	.07889	minimum	.00058
std. dev.	.09228	mode	.00058	maximum	.39476
skewness	1.26182	D:normal	.14132	prob. <.01)	
N 181					

Technological Complexity (X_5)

Technological complexity is a measure of the extent to which a patent has implications in additional technological areas. The greater the number of technological areas, the more complex the patent. The regression result supports the hypothesis that fewer patents will be generated in technological areas that are more complex.

An analysis of the variable showed an equal mode and median value, both of which were only slightly less than the mean value (Table 4 - 12). The distribution is positively skewed but the variance is apparently low enough to allow the hypothesized relationship to be tested.

TABLE 4 - 12

TECHNOLOGICAL COMPLEXITY (X_5)

mean	3.35	median	3.25	minimum	2.26
std. dev.	.5841	mode	3.25	maximum	5.25
skewness	.9261	D:normal	.0919	(prob. <.01)	
N 181					

Interaction Term (X_6)

The interaction term provides an opportunity to view the effect that both technological complexity and the level of technological focus within the industry have on research effort. Based on contemporary literature, the effect is hypothesized to be negative. Though the hypothesis was not supported by the initial regression result, it was supported once X_4 was removed from the model.

The range of values and the highly skewed distribution is expected given the skewness of the two main effects involved in the interaction (Table 4 - 13). As discussed earlier, the high multicollinearity with technological focus means that very little information can be attributed solely to the interaction term when it is regressed against the dependent variable.

TABLE 4 - 13

INTERACTION TERM (X_6)

INTERACTION BETWEEN TECHNOLOGICAL FOCUS (X_4) AND TECHNOLOGICAL COMPLEXITY (X_5)

mean	.34978	median	.23445	minimum	.0021
std. dev.	.35792	mode	.00211	maximum	1.5997
skewness	1.51042	D:normal	.16569	(prob. <.01)	
N	181				

The univariate analysis provides some additional explanations for the observed regression results. The original measurement of the lead time variable required transformation (by taking the square root) due to extreme skewness in the distribution. Even after transformation the variable's distribution was the most skewed and the regression coefficient was not significant.

The distribution of the technological focus variable was also skewed, though not as severely as many other variables. But the variables regression coefficient was nonsignificant nonetheless. Multicollinearity between technological focus and the interaction term may account for this result.

While no independent variable introduced into the model was normally distributed, the two with the least skewed distribution and the smallest variance (X_1 - number of competitors, and X_5 - technological complexity) both proved to be significant in the regression.

The instability of the third significant variable, research concentration, is easily attributed to the extreme maximum value obtained during transformation. However, once the maximum value is removed the variable's coefficient is no longer significant. The following section examines the variable's instability and redefines the relationship between research concentration and the dependent variable.

A REASSESSMENT OF THE RESEARCH CONCENTRATION VARIABLE

Though initially significant, the transformed RCR4 measure showed an unusually high value which, when altered, caused the variable to no longer be significant. The instability of the measure warranted further investigation.

A plot of the data showed a distribution that resembled an inverted "U", with the highest number of patents in the subclass (the models dependent variable) found between research concentration levels of 33 percent and 66 percent. As research concentration increased from moderate to high levels, the negative relationship between research concentration and the number of patents in the subclass was clear and well defined. At low to moderate concentration levels the positive relationship was also clear but a great deal of variation in the data was observed. The initial regression results and the lack of definition observed in the positive slope of the inverted "U" caused the original assumption of an inverted "U" relationship to be questioned.

Before discarding the inverted "U" hypothesis, an analysis was conducted to test the relationship while at the same time avoid irregularities that might occur during a transformation. First, the raw data was separated into three parts, at the 33 percent and 66 percent research concentration levels. The partitioning was consistent with the observed data.

Next, the measure was reintroduced into the model as a dummy variable. The dummy variable was given the value of 1 when research concentration was between 33 percent and 66 percent, and zero when equal to or less than 33 percent or equal to or greater than 66 percent. Thus, the impact of the independent variable on the dependent variable would be felt only at moderate research concentration levels. The regression analysis showed research concentration not to be significant and the model's R^2 declined to .5848.

Given the instability of the measure in the original analysis and the failure of the second analysis to confirm the inverted "U" hypothesis, H_2 must be rejected.

However, as indicated above, the analysis of the data plot showed a positive relationship between research concentration and the number of patents in a subclass at low to moderate concentration levels and a negative one at moderate to high levels. Both the positive and negative relationships are consistent with earlier economic theory (see Chapter Two). Repeated trials of research concentration regressed onto the dependent variable showed the hypothesized decline to occur in the current data after industry research concentration reached approximately 40 percent.

As a result, the following alternative hypothesis is proposed:

H_{2A} **When the share of patents in the patent subclass held by the top four firms (X_2) is less than or equal to 40 percent, as the share of patents in the patent subclass held by the top four firms (X_2) increases, the number of patents granted in a patent subclass (Y) will increase.**

To test the hypothesis the measure was again converted to a dummy variable. The variable was assigned a value of one when research concentration was equal to or less than 40 percent and zero when research concentration was greater than 40 percent.

The results (Table 4 - 14) indicate a significant relationship between research concentration and the dependent variable and an improved R^2. At research concentration levels equal to or below 40 percent the research concentration variable is introduced into the model and effectively reduces the intercept term to zero. As a result, the independent variables now account for more of the variance in the dependent variable, which is reflected in the higher R^2.

When compared to the initial regression results, the full model with the dummy variable shows a loss of significance for both the intercept term and the technological complexity variable. The significance levels for both terms have only marginally moved out of the acceptable range ($p = .1141$ for the intercept term and $p = .1176$ for technological complexity). When the technological focus var

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variable is removed both terms are again highly significant (Table 4 - 15).

There is also a noticeable suppression of the standard error for both terms once technological focus is removed. The technological focus variable has a high standard error that affects both technological complexity and the interaction term when the variable is included in the model. This high standard error can be attributed to the restricted number of values possible for the technological focus variable. Since technological focus is measured as the average of each firm's percent of total patents filed in the subclass, the variable is limited by the number of competing firms. Once removed, the standard error for both technological complexity and the interaction term decrease significantly.

TABLE 4 - 14

MULTIPLE REGRESSION RESULTS: FULL MODEL WITH RESEARCH CONCENTRATION AS DUMMY VARIABLE

Variable	Coefficient (Std. Error)	Significance
X_1 Number of competitors	4.06 (.2522)	.0001
X_2 Research concentration (RCR4 transformed)	-67.07 (11.18)	.0001
X_3 Lead time	.0999 (1.58)	.9497
X_4 Technological focus	78.11 (227.95)	.7323
X_5 Technological complexity	-14.37 (9.13)	.1176
X_6 Interaction between X_4 and X_5	-50.39 (63.04)	.4252
Intercept	50.75 (31.96)	.1141
R^2	.6528	
F value	54.53	.0001
d.f.	6	
N	181	

TABLE 4 - 15

MULTIPLE REGRESSION RESULTS:
RESEARCH CONCENTRATION AS DUMMY VARIABLE
MINUS TECHNOLOGICAL FOCUS

Variable	Full Model Coefficient (Std. Error)	minus Focus Coefficient (Std. Error)
X_1 Number of competitors	4.06**** (.2522)	4.06**** (.2508)
X_2 Research concentration (RCR4 transformed)	-67.07**** (11.18)	-67.32**** (11.13)
X_3 Lead time	.0999 (1.58)	-.0279 (1.56)
X_4 Technological focus	78.11 (227.95)	
X_5 Technological complexity	-14.37 (9.13)	-16.78*** (5.82)
X_6 Interaction between X_4 and X_5	-50.39 (63.04)	-59.22*** (20.19)
Intercept	50.75 (31.96)	105.03**** (19.78)
R^2	.6528	.6526
F value	54.53	65.74
d.f.	6	5
N	181	181
Model significance	P<.0001	P<.0001

***p = .01; ****p = .001

When compared to the earlier model with the focus term removed (Table 4 - 11), the model containing a dummy variable for research concentration has the same four of six independent variables significant. In addition, the revised model has an R^2 of .6526, up from an R^2 of .6013.

SUMMARY

The analysis of the model found four of six independent variables to be significant. Hypothesis H_1, H_5, and H_{4b} were accepted with a fourth (H_{2A}) accepted in the form of a revised hypothesis. Thus, the number of competitors, research concentration, technological complexity, and the interaction of technological complexity with technological focus all help to account for the total number of patents granted in a patent subclass. More than half of the variance in patent activity was explained with the R^2s of alternative models ranging from .6013 to .6528.

The lead time variable proved not to be significant. While still theoretically defensible, the measurement of the variable prevented a valid test of the relationship. The impact of the technological focus variable is felt through the interaction term but the variable itself was removed due to high multicollinearity.

A comparison of sample subclasses showed no discernible differences between those subclasses where 60 and 80 percent of the patent activity could be measured versus those where only 20 and 40 percent of the activity was measurable. This leaves open the possibility of moving the model to subclasses where less the 50 percent of the patent activity is available for analysis in the CASSIS system.

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CHAPTER FIVE

SUMMARY AND CONCLUSIONS

Using the industrial organization approach from economics, the current research presents and tests a model of factors that affect technological change prior to the launch of a new product or innovation. Chapter Five summarizes the current research and the conclusions that were reached. The chapter also reviews the research contributions, managerial implications, research limitations, and opportunities for future research.

RESEARCH SUMMARY

New products and the technological changes that make them possible are increasingly important to both marketing academics and practitioners. The current study is motivated by the need to further understand the technological change process that ultimately results in new products.

Prior research in marketing and economics confirmed the importance of treating technological change as a dynamic, ongoing process and including the impact of competitive relationships. However, earlier studies either failed to focus exclusively on the technological change process or produced inconsistent results based on inconsistent definitions of the relevant industry. The purpose of the current research is to present and test a model of factors that affect technological change prior to the launch of a new product or innovation, while avoiding the weaknesses of earlier studies.

To accomplish this goal the current study introduces a model comprised of variables that have been identified to have an impact on innovative activity within an industry. While the model uses previously established variables, it does so in three unique ways. First, the model uses only those variables important to the technological change process, excluding those that more appropriately relate to the product introduction process. Second, the industry is narrowly defined, thereby confining the model to technological competitors. And, third, the independent variables drawn from the economics and marketing literature are combined in a single model for the first time.

The level of analysis is the individual technological area and the unit of analysis is the assignment of a patent to a technological area. All variables, with the exception of Lead Time, are measured using the electronic data base made available by the U.S. Patent and Trademark Office. The Lead Time variable is measured using hardcopy patent data.

The model (Figure 5 - 1) was tested using multiple regression with OLS estimation of the parameters. The final regression results show four of six independent variables to be significant, with an overall R^2 of .6526.

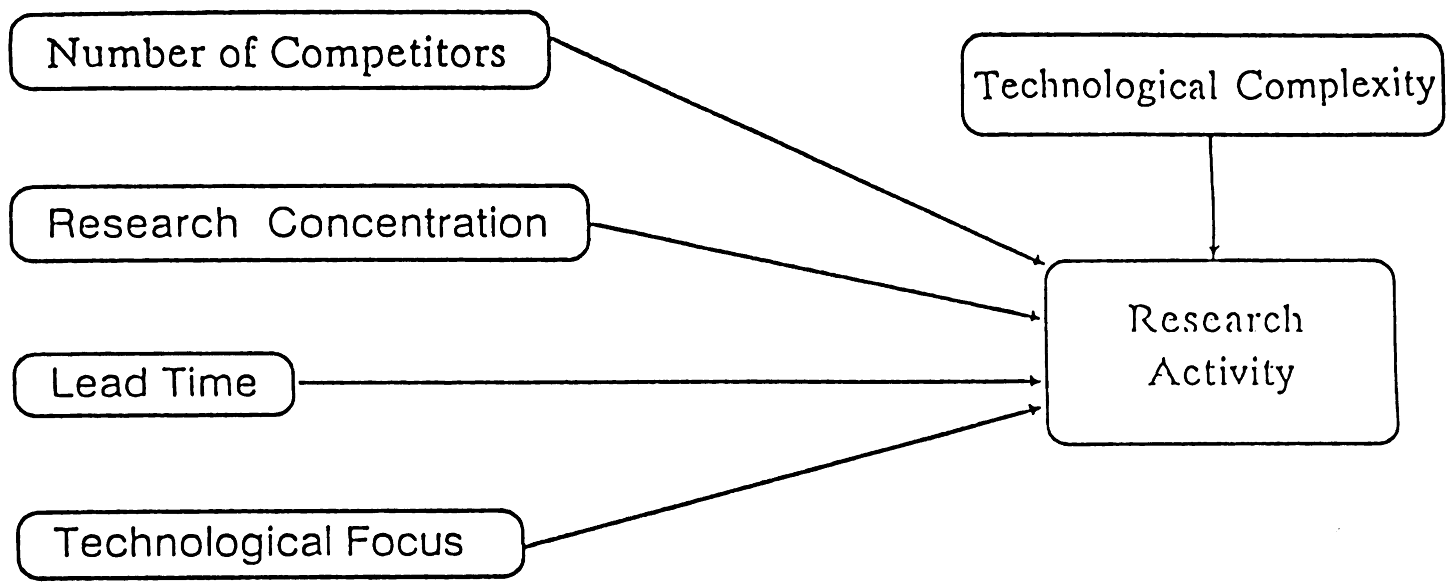

FIGURE 5 - 1

Conceptual Model

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Briefly, the research found the following significant relationships: 1) the greater the number of firms competing in a technological area, the greater the amount of research activity in the area; 2) the greater the technological complexity in a technological area, the lower the amount of research activity in the area; 3) at research concentration levels equal to or less than 40 percent, the greater the research concentration, the greater the amount of research activity in a technological area; and, 4) the greater the combined effect of technological focus and technological complexity in a technological area, the lower the amount of research activity in the area.

The final two results were obtained after adjustments were made to the original model. The original hypothesized relationship between research concentration and research activity was an inverted "U". However, analysis showed the inverted "U" relationship to be unstable and an alternative hypothesis was proposed and tested.

In the original analysis the interaction between technological focus and technological complexity was in the direction hypothesized, but was not statistically significant. The Pearson correlation matrix showed extreme multicollinearity between the technological focus variable and the interaction term. Once technological focus was removed, the interaction term became significant.

The research did not find the following relationships to be significant: 1) the greater the technological focus in a research area, the greater the amount of research activity in the area; and, 2) the greater the lead time between when a pioneer enters a technological area and when the first competitor enters, the lower the amount of research activity in the area.

As mentioned above, high multicollenearity may have prevented the technological focus variable from being significant. OLS only uses information unique to a variable when estimating a coefficient. However, there was very little information unique to the technological focus variable that did not overlap onto the interaction term. The Pearson correlation between technological focus and the dependent variable was in the direction anticipated but was not significant.

Analysis of the lead time variable raised serious questions concerning how the variable was measured. The monthly lead times obtained from the patent data proved to be poorly distributed. Most lead times occurred well within a 12 month period, but outliers caused a significant difference between the mean and median. An attempt was made to bring outlying data points closer by taking the square root but the variable's distribution remained skewed and its regression coefficient nonsignificant.

CONCLUSIONS

As stated in Chapter Two, "Under the simplest economic assumptions...as the number of competitors in an industry increases so will the industry's total research effort." The finding of the current research confirms this theory.

Some critics have suggested that an increasing number of competitors would result in fewer profits per individual firm and an overall drop in total research effort. This has not happened in the current study because under the patent system firms can appropriate the benefits of their research. Each firm continues to benefit from its research effort until its technological approach is displaced by a competing technological approach from another firm. Since the complete displacement of one technological approach by another takes time, firms can continue to do research using the benefits they have appropriated from earlier research efforts. The total amount of research activity will continue to increase with an increase in the number of competing firms as long as firms have some mechanism to appropriate the benefits from their research.

Perhaps even more interesting is the impact of this result when considered in light of the negative relationship found between technological complexity and the amount of research activity. Previous researchers have uniformly concluded that more complex technologies require greater research effort, providing fewer research outputs in a given ti

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time period. This result is confirmed in the current study. When taken together, these two results suggest that as technologies become more complex, a large number of competing firms will be needed in order to maintain a given amount of research activity.

The idea of having a large number of competitors to maintain or increase the amount of research activity also receives limited support from the finding on research concentration. Although increasing research concentration increases the amount of research activity, it does so only if four firm research concentration is at or below 40 percent. This result suggests a situation where firms use the ability to appropriate the benefits of their research to increase their research activity and increase their research share. But the relationship holds only if the research share held by the top four firms is relatively low or, in other words, if the total amount of research activity is spread across a large number of competing firms.

The original model hypothesized an inverted "U" relationship between research concentration and the amount of research activity. The relationship could not be confirmed because the original transformed variable was unstable. But the apparent inverted "U" in the plot of the data, and the strong support in the economic literature suggest the need for further testing. Therefore, conclusions based on the current findings need to be tempered by the need to confirm the positive relationship at concentration levels below 40 percent and to determine what happens at research concentrations above this level.

The interaction between technological focus and technological complexity must also be integrated with earlier findings. Clark's Harvard Business Review article (1989) articulated the concern over the potential impact of being too technologically focused at a time when technologies are becoming increasingly complex. The negative relationship found in the current study supports this concern. As technological complexity increases, firms that are too technologically focused will be at a competitive disadvantage.

This result suggests that successful firms of the future will have a broad technological focus, perhaps even technological conglomerates. But such a conclusion can be easily misinterpreted, especially if the idea of technological conglomerates implies industries dominated by technological giants. In order to be consistent with earlier results, the successful technological conglomerates of the future will need to compete with many other firms in technological areas that have low to moderate research concentration.

Such a conclusion offers a number of challenges. First, it implies that as long as technological complexity increases, technologically diversified firms are better. As firms broaden their technological base they will begin to appropriate benefits from an increasing range of technologies. But it also implies that if the end result is fewer competitors or high research concentration the total amount of research activity will decrease.

In drawing conclusions from the current research it is also necessary to consider the two relationships that were not found to be significant. As mentioned earlier, the technological focus variable was dropped because of a lack of significance and high correlation with the interaction term. One possible reason for a lack of significance is the inclusion of firms in the data base that held very few patents.

Technological focus is measured by first computing a ratio of the number of patents issued to the firm in a patent subclass divided by the total number of patents issued to the firm in all patent subclasses. This ratio is then averaged across all firms patenting in the subclass. As a result, technological focus was high in patent subclasses containing firms that hold only one or two total patents and lower in subclasses that contain firms holding thousands of patents. The measure of technological focus might be improved if firms holding only a few total number of patents are removed. Such firms are relatively unimportant since they do not participate in the patenting process on an ongoing basis.

The general conclusions presented earlier will need to be altered should the improved measure of technological focus prove successful and the variable found significant in the direction anticipated. In this case, successful firms will have to balance the need to broaden their technological base to meet increasingly complex technologies with the need to maintain a sufficient level of technological focus.

The lead time variable was also not significant but may also suffer from poor measurement. The proposed negative relationship between lead time and research activity is based on the hypothesis that pioneer firms increase their research activity in the face of a competitive threat. However, the variable's distribution indicated that in most cases a competitive threat occurred within the first twelve months of entering a technological area. As a result, the variance of the independent variable was simply insufficient to test the relationship.

It is possible that lead time as perceived in the marketing literature is not important at early research stages. The uncertainty of the technological change process may preclude the competitive positioning observed during the product introduction process. In which case, pioneers may continue their research efforts regardless of the actions of other firms.

It is also possible that only some firms entering a technological area are perceived by a pioneer to be competitors, others may be patenting research that makes the pioneers own work more valuable. In this case the pioneer would be more inclined to wait before conducting additional research.

A third possibility is that the entry of additional competing firms, not just the first competing firm, needs to be measured in order to accurately assess the competitive threat perceived by the pioneer. In this case the measure of lead time will need to included both the timing and the number of competing entrants. Clearly, additional research is required before dismissing the variable as inappropriate to the model.

RESEARCH CONTRIBUTIONS

Due to the exploratory nature of the current study the research contributions extend to a variety of areas. First, although the wide-ranging, fast growing technological change literature illustrates the subject's continued academic importance, there are no technological change models in marketing. The current study provides the first model to focus exclusively on the technological change process.

Second, the current study builds on the IO tradition while offering a number of improvements. Economists such as Scherer (1965, 1967, 1984; Scherer and Ross 1990) and Lund (1987,1989) have established the IO approach as a viable method of modeling innovation and technological change.

These studies use conventional IO measures and broadly defined industries. However, using products/markets to define an industry risks excluding firms that have a technological impact but do not participate directly at the product level. While, conversely, other firms may be included whose primary contribution to the industry is nontechnical. As a result, variables such as the number of competitors and economic concentration are based on the activities of firms that are not true technological competitors.

The current research measures variables at the technological level, including only those firms demonstrated to be technological competitors. As a result, the impact of these factors on the total amount of research activity can be more accurately assessed. This technology-based approach suggests that researchers have the option of creating "industries" as technologies develop or overlap.

In addition, traditional IO models contain variables frequently found in the economics literature but not those normally found in marketing. By including technological focus and lead time, the current research is the first study to combine variables from the economics and marketing literature in an IO framework for the purpose of modeling the technological change process.

Also, the current research operationalizes traditional variables in a new manner. This is particularly evident with research concentration and technological complexity. Instead of relying on the broader measure of market share, the current study measures the degree to which research is concentrated in the top four firms. This approach is a more specific measure for studying the technological change process. Measures of technological complexity are difficult to find and often rely on a variety of subjective evaluations. The current study offers a measure that is easy to operationalize and, though still subjective, relies only on the evaluation of the patent examiner.

Third, while recent research has successfully used patent data to indicate a firm's competitive technological strength and to monitor technological areas, few marketers and strategic planners have availed themselves of patent information. In fact, prior to the current research there were no patent based research models in marketing. The current study places patent information in a context that is both recognizable and relevant to marketers.

And, finally, while the relationship between patent activity on the one hand and actual commercialized innovations on the other is beyond the scope of the current model, it is not irrelevant to the value of the current research. A large number of factors affect the eventual commercialization of an innovation. Some are internal to the firm, such as financial constraints and risks of product cannibalization, while others are external, such as the government regulatory process and incongruent international patent laws. The current research provides marketers and researchers concerned with the innovative process a means of measuring and anticipating evolving technologies up to the point of the commercialization decision. The improved measurement of input into the commercialization process at the industry level allows for more accurate anticipation of future innovations.

MANAGERIAL IMPLICATIONS

The primary managerial implication of the current research is the potential for improved understanding of those competitive relationship that are based on technological advantage. Terms such as "industry structure", "technological focus", and "technological complexity" are familiar to practitioners but they are frequently ill-defined. The current study measure these constructs and places them in a model that is easy to use.

With an R^2 of .6526 and four significant variables, the current model gives managers the ability to judge the relative impact of an increase in the number of competitors or a decrease in research concentration. The degree of technological complexity inherent in a technological area is an indicator of how quickly the technology will evolve. And resource allocations decisions can be made by comparing the firm's own technological focus against the technological focus of all firms researching in an area.

With the current model managers have new information regarding those technological areas that are most likely to evolve quickly, and those that will change more slowly. As a result, managers can compare their firm's technological strengths with those of their competitors. If their firm appears to have a technological advantage, managers can prepare to exploit it. Conversely, if it appears that a competing firm is winning the technological race, managers can take defensive measures using current products and technologies. In summary, this model reveals relative technological strengths before they translate into actual changes in market share.

An organizational benefit from the current model is the additional interface it provides between marketers and researchers. Technological change is the source of many new products and product improvements. Past studies have clearly demonstrated the importance of the research/marketing interface in bring new products successfully to market. The current model builds on this interface and provides a common language (i.e. the technological areas that underlay patent classifications) for the exchange of ideas.

Finally, while patent information has always been available in hard copy, its use has frequently been confined to the R&D laboratory and the legal office. At the same time, managers and planners often lack quantifiable information on their company's technological status (Ashton and Sen 1988). The availability of electronic-based patent information and a model for analyzing the information will add to the manager's portfolio of analytical tools.

RESEARCH LIMITATIONS

As an exploratory project, the current research has a number of limitations. First, the current model was tested within a single patent class. This constraint helped to increase the managerial relevance of the test and served to control for interclass differences. However, the findings cannot be generalized across dissimilar classes until the model can be tested in many different patent classes and subclasses.

Second, only those subclasses with at least 50 percent patent activity since 1969 were included in the sample. As a result, the majority (224 of 405) of subclasses in the class were excluded. Subsequent analysis suggests that the 50 percent criteria may not be necessary when using the model, but additional research is necessary.

Third, the current research was designed specifically for use with a patent data base. The intent was not to exclude other data options but rather to exploit an underutilized data source. A test of the current model with a different data base may provide different results, particularly if variables are measured at a broader industry level.

Finally, the findings in the current research cannot be extrapolated to fit any specific industry or product line. The purpose of the current research was to present and test a model of those factors that affect technological change prior to the launching of a new product or innovation. A number of decisions separate from technological development take place prior to commercialization. It will be necessary to marry the current model to one that replicates the commercialization process before such extrapolations can be made.

OPPORTUNITIES FOR FUTURE RESEARCH

Future research opportunities can be broadly classified as; those relevant to model improvement using the current patent data base, those relevant to model improvement using an expanded patent data base, and those relevant to model improvement using a nonpatent data base.

The current model and current data base provide many research opportunities. Repeat testing is necessary to confirm the model's robustness. Regression results based on subclasses from one class can be compared with those from a different patent class. The model can be applied to subclasses that cut across classes. And subclasses with less than 50 percent patent activity since 1969 have yet to be fully tested. In addition, the vertical subclass structure, the categorization of subclasses according to "main lines", has not yet been explored.

The current data base also provides the opportunity to redefine lead time and technological focus. Rather than considering the impact of just the first competitor, lead time can be weighted by the length of time, in years, that each competitor enters the technological area. Technological focus can be redefined as research focused in a broader technological area, as opposed to just the subclass under consideration.

Alternatively, additional patent information, specifically patent citation information, may prove helpful in redefining some or all of the variables and reducing multicollinearity. Recent studies have demonstrated the usefulness of patent citation information in tracking technological developments. Instead of relying exclusively on subclass-based measures, as in the current research, future studies may use citation-based measures in their place.

For example, the number of competitors could be measured as the number of firms granted patents that contain a specific patent citation or group of citations, and lead time could be measured in terms of the length of time between when a patent is granted and when a subsequent patent is granted that cites the earlier patent. A model based exclusively on patent-citation measures or using both citation-based and subclass-based measures can then be compared to the current subclass-based model.

Also, scientific citation and patent citation information can be added to the current model. The average number of scientific citations held by patents in a subclass may reflect the degree to which the patents represent technological changes in "basic" research. A greater amount of "basic" research in a subclass may, in turn, imply a greater total number of patents in the technological area. Alternatively, the average number of patent citations held by patents in a subclass may represent a maturing of the technology. As a result, the greater the average number of patent citations in a subclass, the lower the total number of patents in the area. When pursuing these and other options it will be necessary to exercise care to ensure additional multicollinearity is not introduced.

Finally, the model can be tested or expanded using nonpatent information. Each variable in the model has already been measured using an alternative methodology, (FIGURE 5 - 2). Though previous models suffered weaknesses described earlier (i.e. too broad of industry definition and a lack of technologically specific analysis), the current model can and should be tested without the use of patent data in order to determine how much of the current results were determined by the data set used.

Attempts to improve the model might also include using variables such as firm size, and market share in addition to or as a substitute for research concentration. The correlation between the current measurement of research concentration and traditional market share-based measures also has yet to be demonstrated.

From a managerial perspective perhaps the most important addition would be one that takes the manager closer to commercialization. Linking the current model to one that includes commercialization variables would be an important next step to understanding the nature of technological change.

In short, the current model is designed to provide an important first step in further understanding the nature of technological change and in the use of patent data. Having succeeded in this role, the initial model will hopefully soon become obsolete, a victim of ongoing research.

Variable	Patent-based Measure	NonPatent-based Measure
X_1	number of firms patenting in the subclass	number of firms in an industry (using SIC code or other criteria to define the industry)
X_2	share of patents in subclass held by four top firms	CR4 measure based on the market share held by the four largest firms
X_3	time period between when initial firm is granted a patent in subclass and when second firm is granted a patent in the same subclass	time period between when an innovation is introduced and when a competing product carrying the same or a similar innovation is introduced
X_4	average of each firm's percent of total patents filed in subclass	percent of research effort (i.e. time, dollars, number of researchers) directed at a specific innovation or technological area
X_5	the average number of subclasses each patent in the subclass is assigned to	subjective measure of the degree of complexity as viewed by experts in the field
Y_1	number of patents filed in a subclass during a specific period of time	number of new products or innovations, or the percent of revenue derived from new products or innovations

FIGURE 5 - 2

VARIABLE MEASUREMENT: PATENT-BASED AND NONPATENT-BASED ALTERNATIVES

APPENDIX

APPENDIX A

DEFINITIONS OF TERMS

Technological Area is a research area that deals with a specific technology. The patent classification scheme identifies each technological area as a patent subclass.

Number of Competitors is the number of firms conducting research in a technological area.

Technological Focus is the extent to which firms concentrate their research in a technological area.

Research Concentration is the total percentage of research conducted in a technological area by the four largest firms.

Competitor Lead Time is the period between when the first firm begins research in a technological area and when a competing firm enter the technological area.

Technological Complexity is the number of different technological areas the average patent in a technological area is assigned to.

Research Activity is the amount research output at a specific point in the innovation process. The model uses the total number of patents issued to industry members patenting in a technological area.

Industry Research Structure is defined as the competitive framework within which firms researching in a particular technological area operate.

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