Competition and Innovation in Automobile Markets

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Competition and Innovation in Automobile Markets

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NOMENCLATURE

AP	adjusted accumulated patents
CV	coefficient of variation
GAP	percentage knowledge gap in adjusted accumulated patents
HHI	Herfindahl-Hirschman Index
HHI^{PAT}	Herfindahl-Hirschman Index of annual patents
ln	natural logarithms
λ	speed-of-response
μ	mean
PAT	annual patents
PAT^*	optimal (or equilibrium) value of PAT
s	market share
SHR	market share
σ	standard deviation

t time

X control variables

Z control variables

SUMMARY

Innovation is viewed as critical to fostering the growth of markets, generating efficiencies, and improving welfare. In this study we examine the determinants and the shifting dynamics of innovation in the U.S. automobile market. We use firm-level time-series data over a long horizon (1969-2012) for nine well established firms selling in the U.S. market (GM, Ford, Chrysler, Toyota, Honda, Nissan, Volkswagen, BMW, and Daimler).We examined three aspects related to market competition, innovation, and innovation rivalry in the U.S. automobile industry.

First, we examine the relationship between competition and innovation. We use patent counts as a measure of innovation, and use market shares and market concentration as measures of market competition. Some of our key findings are: (1) increase in firms' market shares result in higher patenting, and the relationship is reasonably non-linear; (2) higher market-wide competition results in an increase in patenting, and the relationship is weakly non-linear; (3) there is relatively strong path-dependence in firms' patenting behavior.

Second, we examine the relationship between knowledge gap and patent rivalry. In particular, we examine how a firm's current patenting behavior is influenced by the knowledge gap between the leader and the firm, firms' market shares, and the indirect effects of knowledge gap and market share. Our key findings are: (1) the relationship between patenting and knowledge gap is non-linear, and is U shaped; (2) an increase

in market share results in higher current patenting; (3) the interaction between firms' market share and technology gap does not have a statistically significant effect on their current patenting.

Third, we examine the changing composition of patents. Over time, the dynamics in a market can change substantially due to competition in the product market, shifting positions of firms from an innovation standpoint, fundamental shifts in technology, changes in regulatory constraints, among other factors. We study the intertemporal shifts in the composition of innovation, and in particular, we examine how a firm's current patenting behavior is influenced by the own patent concentration and rivals patent concentration. Our key findings are: (1) the relationship between knowledge stock and current innovation is complex, and depends on technologies categories; (2) an increase in own patent diversification results in higher current patenting in electrical & electronic and mechanical technologies; (3) an increase in rivals' patent diversification results in higher current patenting in electrical & electronic on mechanical technologies; (4) rivals' knowledge diversification has statistically higher effects on current patenting than own knowledge diversification, and is the main driver of changing compositions in patenting.

CHAPTER 1. INTRODUCTION

1.1 Industry Description

Innovation is viewed as critical to fostering the growth of markets, generating efficiencies, and improving welfare. A significant amount of research has been studied the determinants of innovation, and as we discuss in chapter 2, theoretical and empirical literature provide a wide determinants of innovation. However, those studies fail to reach a general conclusion.

In this study we examine the determinants and the shifting dynamics of innovation in the U.S. automobile market, which, over our sample period, has perhaps been the most vibrant market with most of the major global producers competing to showcase their technological prowess and vying for market competition. Focusing on the U.S. automobile market to examine the relationship between competition and innovation is meaningful for several reasons. First, the U.S. automobile market is economically large. Till the year 2010, the U.S. was the #1 automobile market, before China overtook it starting 2011. Further, during the period 2004-2008, for example, the motor vehicles industry created about 1.1 million jobs in the U.S. This number is, for example, significantly greater than for semiconductors (0.48 million), aerospace (0.47 million) and pharmaceuticals (0.29 million). A recent report notes that the overall automobile industry is the largest in all of U.S. manufacturing sector, and generates large capital investments. Second, the U.S. market has seen dramatic intertemporal changes in the market shares of the main firms as well as patenting profiles. Around 1970, GM and Ford had a combined share of about 65% of the U.S. market. By 2010, this sum had been reduced to about 30%. The American firms' dominance was in part due to the home-market advantages, as well as important innovations that were introduced by them. The U.S. firms' leading positions were challenged by the Japanese firms in the aftermath of introduction of U.S. environmental regulations in the early-1970s, and the dramatic oil price shocks starting in 1973. While Toyota is the largest Japanese firm in the U.S. market by market share, Honda and Nissan are well established and offer significant competition to their rivals. Volkswagen, BMW, and Daimler are the three major manufacturers from Germany. VW competes with the U.S. and Japanese firms in the mass-produced segment, but its market share on average has been rather low. BMW and Daimler sell cars exclusively in the luxury segment, and are not directly comparable to the U.S. firms. However, they compete with Toyota, Honda, and Nissan in the luxury segments, as well as GM's Cadillac lineup to some extent.[1]

The automobile industry shows healthy overall patenting, as well as product and process innovations. According to a USPTO report, the total patent count of the motor

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[1] One of the important reasons why we focus on the U.S. market is the availability of complete data on the major competitors. For the non-U.S. markets, we were unable to obtain complete data on market shares and other attributes over our time period. Overall, the data limitations for the foreign markets were rather severe. We note that ours is not the only study focusing on the U.S. market. The papers by Lieberman et al. (1990), Lieberman and Demeester (1999) and Lieberman and Dhawan (2005), for example, focus on the U.S. market.

vehicles and related industry was 8,298. [2] This compares favorably to other industries such as medical equipment and supplies (9,716), plastics and rubber products (8,289), and is higher than in, for example, aerospace products and parts (2,726), and fabricated metal products (5,495). The motor vehicles patent count was lower than in industries such as basic chemicals (12,109), and pharmaceuticals (13,627). The USPTO report also presents information on the percent of product and process innovations for which patents were considered an effective mechanism for appropriating the returns to innovation. For the motor vehicles and related industry, 38.9% of the managers considered patents as an effective protection of product innovations and 21.7% for process innovation. For comparison, the respective percentages for some other industries were as follows: aerospace (32.9% and 21.4%); computers (41% and 30%); machine tools (36% and 18%); and pharmaceuticals (50.2% and 36.2%). The motor vehicles percentages were higher than in, for example, electronic components (26.7% and 15.2%) and semiconductors (21.3% and 23.3). So whether we examine overall patenting rates or product and process innovation aspects, the motor vehicles industry appears to be quite vibrant relative to many other industries which have high overall rates of innovation and patenting.

[2] Economics and Statistics Administration and United States Patent and Trademark Office (2012): “Intellectual Property and the U.S. Economy: Industries in Focus.” The comparative industry data are for the period 2004-2008.

1.2 Objective of the Research

The primary goal of this research is to develop empirical models for analyzing the determinants of innovation with various aspects. In summary, this research investigates the problems listed below:

1. How market competition and rivals' market shares affect firms' innovations?

2. How does knowledge gap affect firms' innovations?

3. What are the changing composition of patents and why there are those shifting dynamics?

We use patents as an indicator of innovative activity. Patents are awards to firms' research, are visible outcomes of innovative activities, likely to be linked to new technologies introduced to the market, and relate to competition in technologies, market performance, and other aspects of firms' strategies. Apart from patents being a widely used measure of overall innovative activity, our choice of patents is motivated by the fact that we are able to compile a consistent database of patents by the automobile firms for the full sample period 1969-2012. Data on R&D expenditures, an alternative indicator of innovation, were not available for the majority of the firms for most years in our sample period. Lacking consistent data in R&D, we use patent counts as an indicator of innovation.

A salient aspect of our study is that we use firm-level time-series data on measures of competition and innovation over a relatively long period (1969-2012) which enables us to better estimate the dynamic relationships in the market. We use dynamic panel data models to estimate the determinants of firms' innovation. Our panel models control for a range of factors related to GM's bankruptcy, the Daimler-Chrysler merger, environmental regulations, voluntary export restraints, business cycle conditions, among others. To examine the objectives, we focus on nine well established firms selling in the U.S.: GM, Ford, Chrysler, Toyota, Honda, Nissan, BMW, Daimler, and Volkswagen. While there are several other smaller firms in the market, our choice of nine firms is motivated by two reasons. First, these nine firms have, on average, accounted for approximately 91% of the sales in the market over our sample period. Second, data for these firms are consistently available over our entire sample period.

1.3 Brief Summary of Each Chapter

Chapter 1 gives a brief description of the objectives of this research.

Chapter 2 provides the literature review. The theoretical and empirical studies of different topics on innovations are described. The studies of determinants of innovation show that there are no general conclusions, and the effects of various factors on innovation depend on specific structure of the model and parameters, and the relationships are complex.

Chapter 3 describes relationship between competition and innovation. We describe the significant intertemporal fluctuations in firms' market shares and patents, and discuss the relationships between indicators of market competition and patenting.

Chapter 4 discusses the relationship between knowledge gap and innovation. In this chapter, we examine that in an oligopolistic market, if a firm has a knowledge/technology gap with the leader, whether it will innovate more to catch up to close the gap or even surpass the leader, or innovate less and cede ground. We examine how a firm's current patenting behavior is influenced by the knowledge gap between the leader and the firm, firms' market shares, and the indirect effects of knowledge gap and market share.

Chapter 5 focuses on the changing competition of patents. Over time, the dynamics in a market can change substantially due to competition in the product market, shifting positions of firms from an innovation standpoint, fundamental shifts in technology, changes in regulatory constraints, among other factors. In this chapter, we study the intertemporal shifts in the composition of innovation and the determinants of these shifting dynamics.

Chapter 6 discusses the main conclusions of this research.

CHAPTER 2. LITERATURE REVIEW

2.1 Innovation and Competition

The literature examining the linkage between competition and innovation is quite extensive and it is not our objective here to present a comprehensive overview. Some papers in the literature already do this, such as Cohen and Levin (1989), Ahn (2002) , and Gilbert (2006). In this section we review some of the key theoretical results and empirical findings to focus on our empirical analysis.

2.1.1 Theoretical Literature

The early foundations of the literature relating competition to innovation were provided by Schumpeter (1934, 1942) and Arrow (1962). Schumpeter (1934) argued that the prospect of achieving monopoly rent induces a firm to invest in R&D. Schumpeter (1942) noted that once a firm achieves a monopoly position through innovation, it will have an incentive to incur additional innovation expenditures to reinforce this position. A large firm is induced to seek innovation to increase and strengthen its market power. Arrow (1962) considered an inventor's decision in a competitive market versus a monopoly, and showed that pre-invention monopoly power acted as a disincentive for further innovation. Arrow's prediction, in contrast to Schumpeter, was that firms with low market share – in an atomistic competitive market – would generate more innovations.

The market we study, automobiles, is best characterized as an oligopoly. While the above contributions established the bookends on the linkage between competition and innovation, the subsequent literature which used oligopoly models to attempt to resolve the contradictory results produced even more dispersion of results. An important reason is that the oligopoly models vary significantly in their structure and assumptions, such as those related to: mode of competition, Cournot versus Bertrand; whether the payoffs from invention are certain or uncertain; whether the input into patents – R&D – is best described as only containing fixed costs, or a combination of fixed and variable costs; whether the innovation is drastic versus non-drastic (incremental); whether innovation game is played as a preemption or precommitment game; whether the game being modeled is a one-shot or a two-stage game; whether the timing of arrival of the technological opportunities is deterministic or stochastic; efficiency of firms' innovation projects; among others.

To illustrate the diversity of results from the oligopoly models, we briefly describe a few papers below, and in table A.1 we present a summary of some of the theoretical results. Loury (1979) – assuming Cournot competition, fixed and no variable R&D project costs, and uncertain date for project completion – found that as the number of firms increases (decrease in firm's market share), the incentive to invest in R&D decreases. Lee and Wilde (1980) modified Loury's model by assuming that innovation investments involve both an up-front fixed cost, as well as variable costs over the duration of the project. They showed that an increase in the number of firms increases firms' R&D investments, a result exactly the opposite of Loury.

Delbono and Denicolo (1991) noted that Lee and Wilde's results depend on the specific structure of the model related to incentives and payoffs – e.g., the innovation prize is exogenous and independent of the number of firms, and that no account is taken of the possibility that firms can have positive profits before the innovation. Delbono and Denicolo relaxed these assumptions and found that an increase in the number of firms may result in a decrease in firms' R&D investments – a result similar to Loury.

There are several papers that examine patenting strategies when firms face complex tradeoffs between expropriability of innovation and the degree of competition. Anton and Yao (2004), assuming Cournot competition, examine the tradeoff between the efficiency-enhancing aspect of patents and the likelihood of imitation. In their model, only a small innovation with an insignificant reduction in cost will be patented while a large one with a significant reduction in cost will not be patented. However, Mosel (2011), assuming Bertrand competition and a cost of applying for patents, generates the opposite result: only large innovations whose benefits of patenting outweigh the application costs will be filed for patents. Jansen (2011) examines patenting incentives in a model of asymmetric information, and focuses on the size of an innovation. He finds that under Cournot (Bertrand) competition, a firm will tend to patent large (small) innovations, and the incentive to patent grows (decreases) with an increase in the number of rivals. Overall, this literature shows that there is no general result. The precise magnitude and direction of patenting is heavily dependent on the complex interaction between the likely risk of expropriation and the mode of competition.

For our empirical analysis, we note two key aspects that emerge from the above studies:

1. The impact of competition on innovation is ambiguous. There is no clear prediction about the sign of the relationship. The answer depends on a wide range of factors noted above.

2. The models discussed above examine firms' total innovation efforts – total R&D expenditures, or total patents. The theoretical models in this literature do not consider issues related composition of innovation (e.g., does greater competition generate more process or product innovation), or quality of innovation (e.g., does more competition generate low or high quality innovation). Given this, in our empirical study we focus on the effect of competition on the total innovation, as measured by the total number of patents generated by firms.

2.1.2 Empirical Literature

Given the wide range of results from the theory models, a significant empirical literature developed to shed light on the sign and magnitude of this important relationship. The empirical studies on the relationship between competition and innovation have produced no conclusive results. In table A.2 we present a compact summary of some of the empirical studies, which show considerable diversity in the direction and characteristics of the relationship between competition and innovation.

Below we, first, discuss some studies that have examined the relationship between industry-or-market wide measures of competition and innovation. Second, we note some results relating to firm-specific market shares or performance to innovation.

The literature reviews by Cohen and Levin (1989) and Ahn (2002) noted that innovation and market concentration appear positively related in the majority of studies. However, the review by Gilbert (2006) shows no clear conclusions. Turning to specific papers, Acs and Audretsch (1988), Blundell et al. (1995, 1999), and Blind et al. (2006), for example, found a negative relationship between concentration and innovation. In contrast, Scherer (1965, 1967), Levin & Reiss (1984), Scott (1984), and Levin et al. (1985) found little influence of concentration on innovation.

The empirical literature provides some evidence that the relationship between competition and innovation may be nonlinear. Scherer (1965) found a mildly nonlinear relationship between total number of patents and total sales. Blundell et al. (1995) also found nonlinearities: e.g., even though for the market as a whole there was a negative relationship between concentration and innovation, dominant firms were more likely to innovate. Aghion et al. (2001) and Aghion et al. (2005) predict a nonlinear, inverted U-shaped, relationship between competition and innovation. Using a mix of U.K. 2-digit industry data, and U.S. patents data, Aghion et al. (2005) reported evidence to support their model predictions. Hashmi (2013), however, finds exactly the opposite relationship. While Aghion et al. (2005) report an overall positive relationship between innovation and market competitiveness for the U.K. data, Hashmi finds a robust negative relationship. So even after addressing nonlinearities in the relationship, the results vary considerably across studies. There are other studies testing the findings by Aghion et al. (2005), and the main variables and main conclusions are listed in table A.3.

Turning to firm-specific factors, Blundell et al. (1995, 1999) and Lee et al. (2011), for example, found that innovation and market share were positively related. Scherer (1965) and Brouwer and Kleinknecht (1999) found that innovation and firms' sales were positively related. However, other studies found more intricate relationships: e.g., Hashmi and Biesebroeck (2006) find an inverted-U relationship between innovation and market share, and Noel and Schankerman (2013) find a dynamic intertemporal relationship between sales and innovation. Hu (2010) finds that patents increased not due to the expansion of firms' own sales, but by increase in competing imports.

The literature has examined several other factors that may affect firms' patenting. For example, the influence of demand and technological opportunities (Cohen and Levin, 1989), and the influence of industry characteristics (Kondo, 1998). Focusing on issues related to appropriation and strategy, Cohen et al. (2002) suggest that Japanese and U.S. firms can be quite different, and Blind et al. (2006) use German data to study strategic patenting.

2.1.3 Some Automobile Market Considerations

In our review of the literature we noted the wide dispersion in findings relating firms' market shares, and degree of competitiveness, to firms' innovation and patenting. Several papers have emphasized the considerable inter-firm heterogeneity between the U.S. and Japanese automobile firms. For example, Lieberman et al. (1990) compared the productivity of six U.S. and Japanese automobile firms. Though the Japanese firms as a group showed an overall advantage in labor productivity over the U.S. firms, there was evidence of significant inter-firm divergence in productivity. Lieberman et al. argued that the primary cause for the disparity in productivity among those firms was inter-firm differences in management and strategy. Stressing firm-level impacts, Lieberman and Demeester (1999) analyzed the relationship between inventory and productivity in the Japanese automotive industry. Though for most firms the relationship turned out to be negative, the relationship was influenced by inter-firm differences especially for Toyota and Nissan. These two firms showed different patterns compared to other firms in the industry. Lieberman and Dhawan (2005) examined the differences in efficiency and performance among U.S. and Japanese firms, using the Resource-Based-View (RBV) approach. According to RBV, firms rely on unique and critical resources to maintain their competitive advantages. Lieberman and Dhawan found strong inter-firm variation in different facets of the firms' operations and performance. Finally, Lee et al. (2011, 2010) find important differences between U.S. and Japanese firms in patenting and other aspects. While these studies do not address the link between competition and innovation, they point to important heterogeneity across automobile firms in their underlying characteristics, as well as differences between firms grouped by their country of origin.

2.1.4 Summary

The broad research question is clear: What is the relationship between competition and innovation? However, neither the theoretical literature nor the empirical findings provide clear answers. The predictions relating market-share or market-concentration depend on the degree of concentration and market structure, mode of competition – price or quantity, cost structure of innovation projects, nature of specific technologies being used, among other factors. In terms of the empirical literature, the evidence appears to indicate: (1) that market share tends to positively influence innovation; and (2) the impact of market-wide competition is far from clear.

We examine the sign, potential nonlinearities, and quantitative magnitudes in the relationship between firms' market shares and market-wide indicator of competitiveness (Herfindahl Index), and the automobile firms' innovation outputs as measured by patents. Our analysis provides evidence on broad, market-wide, effects, as well as shed light on heterogeneity of responses across firms. As the U.S. automobile market is economically large and shows substantial dynamics in both competition and innovation, it serves as an interesting setting to examine the broader research question.

2.2 Knowledge Gap and Patent Rivalry

There has been a spirited and long discussion about the incentives of innovations and patenting. Other than the basic function of protection, patenting behaviors can be motivated by concerns related to competition in innovation. Those non-protection motivations are referred as strategic patenting behaviors, or innovation rivalry. Generally, firms' innovation behaviors will be guided by relative technological positions compared to rivals. Here we briefly summarize the existing theoretical models as well as empirical evidence discussing this phenomenon of innovation rivalry.

2.2.1 Theoretical Literature

In the theoretical framework of Doraszelski (2003), knowledge stock and the difference in knowledge stock are treated as indicators of relative knowledge positions. In this study, knowledge stock can have negative or positive effects on current innovation. Doraszelski defined the negative influences of knowledge stock on current innovation as "the pure knowledge effect," arguing that as past knowledge stocks increase firms' current possibilities of winning the innovation race, firms are able to reduce their current innovation. He also defined the positive influences of knowledge stock on current innovation as "increasing returns of innovation," arguing that because of the positive returns of knowledge, firms have incentive to increase their current innovation. The net effect of knowledge stock on innovation strategies is complex and is affected by parameters. Doraszelski noted that though initially the increasing returns of innovation may motivate firms to increase current innovation, the pure knowledge effect will eventually dominate: As knowledge stock increases, firms reduce current innovation. To further exam the innovation rivalry among firms, Doraszelski grouped firms based on their knowledge stocks and calculated their knowledge gap. He argued that the effect of knowledge gap on current innovation is not clear: Knowledge gap can reduce the motivation of innovation for both leading and following firms when the possibility of catching up is small, and has negative effects on innovation. Knowledge gap can also increase the motivation of innovation for the following firm to catch up, and has positive effects on innovation. As he noted, because of the positive returns of innovation, initially the leaders may innovate more than the followers. However, because the pure knowledge effect eventually dominates, leader will innovate less than the followers. As a result, though the knowledge gap between the leader and the follower may initially increase, it will eventually decrease. Moreover, Doraszelski noted that knowledge stock has indirect strategic influences on firms' patenting behaviors. When a firm has a sufficiently large knowledge stock, if its rivals are expanding knowledge stocks, the firm will increase innovation. However, when a firm has an insufficiently large knowledge stock, if its rivals are expanding knowledge stocks, the firm will decrease innovation.

Different from the study by Doraszelski, Aghion et al. (2001) argued that both market competition and knowledge gap affect innovation, and the relationships are complex. Given the degree of competition, technology gap can increase, decrease, or even non-monotonically affect patenting, and the relationship between technology gap and current innovation is not clear. Based on this study, Aghion et al. (2005) developed a patenting model by including both market competition and technology gap. They noted that, market competition is a primary determinant of innovation by affecting patenting directly and non-monotonically, while technology gap is an indirect determinant of innovation by affecting patenting indirectly via market competition. They first predicted a non-linear, inverted U relationship between competitions and patenting. Second, they predicted that the inverted U relationship can be moderated by technology gap: in industries with low technology gaps, the inverted-U is steeper. In other words, technology gap has indirect effects on current patenting via market share, and the marginal effects are negative.

There are several other papers that examine technological positions as determinants of innovation. As noted in Grossman and Shapiro (1987), leaders always innovate more than the followers. They argued that when the gap between the leader and the follower decreases to some extent, both the leaders and the followers will increase innovation. Aghion et al. (2001) defined firms as leaders, followers, and neck-and-neck firms, and found that generally, neck-and-neck firms innovate more than the leading firms. Reinganum (1982) examined the impacts of innovation rivalry and found that the effects are complicated and depend on specific structure of the model and parameters: with perfect protection, increasing rivalry will increase innovation, while with imperfect protection, increasing rivalry has ambiguous influences that it may increase or decrease innovation.

Khanna (1995) demonstrated technological positions result in diverse innovation strategies. He defined a technological frontier as the most advanced technology of each firm, and grouped firms based on close technology levels. Within each group, firms compete against each other to obtain technological advantages, and between groups, following groups benefit from spillovers of leading groups. Khanna noted the innovation race is dynamic: Leaders may either decelerate innovations when they are far ahead of the rivals, or accelerate innovations to make catch-up more difficult. While the followers are motivated to innovate more to close the gap with the leader, or even surpass the leader. Lerner (1997) strongly emphasized the technological positions of firms. He noted that though the leaders are likely to innovate more to maintain their leading positions, as long as the knowledge gap between the followers and the leaders is not too large, the followers still have chances to surpass the leaders by innovating more. As a result, followers that trail the leader will innovate more to try to surpass the leader. The "leapfrog" behaviors of followers were also noted in Fudenberg et al.(1983) and Aoki (1991).

For our empirical analysis, we note three key aspects that emerge from the above studies: 1. The impact of technological position is ambiguous. There is no clear prediction about the sign of the relationship between technological position and current patenting. The answer depends on measurement of technological position and other factors noted above. 2. The impact of market competition on innovation is inverted-U shaped. 3. Technology gap can affect current innovation indirectly via market competition. As noted above, we found innovation strategies vary across technological positions, and technology gap is widely used to capture firms' technological positions. As a result, to empirically examine the determinants of patent rivalry, having a clear measurement of technology gap would help us to focus on the innovation behaviors across firms.

2.2.2 Empirical Literature

Given the results from the theory models, the empirical studies on the relationship between innovation rivalry and technological positions have produced relatively conclusive results. Khanna (1995) noted that though followers may simply try to close the gap with the leader, they are likely to leapfrog the leader. As a result, the vigorous competition in innovation motivated firms to innovate more, and pushed forward the technological frontier in the whole industry. Lerner (1997) found evidence that firms that trail the leader innovate more. He calculated firms' percentile ranks in technologies and noted that firms in middle percentages have significantly greater chances to innovate more. Their findings are consistent with some of the predictions of Doraszelski that followers will innovate more than the leaders.

Aside from those two papers that empirically test the technological position as a determinant of innovation and specifically define what technological position is, the influential paper by Aghion et al. (2005) tested the influences of both market competition and technology gap, and had a broad measurement of knowledge gap. First, using Lerner index to calculate market competition, they found empirical evidence that the relationship between competition and innovation is inverted U shaped. Second, they also empirically proved that technology gap can affect innovation indirectly via moderating the influences of competition on patenting. They calculated technology gap by industry-level average proportional distance to the frontier, defined as highest TFP in the industry. By interacting market competition variables with technology gap and using a mix of U.K. 2-digit industry data and U.S. patents data, they found evidence that the inverted U relationship between competition and innovation is steeper in industries with low technology gap. In other words, technology gap indirectly affects patenting via market shares. Third, they also found evidence that at any level of competition, patenting is always higher in low technology gap industries than patenting in the full sample data. This implies that though the marginal effect of technology gap on patenting relies on market competition, this effect is always negative, and the relationship between technology gap and patenting is negative. The study by Lee et al. (2011) also provides evidence that the relationship between innovation and knowledge gap is non-linear. They constructed "technology index" as an indicator of knowledge gap, and a smaller value of technology index indicates a higher knowledge gap. They found the relationship between current innovation and technology index is not linear, and is inverted-U shaped.

The empirical literature provides some evidence of the influences of own knowledge stocks and innovation competition as indicators of knowledge positions. The papers by Lieberman (1987), Zucker et al. (2007), and Noel and Schankerman (2013) found positive influence of own knowledge stock on innovation, and the studies by Jaffe (1986), Zucker et al. (2007), and Noel and Schankerman (2013) show that market innovation has positive influences on firms' current innovation. Noel and Schankerman (2013) confirmed the influences of research taken by rivals. By examining the determinants of patent counts, they found patenting behaviors of competitors have negative effects and reduce firms' patent counts. Also, a higher knowledge concentration, indicated by high level of summed citation shares of few firms, will significantly reduce firms' patent counts. In addition, as noted in the review by Hall et al.(2014), the impacts of market innovation vary across countries. For example, Cohen et al. (2000) and Cohen et al. (2002) statistically demonstrated that U.S. and Japanese firms take different patenting strategies: firms in both countries use patents to protect intellectual property and block technological advance of rivals, and U.S. firms only use rivals' patent information to launch own projects, while Japanese firms even rely on rivals' patents to launch or execute own projects. Branstetter (2001)confirmed empirically that the sign of market innovation is distinct across countries. He explained that patents were affected by spillovers and competition in innovation stimulatingly, and patent counts as observed were the combined outcomes of these two counteracting influences. In empirical specifications, knowledge pools represent spillovers and innovation rivalry stimulatingly, and the sign of the net effect depends on which effect dominates.

2.2.3 Summary

The broad research question is clear: if a firm has a knowledge/technology gap with the leader, does it try to catch up and close the gap or cede ground? However, neither the theoretical literature nor the empirical findings provide clear answers. The predictions of innovation rivalry depend on the technological positions and market competition, among other factors. In terms of the empirical literature, the evidence appears to indicate: (1) market competition and patenting have a non-linear, inverted U relationship; (2) the impact of knowledge gap is far from clear; and (3) knowledge gap tends to moderate the relationship between market competition and innovation.

We examine the indicators of technological positions and market competition as determinants of patent rivalry. In terms of the theoretical literature, technological positions are measured by the technological steps between leaders, neck-and-neck firms, and followers. Our analysis uses the proportional technological gap in knowledge stock between the leader and a specific firm to indicate technological positions, which is consistent with the empirical literature. Since we calculate technology gap by using knowledge stock, we do not include the knowledge stock as an individual independent variable to avoid repetition and potential collinearity. In terms of the theoretical model by Aghion et al. (2001), we include a quadratic term of technology gap to capture the potential non-monotonic effect of knowledge gap. In terms of the theoretical and the empirical literature, market competition is measured by firm-level market share, and to test the inverted-U relationship, we include a quadratic term of market share. We do not include a market-wide competition variable because we focus on a single industry, and the market-wide competitiveness is common for all the nine firms and can be treated as year control variables. By using market share, we can measure the performance in sales compared to others and capture market competition. In terms of the paper by Aghion et al. (2001) and Aghion et al. (2005), the indirect effect of technology gap via market shares is captured by an interaction between market share and technology gap.

2.3 Changing Composition of Patents

Literature on technological trajectories and evolutions suggests having a diversified innovation portfolio is essential (*e.g.*, Nelson, 1959; Dosi, 1982; March, 1991; Leventhal and March, 1993). By keeping a diversified innovation portfolio, firms are able to capture more technological opportunities by innovating in different technology classes. When lacking a diversified background, firms will not be able to generate new innovations effectively for several reasons: first, when firms innovate too narrow within existing fields, they fail to capture the potential opportunities in related fields; second, when firms only innovate too narrow, they are likely to be constrained by previous scope and may occur diseconomies of return in knowledge. However, diversity may not always benefit firms, and innovating too wide without making use of existing knowledge can harm firms' innovations (March, 1991; Leventhal and March 1993). For example, when searching too wide and failing to exploit in depth in existing knowledge, firms would not be an expert in any technological field and their innovation efficiency would be harmed.

A relatively broad literature examines optimal structure of keeping a diversified knowledge portfolio and taking advantage existing knowledge. In the literature, exploring new technologies and innovating in fields that a firm may not have before is defined as "knowledge exploration," and taking use of existing knowledge and developing technologies in previous fields is defined as "knowledge exploitation." Though studies find evidence that knowledge exploration and exploitation affect firms' innovation activities as well as economic performance, the balance between these two factors is far from clear.

For example, as March (1991) noted, by focusing on "*the refinement and extension of existing competences, technologies, and paradigms*," firms can benefit from exploitation. By learning from existing knowledge, firms are able to reduce learning cost, and gain new insights through existing innovation. As a result, due to the constraints in budget, firms tend to focus on their existing technologies without exploring new ones. However, as noted by Cohen and Levinthal (1990), when lacking a background in diversified innovation, firms are likely to miss the opportunities of new technologies and fail to generate new innovations. Hence, how to take advantage in existing technologies while not being constrained is important for firms, especially in developing new technologies (Leonard-Barton, 1992; Granstrand, 1998; Suzuki and Kodama, 2004).

The study by Levinthal and March (1993) argued that it is valuable to balance knowledge exploration and exploitation. Neither knowledge exploration nor knowledge exploitation will always benefit innovation. They introduced 2 learning traps: over-exploration as firms are learning too wide and over-exploitation as firms are learning too narrow. They found these two traps reduce the effectiveness of learning, and it is important to keep the balance between knowledge exploration and exploitation. However, they argued that what is the optimal structure between knowledge exploration and exploitation is not clear.

In the theoretical models, measures of knowledge exploration and exploitation are mixed and can have different interpretations. Cohen and Levinthal (1990) used knowledge stock to capture both knowledge exploration and exploitation for several reasons. First, knowledge stock is accumulated from previous innovation, represents firms familiarity with their existing knowledge, and is an indicator of knowledge exploitation. Second, knowledge stock enhances firms learning process by path-dependence of knowledge, increases learning efficiently in next periods, and is an indicator of knowledge exploitation. Third, knowledge stock helps knowledge exploration in new technological fields. As prior knowledge can be related to the new knowledge, firms are able to understand new knowledge more effectively, evaluate potentially technological opportunities more accurately, and explore new knowledge more creatively. Hence, knolwedge stock is an indicator of knowledge exploration. Given these considerations, knowledge stock helps to capture both knowledge exploration and exploitation. Coehn and Levinthal argued that, , knowledge stock and knowledge diversity both contribute to innovations since they are controlling for knowledge exploration and exploitation.

Empirical findings have mixed measurements in knowledge exploration and exploitation and find mixed evidence. Knowledge diversity is widely used as an indicator of knowledge exploration and has relatively consistent measurement by using the Herfindahl index of concentration in technologies (Hall, 2000). Studies find diversity has positive effects on innovation (*e.g.*, Garcia-Vega, 2006; Quintana-García and Benavides-Velasco, 2008), which is consistent with some of the theoretical predictions. The positive effects of knowledge diversity on current innovation can be summarized as follows: increase in knowledge diversity helps to reduce the risk of R&D, increases the possibilities of taking technological opportunities in related innovation fields, and increases the spillover effects from rivals.

Some empirical studies use knowledge breadth and knowledge depth to measure knowledge exploration and exploitation respectively. Lerner (1994) measured patent scope by patent breadth and emphasized the economic importance of patent scope for firms. He developed a proxy of patent breadth from patent classification by counting the number of total classes a patent is assigned to, and found evidence that patent breadth can statistically increase firms' values. However, he argued that the influences of patent breadth can be decreased by the uniqueness of firms' technologies. Lerner captured the uniqueness of technologies by taking average of the ratios of patents in each subclass, and found evidence that for firms with high uniqueness, they face less substitution, and their values are less sensitive to patent breadth. His measure of technology uniqueness is close to knowledge diversity measurement.

The study by Nicholls-Nixon and Woo (2003) used the U.S. pharmaceutical industry to examine the effects of knowledge breadth on patents. They measured knowledge breadth by counting the number of biotechnologies that a firm reported. However, in their study, knowledge breadth does not have significant influences on patenting. Katila and Ahuja (2002) measured both knowledge breadth and knowledge depth and examined the effects of these two factors on innovation in the global robotics industry. They measured knowledge depth as the percentage of repeated citations used in a specific patent, arguing that making use of previous research shows the familiarity of existing technology. They measured knowledge breadth as the percentage of new citations used in a specific patent, arguing that citing new knowledge shows the tendency of exploring new knowledge. They found the relationship between innovation and knowledge depth is inverted-U shaped, ◀浐◀湁◀炧◀î î î

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have indirect and positive effects on innovation via affecting each other.

Wu and Shanley (2009) took the measurement of knowledge depth by Katila and Ahuja, but defined the variable as exploration. In their study, average number of patents in each technology area is referred as knowledge depth, and diversity of technologies measured by Herfindahl index of concentration is referred as knowledge breadth. They examined the U.S. electromedical device industry and affirmed the inverted-U relationship between patenting and exploration and the positive effects of both knowledge depth and knowledge breadth on patenting. In addition, they noticed that the inverted-U relationship between patenting and exploration is not affected by knowledge depth, but can be moderated by knowledge breadth.

Quintana-García and Benavides-Velasco (2008) used patent stock as a combined measure of knowledge exploration and exploitation. They argued that, patent stock represents existing knowledge and firms' cumulative learning process. By controlling patent stock, they were able to control knowledge exploitation in prior patents. In addition, patent stock is composed by prior patents from both exploratory and exploitative research activities, and controlling patent stock can measure prior experience in both knowledge exploration and exploitation. In their study, as an indicator of both prior knowledge exploration and exploitation, knowledge stock has positive effects on innovation.

The broad research question is clear: what are the determinants of compositional shift in technologies? However, neither the theoretical literature nor the empirical findings provide clear answers, and the measurements are mixed. The predictions of technological trajectories depend on knowledge exploration and exploitation can affect current innovations, among other factors. In terms of the empirical literature, the measurement is mixed, and the evidence appears to indicate: (1) the effects of knowledge exploration is far from clear; (2) the effect of knowledge exploitation is far from clear; and (3) diversity in technology portfolio captures knowledge exploration, and has positive effects on innovation; (4) knowledge stock captures both knowledge exploration and exploitation, and has positive effects on innovation.

We examine the indicators of knowledge exploration and exploitation as determinants of compositional shift in patenting. First, our analysis uses knowledge stock in related classifications to control for both knowledge exploration and exploitation, which is consistent with the empirical literature. Second, our analysis uses Herfindahl index of diversification in technologies as the indicator of knowledge diversification to capture knowledge exploration. Third, literature studies the intra-firm knowledge trajectories and evolutions, while do not mention inter-firm innovation rivalry. Our analysis uses average Herfindahl index of diversification in technologies of rivals to capture rivals' threats in knowledge exploration.

CHAPTER 3. INNOVATION AND COMPETITION

3.1 Introduction

This chapter examines the relationship between innovation and competition. The degree of competition among firms has been recognized as one of the important factors influencing innovation. However, as we discuss in chapter 2.1, neither the theoretical nor the empirical literature provide clear evidence on the sign or the magnitude of this relationship. Studying the relationship between the competition and innovation is important for several reasons. If innovation generates growth of markets and efficiency, then creating institutions and markets that foster innovation are vital to increasing welfare. Further, if relatively more competitive markets generate greater innovation, then antitrust and regulatory policies, for example, would need to be structured and enforced appropriately to facilitate competition.

In this chapter, we examine the relationship between innovation and competition in the U.S. automobile market. We use patents to indicate innovation, and use market shares, HHI, and main rivals' market shares to measure market competition.

3.2 Empirical Specification

Our objective is empirically examine the role played by firm-specific market share and market-wide competitiveness on the intertemporal dynamics of firms' patents. There is a substantial literature on estimation of dynamic specifications related to firms' decision variables, such as physical capital investments, R&D investments, employment, and inventory holdings, among others. Eisner and Strotz (1963), Holt et al. (1960), Sargent (1978), Kennan (1979), Hendry et al. (1984), and Jorgenson (1986), for example, present expositions of the firms' optimization theory behind these econometric models. [3] Following this literature, we use a partial-adjustment framework to structure our empirical specification for patents. Partial-adjustment models have been used for examining innovation dynamics: *e.g.*, Falk (2006) and Lokshin and Mohnen (2012) for R&D, and Kim et al. (2012) for patents. As Hendry et al. (p. 1045) note, partial adjustment models are one of the most common empirical specifications used to study dynamics. The partial-adjustment model is based on a quadratic cost-minimizing framework where firms, when making their optimal adjustments related to the decision variable, aim to minimize disequilibrium and adjustment costs. The underlying models are framed in terms of a 'representative' firm, and then applied to data at various levels of aggregation.

The disequilibrium costs in these models arise due to lost profits from having the relevant decision variable at a sub-optimal level. For example, a delayed adjustment to the innovation path can lead to lost revenues and profits. Higher disequilibrium costs would, therefore, motivate a firm to adjust the innovation path faster. The adjustment costs are incurred when the firm attempts to align the actual quantity of the

[3] As the theoretical basis and econometric issues for these models have been widely discussed in these papers and the broader literature, we do not repeat the details here.

decision variable to its optimal level. A firm's attempt to more quickly alter its innovation path will result in higher adjustment costs. For example, rapid adjustment of the innovation path would require a faster adjustment of stocks of scientific personnel, capacity of research laboratories, reallocation of funds related to R&D, processing and filing of patents, among other factors. Higher adjustment costs would, therefore, motivate a firm to adjust the innovation path more smoothly and slowly. The disequilibrium costs and adjustment costs, therefore, act in opposite directions. This implies that the actual speed of adjustment of the innovation path will be a weighted-average of the two countervailing forces.

Denoting a firm's patents by PAT, the partial-adjustment model is given by (1).

(1) $lnPAT_t - lnPAT_{t-1} = \lambda(lnPAT_t^* - lnPAT_{t-1})$

In (1), PAT_t^* is the optimal (or equilibrium) value of PAT in period t, and λ is the speed-of-adjustment parameter. The actual intertemporal adjustment of patents ($lnPAT_t - lnPAT_{t-1}$) is typically a fraction λ ($0 \leq \lambda \leq 1$) of the desired intertemporal adjustment($lnPAT_t^* - lnPAT_{t-1}$). High (low) values of λ imply high (low) speed-of-response. As the variables are measured in logarithms, the differences in the variables are interpreted as percentage changes and allow us to interpret the coefficients in the specifications (below) as elasticities.

We rewrite (1) as:

(2) $lnPAT_t = (1 - \lambda)lnPAT_{t-1} + \lambda(lnPAT_t^*)$

In (2), PAT_t^* is private information to the firm and not directly observed by the external researcher. We model PAT_t^* as:

(3) $lnPAT_t^* = \psi lnZ_t$

where Z_t includes relevant driving variables.

3.2.1 Own Market Share, HHI, and Patents

Our primary specification is a logarithmic-linear dynamic panel data model which examines the relationship between firms' own market shares, market Herfindahl-Hirschman Index (***HHI***), and patenting activity. Returning to (3), Z_t is modeled as a function of the firm's own market share, the *HHI*, and a set of other control variables:

(4) $ln(Z_t) = \xi_1 ln(SHR_{t-1}^i) + \xi_2 ln(HHI_{t-1}) + \Psi \boldsymbol{X}$,

where $\boldsymbol{X}$ is the vector of control variables discussed below. Using (4), (3) and (2), our panel data model is:

(5) $ln(PAT_t^i) = \alpha^i + \tau_1 ln(PAT_{t-1}^i) + \tau_2 ln(SHR_{t-1}^i)$

$$+\tau_3 ln(HHI_{t-1}) + \vartheta \boldsymbol{X} + \epsilon_t^i.$$

In (5), PAT_t^i is the annual total number of patents for firm i, α^i is the firm-specific intercept, SHR_{t-1}^i is the lagged own-market share of the firm, HHI_{t-1} is one lag of *HHI*, $\boldsymbol{X}$ is a vector of other controls (discussed below), and ϵ_t^i is a firm-specific error term.

Log-linear specifications are common in estimating patent specifications. We do not use negative Binomial models as our sample contains large well-established multinational firms with continuous and relatively high patenting profiles. Negative Binomial models are more appropriate when the sample contains small and startup firms with over-dispersion of patent counts (*e.g.*, many zeros combined with large jumps in patents). Given the continuous nature of our patents data, we use a log-linear specification – which has been used in numerous earlier studies on patenting: *e.g.*, Kondo (1999), Kortum and Lerner (1999, 2000), Hall and Ziedonis (2001), Hu (2010), and von Graevenitz et al. (2013).

We include both firm-level market share and HHI in our estimated specification. Previous studies have included a measure of firm-specific market share (or related variable) and an industry-wide competition measure: e.g., Blundell et al. (1995, 1999) and Scherer (1965). An additional point we note is that in our panel, the correlation between firms' market share and HHI is 0.02 – so there is no obvious collinearity issue. This is motivated by several factors. First, including market share allows us to examine how the market position of the firm itself affects patenting, and including HHI allows us to examine how market-wide competitiveness affects patenting. Including both allows us to examine the effect of one, controlling for the other. Second, the underlying theory models and the extant empirical literature often examine and find different effects of firm-specific market-shares and market-wide competitiveness: *e.g.*, Acs and Audretsch (1988), Blundell et al. (1995, 1999), Aghion et al. (2005), Hashmi and Biesebroeck (2006), Hu (2010), Hashmi (2013), and Noel and Schankerman (2013). Third, our data show dramatic reallocation of market shares across firms over our sample period, and the ensuing time-path of *HHI*. If our sample had only two firms, it would not be meaningful to include both market share and *HHI*. But with nine firms, and significant intertemporal market share and HHI dynamics, it is meaningful to control for both.

The vector ***X*** includes the following control variables:

(a) The U.S. environmental and emissions control standards – Clean Air Act – that were introduced in the early 1970s with subsequent increases in standards in later years affected the patenting behavior of firms due to the need to generate newer products and processes to meet the emissions standards (Lee et al., 2010, 2011). They found that the environmental effect was most pronounced for the initial introduction of standards 1970-1973, with much smaller estimated effects during the 1990-1993 period, and that the effects were asymmetric across firms. There are important differences between the Lee et al. papers and ours. First, our focus is on competition and total patents. They study the link between emissions-control related patents and the regulatory standards. Second, our sample period is much longer. Nevertheless, we follow Lee et al. and control for potential policy-induced effects and create two dummy variables: **Enviro1**=1 if years equal 1969-1974, else Enviro1=0; and **Enviro2**=1 if years equal 1989-1994, else Enviro2=0. Each of our dummy variables covers a slightly wider period than Lee et al. (2011): Our period 1969-1974 instead of their 1970-1973; and our period 1989-1994 instead of their 1990-1993. Our justification for expanding the window for the environmental dummies is that the impending changes in policy were forecastable by the firms as the regulations went through extensive legislative discussions; hence an earlier start year of 1969. And some of the effects on innovation took more time to materialize; hence a slightly expanded terminal year for the dummy, 1974. Similarly for Enviro2 covering the period 1989-1994. The Corporate Average Fuel Economy (CAFE) standards also affected product development, engine design, among other changes. In terms of practical implications, while the standards for passenger cars went into effect earlier, the high fuel economy standard of 27.5MPG was effective starting 1990, with the next increase to 30.5MPG in 2011. The key item, the high standard of 27.5MPG, is roughly covered by our Enviro2 dummy (1989-1994), and overlaps with Lee et al. (2011) discussion of emissions standards. As Enviro1 and Enviro2 are general effects, potentially affecting all firms, we include these as controls in all specification we estimate;

(b) Daimler-Chrysler merger (**Merger**). This was an important event in this industry involving two large and prominent firms. In our data description we provide details of our adjustments to the data to account for this merger.

(c) GM's bankruptcy (**Bankruptcy**). Bankruptcy=1 if year 2009-2012, else Bankruptcy=0. The dummy variable covers GM's bankruptcy period. Our prior is that financial stress and significant losses had the potential to negatively affect GM's innovation activities. Since the Bankruptcy dummy is specific to GM, we include this as an additional control for GM;

(d) Voluntary Export Restraints (**VER**). VER=1 if year equals 1981-1985, else VER=0. VERs were negotiated between the U.S. and Japanese Governments to restrict exports of automobiles from Japan to the U.S. for the specified period. While we are not aware of a study that directly links VER to patenting, our conjecture is that it had the potential to alter firms' incentives to innovate. As VER is a general effect potentially affecting all firms, we include this as a control in all specifications; and

(e) Business cycles (**GDP**). We include GDP as there is an important literature that has examined the cyclicality of firms' innovation activities, and effects of business cycles on R&D and patenting: *e.g.*, Geroski and Walters (1995), Guellec and Ioannidis (1997), Barlevy (2007), Ouyang(2011), and Aghion et al. (2012).

In addition to the above, our estimated specification (5) includes two important controls: (a) a firm-specific intercept α^i; and (b) lagged firm-specific patents PAT^i_{t-1}. The fixed-effect α^i controls for unobserved firm-specific long-run differences in patenting across firms. This provides a control for some of the findings in the literature related to considerable variation in automobile firms' organizational structure, innovation and productivity strategies, and outcomes: *e.g.*, Lieberman et al. (1990), Lieberman and Demeester (1999), Lieberman and Dhawan (2005), and Lee et al.(2011, 2010).

The lagged-dependent variable PAT^i_{t-1} is a critical control for the intertemporal dynamics of firms' patenting. It controls for at least two key aspects. First, it controls for any persistence in the intertemporal path of patents. If the dependent variable

PAT_t^i shows persistence, or path-dependence, and we omit PAT_{t-1}^i, the resulting slope coefficients in the estimated specification can be misleading. Second, PAT_{t-1}^i serves as a control for an important omitted firm-specific time-varying factor that may influence the path of PAT_t^i – firms' R&D expenditures. R&D is a key control in patent production function specifications (*e.g.*, Hall and Ziedonis 2001, Kortum and Lerner 2000, and the literature surveyed there). Unfortunately, we do not have data on the firms' R&D spending. Our attempts to obtain a consistent time-series for the nine firms in our sample were unsuccessful. The primary problem lies with obtaining R&D data for the foreign firms, some of which are not publicly traded in the U.S. exchanges. Our full sample contains nine firms with time-series data for 44 years (1969-2012). Of the total 396 firm-years of observations, R&D data were not available (from Compustat North America or Global, and other firm-level databases) for 158 firm-years. However, PAT_{t-1}^i provides an indirect control for R&D in specification (5).

To examine R&D expenditures, consider (6) which represents a baseline patent production function model relating patents to R&D (e.g., Hausman et al., 1984; Kortum and Lerner, 2000; Hall and Ziedonis, 2001):

(6) $PAT = \theta R\&D^{\beta}$

Converting (6) to log-linear form we get:

(7) $ln(PAT_t^i) = ln\theta^i + \beta ln(R\&D_t^i)$.

In (7), θ^i is the firm-specific fixed-effect, and $R\&D_t^i$ is time-varying firm-specific R&D expenditures. As discussed by Hall and Ziedonis (2001) and numerous other papers in this literature, using deeper lags of R&D provide no useful information beyond including the most current R&D data. Hall and Ziedonis (p.113) write:

"This literature largely concludes that the lag structure is very poorly identified because of the high within-firm correlation of R&D spending over time. When many lags are included in the model, the estimate of the sum of the coefficients is roughly the same as the estimated coefficient of contemporaneous R&D when no lags are included … Experimentation with lag structures using these data confirmed the results in the earlier literature. For this reason … we use contemporaneous levels of R&D spending in our specifications."

Given this, the basic specification (7) mimics the core relationship between R&D and patents. Specification (7) lagged one period gives us (7'):

$$(7')\ \ ln\left(PAT_{t-1}^i\right) = \theta^i + \beta ln\left(R\&D_{t-1}^i\right).$$

Our specification (5) includes the lagged-dependent variable PAT_{t-1}^i. Substituting (7') into (5) implies that the coefficient τ_1 in specification (5) embeds the intertemporal dynamic effects of firms' R&D on patents, by accounting for the term $\beta ln\left(R\&D_{t-1}^i\right)$ from (7').

We note two additional points. First, any systematic steady-state differences across firms in their patenting profile is captured by the firm-specific fixed-effect α^i. If there are steady-state differences in firms' R&D spending, and corresponding steady-state differences in their patenting, it would be controlled by α^i. Second, specification (5) includes real GDP growth. Given that the literature indicates that innovation activities of firms and their R&D has a cyclical component, the GDP growth terms control for these cyclical effects.

While due to lack of consistent and complete data we cannot include R&D directly in specification (5), it incorporates important indirect controls for firms' R&D expenditures by including PAT_{t-1}^i, α^i and GDP growth.

Finally, we experimented with including deeper lags of *SHR* and *HHI*. First, the deeper lags of SHR are highly correlated in the data. For example, the overall correlation between SHR_{t-1}^i and SHR_{t-2}^i for the nine firms in our sample is about 0.95. Examining the firm's individually, the correlations are: GM (0.975), Ford (0.946), Chrysler (0.835), Toyota (0.983), Honda (0.988), Nissan (0.947), VW (0.918), BMW (0.985), and Daimler (0.982). The same problem exists with *HHI*. Including these lags produced a very high degree of collinearity between these deeper lags. Second, and more importantly, when we estimated specification (5) with the two lags entered separately, the second lag was typically insignificant, and did not have any meaningful contribution to explain movements in PAT_t^i. Given these, we do not include deeper lags in our estimated specifications.

We present two sets of dynamic panel data estimates for specification (5): (a) include all the nine firms. Given that our data cover the period 1969-2012, this gives us 396 firm-years of data in this panel; and (b) given the marked differences in the

German firms' patenting profiles, we re-estimate (5) by excluding the German firms. We do not interact the variables in specification (5) by country dummies - For parsimony, each included variable in specification (5) would have to be interacted with a country dummy. This produced significant collinearity between the included variables and then those variables interacted with the country dummies. Since this produces misleading inferences, we avoid this strategy.

3.2.2 Own Market Shares, Main Rivals' Market Shares, and Patents

Over our sample period, the Japanese firms have surged in the extent of competition they have offered to both the US and German firms. They have basically out-competed the US firms and Volkswagen in the mass produced segment, and have offered stiff competition to BMW and Daimler, and GM's Cadillac, for the higher-end or luxury cars. Given this, we consider the Japanese firms as the "main" rivals of both the US and German firms. Since our data are for the US market, we consider the US firms as the "main" rivals for the Japanese firms due to the extensive overlap in the mass-produced segment, as well as them having a home-market advantage. Examining this might provide additional insights into the complex interaction between competition and patenting.

To examine this, we drop HHI from specification (5) and replace it with the market shares of "Other-Country:Main" rivals. The U.S. (Japanese) firms' other-country main rivals are the Japanese (U.S.) firms. For the German firms, we consider the Japanese firms as their other-country main rivals due to the Japanese firms' luxury segments competing with the German firms, as well as with Volkswagen in the mass-produced segment. Our segmentation is also broadly consistent with some of the findings on important differences between, for example, U.S. and Japanese firms (*E.g.*, Lieberman et al.,1990; Lieberman and Demeester ,1999; and Lieberman and Dhawan,2005).

The estimated specification is:

$$(8)\ \ ln(PAT_t^i) = \kappa^i + \gamma_1 ln(PAT_{t-1}^i) + \gamma_2 ln(SHR_{t-1}^i) + \gamma_3 ln(SHR_{t-1}^{Other-Country:Main}) + \xi \boldsymbol{X} + \omega_t^i.$$

As in specification (5), $\boldsymbol{X}$ is the vector of other control variables. In section 5 we provide details about our estimation methods.

3.3 Data Description

In our analysis of the impact of competition on patenting in the U.S. automobile market, we examine data over a 44-year period, 1969-2012. We use 1969 as the start year as that was the first year we could get consistent market share data on all the firms in our sample. The starting date is also important as the late-1960s and early 1970s were important in this industry due to the introduction of emissions and other regulatory controls, as well as the oil price shocks starting 1973. And 2012 was the most recent year for which data were available when we started this project. We examine data on nine firms: GM, Ford, Chrysler, Toyota, Honda, Nissan, Volkswagen, BMW, and Daimler. This set covers the big-three U.S., Japanese, and German firms. While we considered including some of the other firms selling in the

U.S. market, our reasons for restricting it to the nine prominent firms were as follows. First, some of the data we use were consistently available only for these nine firms. For several of the other firms we considered, there were gaps in the data on market shares and sales. Second, the main new entrants in the U.S. market, Hyundai and Kia, were meaningful players only towards the end of our sample period, and their data were incomplete or missing for many of the earlier periods. Third, over our sample period (1969-2012), the nine firms on average accounted for approximately 91% of the sales in the U.S. market, therefore accounting for the vast majority of sales. Given this, we restricted our sample to the nine firms to allow us to do a thorough analysis with complete data on each firm.

It could be argued that BMW and Daimler are luxury brands, and therefore not directly comparable to the other firms. The counter arguments are that Toyota, Nissan, and Honda all have their distinct luxury divisions – Lexus, Infinity and Acura. While the luxury segment is relatively weak for the U.S. firms, Cadillac, for example, is GM's luxury segment. In addition, we note that Toyota's patents, for example, are reported under Toyota Motor Co. and not separately under Toyota and Lexus. So, for the mass market firms, there is no way to segment their patents into the mass produced versus luxury divisions. Moreover, Japanese firms, for example, often use the same platform design, engines, among other components, across their mass-produced and luxury lineups. Given these considerations, we decided to keep BMW and Daimler in our broader sample to offer some comparisons. In our estimation, we present panel data estimates using all nine firms, as well as by grouping firms by countries, allowing us to look at results with and without the German firms.

3.3.1 Patents

For the period 1969-2012, we collected data on patents for the nine firms from the U.S. Patent Office (USPTO). We use successful (granted) patent applications for our analysis. To obtain the total number of patents for each firm, we had to address a couple of important issues related to Ford Motors, and the Daimler-Chrysler merger.

For Ford Motors, the total patents assigned appear under: (i) Ford Motor Co.; and (ii) their technology subsidiary Ford Global Technologies. After 1997, the vast majority of patents for Ford are assigned to this technology subsidiary. Given this, we add the patents for Ford Motor Co. and Ford Global Technologies to obtain the total patents for Ford. This creates a consistent time series for all patents for Ford Motors.

The merger between Chrysler and Daimler was an important event. They merged on (November 12) 1998 and broke up on (May 14) 2007. The merger resulted in the total number of patents for both companies dropping to zero as all new patents were assigned to the new entity 'DaimlerChrysler.' Chrysler and Daimler began to have their own patents assigned again after the break up in 2007. To address this issue, one option for us was to drop both Chrysler and Daimler from the sample. But this is not desirable as it would result in omission of two large and important firms from the sample. Another option was to include a merger dummy to cover the roughly 9 year merger period. But this is also not very useful as the lack of time-series data over this extended merger period would reduce our ability to understand the intertemporal dynamics of competition and patenting. Instead, we use the approach noted below to create a merger-adjusted patents time-series for Chrysler and Daimler.

First, over the 10-year period 1989-1998,[4] we compute the total number of patents for Chrysler and Daimler: $PAT^{Chry+Daim}$. Next we calculate the fraction of total patents accounted for by each company during this 10-year pre-merger period: $(PAT^{Chry})/(PAT^{Chry+Daim})$ and $(PAT^{Daim})/(PAT^{Chry+Daim})$. These two ratios 'roughly' indicate the individual firms' patent shares in the pre-merger period, if the two firms were actually combined. Our data indicate that while there is a small amount of variation in these two fractions, they appear relatively stable over the 10-year pre-merger period. To smooth out shorter-run, year-to-year, variations in this ratio, we use the average fraction from the 10-year pre-merger period. The values of these pre-merger ratios are: $(PAT^{Chry})/(PAT^{Chry+Daim})$ =0.45, and $(PAT^{Daim})/(PAT^{Chry+Daim})$=0.55. Next, we assume that over the actual merged period, the true share of patents accruing to Chrysler remains at 0.45. Using this, we assign 0.45 of the merged DaimlerChrysler entity's total patents to Chrysler, and the remaining 0.55 to Daimler. Using this procedure, we create a merger-adjusted continuous time-series in the patents granted to Chrysler and Daimler over the period they were merged.

[4] We treat this as the pre-merger period in our calculations below. While the merger was consummated on (November 12) 1998, DaimlerChrysler began to have patents assigned to this merged entity starting 1999. Therefore, using 1998 as the terminal year to do our calculations does not affect our analysis. As we note later, altering the time periods to do our calculations does not affect any of our conclusions.

After the merger broke up in 2007, some patents continued to be granted to the combined DaimlerChrysler entity during 2008-2010 due to the administrative and legal processes. For the period 2008-2010, we use the same procedure as noted above to separate the patents assigned to DaimlerChrysler and allocate those to Chrysler and Daimler.

In combination, our above procedure gives us a merger-adjusted time-series in patents for Chrysler and Daimler for the full sample period, 1969-2012. Apart from the 1989-1998 based calculations noted above, we experimented with a five year period 1994-1998, as well as redoing the calculations by leaving out the year 1998. The merger-adjusted time-series we create are not sensitive to the exact pre-merger years we consider to do our calculations.

Even after making the above adjustments to create a continuous time-series for patents for Chrysler and Daimler, there is a discrete jump in patenting for both firms around the period 1998-2002. This is not the entire merger period 1998-2007, but a sub-period. Before 1998 and after 2003, each firm's series looks in conformity with their longer-run patterns. There appears to be some merger-related complexities over the period 1998-2002 that are not being fully captured by our adjustment. While the exact analysis and effects of the merger on the firms' innovation is beyond the scope of this paper, we control for this phenomenon by including a merger dummy (**Merger**): Merger=1 if year 1998-2002, else Merger=0. Since the Merger dummy is specific to Chrysler and Daimler, we include this as an additional control for those two firms only.[5]

Table 3.1 Summary Statistics: Patents

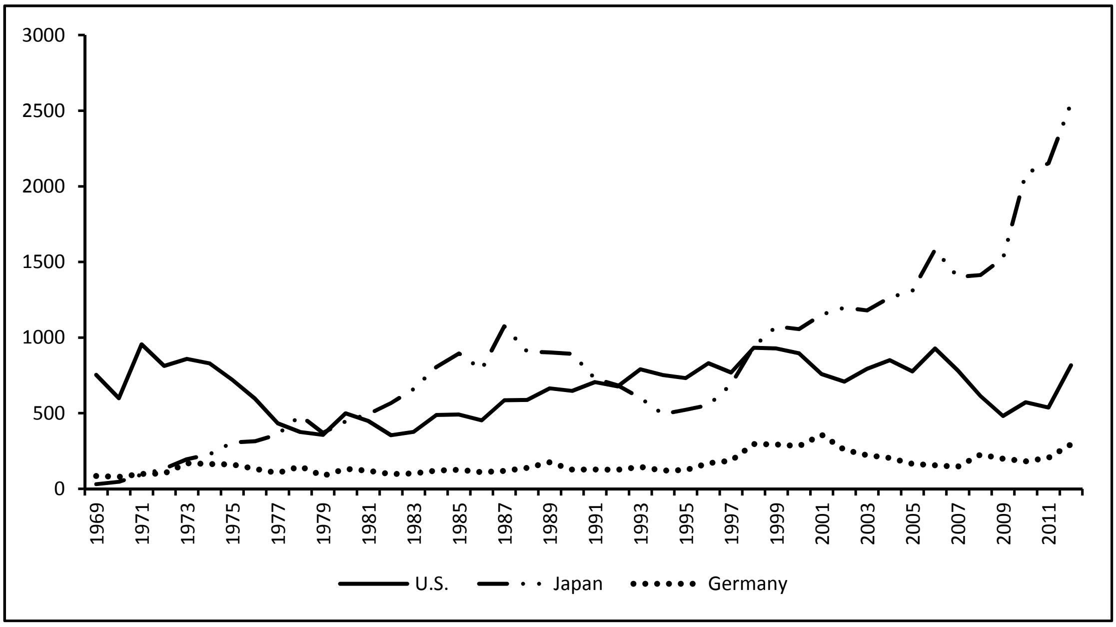
Firm	μ^{PAT}	σ^{PAT}	CV^{PAT}(%)
GM	332.7	145.8	44.3
Ford	259.8	127.5	49.1
Chrysler	78.3	61.7	78.8
Toyota	277.0	240.3	86.8
Honda	351.0	308.2	87.8
Nissan	216.3	95.5	44.2
VW	25.2	12.7	50.4
BMW	27.5	27.8	101.1
Daimler	110.5	45.2	40.9
Patent (Total)	*1678.3*	*653.3*	*38.9*

Notes: μ^{PAT}, σ^{PAT} and CV are the mean, standard deviation and coefficient of variation (percent) of the total number of patents (for the 9 firms), and for each firm.

Table 3.1 presents the summary statistics for the patents data. The sample average number of patents for GM, Ford, Toyota, and Honda are relatively close at 333, 260, 277, and 351, respectively. Chrysler has the lowest patent profile of the three U.S. firms, and Nissan the lowest among the Japanese firms. Daimler, the most active German firm, has a sample mean of 111 patents, which is almost four times larger than VW or BMW. The sample averages conceal important underlying dynamics. Two Japanese firms, Toyota and Honda, have aggressive patenting profiles

5 We do not consider other mergers during our sample period, such as those of Volvo (by Ford) and Saab (by GM), as these were very small firms. Our examination of these mergers revealed very little impact on the acquiring firms.

during the latter half of the sample period during which they surpass the peaks of GM. The German firms individually, or as country total, have relatively stable profiles.



Notes: The data for the US are the sum of USPTO patents for GM, Ford and Chrysler. Japan, for Toyota, Honda and Nissan. Germany, for Volkswagen, BMW and Daimler.

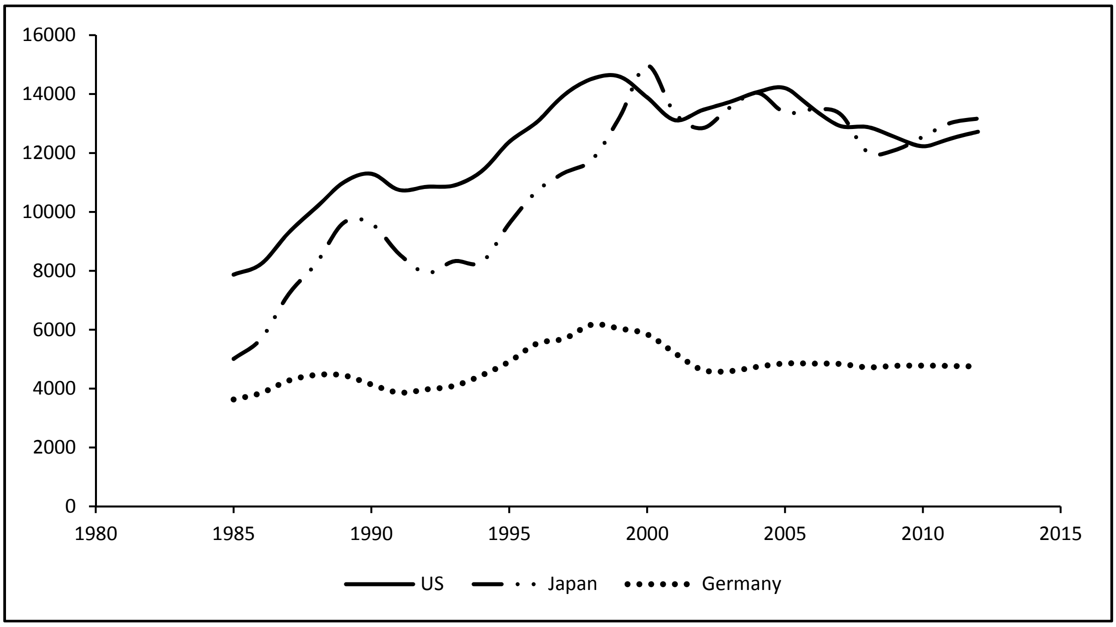
Figure 3.1 Automobile Firms' USPTO Patents – Grouped by Country

Figure 3.1 plots the firms' USPTO patents – grouped as country totals. Overall, the U.S. total shows relative stability. The two big deviations in the U.S. totals come around 1970-1974 (mainly due to sharp increase in GM's patents, potentially related to the Clean Air Act) and 2008-2010 (entirely due to drop in GM's patents during its bankruptcy period). In contrast, the Japanese patents show sharp acceleration towards the end of our sample period. This is almost entirely driven by spikes in patenting by Toyota and Honda. The German profile is one of relative low and stable patenting. The increase in the German profile around 1999 to 2002 is entirely due to an increase in Daimler's patents during that period (related to the merger with Chrysler).

An intriguing feature is the three German firms' low total patent counts compared to the U.S. or Japanese firms. Daimler, the most active firm of the three German companies, has a peak of 250 patents in 2000, which is still much lower than the averages of GM and Ford, and even lower than the average of the Japanese firms in 1985. For VW and BMW, their total numbers of patents are consistently low. This is puzzling given the reputation of the German firms' innovative capabilities.

It is clearly the case that the U.S. market is very important to the German automobile firms. Over our sample period, BMW has sold roughly 23%-28% of its global production in the U.S. market. A similar significance holds for Daimler. In terms of profits, a similar fact holds where the high-demand and high-income U.S. market has been historically important for BMW and Daimler. Given this, one would expect the German firms to have a healthy patenting profile in this important market, much like the Japanese. While the lower patenting profile of the German firms is rather curious, we were unable to find explanation of this in the literature in spite of extensive searching.

To examine if our USPTO automotive patents data on the German firms were an aberration, we examined data from the OECD database containing country-total *triadic* patents. Note that these are not just automotive patents, but all patents from each country. **Figure 3.2** plots the country-total triadic patents. It is clear that Germany's country total triadic patents are an order of magnitude lower than either U.S. or Japan. Figure 3.2 shows that the U.S. and Japanese county total triadic patents are relatively similar, and about four times larger than the German total. Setting aside specific differences, our USPTO-based auto patents (displayed in Figure 1) are not an aberration. German patents appear to be systematically lower.



Notes: The country triadic patent totals data are from the OECD patents database (1985-2012). These are all patents by country (not just automobile).

Figure 3.2 OECD Country Total Triadic Patents – All Patents

We end this section with a comment linking the observations from the data to our econometric estimation. Our patents specification (5) – see section 3 – includes a firm-specific fixed-effect α^i which controls for the long-run steady-state differences in firms' mean levels of patents – noted in the summary statistics presented in Table 3. Whatever firm-specific reason exists to generate different levels across the firms, α^i controls for it. What is important for estimation of the slope coefficients is whether there are intertemporal fluctuations in patents. Examining table 3, we see that the coefficient of variation is quite high for all firms in the sample. Even though the

German firms have lower levels of patenting compared to their U.S. and Japanese counterparts, the coefficient of variation of the German firms' patents are comparable to the other firms.

3.3.2 Market Share and HHI

Data on sales in the U.S. and market shares are from Ward's Automotive. Ward's offers the most comprehensive and historical data on U.S. market sales. According to the data on total light vehicles sales from Ward's Auto, the nine firms in our sample dominate the automobile industry with an average market share of 91% over the sample period 1969 to 2012.

Table 3.2 Summary Statistics: Market Shares and HHI

Firm	μ^{SHR}	σ^{SHR}	CV^{SHR}(%)
GM	34.3	8.6	25.1
Ford	22.2	3.9	17.5
Chrysler	12.6	1.8	14.3
Toyota	7.8	4.3	54.8
Honda	5.0	3.2	63.7
Nissan	4.6	1.7	36.9
VW	2.2	1.1	50.2
BMW	0.8	0.7	85.7
Daimler	1.1	0.7	67.3
HHI (9 firm)	*2066.4*	*580.9*	*28.1*

Notes: μ^{SHR}, σ^{SHR} and CV are the mean, standard deviation and coefficient of variation (percent) of HHI, and the market shares of each firm. HHI is calculated based on the 9 firms in our sample.

Table 3.2 presents the summary statistics on market shares. The sample averages show that the U.S. firms have the highest market shares, and the German firms with the lowest shares. In terms of the underlying dynamics of market shares, the three U.S. firms combined started with a high market share of around 80% in 1969, but this drops to about 45% by 2012. Among the U.S. firms, GM suffered the largest loss of market share. While Ford and Chrysler also had declining shares, they had relatively more stable market share profiles compared to GM. The Japanese firms started with a low market share of about 2% in 1969, and increased to about 35% by 2012. While all three Japanese firms increased their shares, Toyota was perhaps the most successful in challenging GM and Ford. After 2006, Toyota had a market share around 15%, which was close to Ford, and was only about 5% lower than GM in 2010. While the low shares of BMW and Daimler are understandable as they operate in the luxury segment, the low market share of Volkswagen, a mass market firm, reveals significant failure to compete with either the U.S. or the Japanese firms. The total market share of the three German firms was about 5% in 1969, declined to about 2% in the mid-1990s, and then increased to about 7% by 2012. Volkswagen had a market share of about 5% in 1969, reached a low of about 0.5% in 1993, before recovering and increasing to 3% in 2012. Like the U.S. firms, Volkswagen lost ground to the Japanese firms. In recent years, the high-end luxury brands BMW and Daimler have been at par with the mass-market Volkswagen in their U.S. market shares. VW's historic problems are also current ones. As noted in Forbes (07/03/2014): "*Volkswagen has been and continues to be in a new product drought. It simply doesn't have the vehicles or the breadth of product portfolio to capitalize…*" Wall Street 24/7 (05/02/2015) notes: "*The two primary* *arguments about VW's failure in America are that its model line is too limited and the amount of successful competition is too great. The problems converge.*"

As noted above, the nine firms in our sample have accounted for approximately 91% of the U.S. sales over our sample period, 1969-2012, representing the dominant portion of the market. In our estimated specification (5), we use individual firms' market shares as well as a market-wide indicator of competitiveness. For this we construct the Herfindahl–Hirschman Index (**HHI**). Using data on the nine firms, $HHI_t = \sum_i (s_{it}^2)$, $i = 1, \ldots, 9$, where s_i denotes the firm's market share.[6] This gives us a time series in HHI for the 44 years in our sample. For the period 1969-1979, the HHI fluctuated around a mean value of about 2,750, with the highest recorded value around 3,000. After 1979, the HHI declines steadily, with the only noticeable difference coming in the 1986-1995 period when it remained relatively flat around 2,000. It declines to a low of about 1,000 in 2012. While the starting value of about 3000 is not particularly high for oligopolistic markets, the decline over the sample period reflects a marked increase in the degree of competition in the market. As the nine firms in our sample remain in the market for the full 44-year period, the change in the HHI is largely due to the reallocation of market shares away from the U.S. and towards the Japanese firms.

[6] As we do not have detailed financial data for the firms over our sample period, we were not able to construct even an approximate measure of profitability. As we noted earlier, since several of the firms are not traded in the U.S. stock markets, or have been traded relatively recently, creating a consistent database of their economic and financial data are not possible.

3.4 Estimation Results

We estimate the panel models with all nine firms in our sample, as well as a sub-sample that excludes the German firms. We noted earlier that patenting by German firms is much lower compared to the US or Japanese firms. While our empirical model includes a firm fixed-effect as well as a lagged dependent variable to control for firm-specific long-term and dynamic effects, estimating without the German firms provides a check of robustness of our overall results.

In terms of estimation methods, we are cognizant of the fact that our panel has somewhat different characteristics as compared to typical panels which have large N and relatively small T. Our full panel has relatively small N (9) and larger T (44). Under these characteristics, the GMM estimators may not produce the most efficient parameter estimates – although the precise extent of inefficiency in our case is difficult to determine. To address this, along with the GMM estimates, we also report the more conventional instrumental variables (IV) estimates which are less subject to the efficiency problems. By presenting both the GMM and IV estimates, we check for the robustness of our inferences. As we note below, our key results are not sensitive to using GMM versus IV.

3.4.1 Potential Endogeneity

In specification (5), the SHR_{t-1}^{i} explanatory variable is lagged one period. This reduces any obvious endogeneity issue between a firm's own market share and patents. However, time-series persistence in PAT_{t}^{i} (the dependent variable) and

SHR_t^i may lead to potentially complex reverse causality issues. The general issue of reverse causality has been noted in the literature. Blundell et al. (1999), for example, note that instead of increasing innovations, market shares could be increased by innovation because firms that innovate will grow and therefore have higher market shares. To formally examine this, we conducted econometric causality tests. We implement two of the more commonly used tests, by Granger (1969) and Geweke, Meese and Dent (1983). For a given firm, the Granger test uses specification (9) to test for econometric exogeneity:

$$(9)\ ln(SHR_t) = a + \sum_m b_m ln(SHR_{t-m}) + \sum_n c_n ln(PAT_{t-n}) + u_t.$$

The test includes m-lags of the firm's own market share (*SHR*) to capture the variable's own dynamics, and n-lags of the firm's own patents (*PAT*) to examine reverse causality. The null hypothesis is: $c_n = 0\ \forall\ n$.

We test for econometric exogeneity by estimating specification (9) firm-by-firm. Our examination of lag lengths showed that two lags were sufficient (*i.e.*, m=2, n=2); higher-order lags were not significant, and adding them did not change the testing results reported below. For the 9 firms in our sample, the *F-static* (*p-values*) from the Granger test are: GM 1.95 (0.156); Ford 0.82 (0.445); Chrysler 0.34 (0.711); Toyota 2.56 (0.091); Honda 3.01 (0.062); Nissan 1.30 (0.284); Volkswagen 0.84 (0.437); BMW 3.51 (0.040); and Daimler 0.07 (0.932). Based on these test results we reject the null for only three firms – Toyota, Honda, and BMW. The Geweke, Meese and Dent

(1983) test uses a different specification structure compared to Granger, and the estimated specification is:

$$ln(PAT_t \ ) = d + \sum_k p_k ln(SHR_{t-k}) + \sum_w q_w ln(SHR_{t+w}) + \sum_g r_g ln(PAT_{t-g}) + e_t.$$

The specification includes k-lags and w-leads of SHR, and controls for the variable's own dynamics via lagged-dependent variables. The null is: $\mathrm{q_w} = 0 \; \forall \; \mathrm{w}$; *i.e*., future values of *SHR* do not influence current *PAT*. The results were largely similar. To account for the potential endogeneity of *SHR* for the firms noted above, the dynamic panel estimation methodology we adopt – GMM and IV – includes a full set of instruments (see notes to the tables).

In addition, we also tested for the potential endogeneity of the *HHI* in specification (5). The argument here being that significant innovations by a firm can potentially alter the market structure. The *HHI* in specification (5) is lagged one period, and this reduces any obvious endogeneity issues. We used the Granger and the Geweke et al. procedures to test for potential endogeneity of HHI. The tests do not reject the null of econometric exogeneity of *HHI*.

3.4.2 Own Market Share and HHI Estimates

Results from estimating specification (5) are in **Table 3.3**. Next, in **table 3.4**, we present estimates from a modified specification: from the model in table 3.3, we drop the variables Enviro1, Enviro2, VER and HHI, and replace these with year time dummies. The rationale is that the year dummies are perhaps more encompassing and better capture all effects that are common across firms in a given year. This allows us to check for the robustness of our market share and other estimates.

Table 3.3 Own Market Share and HHI

	1. GMM All	2. GMM All-German	3. IV All	4. IV All-German
$ln(PAT_{t-1}^{i})$	0.743*** (0.041)	0.773*** (0.054)	0.780*** (0.048)	0.745*** (0.055)
$ln(SHR_{t-1}^{i})$	0.124** (0.057)	0.115** (0.054)	0.133** (0.049)	0.130** (0.058)
$ln(HHI_{t-1})$	-0.216*** (0.081)	-0.258*** (0.105)	-0.155** (0.081)	-0.284*** (0.090)
Enviro1 (1969-1974) Environmental	0.113*** (0.038)	0.098** (0.046)	0.107 (0.080)	0.119 (0.076)
Enviro2 (1989-1994) Environmental	-0.064 (0.064)	-0.035 (0.067)	-0.067 (0.052)	-0.032 (0.047)
Bankruptcy GM	-0.677*** (0.065)	-0.656*** (0.111)	-0.604*** (0.213)	-0.726*** (0.209)
Merger Daimler-Chrysler	0.174** (0.068)	0.218*** (0.058)	0.127 (0.108)	0.270** (0.152)
VER Voluntary Export Restraints	-0.036 (0.052)	-0.013 (0.076)	-0.037 (0.057)	-0.020 (0.068)
Firm Fixed-Effect	Yes	Yes	Yes	Yes
Year Dummies	No	No	No	No
Observations	378	252	378	252

Notes:

1. Estimated specification is (see chapter 3.2):

(5) $ln(PAT_t^i) = \alpha^i + \tau_1 ln(PAT_{t-1}^i) + \tau_2 ln(SHR_{t-1}^i) + \tau_3 ln(HHI_{t-1}) + \vartheta\boldsymbol{X} + \epsilon_t^i$.

The variables are:

PAT_t^i: Number of patents for firm *i* in year t;

α^i: Firm-specific fixed-effect;

SHR_{t-1}^i: Market share of firm *i*, lagged one period;

HHI_{t-1}: Herfindahl index, lagged one period;

X: vector of control variables Enviro1, Enviro2, VER, Bankruptcy, and Merger.

2. Estimation in column 1 and 2 are via the Arellano-Bond GMM estimator. Robust standard errors are reported in parentheses, and ***, ** and * denote significance at 1%, 5% and 10% levels. The 'All' sample includes the 9 firms in our sample, and the All-German samples include the 6 U.S. and Japanese firms. The annual data for each firm covers the period 1969-2012. Two initial observations are dropped due to taking lags and the first-differencing procedure of the estimator.

3. The results of the specification tests for columns 1 and 2 are as follows.

(a) Over-identification test χ^2 (*p-value*). Column 1: 335.29 (0.516). Column 2: 255.88 (0.135).

(b) Arellano-Bond test for zero autocorrelation in first-differenced errors are as follows. Column 1: Order=1: z=-2.40 (p=0.017). Column 2: Order=1: z= -2.09 (p=0.036).

(c) Wald χ^2 (*p*-value): Column 1: 27.21 (0.000). Column 2: 22.58 (0.000).

Table 3.3 (continued)

4. Estimation in column 3 and 4 are via the IV estimator. Robust standard errors are reported in parentheses, and ***, ** and * denote significance at 1%, 5% and 10% levels. Two initial observations are dropped due to taking lags and using deeper lags of the estimator as IV. $ln(PAT_{t-1}^{i})$ and $ln(SHR_{t-1}^{i})$ are treated as endogenous, $ln(PAT_{t-2}^{i})$, $ln(SHR_{t-2}^{i})$, $ln(HHI_{t-1})$, Enviro1, Enviro2, Merger, Bankruptcy, and VER are used as IVs.

Table 3.4 Own Market Share

	1. GMM All	2. GMM All-German	3. IV All	4. IV All-German
$ln(PAT_{t-1}^{i})$	0.790*** (0.034)	0.804*** (0.039)	0.785*** (0.043)	0.762*** (0.050)
$ln(SHR_{t-1}^{i})$	0.136** (0.061)	0.086* (0.047)	0.132*** (0.042)	0.119*** (0.046)
Bankruptcy GM	-0.594*** (0.079)	-0.652*** (0.117)	-0.609*** (0.205)	-0.725*** (0.212)
Merger Daimler-Chrysler	0.027 (0.077)	0.175** (0.074)	0.025 (0.091)	0.233* (0.130)
Firm Fixed-Effect	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	378	252	378	252

Notes:

1. See table 3.3 for general comments.
2. Compared to table 3.3, in the above table we replace Enviro1, Enviro2, VER and HHI by year time dummies.
3. The results of the GMM specification tests for columns 1 and 2 are as follows.

(a) Over-identification test χ^2 (*p-value*). Column 1: 306.56 (0.464). Column 2: 226.46 (0.074).

(b) Arellano-Bond test for zero autocorrelation in first-differenced errors are as follows. Column 1: Order=1: z=-2.42 (p=0.015). Column 2: Order=1: z= -2.10 (p=0.035).

(c) Wald χ^2 (*p*-value): Column 1: 33.59 (0.000). Column 2: 12.96 (0.024).

4. In columns 3 and 4, $ln(PAT_{t-1}^{i})$ and $ln(SHR_{t-1}^{i})$ are treated as endogenous. $ln(PAT_{t-2}^{i})$, $ln(SHR_{t-2}^{i})$, Bankruptcy, Merger, and Year Dummies are used as IVs.

As we discuss the results below, one important aspect of our results to keep in mind is that they are not sensitive to the specific estimation method used – GMM or conventional IV.

Path-dependence of patenting

The coefficient of the lagged-dependent variable is positive and highly significant, indicating persistence in the path of firms' patents. The estimated elasticities are approximately 0.7 (they are marginally higher at about 0.8 in table 3.4). The lagged-dependent variable elasticities indicate considerable path-dependence in firms' patenting. This is not surprising as we expect firms' R&D processes, and innovation and patenting strategy to show some continuity at least in the short-to-medium term.

Own market share effects

One of the main variables from theory is firms' own market share. In table 3.3, the full-panel estimate of the own market share elasticity is 0.13, and statistically significant. Given the standard errors, the point estimates are not statistically different across the various specifications reported in tables 3.3 and 3.4.This implies that for the typical firm in our sample, an increase in market share leads to higher patenting.

Next, in **table 3.5** and **table 3.6** we present the quantitative effects. In both these tables, if the underlying GMM coefficient estimate in table 3.3 was statistically insignificant, we assign a value of zero to that effect. In table 3.5 we present the actual change in patents as own market share increases by one standard deviation, starting from its sample mean value. And in table 3.6 we present the corresponding percentage change in patents if own market share increases by one standard deviation, starting from its sample mean value. Across the various specifications estimated, the calculations in tables 3.5 and 3.6 show that increase (decrease) in own market share results in an increase (decrease) in patents by about 25-30 (or about 10%-14%).

Table 3.5. Estimated Quantitative Effects – Actual Change: Own Market Share and HHI

	1. GMM All	2. GMM All-German	3. IV All	4. IV All-German
Table 3.3.				
SHR_{t-1}^{i}	23	29	25	33
HHI_{t-1}	-40	-65	-29	-72
Table 3.4. With Year Dummies				
SHR_{t-1}^{i}	25	22	25	30

Notes:

1. Calculations are based on the GMM estimates from table 3.3 and 3.4. Only the main variables of interest are reported to save space.

2. Estimated quantitative effects (as the actual changes in variables) are based on considering a one-standard-deviation change in the relevant independent variable. If the underlying coefficient estimates were insignificant in table 3.3, we assign a value zero to that effect. The estimated quantitative effects are computed as follows. Given the elasticity (significant coefficients in table 3.3), when independent variable *x* changes from $\bar{x}$ to $(\bar{x} + \sigma)$, the change in value of PAT_t^i (starting from the initial value: $\overline{PAT_t^i}$).

Table 3.6. Estimated Quantitative Effects – Percentage Change: Own Market Share and HHI

	1. GMM All	2. GMM All-German	3. IV All	4. IV All-German
Table 3.3.				
SHR_{t-1}^{i}	13.95%	9.28%	14.96%	10.49%
HHI_{t-1}	-6.01%	-7.18%	-4.31%	-7.91%
Table 3.4. With Year Dummies				
SHR_{t-1}^{i}	15.30%	6.94%	14.85%	9.60%

Notes:

1. Calculations are based on the GMM estimates from table 3.3 and 3.4. Only the main variables of interest are reported to save space. The estimated quantitative effects (as percentage changes) are based on considering a one-standard-deviation change in the relevant independent variable. If the underlying coefficient estimates were insignificant in table 3.3, we assign a value zero to that effect.

Finally, in **table 3.7** we present the short-run versus long-run elasticities. Calculation of the long-run elasticities uses the estimates of the short-run elasticities from table 3.3, and the estimate of the patents' path-dependence parameter (the lagged dependent variable). The computed long-run elasticity is an order of magnitude larger than the short-run elasticity, implying that an increase in market share has a markedly larger effect on patenting in the longer-run.

Table 3.7. Estimated Elasticities: Own Market Share

	1. GMM All	2. GMM All-German	3. IV All	4. IV All-German
Table 3.3.				
Short-run	0.124**	0.115**	0.133***	0.130**
Long-run	0.482**	0.507**	0.605***	0.510**
Table 3.4. With Year Dummies				
Short-run	0.136**	0.086*	0.132***	0.119***
Long-run	0.648**	0.439*	0.614***	0.500***

Notes:

1. Short-run elasticities are the estimated coefficients for $ln(SHR_{t-1}^{i})$ reported in table 3.3 and 3.4. (As the specification is estimated in log-linear form, the coefficients are interpreted as elasticities.) An asterisk * indicates that the estimate is significant (see table 3.3 and 3.4).

2. Long-run elasticities are calculated as follows: $\left[\frac{\tau_2}{(1-\tau_1)}\right]$, where τ_2 is the estimated coefficient of $ln(SHR_{t-1}^{i})$ (specification 5) and $\tau_1$is the estimated coefficient of the lagged-dependent variable $ln(PAT_{t-1}^{i})$.

Overall, and based on our discussion in chapter 2.1, our findings are similar in spirit to those in Blundell et al. (1995, 1999), Brouwer and Kleinknecht (1999) and Lee et al. (2011). In addition, our study sheds some light on potential nonlinearities in the relationship between market shares and patenting which we explore in greater detail below.

Market-wide competition (HHI) effects

Our second key variable from theory is market-wide competition. Our measure is the *HHI* – a reduction in *HHI* indicates greater competition. The elasticity estimates from table 3.3 average around -0.25. This indicates that greater overall competition in the market increases firms' patenting. Our finding that an increase in market competition stimulates total innovation is similar in spirit to the results in, for example, Arrow (1962) and Lee and Wilde (1980), and also support the results in Acs and

Audretsch (1988), Blundell et al. (1995, 1999), Blind et al. (2006), Aghion et al. (2005), and Hu (2010). Our findings do not support Schumpeter (1934, 1942), Loury (1979), Delbono and Denicolo (1991), and Hashmi (2013), where greater competition reduces innovation. Our findings also do not favor Scherer (1965), Levin and Reiss (1984), Scott (1984), and Levin et al. (1985) where market power had no effect on innovation.

Nonlinearity in the Relationship between Competition and Patents

Earlier we noted the results in Aghion et al. (2001) and Aghion et al. (2005) predicting a nonlinear, inverted-U shaped, relationship between competition and innovation. Aghion et al. (2005) find some evidence of a nonlinear relationship between competition and patenting. The Aghion et al. (2005, p.703-705) data are fairly aggregated 2-digit industry-level panel with 17 industries covering the time period 1973-1994 (354 industry-year observations in their unbalanced panel). The economic and financial data they use for the U.K. industries are U.K.-based. However, the patents data they use are from the USPTO (See their data details, p.703-705). They write that their patents data are from the (p.704): "*…U. S. patent office, which is where innovations are effectively patented internationally.*" But as we see from our data, foreign firms' propensities to patent in the U.S. varies substantively both across firms and over time. Next they construct a 2-digit industry-average accounting profit-margin. They do not calculate the price-marginal cost Lerner index. Instead they construct a 2-digit industry-average measure of operating profits net of depreciation, provisions and an estimated financial cost of capital divided by sales (p.704-705). It is perhaps useful to note that a 2-digit industry contains myriad types of industries, underlying technologies, and markets, which are often not easily comparable. As an example, the 2-digit category 37 is ‘Transportation Equipment’ and includes such myriad industries and markets such as ‘Motor Vehicle Parts and Accessories’, ‘Railroad Equipment’, ‘Boat Building and Repairing’, ‘Guided Missiles and Space Vehicles’, ‘Aircraft Engines and Engine Parts’, among others. Given such disparate industries, it is difficult to assign meaning to an industry-average measure of profitability. Then they empirically examine the relationship to find a moderately inverted-U relationship.

Hashmi’s (2013) study generates a side-by-side comparison with Aghion et al. (2005). His data for the U.S. cover the years 1976 to 2001, with 116 industries at the 3-digit industry classification (for his 2-digit level there are 20 industries). Using U.S. industry data, he finds a moderately negative relationship between product market competition and patenting, and no evidence to support an inverted-U relationship. For the U.S. data, as competition increases, patenting falls at a mildly diminishing rate. In sharp contrast, the U.K. industry data reveals a mildly inverted U-shaped relationship, and, in general, patenting increases with greater competition.

Aghion et al. (2005) and Hashmi (2013), therefore, show diametrically opposite results. So even with these more sophisticated models and estimated specifications, the evidence on both the sign of the relationship between competition and patenting, and potential nonlinearities, is mixed at best. In some sense, this is similar to the brief summary of the empirical literature in chapter 2.1 – which reveals no conclusive results relating competition to innovation.

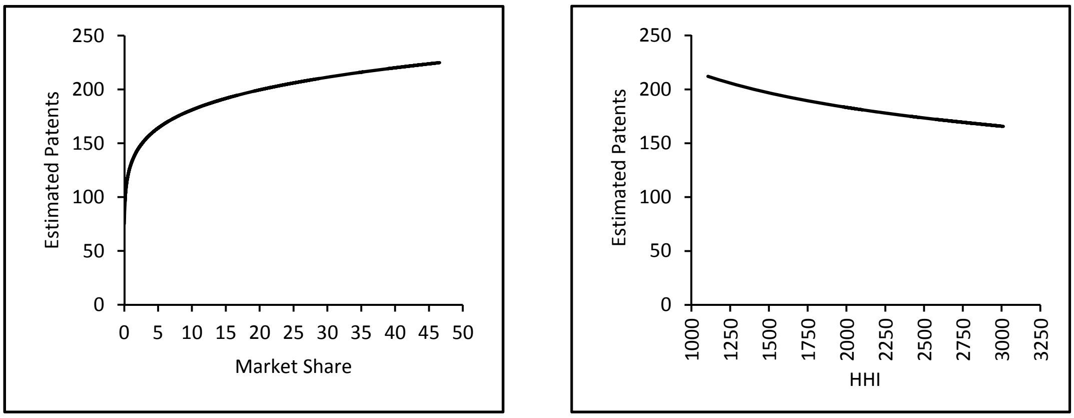
There are important differences between the above studies and ours. First, in contrast to the relatively aggregated 2-digit industry level data used by Aghion et al. (2005), our sample contains firm-level data for a single industry. Second, the time period for their study is 1973-1994. In contrast, ours is a much longer period, 1969-2012. Third, they construct an industry-average accounting profit-margin to proxy industry-wide competitiveness. Ours, in contrast, uses the HHI to proxy competitiveness. We do not have financial information for the firms for the full sample period, and therefore cannot construct a Lerner index. Fourth, their studies, being at the 2-digit industry level, do not contain both firms' market shares and industry measure of competitiveness. Given our more disaggregated study, we control for both firms' market shares and HHI, allowing us to examine the conditional relationships. Fifth, models like Aghion et al. may often be difficult to test as the degree of competition may not traverse the full spectrum – high degree of competition to near monopoly. The U.S. automobile market we study essentially moves from a tighter oligopoly (higher HHI, when the U.S. firms had dominant market share) to a looser oligopoly (lower HHI, with the expansion of the Japanese firms' market shares). Given these substantive differences in data characteristics, direct comparisons between their study and ours is not possible.

Our estimated specification (5) is log-linear, and therefore builds in non-linearity in levels. Using the full-panel estimated coefficients from table 3.3 (column 1), in

figure 3.3 panel (a) we plot the estimated relationship between firms' market shares and patents, and panel (b) the estimated relationship between HHI and patents. From panel (a) we see that the estimated patents increase with market shares, and the curvature is much sharper initially. Over the range of firms' market shares observed in the data (from about 1% to 46%), the *estimated* patents go from about 75 (per year) to 225 (per year). For the HHI effect in panel (b), the curvature is very mild, and over the range of HHI observations in the data (from about 1,000 to 3,000), the estimated patents go from about 212 to 166. Consistent with the calculations presented in tables 5.3 and 5.4, the quantitative effect on patents is much smaller for the HHI as compared to the market share effect.

Panel (a): Market Share

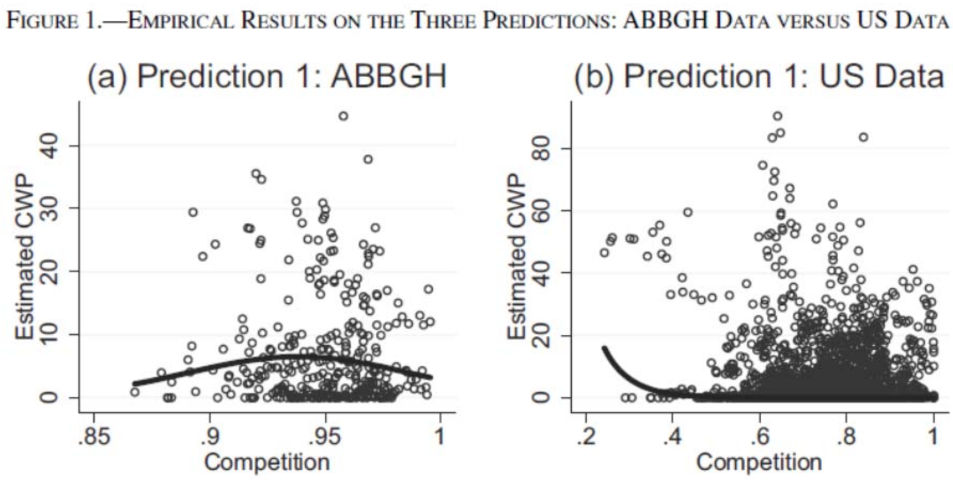
Panel (b): HHI



Note: In panel (a), estimated patents increase as firms' market shares increase. In panel (b), estimated patents increase as HHI decreases – implying that as market-wide competitiveness increases (lower HHI), patenting increases. The above figures reflect the calculations from tables 5.3 and 5.4 where we see that the estimated quantitative effects for firms' market shares are larger than for HHI.

Figure 3.3 Market Share, HHI and Estimated Patents

To provide a visual comparison, in **figure 3.4** we present the figure from Hashmi which shows the side-by-side comparison using U.K. and U.S. 2-digit industry data. As we noted above, our results are not directly comparable to either Hashmi or Aghion et al. (2005) due to the substantial differences in data characteristics. Our HHI results – which shows that increase in market competition leads to increase in patenting – is closer to the findings by Aghion et al. However, if we look at the estimated relationship by Hashmi for the U.S. data, after the initial drop, there appears to be a flat relationship between his measure of competition and patents. In our case (figure 4, panel b), the estimated patents-HHI line also has a very weak gradient.



<u>Note:</u> This figure is reproduced from Hashmi (2013, p. 1659, Figure 1). The solid lines above represent the estimated relationship: Panel (a) is based on the U.K. data used in Aghion et al. (2005, ABBGH); and Panel (b) is based on the U.S. data. As noted in Hashmi (p.1655): "Prediction 1. There is an inverted-U relationship between product market competition and innovation." (This is based on proposition 2 in Aghion et al., 2005, p.715.) The findings from the U.S. and U.K. data are diametrically opposite. Further, if we look at the U.S. figure, the estimated line is virtually flat above their competition measure 0.4.

Figure 3.4 Findings by Hashmi (2013)

Overall, we find evidence of non-linearity in the relationship between competition and patenting, and that an increase in market-wide competition (using HHI) results in marginally greater patenting. As we noted above, our data are not comparable to either Aghion et al. (2005) or Hashmi (2013). In addition, our estimated specifications are richer that the above studies as they include controls for both firms' market shares and HHI, along with other controls.

Other control variables

We briefly comment on our set of control variables. First, the 'Bankruptcy' variable was designed to control for GM's problems during 2009-2012. The estimates show that GM's patenting fell dramatically during the bankruptcy period. Given the dramatic internal organizational restructuring during this period, and potential financial problems, this is perhaps not surprising.

Second, the 'Merger' variable was designed to control for any residual effects of the merger between Daimler and Chrysler that were not addressed in our adjustments to the data to create a merger-adjusted continuous time-series for Chrysler and Daimler. We find that the merger generally appears to have increased patenting, but the statistical significance of the effect is mixed.

Third, the environmental variable Enviro1 (1969-1974) is always positive, but it is only significant for the GMM estimates. The general positive effect tallies with previous findings that the Clean Air Act increased innovation and patenting (*e.g.,* Lee et al., 2010, 2011). The Enviro2 effect is insignificant in all specifications. Our motivation for including the Enviro(.) effects was to control for potential environmental patents related findings of Lee et al. (2010, 2011). As we noted in section 3.1, our study is different from Lee at al. in that our focus is on the relationship between competition and total patents, and our sample period is also very different. However, our overall findings on Enviro(.) are similar in spirit to Lee at al. in that Enviro(.) matters, but the estimated effects vary across groups of firms, as well as across time periods.

Fourth, voluntary export restraints appear to have had no effect on the patenting activity. We did not have a clear prior on this variable, but included this as a control as it was an important event in the U.S. automobile market.

Checks of robustness

Our estimation already builds in several checks and controls to ensure confidence that we are picking up meaningful parameter estimates for firms' own market share and market-wide competitiveness effects. For example: (i) we tested our market share and HHI variables for endogeneity, and the estimation accounts for potential endogeneity; (ii) we presented alternative sets of estimates using GMM and fixed-effects instrumental variables procedures; and (iii) the estimated specification (5) contains a vector of control variables spanning environmental regulations, voluntary export restraints, the Daimler-Chrysler merger, GM's bankruptcy, and aggregate business cycle conditions (GDP growth). Below we report two additional checks.

First, one potential shortcoming of our estimates reported in table 3.3 is that we could not include year-time dummies due to collinearity problems. To take another look at this issue, we carried out the following estimation by: (a) dropping Enviro1, Enviro2 and VER from specification (5); and (b) adding non-overlapping 4-year period dummies 1970-73, 1974-77, …., 2006-09, 2010-12. The last dummy is for 3 years as 2012 is the last year in the sample. Our objective in including these period dummies was to, for example: (i) mimic year-time dummies, but with extended periods for each dummy; (ii) have the set of dummies cover the full sample period to capture any effects over time that could be related to, for example, environmental standards affecting all firms (a strategy similar to that employed in Lee et al. (2011); (iii) potentially control for any broad technological shifts that may have affected the automobile industry over time; and (iv) control for overall changes in the physical presence of foreign producers in the U.S. in terms of opening manufacturing plants, design studios, etc. Many of these operations tend to be staffed by Americans rather than Japanese, and they may give rise to, for example, intermingling of corporate cultures, management styles and innovation related spillovers. We also experimented with varying the time periods for the dummies noted in (b) above (for example, 3 or 5 year periods), and these did not affect our inferences noted in table 3.3.

Second, given that we have a relatively long sample period of 44 years, a reasonable question to ask is whether the estimated slope coefficients of our main variables of interest, SHR_{t-1}^{i} and HHI_{t-1}, are stable over time. To examine this we segmented the sample into two 22-year periods, and reestimated specification (5) for each sub-period. To formally test, we calculated the z-values. The z-statistic is based on Paternoster et al. (1998) who refine the test in Clogg et al. (1995). This allows testing the equality of coefficients in different models when one of the models is nested in the other. This is true in our case as some of the variables – such as Enviro1, Enviro1, VER, Merger and Bankruptcy – are relevant for the sub-periods used for testing the equality of coefficients, 1969-1990 or 1991-2012. We also carried out an alternative test by re-estimating specification (5) by adding a dummy variable to delineate the two sub-periods, as well as interacting this dummy with SHR and HHI, our main variables of interest. Using this procedure and testing resulted in the same conclusion – that we cannot reject the null of equality of coefficients: the z-values (*p-values*) are 0.04 (0.966) for SHR^{i}_{t-1} and 0.17 (0.868) for HHI_{t-1}. Based on our tests, we could not reject the null for the equality of coefficients across the two sub-periods.

3.4.3 Own Market Share and Rivals' Shares

As we noted in chapter 3.2, we examine if firms' patenting profiles are sensitive to the market shares of the main foreign competitors – Other-Country:Main rivals. Parsimonious to tables 3.3 and 3.4, these estimates are presented in **tables 3.8** and **3.9**.

Table 3.8 Own Market Share and Main Rivals' Market Shares

	1. GMM All	2. GMM All-German	3. IV All	4. IV All-German
$ln(PAT_{t-1}^{i})$	0.760*** (0.048)	0.783*** (0.061)	0.796*** (0.047)	0.790*** (0.055)
$ln(SHR_{t-1}^{i})$	0.161*** (0.058)	0.241** (0.100)	0.154*** (0.050)	0.191** (0.084)
$ln(SHR_{t-1}^{Other-Country:Main})$	0.097* (0.058)	0.184** (0.086)	0.082** (0.041)	0.164*** (0.063)
Enviro1 (1969-1974) Environmental	0.157*** (0.050)	0.231*** (0.078)	0.147* (0.082)	0.200*** (0.087)
Enviro2 (1989-1994) Environmental	-0.086 (0.064)	-0.083 (0.058)	-0.084 (0.052)	-0.079 (0.048)
Bankruptcy GM	-0.597*** (0.077)	-0.584*** (0.086)	-0.552*** (0.212)	-0.607*** (0.217)
Merger Daimler-Chrysler	0.141** (0.071)	0.163** (0.065)	0.097 (0.109)	0.186 (0.151)
VER Voluntary Export Restraints	-0.082 (0.050)	-0.075 (0.079)	-0.069 (0.054)	-0.074 (0.064)
Firm Fixed-Effect	Yes	Yes	Yes	Yes
Year Dummies	No	No	No	No
Observations	378	252	378	252

Notes:

1. Estimated specification is (see chapter 3.2):

(8) $ln(PAT_t^i) = \kappa^i + \gamma_1 \ln(PAT_{t-1}^i) + \gamma_2 \ln(SHR_{t-1}^i) + \gamma_3 \ln(SHR_{t-1}^{Other-Country:Main}) + \xi \boldsymbol{X} + \omega_t^i$.

The variables are as follows:

PAT_t^i: Number of patents for firm *i* in year t.

κ^i: Firm-specific fixed-effect.

SHR_{t-1}^i: Market share of firm *i*, lagged one period.

$SHR_{t-1}^{Other-Country:Main}$: Market share of other-country 'main' rivals of firm *i*, lagged one period.

X: vector of control variables Enviro1, Enviro2, VER, Bankruptcy, and Merger.

2. Estimation in column 1 and 2 are via the Arellano-Bond GMM estimator. Robust standard errors are reported in parentheses, and ***, ** and * denote significance at 1%, 5% and 10% levels.

3. The results of the specification tests for columns 1 and 2 are as follows.

(a) Over-identification test χ^2 (*p-value*). Column 1: 331.16 (0.580). Column 2: 244.71 (0.271).

(b) Arellano-Bond test for zero autocorrelation in first-differenced errors are as follows. Column 1: Order=1: z=-2.42 (p=0.015). Column 2: Order=1: z= -2.05 (p=0.040).

(c) Wald χ^2 (*p*-value): Column 1: 629.27 (0.000). Column 2: 424.18 (0.000).

4. Estimation in column 3 and 4 are via the IV estimator. Robust standard errors are reported in parentheses, and ***, ** and * denote significance at 1%, 5% and 10% levels. $ln(PAT_{t-1}^i)$ and $ln(SHR_{t-1}^i)$ are treated as endogenous, $ln(PAT_{t-2}^i)$. $ln(SHR_{t-2}^i)$, $\ln(SHR_{t-1}^{Other-Country:Main})$, Bankruptcy, Merger, and VER are used as IVs.

Table 3.9 Own Market Share and Main Rivals' Market Shares

	1. GMM All	2. GMM All-German	3. IV All	4. IV All-German
$ln(PAT_{t-1}^{i})$	0.792*** (0.035)	0.796*** (0.039)	0.793*** (0.045)	0.771*** (0.052)
$ln(SHR_{t-1}^{i})$	0.151** (0.066)	0.214** (0.084)	0.149*** (0.044)	0.200*** (0.067)
$ln(SHR_{t-1}^{Other-Country:Main})$	0.081 (0.059)	0.208** (0.084)	0.068 (0.052)	0.164** (0.068)
Bankruptcy GM	-0.607*** (0.077)	-0.705*** (0.086)	-0.606*** (0.207)	-0.755*** (0.217)
Merger Daimler-Chrysler	0.013 (0.071)	0.144** (0.073)	0.007 (0.094)	0.195 (0.129)
Firm Fixed-Effect	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	378	252	378	252

Notes:

1. See table 3.8 for general comments.

2. Compared to table 3.8, in the above table we replace Enviro1, Enviro2, VER and HHI by year time dummies.

3. The results of the GMM specification tests for columns 1 and 2 are as follows.

(a) Over-identification test χ^2 (*p-value*). Column 1: 303.88 (0.507). Column 2: 222.87 (0.105).

(b) Arellano-Bond test for zero autocorrelation in first-differenced errors are as follows. Column 1: Order=1: z=-2.43 (p=0.015). Column 2: Order=1: z= -2.07 (p=0.039).

(c) Wald χ^2 (p-value): Column 1: 43.82 (0.000). Column 2: 31.77 (0.000).

4. In columns 3 and 4, $ln(PAT_{t-1}^{i})$ and $ln(SHR_{t-1}^{i})$ are treated as endogenous. $ln(PAT_{t-2}^{i})$, $ln(SHR_{t-2}^{i})$, $ln(SHR_{t-1}^{Other-Country:Main})$, Bankruptcy, Merger, and Year Dummies are used as IVs.

Own market share effects

The estimated own market share elasticities are highly significant and similar to those presented in tables 3.3 and 3.4. The implied quantitative effects are presented in **Table 3.10** (actual changes) and **Table 3.11** (percentage changes). The implied elasticities are presented in **Table 3.12** and **3.13**. Overall, the inferences related to firms' own market share remain the same even though we dropped HHI and included the main foreign rivals' market share variable.

Other-Country:Main rivals' market shares

To note again, specification (8) is different from (5) in that we drop HHI and add the main rivals' market share variables. In the panel, the correlation between firms' own market shares and Other-Country:Main rivals' shares is -0.32; this correlation is not high enough to cause collinearity problems.

In table 3.8, the *other-country* 'main' rivals, the panel estimates are positive ranging from about 0.8 to 0.18 and significant. However, as we move to table 3.9, while the point estimates are relatively similar, the estimates are not statistically significant for the full sample. Overall, the estimates indicate that as firms' other-country primary rivals' market shares increase (decrease), firms increase (decrease) patenting. Looking at the big picture scenario, it appears that the threat the firms perceive to their competitive positions from their (main) foreign rivals induces them to increase their innovative activity as measured by patents. Our overall finding

– that an increase in competitive threat from their (main) foreign rivals will lead to more patents – is similar in spirit to the hypothesis of competitive threat by Hu (2010).

Table 3.10 Estimated Quantitative Effects - Actual Change: Main Rivals' Market Shares

	1. GMM All	2. GMM All-German	3. IV All	4. IV All-German
Table 3.8.				
SHR_{t-1}^{i}	30	61	29	48
$SHR_{t-1}^{Other-Country:Main}$	18	46	15	41
Table 3.9. With Year Dummies				
SHR_{t-1}^{i}	28	54	28	51
$SHR_{t-1}^{Other-Country:Main}$	0	53	0	41

Notes:

1. Calculations are based on the GMM estimates from table 3.8 and 3.9. Only the main variables of interest are reported to save space.
2. Estimated quantitative effects (as actual changes in variables) are based on considering a one-standard-deviation change in the relevant independent variable. If the underlying coefficient estimates were insignificant in table 8, we assign a value zero to that effect. The estimated quantitative effects are computed as follows. Given the elasticity (significant coefficients in table 3.8 and 3.9), when independent variable *x* changes from $\bar{x}$ to $(\bar{x} + \sigma)$, the change in value of PAT_t^i (starting from the initial value: $\overline{PAT_t^i}$).

Table 3.11 Estimated Quantitative Effects – Percentage Change: Main Rivals' Market Shares

	1. GMM All	2. GMM All-German	3. IV All	4. IV All-German
Table 3.8.				
SHR_{t-1}^{i}	18.11%	19.45%	17.33%	15.41%
$SHR_{t-1}^{Other-Country:Main}$	7.40%	11.91%	6.25%	10.62%
Table 3.9. With Year Dummies				
SHR_{t-1}^{i}	16.99%	17.27%	16.76%	16.14%
$SHR_{t-1}^{Other-Country:Main}$	0.00%	13.47%	0.00%	10.62%

Notes:

1. Calculations are based on the GMM estimates from table 3.8 and 3.9. Only the main variables of interest are reported to save space.
2. Estimated quantitative effects are based on considering a one-standard-deviation change in the relevant independent variable. If the underlying coefficient estimates were insignificant in table 3.8 and 3.9, we assign a value zero to that effect.

Table 3.12 Estimated Elasticities: Own Market Share

	1. GMM All	2. GMM All-German	3. IV All	4. IV All-German
Table 3.8.				
Short-run	0.161***	0.241**	0.154***	0.191**
Long-run	0.671***	1.111**	0.755***	0.910**
Table3.9. With Year Dummies				
Short-run	0.151**	0.214**	0.149***	0.200***
Long-run	0.726**	1.049**	0.720***	0.873***

Notes:

1. Short-run elasticities are the estimated coefficients for $ln(SHR_{t-1}^{i})$ reported in table 3.8 and 3.9. (As the specification is estimated in log-linear form, the coefficients are interpreted as elasticities.) An asterisk * indicates that the estimate is significant (see table 3.8 and 3.9).

2. Long-run elasticities are calculated as follows: $\left[\frac{\tau_2}{(1-\tau_1)}\right]$, where τ_2 is the estimated coefficient of $ln(SHR_{t-1}^{i})$ (specification 5.1) and $\tau_1$is the estimated coefficient of the lagged-dependent variable $ln(PAT_{t-1}^{i})$.

Table 3.13 Estimated Elasticities: Main Rivals' Market Share

	1. GMM All	2. GMM All-German	3. IV All	4. IV All-German
Table 3.8.				
Short-run	0.097*	0.184*	0.082**	0.164***
Long-run	0.404*	0.848*	0.402**	0.781***
Table 3.9. With Year Dummies				
Short-run	0.081	0.208**	0.068	0.164**
Long-run	0.389	1.020**	0.329	0.716**

Notes:

1. Short-run elasticities are the estimated coefficients for $ln(SHR_{t-1}^{Other-Country:Main})$ reported in table 3.8 and 3.9. (As the specification is estimated in log-linear form, the coefficients are interpreted as elasticities.) An asterisk * indicates that the estimate is significant (see table 3.8 and 3.9).

2. Long-run elasticities are calculated as follows: $\left[\frac{\tau_2}{(1-\tau_1)}\right]$, where τ_2 is the estimated coefficient of $ln(SHR_{t-1}^{Other-Country:Main})$ (specification 6.1) and $\tau_1$is the estimated coefficient of the lagged-dependent variable $ln(PAT_{t-1}^{i})$.

3.5 Conclusions

We use firm-level data to examine the relationship between competition and patenting in the U.S. automobile market. The combination of the U.S. market's economic importance, market dynamics, and the significant intertemporal fluctuations in firms' market shares and patents make this an interesting market to examine the link between competition and innovation. As we noted in chapter 2.1, a substantive theoretical literature has provided deep insights into this relationship. Perhaps the most recent and sophisticated models exploring this relationship are by Aghion et al. (2001) and Aghion et al. (2005). Overall, the theoretical literature is inconclusive in terms of the 'sign' of the relationship. The empirical literature, reflects this theoretical ambiguity, and has produced widely differing estimates. In recent years, while Aghion et al. (2005) find evidence of non-linearity using aggregated U.K. 2-digit industry data, Hashmi (2013) using U.S. industry data finds results that are diametrically opposite to Aghion et al. (2005).

Based on dynamic panel data estimates, our main findings are as follows. First, we find that an increase in firms' market shares leads to an increase in patenting, and the relationship is moderately non-linear. Second, we find that higher market-wide competition results in an increase in patenting, and the relationship is weakly non-linear. Our results on market-wide competition appear similar in spirit to those of Aghion et al. (2005), although our firm-level data and control variables are very different from their aggregated 2-digit industry). The typical study in this literature does not control for both these effects. In this sense our empirical specification has a more complete set of controls.

In other results, we find that GM's bankruptcy, representing an extreme case of firm-specific decline in fortunes, results in a sharp drop in a patenting. The Daimler Chrysler merger, representing the combination of two very large and prominent firms, results in a relatively small increase in patenting, primarily attributable to Chrysler.

CHAPTER 4. KNOWLEDGE GAP AND PATENT RIVALRY

4.1 Introduction

This chapter examines the relationship between knowledge gap and patent rivalry. Technological positions of firms have been recognized as one of the important factors influencing innovation, and are usually measured by technology gaps between firms. However, neither the theoretical nor the empirical literature provides clear evidence on the sign of the relationship. Studying the relationship between innovation and knowledge gap is important for several reasons. First, since innovation generates growth of markets and efficiency, creating institutions and markets that foster innovation are vital to increasing welfare. Second, if the relationship is negative, a firm which has a knowledge/technology gap with the leader would cede ground, then regulatory and subsidy policies, for example, would need to be structured and enforced appropriately to close technology gap and facilitate innovation.

In this chapter we examine the effects of innovation rivalry and market competition on patenting in the U.S. automobile market. We use accumulated patents to measure firms' knowledge stock, and compare firms' knowledge stocks to get their relative technological positions. We use the proportional technological distance a firm is from the technological frontier in terms of accumulated patents to capture patenting rivalry.

4.2 Empirical Specification

The main specification is described in chapter 3.2.1. In this chapter, our primary specification is a dynamic panel data model which examines the relationship between patenting rivalry and patenting activity. Returning to (3), Z_t is modeled as a function of the firm's own technology gap and a set of other control variables:

$$(4') \ ln(Z_t) = \xi_1 GAP_{i,t-2} + \xi_2 GAP_{i,t-2}^2 + \xi_3 Shr_{i,t-2} + \Psi \boldsymbol{X},$$

where $\boldsymbol{X}$ is the vector of control variables discussed below. Using (4), (3) and (2), our panel data model is:

$$(5') \ ln(PAT_t^i) = \alpha^i + \tau_1 ln(PAT_{t-1}^i) + \tau_2 GAP_{i,t-2}$$

$$+\tau_3 GAP_{i,t-2}^2 + \tau_4 Shr_{i,t-2} + \vartheta \boldsymbol{X} + \epsilon_t^i.$$

In (5'), PAT_t^i is the annual total number of patents for firm i, α^i is the firm-specific intercept, $GAP_{i,t-2}$ is the second lag of knowledge gap from the frontier of the firm, $Shr_{i,t-2}$ is the second lag of own market share of the firm, $\boldsymbol{X}$ is a vector of other controls (discussed below), and ϵ_t^i is a firm-specific error term.

The rationale for using knowledge gap and market share two periods back is as follows. We assume that before a firm formulating its current patenting strategy, it needs time to be fully informed about competitors' patenting strategies and their knowledge stocks. Second, $PAT_{i,t-1}$ is included in the calculation of the variable

$GAP_{i,t-1}$ (discussed in chapter 4.3.2), and using the second lag avoid repetition and the potential problem of collinearity. With these reasons, we use knowledge gap and market share in lagged two periods.

We include both quadratic term of knowledge gap and market share in our estimated specification. This is motivated by several factors. First, including knowledge gap allows us to examine how the technological position of the firm itself affects patenting, and whether the influence is non-linear. Second, the underlying theory model by Aghion et al. find the relationship between market competition and patenting will be affected by technology gap, and including both market share and knowledge gap allows us to examine the effect of one, controlling for the other. Third, our data (detailed in section 4) show dramatic reallocation of market shares across firms over our sample period, and controlling for market shares provide additional insight into the dynamics in competition and innovation.

The vector ***X*** includes the following control variables described in chapter 3.2.1:

(a) Daimler-Chrysler merger (**Merger**).

(b) GM's bankruptcy (**Bankruptcy**).

(c) Year dummies.

The vector ***X*** may include the following control variables:

(d) $Shr_{i,t-2}^2$: the extant empirical literature predicts a non-linear relationship between market share and current patenting. We include the quadratic term of market share to test the inverted-U relationship predicted by Aghion et al. (2005).

(e) $Shr_{i,t-2} * GAP_{i,t-2}$: Aghion et al. (2005) predicts the influences of market competition on innovation can be altered by technological distance of a firm is from the frontier. Controlling the interaction between market share and technology gap allows us to examine whether patenting rivalry will be moderated by market share of not.

Our controls for a firm-specific intercept α^i and lagged firm-specific patents PAT_{t-1}^i are described in section 3.2.1.

4.3 Data Description

4.3.1 Innovation Knowledge Stocks

In our econometric analysis, we use knowledge stock to control for a firm's gap between the leader and the firm. Stocks of innovation knowledge are a complex phenomenon and difficult to measure. One way to measure knowledge stock would be to use cumulative R&D expenditures for each firm. Unfortunately, R&D data are not available on a consistent basis for the firms in our sample.[7] Another way to measure knowledge stocks is to use firms' patents data to create cumulative patent counts.

A basic measure of the raw, unadjusted, cumulative patents would be as follows. Starting from 1969, our first year of data, we create a "cumulative patents" series: $AP_{i,t} = \sum_{s=0}^{\infty} PAT_{i,(t-s)}$, where $PAT_{i,t}$ is the total number of patents of firm i in year t, and $AP_{i,t}$ is the cumulative patents of firm i in year t. The time series in $AP_{i,t}$ represents a firm's innovation knowledge stock path. If a firm's annual number of patents $PAT_{i,t}$ is high, then its $AP_{i,t}$ path will rise at a faster rate.

[7] While R&D data are available for the more recent years, their historical data are not available because they were not publicly traded in the U.S. exchanges.

The above $AP_{i,t}$ measure, however, does not account for two aspects that have been noted in the literature. First relates to the intertemporal obsolescence of the underlying technology behind a patent, which may arise in part due to the emergence of newer technologies. This implies we need to adjust $AP_{i,t}$ for the rate of depreciation of patents. Second relates to the potentially phased-in, or delayed, use of a patent which could arise due to issues related to, for example, commercialization. This implies that we need to adjust $AP_{i,t}$ for the rate of diffusion of patents.

To implement these adjustments to the raw $AP_{i,t}$ series, we use the method proposed by Popp (2003). The patent depreciation and diffusion "adjusted" cumulative series is given by: $AdjAP_{i,t} = \sum_{s=0}^{\infty} e^{-w_1 s}\left(1 - e^{-w_2(1+s)}\right) * PAT_{i,(t-s)}$, where w_1 is the patent depreciation rate, and w_2 is the patent diffusion rate. Following Popp, we use a depreciation rate of 10% and a diffusion rate of 25%. Aggregating all previous patents with these depreciation and diffusion rate adjustments, we get a firm-specific time series $AdjAP_{i,t}$ which represents the time path of a firm's knowledge stock. As we note later in our estimation and checks of robustness, our broad inferences are not sensitive to some variations around the 10% and 25% rates noted above.

Since the patent data prior to our sample period are not available, the patent stock data are truncated. To construct the patent stocks without a sharp increase in early years, we need to have an initial benchmark of the stocks. Generally, the initial stock is measured by dividing the initial observation by the sum of the depreciated rate and the average growth rate of the variable (*e.g.*, Hall et al., 2010; Noel and Schankerman, 2013). Given our adjustment formula, we modify this method and define initial benchmark of accumulated patent stocks as the initial sample value of patents divided by the sum of the depreciation rate, the diffusion rate, and the average growth in annual patenting in the first four years of the sample: $benchmark_i = \frac{PAT_{i,1}}{w_1+w_2+g_i}$. When we construct the accumulated patent stocks, we initialize the stock at the beginning of the sample period and include the benchmarks in patent stocks: $PAT_{i,0} = benchmark_i$.

The summary statistics for the unadjusted and adjusted accumulated patents are presented in **Table 4.1** and **Table 4.2**.

Table 4.1 Summary Statistics: Raw, Unadjusted, Cumulative Patents (AP)

Firm	μ^{AP}	σ^{AP}	CV^{AP}(%)
GM	8631.9	4228.2	48.9
Ford	4561.8	3259.1	71.4
Chrysler	1347.5	1151.2	85.4
Toyota	4021.4	3267.0	81.2
Honda	4291.6	4507.6	105.0
Nissan	4336.7	3073.6	70.8
VW	556.4	320.7	57.6
BMW	327.3	336.6	102.8
Daimler	2252.1	1481.4	65.8

Notes:

μ^{AP}, σ^{AP} and CV^{AP} are the mean, standard deviation and coefficient of variation (percent) of the cumulative patents for each firm.

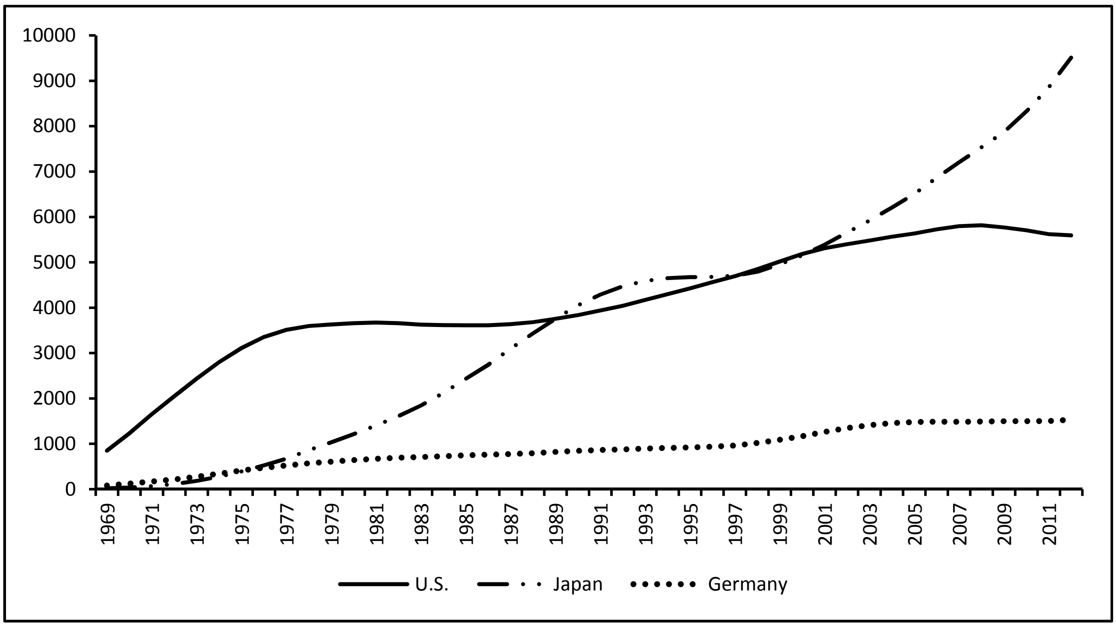
Table 4.2 Summary Statistics: Adjusted Cumulative Patents (AdjAP)

Firm	μ^{AdjAP}	σ^{AdjAP}	CV^{AdjAP}(%)
GM	2280.4	516.0	22.6
Ford	1395.0	656.6	47.1
Chrysler	442.6	295.2	66.7
Toyota	1158.2	789.9	68.2
Honda	1385.1	1347.1	97.3
Nissan	1199.5	687.6	57.3
VW	142.8	60.6	42.5
BMW	105.2	99.0	94.2
Daimler	640.2	287.6	44.9

Notes:

1. Accumulated patents are adjusted by depreciation rate, diffusion rate, and benchmark at year 0.
2. μ^{AdjAP}, σ^{AdjAP} and CV^{AdjAP} are the mean, standard deviation and coefficient of variation (percent) of the adjusted cumulative patents for each firm.

Table 4.2 presents the summary statistics for the adjusted accumulated patents data. GM has the highest average adjusted accumulated patent profile of 2,280 among the nine firms. The sample average number of patents for Ford, Toyota, Honda, and Nissan are relatively close at 1,395, 1,158, 1,385, and 1,200, respectively. Chrysler has the lowest patent stock profile of the three U.S. firms. Daimler, the most active German firm, has a sample mean of 640 accumulated patents, which is four or five times larger than VW or BMW. The sample averages conceal important underlying dynamics. The three Japanese firms have greater annual patents and have increasing accumulated patent profiles during latter half of the sample period, among which Honda has the most rapid growth rate in accumulated patent profile. In the last decade of the sample period, Honda has surpassed GM and became the leading company in accumulated patents. The German firms individually, or as country total, have relatively stable and lower growth rates in accumulated patent profiles.



Notes:

1. Adjusted accumulative patents are calculated by:

$$AP_{i,t} = \sum_{s=0}^{\infty} e^{-w_1 s}\left(1 - e^{-w_2(1+s)}\right) * PAT_{i,(t-s)}$$

$$PAT_{i,0} = benchmark_i = \frac{PAT_{i,1}}{w_1 + w_2 + g_i}$$

w_1=0.10, and is the rate of depreciation;

w_2=0.25, and is the rate of diffusion;

g_i is the average growth in annual patenting in the first four years of firm *i*

2. The data for the US are the sum of adjusted accumulative patents for GM, Ford and Chrysler. Japan, for Toyota, Honda and Nissan. Germany, for Volkswagen, BMW and Daimler.

Figure 4.1 Firms' Adjusted Cumulative Patents – Grouped by Country

Figure 4.1 plots the firms' USPTO accumulated patents – grouped as country totals. Overall, the U.S. total of accumulated patents shows relative stability. The two big deviations in the U.S. totals come around 1970-1974 (mainly due to sharp increase in GM's patents, potentially related to the Clean Air Act) and 2008-2010 (entirely due to drop in GM's patents during its bankruptcy period). In other time, the U.S. total shows a flat trend. In contrast, the Japanese accumulated patents show sharp acceleration towards the end of our sample period, and has surpassed the U.S. total around 2000. This is almost entirely driven by spikes in patenting by Toyota and Honda. The German profile is one of relative low and stable patent accumulation. The increase in the German profile around 1999 to 2002 is entirely due to an increase in Daimler's patents during that period (related to the merger with Chrysler)

4.3.2 Knowledge Gap

Our discussion in chapter 2.2 appears to indicate that one of the determinants of patenting responses is relative technological positions. Following our discussion, to further empirically assess the patent rivalry, we introduce a measure of the technology gap between firms to indicate relative technological positions. Following the predictions by Doraszelski, Aghion et al, and among others, we use the proportional technological distance a firm is from the technological frontier in terms of accumulated patents to capture the technology gap by Aghion et al. : $GAP_t^i = (AP_t^L - AP_t^i)/AP_t^L$ where L denotes the firm with the highest knowledge stock in the current year, which is defined as "the leader." A low value of GAP_t^i indicates that this firm is close to the leader in accumulated patents, while a high value of GAP_t^i indicates that this firm is far away from the leader in accumulated patents.

During our sample period, GM was the leader for 34 years, and was replaced by Honda in 2003, which continued as the leader till the end of our sample period. Honda had an acceleration of its annual patents towards the end of our sample period, leading to a sharp increase in its accumulated patents. The other major firm, Toyota, also had sharp increase in its annual patents towards the latter part of our sample, which lead to marked increase in its accumulated patents. Though Toyota had lower accumulated stocks in the early years, with significant increases in annual patenting, it was #4 in accumulated patents from 2001 to 2009, right behind GM, Ford, and Honda. Toyota surpassed GM in 2010 and Ford in 2011, and has been #2 since 2011.

Table 4.3 Summary Statistics: Technology Gap Based on Adjusted Cumulative Patents (GAP)

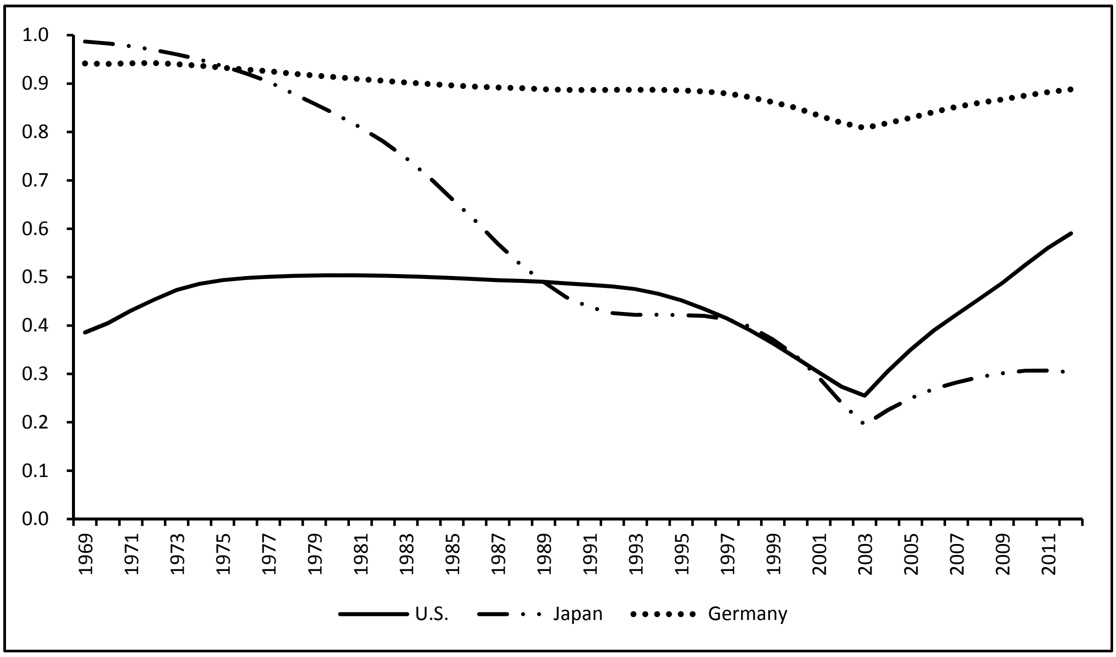
Firm	μ^{GAP}	σ^{GAP}	CV^{GAP}(%)
GM	0.06	0.14	222.72%
Ford	0.46	0.15	31.98%
Chrysler	0.83	0.09	10.26%
Toyota	0.59	0.23	39.21%
Honda	0.54	0.38	71.48%
Nissan	0.56	0.24	41.67%
VW	0.95	0.02	2.13%
BMW	0.96	0.03	2.78%
Daimler	0.75	0.07	9.55%

Notes:

1. Technology gap is calculated by adjusted accumulated patents.

2. μ^{GAP}, σ^{GAP} and CV^{GAP} are the mean, standard deviation and coefficient of variation (percent) of technology gap

The summary statistics for the technology gap based on adjusted accumulated patents are presented in **Table 4.3**. GM has the lowest average technology gap among the nine firms since it was the leader in the most of the time. The sample average number of technology gap for Ford, Toyota, Honda, and Nissan are relatively close at approximately 0.5-0.6, respectively. Chrysler has the highest technology gap of the three U.S. firms. Daimler, the most active German firm, has a sample mean of 0.75 in technology gap, which is still 1/3 higher than the Japanese firms. The sample averages conceal important underlying dynamics. The three Japanese firms have greater annual patents and have increasing accumulated patent profiles during latter half of the sample period, among which Honda has the most rapid growth rate in accumulated patent profile. In the last decade of the sample period, Honda has surpassed GM and became the leading company in accumulated patents. The dynamics in their annual patenting and patent stock lead to the high standard errors of the three Japanese firms The German firms individually, or as country total, have relatively stable and high technology gap in accumulated patent profiles.



Notes:

1. Knowledge gap is calculated from adjusted accumulative patents:

$$GAP_t^i = (AP_t^L - AP_t^i)/AP_t^L$$

L denotes the firm with the highest knowledge stock in the current year

AP_t^i denotes the adjusted accumulative patents of firm i

2. The figure plots average knowledge gap by country. The average for the US is the average of knowledge gap for GM, Ford and Chrysler. Japan, for Toyota, Honda and Nissan. Germany, for Volkswagen, BMW and Daimler.

Figure 4.2 Firms' Knowledge Gap – Average by Country

Figure 4.2 plots the firms' USPTO average knowledge gap – grouped as country. Overall, the U.S. total of accumulated patents shows relative stability. The big deviation in the U.S. average knowledge gap comes around 2003, when Honda replaced GM and became the leader with highest adjusted accumulative patents. In other time, before 2003, the U.S. average shows a flat decreasing tread, and after 2003, the U.S. average shows an increasing trend. In contrast, the Japanese average shows sharp decline towards the end of our sample period. The two deviations in the Japanese average knowledge gap comes around 1990 and 2003 (mainly due to that

Honda became the new leader), and has been lower than the U.S. average since around 1990. This is almost entirely driven by spikes in patenting by Toyota and Honda, which reduces the difference in adjusted accumulated patents between the leader and the Japanese group. The German average is relative high and stable. The decrease in the German average around 2003 is entirely due to an increase in Daimler's patents during that period (related to the merger with Chrysler).

Next, we construct another measure of knowledge gap. In the measure described above, following the literature, we use proportional difference between a leading firm and a specific firm to capture the relative technological positions. The value of $GAP_{i,t}$ is from 0 to 1, and is 0 for the leader, which indicates that, we are unable to empirically measure the behaviors of the leading firms since its indicator is always 0. However, a leading firm can have totally different innovation strategies comparing to other firms. In addition, in our sample, GM was the leader for most of the time with 0 value of $GAP_{i,t}$. As, a result, we are unable to empirically test the relationship between innovation and patent rivalry for GM for a large time period. Given this consideration, we construct another measure of relative technological positions based on firms' ranks in accumulated patents. We use the proportional technological distance a firm is from the industry median in terms of accumulated patents to capture the technology gap: $GAP_{i,t}^{Median} = (AP_t^i - AP_t^{Median})/AP_t^{Median}$, where $Median$ denotes the firm with the median knowledge stock in the current year, which in our sample is the firm ranking 5 in accumulated patents. Unlike $GAP_{i,t}$, $GAP_{i,t}^{Median}$ can range from negative to positive values: a negative value of $GAP_{i,t}^{Median}$ indicates that a firm is behind the industry median in accumulated patents, 0 value of $GAP_{i,t}^{Median}$ indicates that a firm is the industry median in accumulated patents, and a positive value of $GAP_{i,t}^{Median}$ indicates that this firm is the industry median in accumulated patents. The industry median has been changing over time and is not consistently 0 for any of the firms. With this measurement, we are able to capture the influences of knowledge gap for all the firms. We use this variable as a robustness check.

4.3.3 Market Shares

We have presented the summary statistics in chapter 3.3.2. In our estimated specification (5'), we use individual firms' market shares as a market indicator of competitiveness. We do not use the Herfindahl–Hirschman Index (HHI) or other concentration ratio to indicate competitiveness. The rationale is that first, market-wide competitiveness indicators are common for all the firms. Year dummies are perhaps more encompassing and better capture all effects that are common across firms in a given year. This allows us to check for the robustness of our market share and other estimates. Second, the main variable used to calculate market competition in Aghion et al. (2005) is Lerner index, and is not concentration ratios and describes profitability of firms. By using market share as indicators of market competition, our study is similar in spirit to Aghion et al. (2005).

4.4 Estimation Results

Results from estimating specification (5') are in **Table 4.4** and **Table 4.5**, using different estimation method GMM and IV, respectively. From the results in the tables, one important aspect of our results to keep in mind is that, conclusions of patenting rivalry and market competition are not sensitive to the specific estimation method used – GMM or conventional IV.

Table 4.4 GMM

$ln(PAT_{t-1}^{i})$	0.824*** (0.016)	0.819*** (0.019)	0.822*** (0.018)	0.821*** (0.019)
Bankruptcy GM	-0.280*** (0.106)	-0.301*** (0.091)	-0.345*** (0.078)	-0.321*** (0.097)
Merger Daimler-Chrysler	-0.008 (0.051)	-0.011 (0.056)	-0.012 (0.054)	-0.015 (0.054)
GAP_{t-2}	-0.834*** (0.187)	-0.860*** (0.228)	-1.054*** (0.319)	-0.945*** (0.178)
GAP_{t-2}^{2}	1.050*** (0.226)	1.113*** (0.271)	1.195*** (0.302)	1.159*** (0.243)
Shr_{t-2}	1.762*** (0.644)	2.942* (1.762)	1.464*** (0.545)	2.434 (1.875)
Shr_{t-2}^{2}	NA	-2.248 (2.543)	NA	-1.541 (2.809)
$Shr_{t-2} * GAP_{t-2}$	NA	NA	1.098 (1.245)	0.432 (0.980)
Firm Fixed-Effect	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	369	369	369	369

Notes:

1. Estimated specification is (see chapter 4.2):

(5′) $ln(Pat_{i,t}) = \alpha^{i} + \tau_1 \, ln(Pat_{i,t-1}) + \tau_2 TechSpread_{i,t-2} + \tau_3 TechSpread_{i,t-2}^{2} + \tau_4 Shr_{i,t-2} + \vartheta \boldsymbol{X} + \epsilon_t^{i}$.

The variables are:

$Pat_{i,t}$ – Number of patents for firm *i* in year t;

α^{i} – Firm-specific fixed-effect;

$GAP_{i,t-2}$ – Technology gap calculated by accumulated patents, lagged two period;

$Shr_{i,t-2}$– Market share of firm *i*, lagged two period;

X : vector of control variables, may include Shr_{t-2}^{2} and $Shr_{t-2} * GAP_{t-2}$, includes Bankruptcy, merger, and year dummies.

2. Estimations are via the Arellano-Bond GMM estimator. Robust standard errors are reported in parentheses, and ***, ** and * denote significance at 1%, 5% and 10% levels. The annual data for each firm covers the period 1969-2012. Three initial observations are dropped due to taking lags and the first-differencing procedure of the estimator.

3. The results of the specification tests are as follows.

(a) Over-identification test χ^2 (*p-value*). Column 1: 297.05 (0.601); Column 2: 296.92 (0.603); Column 3: 296.18 (0.615); Column 4: 296.85 (0.605).

(b) Arellano-Bond test for zero autocorrelation in first-differenced errors are as follows. Column 1: Order=1: z= -2.36 (p= 0.018), Order=2: z=1.45 (p=0.147); Column 2: Order=1: z=-2.36 (p=0.018), Order=2: z=1.46 (p=0.143); Column 3: Order=1: z=-2.36 (p=0.018), Order=2: z=1.47 (p=0.142). Column 4: Order=1: z= -2.36 (p=0.018), Order=2: z=1.47 (p= 0.142).

(c) Wald χ^2 (*p*-value): Column 1: 34.83(0.000); Column 2: 26.82 (0.000); Column 3: 32.01 (0.000); Column 4: 42.04 (0.000).

Table 4.5 IV

$ln(PAT_{t-1}^{i})$	0.855*** (0.041)	0.849*** (0.041)	0.853*** (0.040)	0.849*** (0.042)
Bankruptcy GM	-0.207 (0.241)	-0.254 (0.246)	-0.318 (0.252)	-0.254 (0.254)
Merger Daimler-Chrysler	-0.042 (0.085)	-0.045 (0.085)	-0.047 (0.084)	-0.045 (0.085)
GAP_{t-2}	-0.812*** (0.251)	-0.848*** (0.261)	-1.174*** (0.324)	-0.849** (0.350)
GAP_{t-2}^{2}	1.040*** (0.256)	1.145*** (0.263)	1.283*** (0.285)	1.146*** (0.286)
Shr_{t-2}	1.836*** (0.566)	4.020*** (1.447)	1.345** (0.641)	4.010* (2.161)
Shr_{t-2}^{2}	NA	-4.164* (2.352)	NA	-4.150 (3.229)
$Shr_{t-2} * GAP_{t-2}$	NA	NA	1.808 (1.146)	0.009 (1.442)
Firm Fixed-Effect	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	378	378	378	378

Notes:

1. See table 4.4 for general comments.

2. Estimations are via the IV estimator. Robust standard errors are reported in parentheses, and ***, ** and * denote significance at 1%, 5% and 10% levels. The annual data for each firm covers the period 1969-2012. Two initial observations are dropped due to taking lags and using deeper lags of the estimator as IV. $ln(Pat_{i,t-1})$ is treated as endogenous, $ln(Pat_{i,t-2})$, $GAP_{i,t-2}$, $GAP_{i,t-2}^{2}$, $Shr_{i,t-2}$, and $\mathbf{X}$ are used as IVs.

Path-dependence of patenting

The coefficient of the lagged-dependent variable is positive and highly significant, indicating persistence in the path of firms' patents. The estimated elasticities are approximately 0.8. The lagged-dependent variable elasticities indicate considerable path-dependence in firms' patenting. This is not surprising as we expect firms' R&D processes, and innovation and patenting strategy to show some continuity at least in the short-to-medium term.

Knowledge gap effects

One of the main variables from theory is firms' technology positions, which are captured by knowledge gap. In table 4.4 and 4.5, the full-panel estimate of knowledge gap is approximately -0.8, and the estimate of quadratic knowledge gap is approximately 1, both statistically significant. Given the standard errors, the point estimates are not statistically different across the various specifications reported in tables 4.4 and 4.5. This implies that the relationship between innovation and knowledge gap is non-linear: for the typical firm in our sample, when knowledge gap is small, an increase in knowledge gap leads to lower patenting; when knowledge gap is high, an increase in knowledge gap leads to higher patenting. In terms of technological positions of firms, first, leading firm innovates more than firms trailing the leader, and maintains its leading position. Second, firms trailing the leader innovate less and fall behind the leader. Among the trailing firms, those that are further away have high knowledge gap, and innovate less. As a result, within the trailing group, firms maintain their relative positions. Third, followers innovate more to catch up. Following firms have high knowledge gap, and an increase in knowledge gap leads to higher patenting.

Overall, and based on our discussion in chapter 2.2 and table 4.4 and 4.5, we find a U relationship between knowledge gap and patenting. Our findings are similar in spirit to those in Doraszelski (2003) and Aghion et al. (2001).

Next, we present the quantitative effects. First, we calculate the dividing point in the effects of knowledge gap. From our estimators, for the typical firm in our sample, when knowledge gap is approximately smaller than 0.4, an increase in knowledge gap leads to lower patenting; When knowledge gap is approximately higher than 0.4, an increase in knowledge gap leads to higher patenting. Second, we use the average value of technology gap, approximately 0.63, to calculate the average effect of technology gap on patenting in our data. Since the average value is 0.63 and is higher than the dividing point, across the specifications estimated, our calculations show that with the sample mean value, knowledge gap has a positive effect on patenting. This implies that on average, an increase in technology gap increases patenting.

Earlier we noted the results in Aghion et al. (2005) predicting a negative relationship between technology gap and patenting, and our result is in contrast to their findings. However, their estimates provide evidence that the marginal effect of technology gap on patenting is positive (Table III, pp719). According to Aghion et al. (2005), technology gap affects patenting indirectly, and the marginal effect of technology gap is:

$$Aghion\ et\ al.(2005){:}\ \frac{\partial ln(Pat_{jt})}{\partial Gap_{jt}} = \beta_1 Competition_{jt} + \beta_2 Competition_{jt}^2$$

They have two sets of estimates: (1) $\beta_1 = 1.43$, $\beta_2 = -1.30$; (2) $\beta_1 = 3.82$, $\beta_2 = -3.84$. Given the competition value is from 0 to 1, estimators in set (1) always provide positive effect. Given the mean and standard errors of competition (Table IV pp727), estimators in set (2) provides general positive effect. The implication from their estimators suggests a positive effect between technology gap and patenting, which is similar in spirit to our finding.

Own market share effects

Our second key variable from theory is market competition, and our measure is market share. In table 4.4 and 4.5, the full-panel estimate of market share is approximately 1.8 and statistically significant. This implies that for the typical firm in our sample, an increase in market share leads to higher patenting. The estimate of quadratic market share is insignificant, implying we do not find evidence of the inverted-U relationship between market competition and innovation, and our finding is different to Aghion et al. (2005).

Indirect market share effects

Our third key variable from theory is the indirect effect of knowledge gap via market share, and our measure is the interaction of market share and knowledge gap. In table 4.4 and 4.5, the full-panel estimate of the interaction is insignificant. This implies that knowledge gap does not indirectly affect patenting, and the relationship between market share and patenting is not affected by technology gap. This is in contrast to Aghion et al. (2005).

Next, we report several check of robustness. To save space, below we only report the main coefficients of interest (the estimated specifications include all the control variables noted in table 4.4 and 4.5).

C1: The exclusion of the German firms does not alter the main inferences. Though the knowledge gaps of German firms are relatively stable, their annual patenting profiles are slightly increasing. It is reasonable to doubt that the increasing part of the U relationship between technology gap and patenting is driven by German firms. We find the U relationship is robust after dropping the German firms, and the increasing part of the U relationship is not solely caused by the German firms. We re-estimate the full specification with the U.S. and Japanese firms only:

$$(C1.GMM)\ lnPat_t^i = \underset{(0.040)}{0.843}\, lnPat_{t-1}^i - \underset{(0.178)}{0.666}\, GAP_{i,t-2} + \underset{(0.254)}{0.981}\, GAP_{i,t-2}^2 + \underset{(0.716)}{1.977}\, Shr_{i,t-2} + Controls$$

$$(C1.IV)\ lnPat_t^i = \underset{(0.049)}{0.849}\, lnPat_{t-1}^i - \underset{(0.263)}{0.684}\, GAP_{i,t-2} + \underset{(0.232)}{1.014}\, GAP_{i,t-2}^2 + \underset{(0.561)}{1.951}\, Shr_{i,t-2} + Controls$$

$*\ Robust\ standard\ errors\ in\ parentheses$

We note that while there are marginal differences in the estimated quantitative effects, our key inferences remain intact, even after adding Shr_{t-2}^2 and $Shr_{t-2} * GAP_{t-2}$.

C2: Re-estimate full specification by including lag-ONE of GAP and Shr. We use lag-TWO of GAP and Shr given the considerations of potential lag in taking strategic patenting actions and to avoid the repetition of Pat_{t-1}^i as a dependent variable as Pat_{t-1}^i is used in the calculation of $GAP_{i,t-1}$. We re-estimate the full specification with lag-ONE of GAP and Shr. One important aspect of this estimation to keep in mind is that Shr_{t-1} is proved to be endogenous, and we add Shr_{t-2} into IVs when estimating with IV:

$$(C2. GMM)\ lnPat_t^i$$

$$= \underset{(0.015)}{0.834}\, lnPat_{t-1}^i \underset{(0.180)}{-0.878}\, GAP_{i,t-1} + \underset{(0.248)}{1.193}\, GAP_{i,t-1}^2 + \underset{(0.638)}{1.736}\, Shr_{i,t-1}$$

$$+ Controls$$

$$(C2. IV)\ lnPat_t^i$$

$$= \underset{(0.042)}{0.863}\, lnPat_{t-1}^i \underset{(0.240)}{-0.716}\, GAP_{i,t-1} + \underset{(0.258)}{0.981}\, GAP_{i,t-1}^2$$

$$+ \underset{(0.580)}{1.789}\, Shr_{i,t-1} + Controls$$

$* \ Robust\ standard\ errors\ in\ parentheses$

We note that while there are marginal differences in the estimated quantitative effects, our key inferences remain intact, even after adding Shr_{t-1}^2 and $Shr_{t-1} * GAP_{t-1}$.

Third, we replace $Shr_{i,t-2}$ with $ln(Shr_{i,t-2})$ in equation (5) and dropped the quadratic term of $Shr_{i,t-2}$. We also experimented with re-estimating equation (5) with citation-adjusted data. To conserve space we do not report the resulting estimates. While there are marginal differences in the estimated quantitative effects, our overall inferences are similar to these alternative measurements of market competition and innovation.

Finally, we replace $GAP_{i,t-2}$ with $GAP_{i,t}^{Median}$. $GAP_{i,t}^{Median}$ can be negative, 0, or positive, indicating relative positions of firms in accumulated patents comparing to the industry median. Unlike $GAP_{i,t-2}$, because of the changing industry median, $GAP_{i,t}^{Median}$ is not consistently 0 for any firms in our sample, which allows us to capture the influences of knowledge gap for all firms:

$$(C3.GMM)\ lnPat_t^i$$
$$= \underset{(0.019)}{0.821}\ lnPat_{t-1}^i \underset{(0.012)}{-0.027}\ GAP_{i,t-1}^{Median} + \underset{(0.000)}{0.001} GAP_{i,t-1}^{Median^2}$$
$$+ \underset{(0.520)}{1.443}\ Shr_{i,t-1} + Controls$$

$$(C3.IV)\ lnPat_t^i$$
$$= \underset{(0.044)}{0.844}\ lnPat_{t-1}^i \underset{(0.009)}{-0.022}\ GAP_{i,t-1}^{Median} + \underset{(0.000)}{0.001} GAP_{i,t-1}^{Median^2}$$
$$+ \underset{(0.564)}{1.429}\ Shr_{i,t-1} + Controls$$

$*\ Robust\ standard\ errors\ in\ parentheses$

We note that the relationship between relationship between $GAP_{i,t}^{Median}$ and patenting is still U shaped: The estimate of $GAP_{i,t}^{Median}$ is approximately -0.02, and the estimate of quadratic $GAP_{i,t}^{Median}$ is approximately 0.001, both statistically significant. The minimum level of patenting occurs when $GAP_{i,t}^{Median}$ is approximately 0.025, which is higher than the industry median 0. In terms of values of $GAP_{i,t}^{Median}$, first, when $GAP_{i,t}^{Median}$ is negative, the firm is behind the industry median, a higher $GAP_{i,t}^{Median}$ means smaller knowledge gap compared to the industry median. In this case, an increase in $GAP_{i,t}^{Median}$ means less behind compared to the industry median, and an increase in $GAP_{i,t}^{Median}$ leads to lower patenting. Second, when $GAP_{i,t}^{Median}$ is positive but small, in our case, approximately smaller than 0.025, the firm is close to and slightly ahead of the industry median, and an increase in

$GAP_{i,t}^{Median}$ leads to lower patenting. Third, when $GAP_{i,t}^{Median}$ is positive and large, in our case, approximately higher than 0.025, the firm is ahead of the industry median, and is relatively leading in accumulated patents. In this case, an increase in $GAP_{i,t}^{Median}$ means more ahead compared to the industry median, and an increase in $GAP_{i,t}^{Median}$ leads to higher patenting. In terms of technological positions of firms, first, firms falling behind of the industry median innovate more to catch up, and the closer to the industry median, the lower patenting firms have. Second, the lowest patenting occurs when the firm is close to and slightly ahead of the industry median. Third, leading firm innovates more and maintains its leading position. The more ahead of the industry median, the higher patenting a firm has.

Though the relationship between $GAP_{i,t}^{Median}$ and patenting is still U shaped, the inferences are slightly different from before: in the previous measurement of knowledge gap, a firm is always behind the leader, and the U relationship indicates the patenting strategies in response to the innovation level of the leader. In $GAP_{i,t}^{Median}$, a firm can behind or ahead of the industry median, and the U relationship indicates the patenting strategies in response to the industry median. The conclusions from these two different U relationships are similar in terms of technological positions of firms: followers innovate more to catch up, and are likely to reduce patenting when they are able to reduce the difference in accumulated patents, while leaders innovate more and are able to maintain their leading positions.

Panel (a): Full sample Panel (b): U.S. and Japan Only

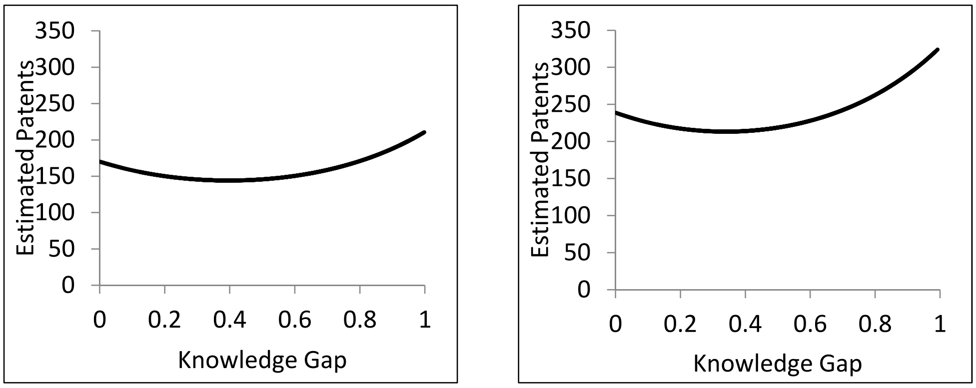


Figure 4.3 Knowledge gap and Estimated Patents

In **figure 4.3** we plot estimated relationship between firms' knowledge gap and patents using estimator of GMM (a) with all the nine firms, and (b) without German firms. From figure 2 we see that the relationship between knowledge gap and patents is U shaped: in panel (a), estimated patents decreases with knowledge stock initially from 170 to 140, and the curvature is very mild; then estimated patents increases with knowledge stock from 140 to 210, and the curvature is very mild. In panel (b), estimated patents decreases with knowledge stock initially from 240 to 210, and the curvature is very mild; then estimated patents increases with knowledge stock from 210 to 320, and the curvature is very mild. Comparing panel (a) and panel (b), we found U.S. and Japanese firms are more likely to innovate compared to German firms, which is consistent with patenting profiles of the nine firms. In both panels, comparing the estimated patents at GAP=0 and GAP=1, we find followers tend to innovate more than both the leader and trailing firms, indicating the catching up behaviors of the followers (Khanna, 1995; Lerner, 1997; Aghion et al., 2001; Doraszelski, 2003).

Based on the results in table 4.4 and 4.5, and the checks for robustness, our broad conclusions are as follows.

1. Technology gap between the leader and a following firm has a U shaped relationship with patenting. Our estimates in table 4.4 and 4.5 reveal that the relationship is somewhat complex. Knowledge gap has negative effect when firms are relatively closer to the frontier, and has positive effect when firms are relatively further away. One way to interpret this result is that if a firm is in the leading (low gap) group, it has lower incentive to innovate/patent and has small possibility of falling behind. In the group that is farther away from the leader (high gap), it has higher incentive to innovate/patent in order to catch up. This implies that as the leading edge moves higher, firms that are in the trailing group, they relatively fall behind, and firms that are in the lagging group, they relatively catch up.

Comparing these high and low gap groups, some of the results appear to be in line with predictions (e.g., Khanna, 1995) that the leading firms (lower-gap group) would innovate less than the following firms (higher-gap group). While some of the results appear to be in contrast with predictions (e.g., Lerner, 1997) that firms trailing the leader would innovate more. Comparing these two groups with the leader, the results are in line with predictions (e.g., Khanna, 1995; Grossman and Shapiro, 1987; Doraszelski, 2003) that leading firm would innovate more, especially when the gap decreases to some extent. While the results appear to be in contrast to some of the predictions (e.g., Aghion et al., 2001) that generally neck-and-neck firms would innovate more than both the followers and the leaders.

2. An increase in the market share results in higher current patenting. We do not find evidence of the inverted-U relationship between market competition and patenting. This result appears to be in contrast to some of the predictions (Aghion et al., 2005) .

3. Knowledge gap does not indirectly affect patenting via market shares, and the effect of market share is not moderated by knowledge gap. The interaction variable controls for the indirect effects of knowledge gap and market share on patenting, and appears to indicate that there is no indirect effect, which appears to in contrast to the findings in Aghion et al. (2005). Our estimates in table 4.4 and 4.5 reveal that the effects of both knowledge gap and market share are direct.

4.5 Conclusions

We use firm-level data to examine the effects of innovation rivalry and market competition on patenting in the U.S. automobile market. The combination of the U.S. market's economic importance, market dynamics, and the significant intertemporal fluctuations in firms' market shares and patents make this an interesting market to examine the link between competition and innovation.

Based on dynamic panel data estimates, our main findings are as follows. First, we find that the relationship between technology gap and patenting is non-linear and is U shaped, and an increase in knowledge gap first leads to a decrease and then an increase in patenting. Second, we find that higher market share results in an increase in patenting, and we do not find the non-linear inverted-U relationship. Third, we find that the relationship between market competition and patenting is not moderated by technology gap, and technology gap does not affect patenting via market competition. Our results on market-wide competition appear to be different from Aghion et al. (2005). The typical study in the literature of the effects of knowledge gap does not control for both market competition and knowledge gap. In this sense our empirical specification has a more complete set of controls.

CHAPTER 5. CHANGING COMPOSITION OF PATENTS

5.1 Introduction

This chapter examines the shifting dynamics in compositions of patents in the U.S. automobile market. The U.S. market has seen dramatic intertemporal changes in patenting profiles of the main firms. As an industry relies heavily on mechanical, mechanical technologies have been the core innovation for years. However, in recent years, the proportion of mechanical technologies dropped sharply. In early 1970s, the percentage of mechanical technologies in the overall patenting in the auto industry was around 50% and increased to around 60% in 1980s. It reached a peak of 76% in 1986, and began to decline after that. In 2010, the percentage of mechanical technologies declined to 36%. In contrast, technologies related to computers and communications had been around 3% in 1970s and early 1980s, and has been increasing since middle 1980s. In 2012, its percentage has reached to around 28%, which is just below mechanical technologies. Those changing percentages imply shifting dynamics in compositions of patents in the U.S. automobile market. By focusing on the auto industry, we are able to understand the evolution of patents by categories as well as inter-firm innovation rivalry.

First, we use patents as an indicator of innovative activity. Second, we compile detailed microdata on patents by categories/sub-categories. The objective is to examine the changing composition (by category) of patents, and the potential roles played by, for example, inter-firm innovation rivalry, environmental regulations, and mergers and acquisitions, for these shifting dynamics. Aside from shedding light on the drivers of patent compositional shifts, the paper will also develop a set of stylized facts and patterns of patent composition in this industry.

5.2 Empirical Specification

The main specification is described in section 3.2.1. In this chapter, our objective is to empirically examine the role played by firm-specific knowledge gap on the intertemporal dynamics of firms' patents. Our primary specification is a dynamic panel data model which examines the relationship between patenting rivalry and patenting activity. Returning to (3), Z_t is modeled as a function of the firm's own knowledge stock in related fields, own patent concentration, rivals' average patent concentration, and a set of other control variables:

$$(4'')\ \ ln(Z_t) = \xi_1 ln(AP_{i,\,t-2}^{k}) + \xi_2 ln(HHI_{i,t-1}^{PAT}) + \xi_3 ln(\overline{HHI_{J,t-1}^{PAT}}) + \Psi \boldsymbol{X},$$

where $\boldsymbol{X}$ is the vector of control variables discussed below. Using (4''), (3) and (2), our panel data model is:

$$(5'')\ \ ln(PAT_{i,t}^{k}) = \alpha^i + \tau_1\, ln\big(PAT_{i,t-1}^{k}\big) + \tau_2 ln(AP_{i,\,t-2}^{k})$$

$$+\tau_3 ln(HHI_{i,t-1}^{PAT}) + \tau_4 ln(\overline{HHI_{J,t-1}^{PAT}}) + \vartheta \boldsymbol{X} + \epsilon_t^i.$$

In (5''), *k*=Total, C1, C2, C4, C5, and C6, and the details of patent classifications are described in section 4; $PAT_{i,t}^{k}$ is the number of annual patents for firm *i* in year *t* in class k, α^i is the firm-specific intercept, $AP_{i,\,t-2}^k$ is the second lag of adjusted knowledge stock of firm i in year t, $HHI_{i,t-1}^{PAT}$ is the lag of own patent concentration of the firm, $\overline{HHI_{j,t-1}^{PAT}}$ is the lag of rivals' average patent concentration, $\boldsymbol{X}$ is a vector of other controls (discussed below), and ϵ_t^i is a firm-specific error term.

The rationale for using knowledge stock two periods back is as follows. We assume that before a firm formulating its current patenting strategy, it needs time to be fully informed about competitors' patenting strategies and their knowledge stocks. Second, $PAT_{i,t-1}^k$ is included in the calculation of the variable $AP_{i,\,t-1}^k$ (discussed in chapter 4.3), and using the second lag avoid repetition and the potential problem of collinearity. With these reasons, we use knowledge stock in lagged two periods.

We include knowledge stock, own patent concentration, and rivals' average patent concentration in our estimated specification. This is motivated by several factors. First, the underlying theory model by Cohen and Levinthal (1990) find prior knowledge can capture both knowledge exploration and exploitation, and including knowledge stock allows us to examine how the previous knowledge of the firm itself affects patenting as a combined measurement. Second, the underlying theory models (*e.g.*, Nelson, 1959; Dosi, 1982; March, 1991; Leonard-Barton, 1992; Leventhal and March, 1993; Granstrand, 1998) find keeping a diversified knowledge portfolio enhances firms to develop new knowledge effectively, and including concentration in patents allows us to examine the effect of knowledge diversification on current innovation. Third, our data (detailed in chapter 5.3) show dramatic reallocation of patents shares across different patent categories over our sample period, and controlling for both own patent concentration and rivals' average patent concentration provide additional insight into the dynamics in innovation and innovation rivalry.

The vector $\boldsymbol{X}$ includes the following control variables described in chapter 3.2.1:

(a) Daimler-Chrysler merger (**Merger**).

(b) GM's bankruptcy (**Bankruptcy**).

(c) Year dummies.

Our controls for a firm-specific intercept α^i and lagged firm-specific patents PAT_{t-1}^i are described in chapter 3.2.1.

5.3 Data Description

5.3.1 Patent Categories

In our econometric analysis, we follow the classification by Hall et al. (2001) to classify the patents. We use the main current U.S. class assigned by USPTO to each patent to group patents into 6 main categories and 37 subcategories. They are: (1) Chemical (6 sub-categories); (2) Computers & Communications (5 sub-categories); (3) Drugs & Medical (4 sub-categories); (4) Electrical & Electronic (7 sub-categories); (5) Mechanical (6 sub-categories); (6) Others (9 sub-categories). Instead of patent counts, we use annual patent shares in each category to show the distribution of patents and the shifting dynamics in technologies. We calculate patent shares of categories as follows:

$$PATSHR_{i,t}^k = \frac{PAT_{i,t}^k}{PAT_{i,t}}, k = 1, 2, \ldots, 6.$$

, where $PAT_{i,t}^{k}$ is total patents in in category k for firm i, $PAT_{i,t}$ is total patents for firm i.

We also perform firm-level and market-total time-series analysis to show the trend in patenting of a certain category:

$$PATSHR_{i,t}^{k} = \alpha + \beta PATSHR_{i,t-1}^{k} + \gamma Trend + \mu$$

We briefly summarize the distribution and the trends of patents among the 6 main categories.

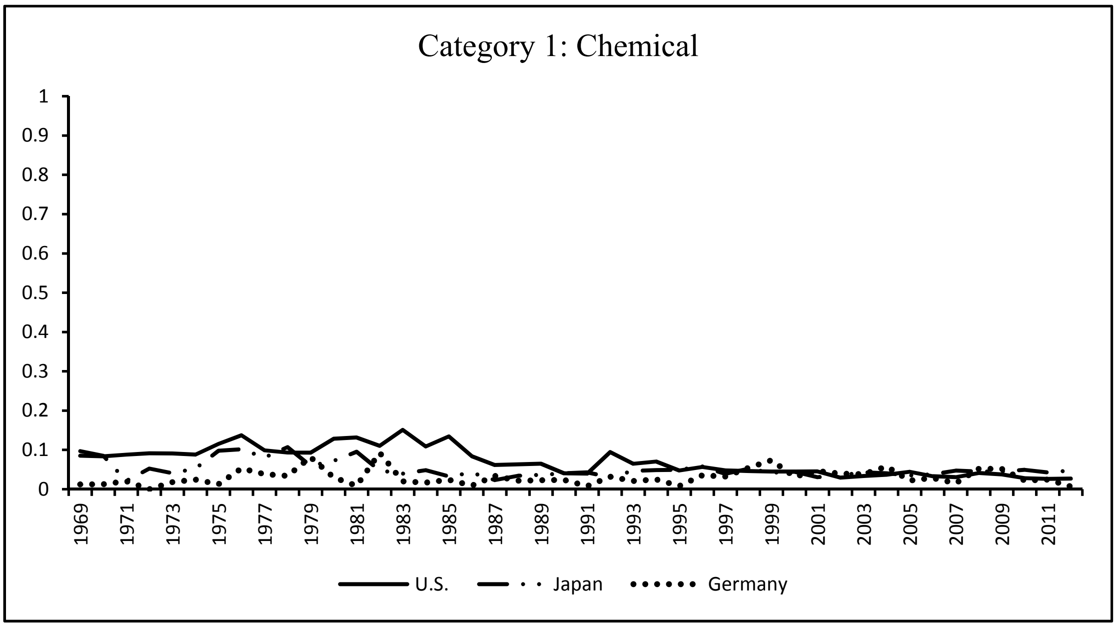
Table 5.1 Summary Statistics: Category 1 Chemical

Firm	μ^{Shr}	σ^{Shr}	CV^{Shr}(%)	Time Trend
GM	5.76	2.53	43.89%	-0.073* (0.042)
Ford	11.08	7.84	70.78%	-0.225*** (0.065)
Chrysler	3.30	3.61	109.58%	-0.082* (0.041)
Toyota	6.09	2.87	47.14%	-0.051 (0.033)
Honda	3.95	3.41	86.39%	-0.025 (0.042)
Nissan	5.36	3.97	74.15%	-0.038 (0.039)
VW	2.71	3.64	134.22%	-0.038 (0.041)
BMW	1.00	2.76	277.25%	0.018 (0.015)
Daimler	3.57	2.59	72.70%	0.058* (0.032)
Total	5.86	2.11	36.11%	-0.051** (0.020)

Notes:

1. $PATSHR_{k,i} = \frac{PAT_{k,i}}{PAT_i}, k = 1, 2, \ldots, 6$. $PAT_{k,i}$ is total patents in in category k for firm i, PAT_i is total patents for firm *i*
2. μ^{SHR}, σ^{SHR} and CV^{SHR} are the mean, variance and coefficient of variation (percent) of the shares of patents in category *k* for firm *i*.
3. t is the estimated time trend from equation $PatShr_t^{ik} = \alpha + \beta PatShr_{t-1}^{ik} + \gamma Trend + \mu$ with robust standard errors in parentheses, and *, ** and *** denote significance at 10%, 5% and 1% levels.

The summary statistics of patent shares by firm by and market total in category 1 (Chemical) are presented in table **5.1**. The mean of patent share in this category ranges from 1 (BMW) to 11 (Ford), and the difference among firms is small. The average annual patent shares of U.S. group and the Japanese group are high and close, and the German group has the relatively low patents in this category. The low standard errors of all the firms and the market total indicate that there are little dynamics in annual chemical patenting. As a traditional technology area, firms are relatively less active in this category. For the U.S. firms, time trend is negative and significant, indicating U.S. firms are relatively reducing their chemical patenting. For the Japanese firms, time trend is insignificant, indicating Japanese firms are relatively stable in chemical patenting. For VW and BMW, time trend is insignificant, indicating they are relatively stable in chemical patenting. For Daimler, time trend is significant and small, indicating that it is relatively increasing its chemical patenting slightly. For market total, the time trend is negative, indicating the overall market is relatively reducing chemical patenting, which is mainly driven by U.S. firms.



Notes:

1. Patent share is calculated by

$PATSHR_{k,i} = \frac{PAT_{k,i}}{PAT_i}, k = 1, 2, \ldots, 6.$ $PAT_{k,i}$ is total annual patents in in category k for country i, PAT_i is total annual patents for country i

2. The data for the US are the sum of USPTO patents in Category 1 (Chemical) for GM, Ford and Chrysler. Japan, for Toyota, Honda and Nissan. Germany, for Volkswagen, BMW and Daimler.

Figure 5.1 Firms' Patent Shares (by country): C1 (Chemical)

Figure 5.1 plots the firms' patents shares in category 1 (Chemical) – grouped as country totals. The percentage of Chemical patents was around 0.1 for all the firms around early stages, and has been much lower than 0.1 since around 1991, indicating that the firms in our sample make few and decreasing amount of innovations in the area of chemical technologies. Overall, the U.S. profile has relatively highest percentage in Chemical patents, while the Japanese and German profiles are close and relatively stable. From the figure, it is obvious that U.S. firms have declining patent shares in Chemical patents during the full sample period, while the Japanese and German firms do not have significant trends, which is consistent with the discussion in table 5.1. In addition, though U.S. profile was the highest in early stages, since around 1997, the three countries have close and stable market shares in category 1.

Table 5.2 Summary Statistics: Category 2 Computers & Communications

Firm	μ^{Shr}	σ^{Shr}	CV^{Shr}(%)	Time Trend
GM	13.38	23.07	172.38%	0.120* (0.061)
Ford	10.19	8.42	82.68%	0.209** (0.086)
Chrysler	10.55	10.62	100.75%	0.251** (0.122)
Toyota	10.06	6.98	69.37%	0.263*** (0.088)
Honda	8.97	6.31	70.32%	0.265*** (0.085)
Nissan	13.32	7.91	59.34%	0.282*** (0.078)
VW	8.46	13.28	157.01%	0.328** (0.139)
BMW	14.77	14.99	101.49%	0.719*** (0.155)
Daimler	8.30	8.50	102.34%	0.395*** (0.120)
Total	9.91	6.80	68.62%	0.112 (0.069)

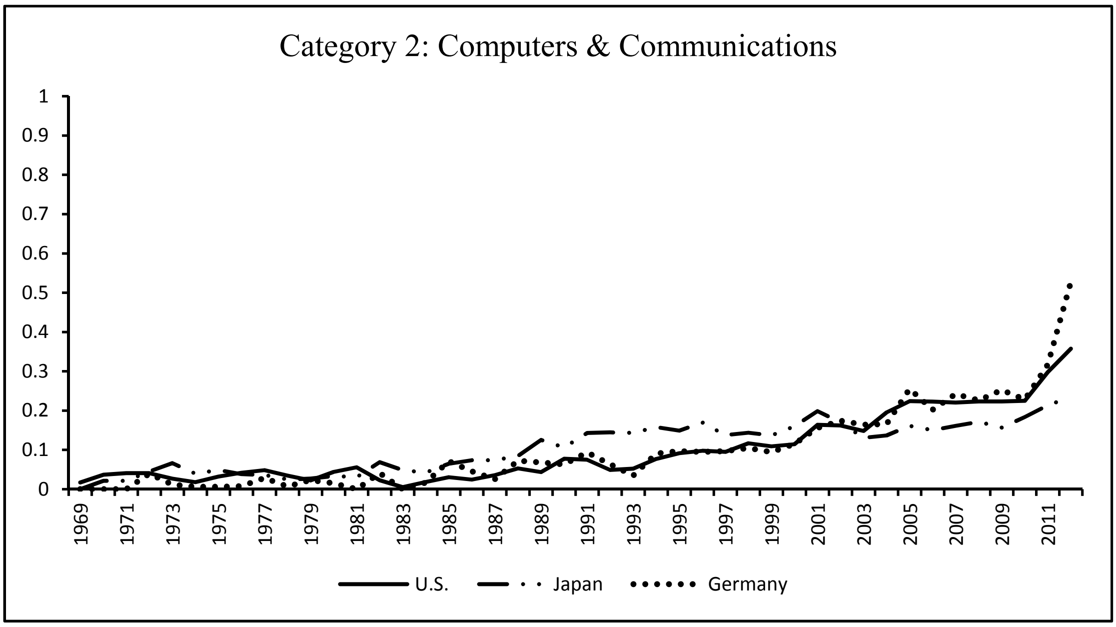
Notes:

1. $PATSHR_{k,i} = \frac{PAT_{k,i}}{PAT_i}, k = 1, 2, \ldots, 6.$ $PAT_{k,i}$ is total patents in in category *k* for firm *i*, PAT_i is total patents for firm *i*

2. μ^{SHR}, σ^{SHR} and CV^{SHR} are the mean, variance and coefficient of variation (percent) of the shares of patents in category *k* for firm *i*.

3. t is the estimated time trend from equation $PatShr_t^{ik} = \alpha + \beta PatShr_{t-1}^{ik} + \gamma Trend + \mu$ with robust standard errors in parentheses, and *, ** and *** denote significance at 10%, 5% and 1% levels.

The summary statistics of patent shares by firm by and market total in category 2 (Computers & Communications) are presented in **table 5.2**. The mean of patent share in this category ranges from 8 to 13, and the difference among firms is small. The average annual patents of U.S., Japan, and German firms are close, implying the nine firms are close in patenting profiles in category 2. GM has the highest standard errors, indicating it has dynamics in patenting strategies in category 2. The standard errors of other firms are close. The time trend in category 2 is positive and significant for all the nine firms, indicating all the nine firms are relatively innovating more in this area.



Notes:

1. Patent share is calculated by

$PATSHR_{k,i} = \frac{PAT_{k,i}}{PAT_i}, k = 1, 2, \dots, 6.$ $PAT_{k,i}$ is total annual patents in in category k for country i, PAT_i is total annual patents for country *i*

2. The data for the US are the sum of USPTO patents in Category 2 (Computers & Communications) for GM, Ford and Chrysler. Japan, for Toyota, Honda and Nissan. Germany, for Volkswagen, BMW and Daimler.

Figure 5.2 Firms' Patent Shares (by country): C2 (Computers & Communications)

Figure 5.2 plots the firms' patents shares in category 2 (Computers & Communications) – grouped as country totals. The percentage of Computers & Communications patents started at around 0 in 1969, increased to around 0.1 and surpassed chemical patents in early 1990s, and increased to over 0.2 for all the nine firms in 2000s, especially for the U.S. and Japanese firms whose country profiles were over 0.3 in 2010s. From the figure, all the firms in our sample are innovating more in Computers & Communications patents. Respond to the rapid development in computers & communications technologies in other industries, automobile firms in our sample speed up innovation in this area to embrace new technologies. Though treated as more traditional companies in innovation, given the strong development in mobile and computer technologies in recent years, automobile innovate more and more heavily in this area to keep pace with the overall environment. Overall, the Japanese profile has relatively highest percentage in Computers & Communications patents, while the U.S. and German profiles were close before around 2003, and U.S. firms have been developing fast since 2003 and are close to the Japanese firms in this area. From the figure, it is obvious that all three countries have increasing trend in Computers & Communications patents, which is consistent with the discussion in table 5.2.

Category 3 is about drugs and medical. Given the characteristics of the auto industry, patents are generally not related to category, and the patent counts in this category are almost consistently 0. In addition, drugs and medical technologies are not important for the auto industry and will not affect their market shares and products. Given these considerations, we do not report the summary statistics of category 3 and dropped them in following analysis to save space.

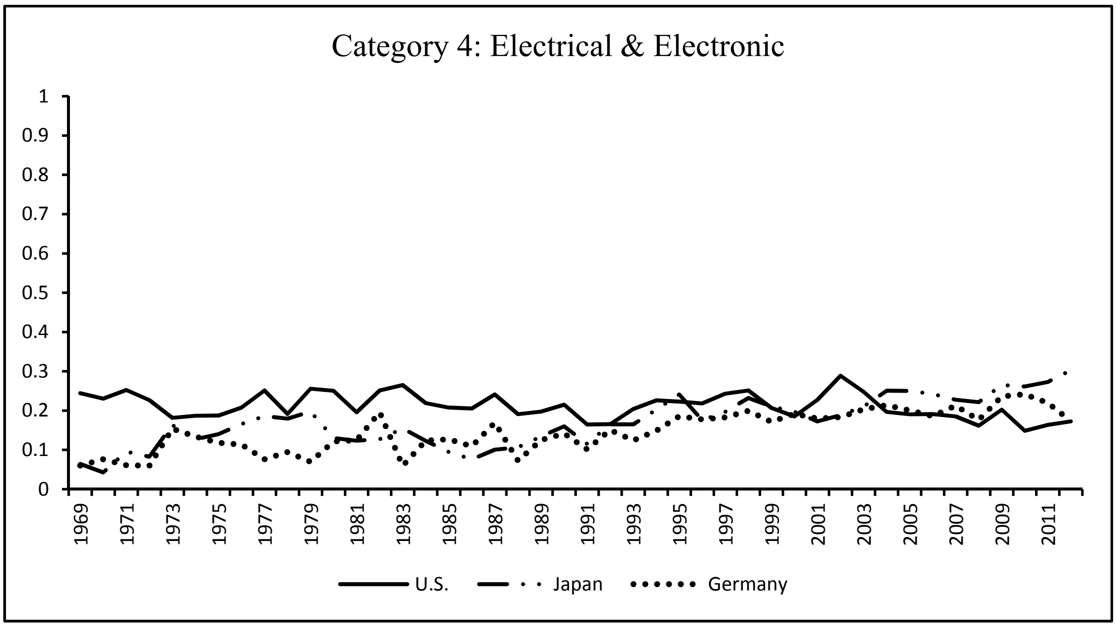
Table 5.3 Summary Statistics: Category 4 Electrical & Electronic

Firm	μ^{Shr}	σ^{Shr}	CV^{Shr}(%)	Time Trend
GM	21.57	5.63	26.11%	-0.128** (0.058)
Ford	19.40	5.19	26.76%	0.049 (0.058)
Chrysler	19.66	7.59	38.60%	-0.120 (0.088)
Toyota	17.51	8.36	47.75%	0.315*** (0.099)
Honda	15.56	6.83	43.91%	0.205** (0.085)
Nissan	18.19	7.49	41.17%	0.126* (0.064)
VW	11.06	9.09	82.21%	0.442*** (0.133)
BMW	14.33	11.09	77.40%	0.286* (0.152)
Daimler	15.45	5.86	37.93%	0.371*** (0.065)
Total	19.40	3.38	17.43%	0.071** (0.027)

Notes:

1. $PATSHR_{k,i} = \frac{PAT_{k,i}}{PAT_i}, k = 1, 2, \ldots, 6$. $PAT_{k,i}$ is total patents in in category *k* for firm *i*, PAT_i is total patents for firm *i*
2. μ^{SHR}, σ^{SHR} and CV^{SHR} are the mean, variance and coefficient of variation (percent) of the shares of patents in category *k* for firm *i*.
3. t is the estimated time trend from equation $PatShr_t^{ik} = \alpha + \beta PatShr_{t-1}^{ik} + \gamma Trend + \mu$ with robust standard errors in parentheses, and *, ** and *** denote significance at 10%, 5% and 1% levels.

The summary statistics of patent shares by firm by and market total in category 4 (Electrical & Electronic) are presented in **table 5.3**. The mean of patent share in this category ranges from 11 (VW) to 22 (GM), and the difference among firms is small. The average annual patent shares of U.S. group and the Japanese group are high and close, and the German group has the relatively low patents in this category. The low standard errors of all the firms and the market total indicate that there are little dynamics in annual electrical & electronic patenting. From the sign of time trend, firms show heterogeneity in patenting behaviors in this area. For the U.S. firms, time trend is negative or significant, indicating U.S. firms are relatively reducing or maintaining their electrical & electronic patenting. For the Japanese and German firms, time trend is insignificant, indicating Japanese and German firms are relatively increasing their electrical & electronic patenting. For market total, the time trend is positive, indicating the overall market is relatively increasing electrical & electronic patenting, which is mainly driven by Japanese and German firms.



Notes:

1. Patent share is calculated by

$PATSHR_{k,i} = \frac{PAT_{k,i}}{PAT_i}, k = 1, 2, \ldots, 6.$ $PAT_{k,i}$ is total annual patents in in category k for country i, PAT_i is total annual patents for country i

2. The data for the US are the sum of USPTO patents in Category 4 (Electrical & Electronic) for GM, Ford and Chrysler. Japan, for Toyota, Honda and Nissan. Germany, for Volkswagen, BMW and Daimler.

Figure 5.3 Firms' Patent Shares (by country): C4 (Electrical & Electronic)

Figure 5.3 plots the firms' patents shares in category 4 (Electrical & Electronic) – grouped as country totals. Overall, the U.S. profile has relatively highest and stable percentage in Electrical & Electronic patents, which is around 0.2, and has slightly declined since around 2003. The Japanese and German profiles are close and increasing, and they have surpassed U.S. firms in this area since middle 2000s. From the figure, it is obvious that U.S. has slightly declining trend while Japan and Germany have increasing trends in Electrical & Electronic patents, which is consistent with the discussion in table 5.3. Similar to computer & communication technologies, the frontier in electrical & electronic technologies are keep moving forward, and firms must innovate to keep up with the frontier

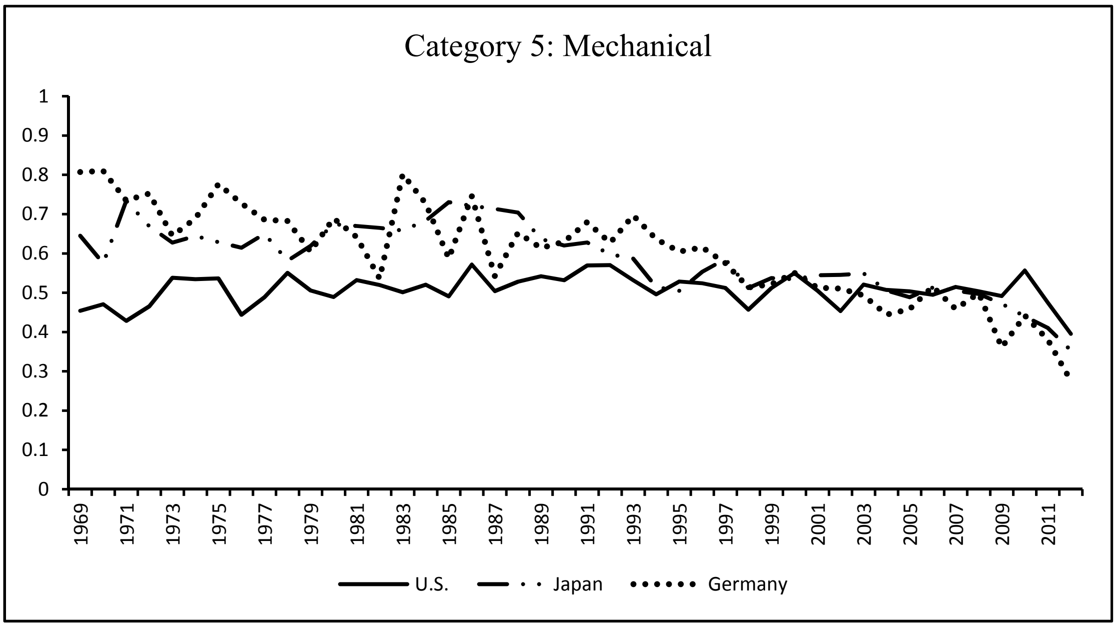
Table 5.4 Summary Statistics: Category 5 Mechanical

Firm	μ^{Shr}	σ^{Shr}	CV^{Shr}(%)	Time Trend
GM	47.45	14.95	31.51%	-0.189** (0.077)
Ford	50.54	5.99	11.86%	0.048 (0.065)
Chrysler	51.42	9.19	17.87%	-0.122 (0.123)
Toyota	59.74	12.01	20.11%	-0.332** (0.150)
Honda	63.45	12.91	20.35%	-0.341* (0.178)
Nissan	54.19	9.94	18.34%	-0.560*** (0.118)
VW	62.98	22.27	35.36%	-0.508*** (0.170)
BMW	57.96	23.18	39.99%	-1.193*** (0.219)
Daimler	60.12	11.68	19.43%	-0.911*** (0.116)
Total	54.67	6.30	11.53%	-0.106** (0.041)

Notes:

1. $PATSHR_{k,i} = \frac{PAT_{k,i}}{PAT_i}, k = 1, 2, \ldots, 6.$ $PAT_{k,i}$ is total patents in in category *k* for firm *i*, PAT_i is total patents for firm *i*
2. μ^{SHR}, σ^{SHR} and CV^{SHR} are the mean, variance and coefficient of variation (percent) of the shares of patents in category *k* for firm *i*.
3. t is the estimated time trend from equation $PatShr_t^{ik} = \alpha + \beta PatShr_{t-1}^{ik} + \gamma Trend + \mu$ with robust standard errors in parentheses, and *, ** and *** denote significance at 10%, 5% and 1% levels.

The summary statistics of patent shares by firm by and market total in category 5 (Mechanical) are presented in **table 5.4**. Being the core technology in the automobile industry, mechanical innovations have the highest percentage in all the 6 categories. The mean of patent share in this category ranges from 47 (GM) to 63 (Honda), and the difference among firms is relatively large. The U.S. group has the lowest patent share in mechanical technologies compared to the Japanese and German groups. The German group has the highest standard error in mechanical technologies compared to the U.S. and Japan group. As a traditional and core technology area for the auto industry, mechanical technologies are losing power and attraction for the auto industry. The time trend is negative of all the firms and market total, except Ford and Chrysler, indicating firms are relatively innovating less in mechanical technologies. Compared to category 2 (Computers & Communications) and 4 (Electrical & Electronic) which have advancing technological frontiers, mechanical technologies have relative small development, which can be one of the explanations that the time trend is negative: given the little advancement in mechanical technologies, firms are able to reduce their innovation in this category while maintaining their advantages.



Notes:

1. Patent share is calculated by

$PATSHR_{k,i} = \frac{PAT_{k,i}}{PAT_i}, k = 1, 2, \ldots, 6.$ $PAT_{k,i}$ is total annual patents in in category k for country i, PAT_i is total annual patents for country i

2. The data for the US are the sum of USPTO patents in Category 5 (Mechanical) for GM, Ford and Chrysler. Japan, for Toyota, Honda and Nissan. Germany, for Volkswagen, BMW and Daimler.

Figure 5.4 Firms' Patent Shares (by country): C5 (Mechanical)

Figure 5.4 plots the firms' patents shares in category 5 (Mechanical) – grouped as country totals. Overall, the U.S. profile has relatively lowest and stable percentage in Electrical & Electronic patents, which is around 0.5, and has slightly declined since around 2003. The Japanese and German profiles are close and high: their percentages in Mechanical patents were around 0.7 before 1990s, and declined to around 0.5 in middle 2000s, especially for the Japanese firms, which declined to around 0.3 in 2012. From the figure, it is obvious that U.S. has slightly stable profile while Japan and Germany have decreasing trends in Mechanical patents, which is consistent with the discussion in table 5.4. Mechanical technologies are the core and traditional technologies in the automobile industry. However, given the strong impact of new technologies such computer & communication, and electrical & electronic innovations in recent years, mechanical technologies are relatively shoved aside, yet mechanical technologies still have the highest percentage in all the 6 categories mainly because of the characteristics of the automobile industry.

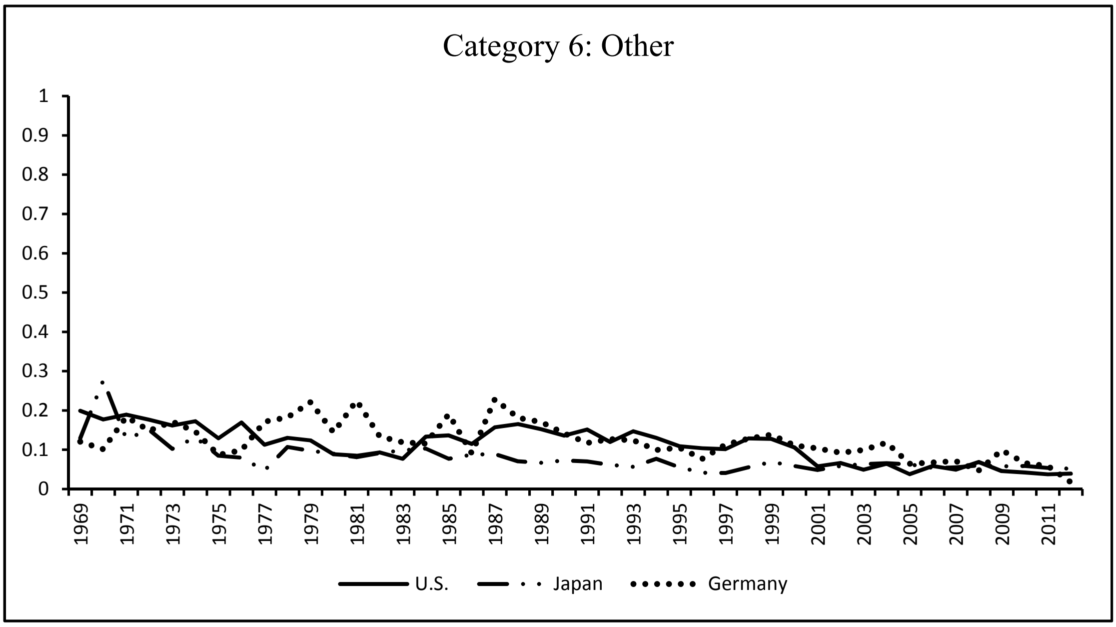
Table 5.5 Summary Statistics: Category 6 Others

Firm	μ^{Shr}	σ^{Shr}	$CV^{Shr}(\%)$	Time Trend
GM	11.80	5.54	46.99%	-0.243*** (0.039)
Ford	8.77	4.61	52.60%	-0.117* (0.059)
Chrysler	14.96	6.98	46.64%	-0.138*** (0.048)
Toyota	6.37	7.41	116.35%	-0.285*** (0.089)
Honda	7.89	4.97	63.01%	-0.231* (0.120)
Nissan	8.57	4.37	50.98%	-0.072 (0.089)
VW	11.87	11.99	101.03%	-0.194** (0.073)
BMW	9.68	12.10	125.01%	-0.510** (0.234)
Daimler	12.73	4.99	39.17%	-0.180 (0.186)
Total	10.03	3.70	36.94%	-0.118*** (0.036)

Notes:

1. $PATSHR_{k,i} = \frac{PAT_{k,i}}{PAT_i}, k = 1, 2, \ldots, 6$. $PAT_{k,i}$ is total patents in in category *k* for firm *i*, PAT_i is total patents for firm *i*
2. μ^{SHR}, σ^{SHR} and CV^{SHR} are the mean, variance and coefficient of variation (percent) of the shares of patents in category *k* for firm *i*.
3. t is the estimated time trend from equation $PatShr_t^{ik} = \alpha + \beta PatShr_{t-1}^{ik} + \gamma Trend + \mu$ with robust standard errors in parentheses, and *, ** and *** denote significance at 10%, 5% and 1% levels.

The summary statistics of patent shares by firm by and market total in category 6 (Other) are presented in table 5.5. All technologies that are not grouped in category 1-5 are grouped in this category. The mean of patent share in this category ranges from 6 (Toyota) to 13 (Daimler), and the difference among firms is small. The low mean and low standard errors indicates that there are few dynamics in this area.



Notes:

1. Patent share is calculated by

$PATSHR_{k,i} = \frac{PAT_{k,i}}{PAT_i}, k = 1, 2, \ldots, 6.$ $PAT_{k,i}$ is total annual patents in in category k for country i, PAT_i is total annual patents for country i

2. The data for the US are the sum of USPTO patents in Category 6 (Other) for GM, Ford and Chrysler. Japan, for Toyota, Honda and Nissan. Germany, for Volkswagen, BMW and Daimler.

Figure 5.5 Firms' Patent Shares (by country): C6 (Other)

Figure 5.5 plots the firms' patents shares in category 6 (Other) – grouped as country totals. Overall, the U.S. and Germany profiles are close and high around 0.2, while the Japanese profile is relatively the lowest and is around 0.1. From the figure, it is obvious that all the three countries have decreasing trends in miscellaneous innovations, which is consistent with the discussion in table 5.5. Since all other miscellaneous technologies are grouped in this category, the declining trends indicate firms are more specified in other technologies (mainly in Category 2 and 4), especially for the Japanese firms.

Comparing the 6 categories, especially Chemical, Computers & Communications, Electrical & Electronic, and Mechanical, we found evidence of technological distribution. First, chemical is relatively the least important category, and firms are reducing their innovation shares. Second, being untraditional for the auto industry and plays a more important role in current society, computers and communications technology has drawn the attention of all the firms with increasing patent shares. Third, Electrical & Electronic technologies are of the second importance for the auto industry as indicated by sample mean, and firms are innovating more in this area. Fourth, Mechanical technologies are most important for the auto industry, as indicated by the highest average patent share. However, being traditional, mechanical technologies are losing power and firms innovate less in this area. The decline in mechanical technologies is mainly caused by the increase in computers & communications and electrical & electronic technologies.

5.3.2 HHI in Patents

Our discussion in chapter 2.3 appears to indicate that one of the determinants of patenting is technology diversity. Following our discussion, to further empirically assess the shifting dynamics in technologies, we introduce a measure of the technology diversity. Following the literature (Hall, 2002), we use the Herfindahl index of concentration to capture the concentration of technologies, and the average value of HHI of rivals to capture inter-firm innovation rivalry.

The variables of HHI are constructed as follows:

$$HHI_{i,t}^{PAT} = \sum_{k=1}^{6} (\frac{PAT_{i,t}^{k}}{PAT_{i,t}})^2$$

$$\overline{HHI_{J,t}^{PAT}} = (\sum_{j=1, j \neq i}^{9} HHI_{j,t}^{PAT})/8$$

, where $PAT_{i,t}^{k}$ is the annual patent counts in category *k* of firm *i* in year *t*, $PAT_{i,t}$ is total annual patent counts of firm *i* in year *t*. We use percentage values to calculate HHI, and HHI ranges from 0 to 10000. A higher HHI indicates a firm is more concentrated in a specific category, and an extreme value of 1 indicates a firm focuses on a selected category. If technologies are distributed equally across 6 categories, HHI will have a value of 1700. Given the consideration that category 3 is not important for the auto industry, if technologies are distributed equally across other 5 categories, HHI will have a value of 2400.

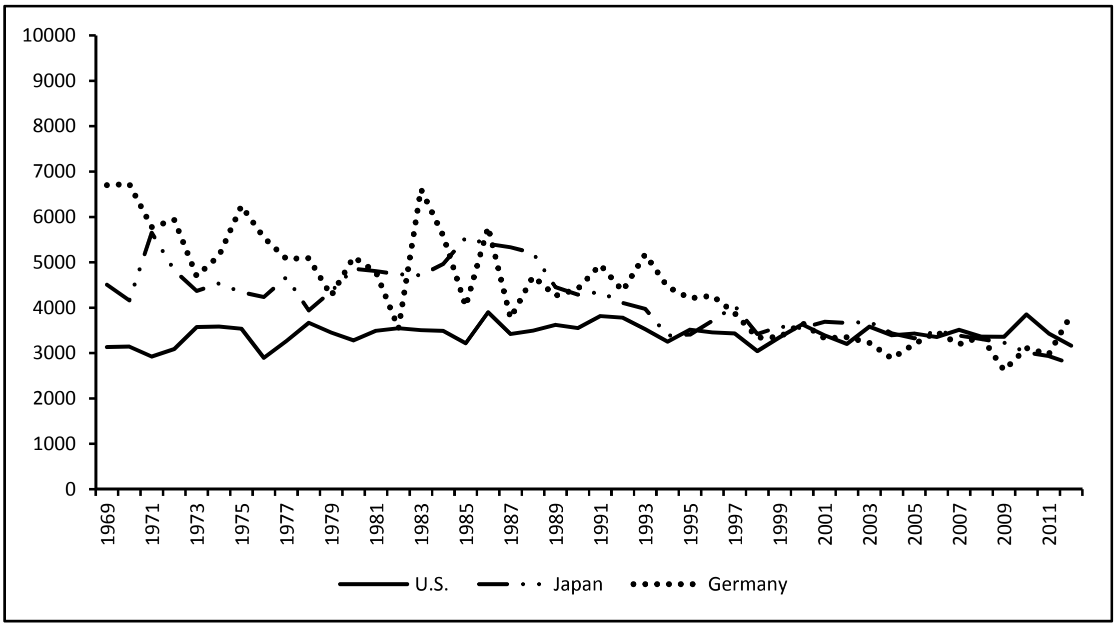
Table 5.6 Summary Statistics: HHI

Firm	μ^{HHI}	σ^{HHI}	CV^{HHI}(%)	Time Trend
GM	3873.62	1307.50	33.75%	14.076 (14.001)
Ford	3445.72	429.57	12.47%	6.060 (4.692)
Chrysler	3685.90	747.65	20.28%	-9.688 (9.438)
Toyota	4372.50	1052.71	24.08%	-30.373** (12.544)
Honda	4709.50	1373.14	29.16%	-32.211* (16.360)
Nissan	3798.82	734.74	19.34%	-44.052*** (12.174)
VW	5200.06	2088.70	40.17%	-44.740** (17.620)
BMW	4892.19	2442.86	49.93%	-122.015*** (29.021)
Daimler	4365.75	1103.58	25.28%	-74.208*** (11.678)
Total	3711.26	449.11	12.10%	-6.803** (2.963)

1. μ^{SHR}, σ^{SHR} and CV^{SHR} are the mean, variance and coefficient of variation (percent) of HHI for firm *i*.
2. HHI is calculated within firm *i*: $HHI^i = \sum_{k=1}^{6} SHR_{k,i}^2$
3. t is the estimated time trend from equation $HHI_{k,t} = \alpha + \beta HHI_{k,t-1} + \gamma Trend + \mu$ with robust standard errors in parentheses, and *, ** and *** denote significance at 10%, 5% and 1% lev

The summary statistics for the HHI based on annual patent distribution are presented in **Table 5.6**. The mean of HHI ranges from 3445 (Ford) to 5200 (VW), and the difference among firms is large. Since the mean of HHI is much higher than the values of equal-distribution (1700 for 6 categories and 2400 for 5 categories), we expect unequal patent segmentation among the different technological areas, which is consistent with our discussion in section 5.3.1.The average HHI of the U.S. group is lowest, and the mean values of the Japanese and German firms are close and high. The

U.S. group has lowest standard errors, and German firms have highest standard errors. The means and standard errors imply U.S. firms have relatively the most diversified patent profiles, and the most stable segmentation, while the German firms have the most concentrated patent profiles, and a lot dynamics in segmentation. The time trend is insignificant for the U.S. group, negative for the Japanese and German group, indicating that though U.S. firms are relatively stable in patenting segmentation, Japanese and German firms are reducing concentration and becoming more diversified in technologies. The time trend of the overall market is negative, indicates the auto industry is becoming more diversified in patents, and is mainly driven by Japanese and German firms.



Notes:

1. HHI is calculated within country *i*: $HHI^i = \sum_{k=1}^{6} PATSHR_{k,i}^2$

Patent share is calculated by

$PATSHR_{k,i} = \frac{PAT_{k,i}}{PAT_i}, k = 1, 2, \ldots, 6.$ $PAT_{k,i}$ is total annual patents in in category *k* for country *i*, PAT_i is total annual patents for country *i*

2.The data for the US are the sum of USPTO patents for GM, Ford and Chrysler. Japan, for Toyota, Honda and Nissan. Germany, for Volkswagen, BMW and Daimler.

Figure 5.6 Firms' Patent HHI – Grouped by Country

Figure 5.6 plots the firms' patents HHI – grouped as country totals. Overall, the U.S. profile has relatively lowest and stable trend in patent concentration and is around 3000. The Japanese and German profiles are close and high: before around 1999, the HHI of both countries was around 5000 with large fluctuations, and HHI of Germany was slightly higher than that of Japan. The HHI of Japan slowly declined after around 1987, while that of Germany slowly declined after around 1994. After around 1999, the HHI of Japan and Germany were close to that of U.S. From the figure, it is obvious that U.S. has stable patenting diversity, while Japan and Germany had high patenting concentration in the early and middle stages, and became as diversified as U.S. in the late stage. The evidence from the figure is consistent with the discussion in table 5.6.

We also include Jacquemin-Berry entropy measure of diversification to capture the knowledge diversity of patenting profiles. The formulation of the entropy measure is:

$$Entropy_{i,t} = \sum_{k=1}^{6} PATSHR_{i,t}^{k} ln(1/PATSHR_{i,t}^{k}),$$

where $PATSHR_{i,t}^{k}$ is the proportion of patents in category k for firm i in year t. An increase in $Entropy_i$ indicates higher patenting diversity, and when a firm focuses on only one category, entropy is 0. According to Jacquemin and Berry (1979), entropy measure is more sensitive to diversity than HHI by providing larger values. In our data, the average of entropy is 1.09, which is higher than HHI. We also construct rivals' average entropy to capture the influences of knowledge diversity across firms:

$$\overline{Entropy_{J,t}} = (\sum_{j=1, j\neq i}^{9} Entropy_{j,t})/8$$

We will use Entropy for robustness checks.

5.4 Estimation Results

Results from estimating specification (5'') are in **Table 5.7** and **Table 5.8**, using different estimation method GMM and IV, respectively. From the results in the tables, one important aspect of our results to keep in mind is that, conclusions of knowledge stock and patent concentration (own/rival) are not sensitive to the specific estimation method used – GMM or conventional IV.

Table 5.7 GMM

	$ln(PAT_t^{Total})$	$ln(PAT_t^{C1})$	$ln(PAT_t^{C2})$	$ln(PAT_t^{C4})$	$ln(PAT_t^{C5})$	$ln(PAT_t^{C6})$
$ln(PAT_{i,t-1}^k)$	0.874*** (0.021)	0.409*** (0.094)	0.619*** (0.058)	0.678*** (0.060)	0.805*** (0.034)	0.699*** (0.020)
Bankruptcy GM	-0.693*** (0.065)	-1.467*** (0.157)	-0.374*** (0.142)	-1.726*** (0.139)	-1.543*** (0.120)	-1.627*** (0.167)
Merger Daimler-Chrysler	-0.015 (0.059)	0.837*** (0.165)	0.085 (0.107)	0.198*** (0.069)	0.058 (0.080)	0.038 (0.084)
$ln(AP_{i,\,t-2}^k)$	-0.051 (0.040)	0.237*** (0.061)	0.087** (0.034)	0.058*** (0.017)	-0.030 (0.043)	0.151*** (0.047)
$ln(HHI_{i,t-1}^{PAT})$	-0.345** (0.174)	-0.008 (0.228)	0.029 (0.160)	-0.559** (0.255)	-0.661*** (0.168)	0.023 (0.259)
$ln(\overline{HHI_{J,t-1}^{PAT}})$	-2.749*** (0.635)	0.934 (1.405)	-0.382 (1.053)	-3.615** (1.520)	-2.933*** (0.901)	-3.030** (1.387)
Firm Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	369	369	369	369	369	369

Notes:

1. Estimated specification is (see chapter 5.2):

$$(5'')\ ln(PAT_{i,\,t}^k) = \alpha^i + \tau_1 ln(PAT_{i,\,t-1}^k) + \tau_2 ln(AP_{i,\,t-2}^k) + \tau_3 ln(HHI_{i,t-1}^{PAT}) \ + \tau_4 ln(\overline{HHI_{J,t-1}^{PAT}}) + \vartheta \boldsymbol{X} + \epsilon_t^i,$$

where *i*=firm, *t*=year, and *k*=patent category (Total, C1 Chemical, C2 Computers & Communications , C4 Electrical & Electronic, C5 Mechanical, and C6 Others).

The variables are:

$PAT_{i,t}^k$ – Number of patents for firm *i* in year *t* in class *k*;

α^i – Firm-specific fixed-effect;

$AP_{i,\,t-2}^k$ – Adjusted patent stock for firm *i* in year *t* in class *k*, lagged two period. Calculated as follows: $HHI_{i,t}^{PAT} = \sum_{k=1}^{6}(\frac{PAT_{i,t}^k}{PAT_{i,t}})^2$;

$HHI_{i,t-1}^{PAT}$– Concentration in annual patents for firm *i* in year *t* in class *k*, lagged one period;

$ln(\overline{HHI_{J,t-1}^{PAT}})$– Average concentration in annual patents of rivals for firm *i* in year *t* in class *k*, lagged one period. Calculated as follows:

$\overline{HHI_{J,t}^{PAT}} = (\sum_{j=1,j\neq i}^{9} HHI_{j,t}^{PAT})/8.$

X : vector of control variables, , includes Bankruptcy, merger, and year dummies.

2. Estimations are via the Arellano-Bond GMM estimator. Robust standard errors are reported in parentheses, and ***, ** and * denote significance at 1%, 5% and 10% levels. The annual data for each firm covers the period 1969-2012. Three initial observations are dropped due to taking lags and the first-differencing procedure of the estimator.

Table 5.8 IV

	$ln(PAT_t^{Total})$	$ln(PAT_t^{C1})$	$ln(PAT_t^{C2})$	$ln(PAT_t^{C4})$	$ln(PAT_t^{C5})$	$ln(PAT_t^{C6})$
$ln\left(PAT_{i,t-1}^{k}\right)$	0.912*** (0.047)	0.972*** (0.139)	0.709*** (0.080)	0.782*** (0.061)	0.883*** (0.049)	0.914*** (0.061)
Bankruptcy GM	-0.635*** (0.196)	-0.926*** (0.355)	-0.363** (0.141)	-1.507*** (0.187)	-1.306*** (0.353)	-1.169*** (0.260)
Merger Daimler-Chrysler	-0.048 (0.090)	0.137 (0.282)	0.024 (0.133)	0.139 (0.105)	-0.016 (0.106)	-0.152 (0.142)
$ln(AP_{i,\,t-2}^{k})$	-0.072** (0.036)	-0.037 (0.083)	0.060 (0.045)	0.053** (0.025)	-0.076** (0.038)	0.088*** (0.034)
$ln(HHI_{i,t-1}^{PAT})$	-0.302** (0.122)	0.593** (0.292)	0.056 (0.187)	-0.505** (0.218)	-0.653*** (0.149)	0.235 (0.204)
$ln(\overline{HHI_{J,t-1}^{PAT}})$	-2.482*** (0.762)	1.435 (1.713)	-0.333 (1.132)	-4.025*** (1.324)	-2.920*** (0.942)	-3.102*** (1.163)
Firm Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	378	378	378	378	378	378

Notes:

1. See Table 5.7 for general comments.

2. Estimations are via the IV estimator. Robust standard errors are reported in parentheses, and ***, ** and * denote significance at 1%, 5% and 10% levels. The annual data for each firm covers the period 1969-2012. Two initial observations are dropped due to taking lags and using deeper lags of the estimator as IV. $ln\left(Pat_{i,t-1}\right)$ is treated as endogenous, $ln\left(Pat_{i,t-2}\right)$, $ln(AP_{i,\,t-1}^{k}), ln(HHI_{i,t-1}^{PAT})$, $ln(\overline{HHI_{J,t-1}^{PAT}})$, and **X** are used as IVs.

Path-dependence of patenting

The coefficient of the lagged-dependent variable is positive and highly significant, indicating persistence in the path of firms' patents. The coefficient value varies across categories, indicating different elasticities in path-dependence of patenting in different technology fields. The estimated elasticities are approximately 0.9 for overall patenting, 0.8 for Category 5 (Mechanical) which is highest, 0.4 for Category 1 (Chemical) which is lowest, and 0.6-0.7 for Category 2 (Computers & Communications), Category 4 (Electrical & Electronic), and Category 6 (Other). The degrees of path-dependence across categories are consistent with the patent distribution in the overall patenting portfolio, and the overall dependence is mainly driven by the largest technology field - Category 5 (Mechanical). The lagged-dependent variable elasticities indicate considerable path-dependence in firms' patenting. This is not surprising as we expect firms' R&D processes, and innovation and patenting strategy to show some continuity at least in the short-to-medium term.

Knowledge stock effects

One of the main variables from theory is firms' prior knowledge, which is captured by knowledge stock in related fields. In table 5.7 and 5.8, the full-panel estimate of knowledge gap is negative for overall patenting and Category 5 (Mechanical), positive for Category 1 (Chemical), Category 2 (Computers & Communications), Category 4 (Electrical & Electronic), and Category 6 (Other). Given the standard errors, the point estimates are not statistically different across the various specifications reported in tables 5.7 and 5.8. This implies that the relationship between innovation and knowledge stock is negative for the main category, which leads to the overall negative effect in the overall patent portfolio, and positive for other categories. In the literature, knowledge stock captures both knowledge exploration and exploitation, and a balanced portfolio in these two dimensions can enhances current innovation, while an unbalance portfolio can reduce current innovation. Given the large patent share, first, firms may be hampered by their existing mechanical technologies because of the unbalance between knowledge exploration and exploitation; second, because of the large knowledge stock, firms may incur diseconomies of scale.

Own patent concentration

Our second key variable from theory is knowledge diversity, and our measure is patent concentration. In table 5.7 and 5.8, the full-panel estimate of patent concentration is approximately -0.3 and statistically significant for the overall portfolio, -0.5 and statistically significant for Category 4 (Electrical & Electronic), -0.6 and statistically significant for Category 5 (Mechanical), and insignificant for Category 1 (Chemical), Category 2 (Computers & Communications), and Category 6 (Other). This implies that for the typical firm in our sample, an increase in patent diversification leads to higher patenting in electrical & electronic and mechanical technologies. As these two groups are two largest categories in the auto industry, a decrease in patent concentration or an increase in patent diversification indicates more research activities in other fields. These two technology fields benefit from the research activities in other fields, and drive the positive effect of knowledge diversification on current innovation for the overall portfolio. The positive relationship between current innovation and patent diversification is consistent with the literature that knowledge diversification can increase innovation by capturing technological opportunities.

Rivals' average patent concentration

Our third key variable inter-firm innovation rivalry and our measure is the average patent concentration of rivals. In table 5.7 and 5.8, the full-panel estimate of rivals' average patent concentration is approximately -2.5 and statistically significant for the overall portfolio, -4.0 and statistically significant for Category 4 (Electrical & Electronic), -3.0 and statistically significant for Category 5 (Mechanical), -3.0 and statistically significant for Category 6 (Other), and insignificant for Category 1 (Chemical) and Category 2 (Computers & Communications). This implies that for the typical firm in our sample, an increase in rivals' patent diversification leads to higher patenting in electrical & electronic, mechanical, and other technologies. Comparing the coefficients and standard errors of own and rivals' patent concentration, rivals patent concentration has significantly higher effects on a firms' current innovation. Since own knowledge diversification indicates the possibility of capturing technological opportunities, rivals' patent diversification indicates their potential in capturing those opportunities. Given the innovation competition and the limited technological opportunities, rivals' patent diversification also implies their ability to compete in new innovation. Given the relative values of own patent concentration and rivals' patent concentration, firms pay more attention to the innovation rivalry indicated by rivals' knowledge diversity.

Next, we report several check of robustness. To save space, in the tables we only report the main coefficients of interest (the estimated specifications include all the control variables noted in table 5.7 and 5.8).

Table 5.9 GMM (No Germany)

	$ln(PAT_t^{Total})$	$ln(PAT_t^{C1})$	$ln(PAT_t^{C2})$	$ln(PAT_t^{C4})$	$ln(PAT_t^{C5})$	$ln(PAT_t^{C6})$
$ln(PAT_{i,t-1}^{k})$	0.897*** (0.030)	0.503*** (0.075)	0.651*** (0.070)	0.749*** (0.050)	0.855*** (0.042)	0.721*** (0.018)
$ln(AP_{i,\,t-2}^{k})$	-0.035 (0.042)	0.320*** (0.057)	0.102 (0.062)	0.105*** (0.032)	-0.066 (0.053)	0.175*** (0.035)
$ln(HHI_{i,t-1}^{PAT})$	-0.375* (0.214)	0.378 (0.375)	-0.168 (0.318)	-0.809** (0.334)	-0.705*** (0.233)	-0.182 (0.326)
$ln(\overline{HHI_{J,t-1}^{PAT}})$	-3.486*** (0.992)	2.472 (2.445)	-2.485 (1.836)	-7.540*** (2.127)	-3.914*** (1.204)	-3.899** (1.621)

Note: Variables and methods same as table 5.7, but the three German firms are excluded from sample.

Table 5.10 IV (No Germany)

	$ln(PAT_t^{Total})$	$ln(PAT_t^{C1})$	$ln(PAT_t^{C2})$	$ln(PAT_t^{C4})$	$ln(PAT_t^{C5})$	$ln(PAT_t^{C6})$
$ln(PAT_{i,t-1}^{k})$	0.879*** (0.056)	0.968*** (0.157)	0.706*** (0.106)	0.786*** (0.067)	0.876*** (0.048)	0.865*** (0.064)
$ln(AP_{i,\,t-2}^{k})$	-0.027 (0.037)	0.051 (0.103)	0.078 (0.075)	0.075** (0.031)	-0.076* (0.041)	0.130*** (0.039)
$ln(HHI_{i,t-1}^{PAT})$	-0.358** (0.166)	1.123** (0.496)	-0.132 (0.343)	-0.790*** (0.279)	-0.698*** (0.189)	0.090 (0.282)
$ln(\overline{HHI_{J,t-1}^{PAT}})$	-3.441*** (0.980)	2.706 (3.197)	-2.690 (2.089)	-7.616*** (1.964)	-4.010*** (1.167)	-4.065** (1.609)

Note: Variables and methods same as table 5.8, but the three German firms are excluded from sample.

First, the exclusion of the German firms does not alter the main inferences. We re-estimate the full specification with the U.S. and Japanese firms only and the results are reported in table 5.9 and 5.10. We note that while there are the estimated quantitative effects are increased, our key inferences remain intact.

Table 5.11 GMM (sub-HHI)

	$ln(PAT_t^{Total})$	$ln(PAT_t^{C1})$	$ln(PAT_t^{C2})$	$ln(PAT_t^{C4})$	$ln(PAT_t^{C5})$	$ln(PAT_t^{C6})$
$ln(PAT_{i,t-1}^k)$	0.846***	0.379***	0.607***	0.646***	0.783***	0.670***
	(0.026)	(0.095)	(0.057)	(0.057)	(0.049)	(0.019)
$ln(AP_{i,\,t-1}^k)$	-0.046	0.243***	0.077**	0.063***	-0.037	0.147***
	(0.040)	(0.057)	(0.038)	(0.023)	(0.040)	(0.050)
$\ln(HHI_{i,t-1}^{SubPAT})$	-0.191*	-0.115	-0.086	-0.452**	-0.373***	0.027
	(0.100)	(0.203)	(0.092)	(0.203)	(0.137)	(0.190)
$ln(\overline{HHI_{j,t-1}^{SubPAT}})$	-1.158**	0.829	-0.215	-2.167*	-1.377**	-0.639
	(0.496)	(0.975)	(0.660)	(1.305)	(0.602)	(1.333)

Notes:

1. The variables are:

$HHI_{i,t-1}^{SubPAT}$ – Concentration in annual patents in 37 sub-categories, lagged one period. Calculated as follows:

$HHI_{i,t}^{SubPAT} = \sum_{m=1}^{37}(\frac{PAT_{i,t}^m}{PAT_{i,t}})^2$, m=patent sub-category (Sub C1-Sub C37);

$\overline{HHI_{j,t-1}^{SubPAT}}$ – Average concentration in annual patents in 37 sub-categories of rivals, lagged one period. Calculated as follows:

$\overline{HHI_{j,t}^{SubPAT}} = (\sum_{j=1,j\neq i}^{9} HHI_{j,t}^{SubPAT})/8.$

2. Other variables and methods same as table 5.7

Table 5.12 IV (sub-HHI)

	$ln(PAT_t^{Total})$	$ln(PAT_t^{C1})$	$ln(PAT_t^{C2})$	$ln(PAT_t^{C4})$	$ln(PAT_t^{C5})$	$ln(PAT_t^{C6})$
$ln(PAT_{i,t-1}^k)$	0.911***	0.963***	0.705***	0.756***	0.909***	0.933***
	(0.051)	(0.152)	(0.081)	(0.063)	(0.053)	(0.072)
$ln(AP_{i,\,t-1}^k)$	-0.086**	-0.011	0.047	0.050*	-0.099***	0.074**
	(0.038)	(0.089)	(0.045)	(0.027)	(0.037)	(0.038)
$\ln(HHI_{i,t-1}^{SubPAT})$	-0.192*	0.373	-0.076	-0.332**	-0.401***	0.244
	(0.100)	(0.246)	(0.172)	(0.159)	(0.120)	(0.191)
$ln(\overline{HHI_{j,t-1}^{SubPAT}})$	-1.061	1.621	-0.230	-1.836**	-1.602**	-0.475
	(0.666)	(1.235)	(0.900)	(0.936)	(0.659)	(0.993)

Notes:

1. See table 5.11.

2. $ln(PAT_{i,t-1})$ is treated as endogenous, $ln(PAT_{i,t-2})$, $ln(AP_{i,\,t-1}^k), ln(HHI_{i,t-1}^{SubPAT})$, $ln(\overline{HHI_{j,t-1}^{SubPAT}})$, and **X** are used as IVs.Other variables and methods same as table 5.8

Second, using patent concentration in 6 main sub-categories in equation (5) with patent concentration in 37 sub-categories does not alter the main inferences. We re-estimate the full specification with $HHI_{i,t-1}^{SubPAT}$ and $\overline{HHI_{J,t-1}^{SubPAT}}$, and the results are reported in table 5.11 and 5.12. We note though the coefficients are changed because of changed indicator of patent concentration, our key inferences remain intact.

Table 5.13 GMM (entropy)

	$ln(PAT_t^{Total})$	$ln(PAT_t^{C1})$	$ln(PAT_t^{C2})$	$ln(PAT_t^{C4})$	$ln(PAT_t^{C5})$	$ln(PAT_t^{C6})$
$ln\left(PAT_{i,t-1}^{k}\right)$	0.885*** (0.027)	0.405*** (0.090)	0.622*** (0.056)	0.680*** (0.053)	0.793*** (0.036)	0.694*** (0.023)
Bankruptcy GM	-0.630*** (0.059)	-1.465*** (0.170)	-0.355** (0.144)	-1.664*** (0.157)	-1.550*** (0.108)	-1.547*** (0.166)
Merger Daimler-Chrysler	-0.020 (0.058)	0.837*** (0.157)	0.087 (0.107)	0.197*** (0.058)	0.065 (0.076)	0.054 (0.083)
$ln(AP_{i,\,t-1}^{k})$	-0.053 (0.036)	0.245*** (0.059)	0.084** (0.034)	0.060*** (0.020)	-0.016 (0.043)	0.158*** (0.043)
$Entropy_{i,t-1}$	0.566* (0.336)	-0.332 (0.505)	0.165 (0.525)	1.273*** (0.470)	0.990*** (0.340)	0.436 (0.380)
$\overline{Entropy_{J,t-1}}$	4.917** (2.360)	-4.212 (3.884)	1.773 (4.107)	9.899*** (3.783)	6.298** (2.801)	6.660** (3.246)
Firm Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	369	369	369	369	369	369

Notes:

1. The variables are:

$Entropy_{i,t-1}$–Jacquemin-Berry entropy measure of diversification, lagged one period.

Calculated as follows:

$$Entropy_{i,t} = \sum_{k=1}^{6} PATSHR_{i,t}^{k} ln(1/PATSHR_{i,t}^{k})\,, PATSHR_{i,t}^{k} = \frac{PAT_{i,t}^{k}}{PAT_{i,t}}, k = 1, 2, \ldots, 6.$$

$ln(\overline{HHI_{J,t-1}^{PAT}})$– Average concentration in annual patents of rivals, lagged one period.

Calculated as follows:

$\overline{Entropy_{J,t}} = (\sum_{j=1, j\neq i}^{9} Entropy_{j,t})/8$

2. Other variables and methods same as table 5.7

Table 5.14 IV (entropy)

	$ln(PAT_t^{Total})$	$ln(PAT_t^{C1})$	$ln(PAT_t^{C2})$	$ln(PAT_t^{C4})$	$ln(PAT_t^{C5})$	$ln(PAT_t^{C6})$
$ln(PAT_{i,t-1}^{k})$	0.924*** (0.048)	0.991*** (0.144)	0.711*** (0.081)	0.782*** (0.059)	0.876*** (0.050)	0.918*** (0.061)
Bankruptcy GM	-0.579*** (0.210)	-0.968*** (0.325)	-0.347** (0.136)	-1.426*** (0.201)	-1.305*** (0.360)	-1.067*** (0.284)
Merger Daimler-Chrysler	-0.056 (0.090)	0.120 (0.286)	0.026 (0.133)	0.141 (0.103)	-0.013 (0.103)	-0.146 (0.140)
$ln(AP_{i,\,t-1}^{k})$	-0.074** (0.036)	-0.054 (0.088)	0.057 (0.044)	0.052** (0.026)	-0.063* (0.036)	0.100*** (0.034)
$Entropy_{i,t-1}$	0.551 (0.339)	-1.188* (0.701)	0.184 (0.503)	1.289*** (0.449)	1.029*** (0.366)	0.328 (0.419)
$\overline{Entropy_{J,t-1}}$	5.016* (2.631)	-5.701 (5.330)	2.108 (3.944)	10.725*** (3.653)	6.807** (2.860)	7.895** (3.303)
Firm Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	378	378	378	378	378	378

Notes:

1. See table 5.13

2. $ln(PAT_{i,t-1})$ is treated as endogenous, $ln(PAT_{i,t-2})$, $ln(AP_{i,\,t-1}^{k})$, $Entropy_{i,t-1}$, $\overline{Entropy_{J,t-1}}$, and **X** are used as IVs.Other variables and methods same as table 5.8

Third, using patent entropy in equation (5) does not alter the main inferences. We re-estimate the full specification by replacing $ln(HHI_{i,t-1}^{PAT})$ and $ln(\overline{HHI_{J,t-1}^{PAT}})$ with $Entropy_{i,t-1}$ and $\overline{Entropy_{J,t-1}}$. We do not use logarithm values of Entropy because the calculation of entropy already includes logarithm. The results are reported in **table 5.13** and **5.14**. We note that since an increase in entropy means an increase in patenting diversity, our key inferences remain intact.

Finally, we use lag one of knowledge stock to re-estimate equation (5’’). We also experimented with re-estimating equation (5’’) adding average knowledge stock of rivals in related fields. To conserve space we do not report the resulting estimates. While there are marginal differences in the estimated quantitative effects, our overall inferences are similar to these alternative measurements of knowledge exploration and exploitation.

Based on the results in table 5.7 and 5.8, and the checks for robustness, our broad conclusions are as follows.

1. Knowledge stock has positive or negative effects. Our estimates in table 5.7 and 5.8 reveal that the relationship between knowledge stock and current innovation is somewhat complex and depends on patent categories. Knowledge stock has negative effect on mechanical technologies, and has positive effect on chemical, computers & communications, electrical & electronic, and other technologies. One way to interpret this result is that if since mechanical technologies have the largest patent share in the overall portfolio, they also have the largest knowledge stock, and hence have potential diseconomies of scale. As a result, an increase in knowledge stock in mechanical technologies has decreasing returns, while an increase in knowledge stock in other categories brings increasing returns. In addition, given the rapid development in mobile and computer technologies, traditional technologies like mechanical are developing relatively slow, which potentially leads to the opposite effects of knowledge stocks. Our findings are consistent with the literature that firms are likely to be hampered by their previous knowledge in this field and innovate too narrow. Since knowledge stock captures knowledge exploration and exploitation, our results is consistent with the predictions that knowledge exploration and exploitation

can benefit current innovation (Cohen and Levinthal, 1990), but will not always benefit current innovation (*e.g.*, Gilbert and Shapiro, 1990; Klemperer, 1990; March, 1991; Leonard-Barton, 1992; Levinthal and March, 1993; Granstrand, 1998).

2. An increase in the knowledge diversification can have positive or insignificant effects. Our estimates in table 5.7 and 5.8 reveal that the relationship between knowledge diversification and current innovation is somewhat complex and depends on patent categories. When diversification in technology increases, firms will innovate more in electrical & electronic and mechanical technologies, while innovations in other categories are not affected. As the two main innovation categories in the auto industry, electrical & electronic and mechanical technologies benefit most from potential technological opportunities indicated by own knowledge diversification, while other technologies with small percentages in total patenting do not significantly benefit from firms' own knowledge diversification. This is in line with some of the predictions that having a diversified knowledge portfolio can increase innovation (*e.g.*, Nelson, 1959; Dosi, 1982; Cohen and Levinthal, 1990; March, 1991; Leventhal and March, 1993).

3. An increase in rivals' knowledge diversification can have positive or insignificant effects. Our estimates in table 5.7 and 5.8 reveal that the relationship between rivals' knowledge diversification and current innovation is somewhat complex and depends on patent categories. In our study, knowledge diversification is an indicator of own potential technological opportunities, and rivals' average knowledge diversification reveals rivals' general technological opportunities. Since

technological opportunities are directly related to future innovation, rivals' technological opportunities reveal their potential future innovation outcomes. As a result, by measuring rivals' knowledge diversification, firms are able to measure rivals' general innovation competitiveness. Given the characteristics of the auto industry, electrical & electronic and mechanical technologies are the two main innovation categories and represent firms' core competitiveness in innovation. By innovating more in these two categories, firms are able to maintain their technological positions and compete with the potential expansion in innovation of rivals. Hence, when rivals' diversification in technology increases, firms will innovate more in electrical & electronic and mechanical technologies as to compete in core technologies, while innovations in other categories are not affected since they have low patenting percentage and are relatively not that important for the auto industry. The quantitative effects of rivals' knowledge diversification is higher than that of own knowledge diversification, indicating inter-firm innovation rivalry is a more important driver of innovation activities than own knowledge diversity.

The estimation of key variable helps to understand the shifting dynamics in patent segmentation. First, we find knowledge stock has mixed effects and can increase or decrease innovation. Second, we find knowledge diversification increases patenting especially for core technologies, which are electrical & electronic and mechanical in the auto industry. Third, we find rivals knowledge diversification increases patenting especially for core technologies, which are electrical & electronic and mechanical in the auto industry. Finally, we find rivals' knowledge diversification captures inter-firm patent rivalry and is the main driver of changing composition in patenting. Comparing the quantitative effects of own and rivals' patent concentration and rivals' patent, we find that, the effects of own patent concentration only has marginal difference on Category 4 and 5, implying a common effect on technologies in these two fields. While the rivals' patent concentration has statistically higher effects on Category 4 than Category 5, implying a higher growth rate in electrical & electronic patents than mechanical patents. In terms of patent share, electrical & electronic technologies in Category 4 have increasing patent share, and mechanical technologies in Category 5 have declining patent share. This is consistent with the time trend described in section 3.

5.5 Conclusions

We use firm-level data to examine the evolution of patents by categories and inter-firm innovation rivalry in the U.S. automobile market. The combination of the U.S. market's economic importance, market dynamics, and the significant intertemporal fluctuations in firms' patents make this an interesting market to examine the link between competition and innovation.

Based on dynamic panel data estimates, our main findings are as follows. First, we find knowledge stock has negative effect on mechanical technologies, and has positive effect on chemical, computers & communications, electrical & electronic, and other technologies. Second, we find that knowledge diversification has positive effects on electrical & electronic and mechanical technologies. Third, we find that rivals' knowledge diversification has positive effects on electrical & electronic, mechanical, and other technologies, and the effects are statistically higher than those of own knowledge diversification. Finally, we find that rivals' knowledge diversification has statistically higher effects on current patenting than own knowledge diversification, and is the main driver of changing compositions in patenting. The typical study in the literature of the effects of knowledge exploration and exploitation does not control for inter-firm innovation rivalry. In this sense our empirical specification has a more complete set of controls.

CHAPTER 6. CONCLUSIONS

In this research, we examine numerical models for analyzing the determinants of patenting behaviors in an oligopolistic market. These models consist of market shares, market competition, knowledge stock, knowledge gap, and composition of patents. Previous research found that the relationships are complex and depend on specific structure of the model and parameters. We use firm-level time-series data over a long horizon (1969-2012) for nine well established firms selling in the U.S. market (GM, Ford, Chrysler, Toyota, Honda, Nissan, Volkswagen, BMW, and Daimler).We examined three aspects related to market competition, innovation, and innovation rivalry in the U.S. automobile industry. Furthermore, we include the two or more factors listed above in one specific model. For example, the typical study in the literature of the effects of knowledge gap does not control for both market shares and knowledge gap, and our empirical specification has a more complete set of controls.

First, we examine the relationship between competition and innovation. We use two indicators of competition: HHI and main rivals' market shares. Some of our key findings are: (1) increase in firms' market shares result in higher patenting, and the relationship is reasonably non-linear; (2) higher market-wide competition results in an increase in patenting, and the relationship is weakly non-linear; (3) there is relatively strong path-dependence in firms' patenting behavior. We also compare our findings to those of Aghion et al. (2005) and Hashmi (2013).

Second, we examine the relationship between knowledge gap and patent rivalry. We consider the competition in both market shares and knowledge positions, and included both factors in our model. We also include the interaction between these two factors and examined the indirect effects of knowledge gap and market share. Our key findings are: (1) the relationship between patenting and knowledge gap is non-linear, and is U shaped; (2) an increase in market share results in higher current patenting; (3) the interaction between firms' market share and technology gap does not have a statistically significant effect on their current patenting.

Third, we examine the changing composition of patents. We use the detailed information of patents and group them into 6 main categories and 36 sub-categories based on their technology fields. In particular, we examine how a firm's current patenting behavior is influenced by the own patent concentration and rivals patent concentration. Our key findings are: (1) the relationship between knowledge stock and current innovation is complex, and depends on technologies categories: knowledge stock has negative effect on mechanical technologies, and has positive effect on chemical, computers & communications, electrical & electronic, and other technologies; (2) an increase in own patent diversification results in higher current patenting in electrical & electronic and mechanical technologies; (3) an increase in rivals' patent diversification results in higher current patenting in electrical & electronic on mechanical technologies; (4) rivals' knowledge diversification has statistically higher effects on current patenting than own knowledge diversification, and is the main driver of changing compositions in patenting. We also develop a set of stylized facts and patterns of patent composition in this industry.

Appendix A: Literature Review Table

Table A.1 Selected Theoretical Papers: Relationship between Competition and Innovation

Paper	Innovation Variable(s)	Competition Variable(s) and (or) Market Structure	Results(s)
Aghion et al. (2001)	R&D	Product-market competition. Bertrand	Negative: Schumpeterian effect Positive: escape competition
Aghion et al. (2005)	Patents	Industry price-cost margins Bertrand	Non-linear, Inverted U-shaped
Arrow (1962)	General Innovation	Monopoly. Perfect competition.	Positive
Anton and Yao(2004)	Patents	Cost efficiency and profits Cournot	Patent small innovations
Delbono and Denicolo (1991)	R&D	Number of rivals Cournot oligopoly	Negative
Jansen (2011)	Patents	Number of rivals Cournot. Bertrand	Cournot: positive. Bertrand: negative.
Lee and Wilde (1980)	R&D	Number of rivals	Positive
Loury (1979)	R&D	Number of rivals	Negative
Mosel (2011)	Patents. R&D	Cost reduction and profits Bertrand	Patent big innovations
Schumpeter (1942)	General innovation	Monopoly. Perfect competition.	Negative

Table A.2 Selected Empirical Papers: Relationship between Competition and Innovation

Panel A: Firm Specific Shares and Related Variables			
Paper	Innovation Variables(s)	Market Performance Variable(s)	Results(s)
Blundell et al. (1995)	Commercialized innovations	Market share	Positive
Blundell et al. (1999)	Commercialized innovations Patents	Market share	Positive
Brouwer & Kleinknecht (1999)	Patents	Sales	Positive
Hu (2010)	Patents	Imports	Insignificant
Hashmi & Biesebroeck (2006)	R&D	Profit margin. Market share	Non-linear, inverted-U shaped
Lee et al. (2011)	Patents	Market share	Positive
Noel & Schankerman (2013)	R&D	Sales	Effect varies across periods
Scherer (1965)	Patents	Sales	Positive, non-linear
Panel B: Market-Wide Competition and Related Variables			
Paper	Innovation Variables(s)	Competition Variable(s)	Results(s)
Acs & Audretsch (1988)	Patents	Concentration ratio	Negative
Aghion et al. (2005)	Patents	Industry price-cost margins	Non-linear, inverted-U shaped
Blundell et al. (1995)	Commercialized innovations	Concentration ratio	Negative
Blundell et al. (1999)	Commercialized innovations Patents	Concentration ratio	Negative
Blind et al. (2006)	Patents	Competition intensity	Positive
Hu (2010)	Patents	Competing imports	Positive
Hashmi (2013)	Patents	Price cost margins	Negative
Levin & Reiss (1984)	R&D	HHI	Insignificant
Levin et al. (1985)	R&D; Innovation	Concentration ratio	Insignificant
Scherer (1965)	Patents	Concentration ratio	Insignificant

Table A.3 Selected Empirical Papers: Relationship between Competition and Innovation (after Aghion et al., 2005)

Paper	Innovation Variables(s)	Competition Variable(s)	Results(s)
Aghion et al. (2005)	Patents	Industry price-cost margins	Non-linear, inverted-U shaped
Aghion et al. (2005)	TFP	liberalized entry	General test: Positive
Aghion et al. (2008)	TFP growth	Price-cost margins	General test: 1970-2004: negative and linear; 1988–2003: negative, non-linearity vary across models
Aghion et al. (2009)	Patents	Average profitability	General test Non-linear, inverted-U shaped
Aghion et al. (2012)	TFP; Product innovation measured by share of value generated by new products	Lerner index; interaction between Lerner and HHI of subsidy	General test: TFP: Competition: insignificant; Interaction: Positive. Product innovation ratio: Competition: positive; Interaction: Insignificant.
Almeida and Fernandes (2008)	Dummy of technological innovation	Dummies based on number of competitors: No, weak, medium, or strong competition	General test: Positive
Amiti and Khandelwal (2013)	Quality upgrade	Import competition.	General test: Products close to the quality frontier: positive; Products distant from the quality frontier: negative.

Table A.3 (continued)

Ayyagari et al. (2011)	Dummies of innovation activities; Aggregate innovation index	Number of competitors and dummies of competition environments.	General test: Foreign competition variables: positive; Other competition variables: generally insignificant.
Berubé et al. (2012)	R&D	Profit-elasticity; Industry and firm price cost margins	General test: Profit elasticity: Non-linear, inverted-U shaped; Price cost margins: positive
Blind et al. (2006)	Dummy of patenting motivations	Competition intensity	General test: Positive
Bloom et al. (2016)	Patents; Information technology; TFP	Chinese import competition	General test: Positive
Correa (2012)	Patents	Price cost margins	Test of the inverted-U (Aghion et al., 2005): Relationship varies across periods
Dabla-Norris et al. (2012)	TFP	Degree of competition from survey: expectation of customer behaviors	General test: Insignificant
Fu (2008)	Patents; Innovation Efficiency	FDI	General test: Positive
Fu and Gong (2009)	Technical change and efficiency improvement, both decomposed from TFP	HHI	General test: Negative for technical change with international spillovers, otherwise insignificant
Gorodnichenko et al. (2010)	Dummies of new product, new technology, and new accreditation	Pressure from competition: None, Low, Medium, and High	General test: Positive
Hashmi (2013)	Patents	Price cost margins	Test of the inverted-U (Aghion et al., 2005): Negative
Hu (2010)	Patents	Competing imports	General test: Positive

Table A.3 (continued)

Lederman (2009)	Probability of New Product	business density: number of firms per capita	General test: Insignificant
Lederman (2010)	Probability of innovation	Index of ease of entry; business density: number of firms per capita	General test: Insignificant
Lee et al. (2011)	Production technology	HHI	General test: Positive
Li et al. (2013)	Technological progress measured by TFP	FDI stock	General test: Positive, non-linearity from interactions with R&D stock or capital stock: negative interactions.
Liu et al. (2014)	"Make" innovation: ratio of expenditure on innovation to the total number of firms; "Buy" innovation: ratio of expenditure on buying innovation to the total number of firms	intensity of competition: the share of output; Industry concentration: ratio of total output value to total number of firms	General test: Intensity of competition: "Make": Negative; "Buy": Positive. Industry concentration: positive
Peneder and Woerter (2014)	Ordinal variables related to R&D	Ordinal variables related to number of competitors	Test of the inverted-U (Aghion et al., 2005): Non-linear, inverted-U shaped
Peroni & Gomes Ferreira (2012)	R&D	Profit elasticity; Industry price cost margin	General test: Non-linear, U shaped
Polder and Veldhuizen (2012)	R&D	Profit-elasticity; Industry and firm price cost margins	Test of the inverted-U (Aghion et al., 2005): Profit-elasticity: Non-linear, inverted-U shaped; Industry price cost margins: Insignificant; Firm price cost margins: positive
Qian (2007)	R&D; patents	IRP protection	General test: Patent: insignificant; R&D: inverted-U shaped

Table A.3 (continued)

Schmeiele (2012)	Dummies of innovation activities abroad: R&D, new products, and new processes	Competition variables in home country: price competition; competitive situation; competition of new rivals; number of competitors	General test: Generally insignificant
Sjöholm and Lundin (2013)	R&D	Price-cost margin	General test: High-tech firms: non-linear, inverted-U shaped; Other firms: Insingificant
Tang (2006)	R&D; Product and process innovations; Acquisition of technology	4 different competition perception indicators: (1) Easy substitution of products; (2) Constant arrival of competing products; (3) Quick obsolescence of products; (4) Rapid change of production technologies	General test: (1) Easy substitution of products: negative; (2) Constant arrival of competing products: positive; (3) Quick obsolescence of products: positive for R&D or product innovation; negative for acquisition of technology or process innovation (4) Rapid change of production technologies: positive
Teshima (2008)	R&D; R&D intensity	Import competition	General test: Positive
Tingvall and Karpaty (2010)	R&D	HHI	Test of the inverted-U (Aghion et al., 2005): Non-linear, inverted-U shaped
Tingvall & Poldah (2006)	R&D	Industry and firm price cost margin; HHI	Test of the inverted-U (Aghion et al., 2005): Price cost margin: Positive; HHI: Non-linear, inverted-U shaped

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