Technological Environment, Learning Capabilities and Technological Catch-up of Laggards from Emerging Economies

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Abstract

This study investigates the technological catch-up of laggards from emerging Asian countries (China, Korea, and Taiwan). We examine how the technological environments and organizational learning capabilities influence the technological catch-up of laggards by tracking their patenting activities. We highlight the importance of changes in the technological environment and laggards' capabilities to seize emerging technological opportunities, especially from paradigm shifts. We find that laggards in emerging economies tend to succeed in catching up in areas where technological opportunities are abundant and the technology life cycle is relatively short. We also find that adopting new technologies increases their chances of catching up successfully to industry incumbents. We suggest that laggards with weak or mediocre combinative capabilities should seek a good balance between exploitative learning and explorative learning by searching for diverse knowledge only at a moderate level in order to improve their chances of catching-up.

Keywords: first movers, laggards, innovations, emerging economies, technological catch-up, technological opportunities, technology life cycles, emerging economies

INTRODUCTION

Scholars of strategic management have outlined many first-mover advantages leading to monopolistic economic rents and arising from various sources, such as technological leadership, learning curve effects, preemption of assets, and buyer switching costs (Lieberman and Montgomery, 1988; Murthi, et al., 1996; Robinson et al., 1992; Vanderwerf and Mahon, 1997). However, latecomers or laggards do not necessarily occupy unfavorable market positions, and their performance is not necessarily worse than that of first movers. Recently, arguments have been made that first-mover advantages are comparative rather than absolute (Makadok, 1998; Robinson and Min, 2002) and that laggards can adopt certain strategies to gain competitive advantages in the market (Cho et al., 1998; Mathews, 2002; Robinson et al., 1992; Shankar et al., 1998). However, laggard firms must still attempt to acquire technologies within their industries and catch up with first movers. Existing research neglects these catch-up efforts on the part of laggards, especially those from emerging economies.

In most technological sectors, American, Japanese, and European firms are acknowledged as first movers. These firms have accumulated technological capabilities for many years and are now recognized as global technology leaders. Firms in developing Asian countries are behind western firms in most technological fields. However, recently, major firms in such East Asian countries as Korea, Taiwan, and China have rapidly developed their own technological capabilities. As a powerful proof, patent records from the U.S. Patent and Trademark Office (USPTO) show a distinct trend since the end of the 1970s, at which time East Asian countries had been granted very few patents. However, the number of patents granted has increased exponentially since the late 1980s in Korea and Taiwan and since the turn of the 21st century in the case of China (see Fig. 1). In the process, some Asian technological laggards (e.g., Samsung,

LG and Hyundai-Kia Motors from Korea, Acer and HTC from Taiwan, Huawei from China) have shown that under certain conditions, laggards can overcome disadvantages and use latecomer-specific advantages to catch up with incumbent, first-mover firms. Investigation of these catch-up strategies is worthwhile for researchers in the fields of strategy and international management, particularly investigation of how and under what conditions laggards can catch up with incumbent leaders.

Insert <Figure 1> here

Recently, the catch-up behavior of technological laggards has been discussed in studies of how certain Asian laggard firms successfully caught up with incumbent leaders in advanced countries (Cho et al., 1998; Fan, 2006; Kim, 1997; Lee and Lim, 2001; Park and Lee, 2006; Song et al., 2001; Li and Kozhikode, 2008). However, generalization is difficult based on the results of most of these studies, as they focus on specific, usually successful, cases. As a result, our understanding of why some laggards manage to catch up successfully while others fail to do so is still limited. To overcome these limitations of existing research, this study provides new theoretical insights into the causes of success of catch-up by laggard firms in emerging Asian economies. Tracking the innovation activities of Asian laggards in a large sample setting provides rigorous empirical evidence that enables generalization on a larger scale.

In this study, the conditions for successful technological catch-up are identified in terms of both external/environmental and organizational factors. Though some prior studies offered good insights into how technological regimes affect catch-up success, most were conducted at the

country or industry level (e.g., Lee and Lim, 2001; Park and Lee, 2006). Only a few case studies systemically examine technological catch-up efforts at the firm level or identify factors that influence these efforts. This study contributes to the literature by examining technological catch-up of laggards at the firm level. Technological environments and organizational capabilities are identified as the main determinants of success in technological catch-up.

In order to catch up with incumbent leaders successfully, laggards must seek technological environments that are favorable to their position, those that offer ample technological opportunities and those with a short technological life cycle. Laggard firms should also develop their own distinctive organizational capabilities to enable them to take advantage of favorable technological environments and increase their chances of success. Technological forecasting and combinative capabilities are specifically advantageous in the process of successful catch-up for laggard firms in emerging economies. Overall, in this paper, we emphasize the importance of emerging opportunities in the technological environment and laggard firms' capabilities to seize these opportunities.

In this study (as opposed to previous studies that define the term "catch-up" unidimensionally), three types of technological catch-up are identified: quantitative, qualitative, and comprehensive. Quantitative catch-up focuses on the growth rate of a firm's technological assets, measured as number of patents in this study. Qualitative catch-up emphasizes a laggard firm's capability to develop technologically important innovations. Comprehensive catch-up occurs when a laggard achieves both quantitative catch-up and qualitative catch-up. The effects of both the learning capabilities of laggards and the technological environments to which they belong are examined in terms of these three types of catch-up.

This paper is organized as follows. The literature review identifies sources of advantage for

technological laggards. Hypotheses regarding the technological catch-up of laggard firms in terms of technological environments and organizational capabilities are then developed. The subsequent sections present the research methodology and statistical findings of this study. Finally, the theoretical contribution and implications of this research are discussed.

THEORY AND HYPOTHESES

Prior literature on entry order identified many advantages for first movers. For example, first movers can build customer loyalty and avoid switching costs; they can preempt important resources and opportunities; they can also gain technological leadership advantages through learning curve effects (Lieberman and Montgomery, 1988). These competitive advantages for incumbents are important market barriers to laggards (latecomers), making catch-up tremendously difficult. However, latecomers do enjoy some advantages over early movers, such as benefits from information spillover (Cho et al., 1998).

Given the liability of newness, laggards are unlikely to catch up if they follow old game rules established by incumbent leaders or attempt to follow existing technological trajectories. Laggards are more successful when they seize emerging opportunities within their technological environments, which may contribute to a paradigm shift that may undermine the very technological trajectories that previously provided advantages to market incumbents. Developing distinctive organizational capabilities allows laggard firms to identify and take advantage of emerging technological opportunities earlier than incumbent firms, which are committed to existing trajectories.

Prior literature defines a latecomer as a firm that is a late entrant to an industry, initially resource-poor, but regards catching up as its primary goal (Mathews, 2002). Drawing on

Mathews (2002), in this study, technological laggards are defined as firms that (1) entered a technological area much later than incumbent leader firms; (2) lag behind industry incumbents in terms of technological capabilities, and thus suffer competitive disadvantages and perform poorly in terms of global competition; and (3) regard catching up with technological leaders as a primary strategic goal despite their poor technological capabilities, and thus are more inclined to invest in innovative activities.

As in previous studies, success in technological catch-up is defined in this study in terms of relative innovation speed and quality. Specifically, in this study, a technological laggard is defined as having successfully caught up when its technological capabilities have rapidly improved and the technological gap between itself and industry incumbents has been reduced by faster achievement of innovation and/or innovations of higher impacts.

Technological Environment and Technological Catch-up

The literature on organizational theory generally regards an organization as an open system upon which surrounding environmental conditions have substantial impacts (Katz and Kahn, 1966; Lawrence and Lorsch, 1967; Pfeffer, 1972; Thompson, 1967). Many environmental factors can affect organizations, especially those that pursue technological catch-up or innovation. The innovation literature suggests that knowledge conditions in the external environment of an entrant into the market may carry important implications for its survival (Sarkar et al., 2006). Nelson and Winter (1982) showed that technological environments, including technological opportunities, cumulativeness, and appropriability of knowledge, have major effects on the intensity of innovation, the degree of industrial concentration, and the rate of entry in any industry. Lee and Lim (2001) and Park and Lee (2006) found that technological regime, defined as “the combination of technological opportunities, appropriability of innovations,

cumulativeness of technical advances and the properties of the knowledge base underpinning firms' innovative activities" (Breschi et al., 2000: 390), affected the innovation activities in emerging economies and their chances of catching up successfully. An understanding of how the technological environment influences the technological catch-up activities of laggards requires identification of the technological conditions that favor laggards while undermining incumbent leaders.

Previous research found that among the many diverse aspects of technological environments, emerging technological opportunities emanating from paradigm shifts in the market and technological domains may lead to a reversal of fortune for incumbents and challengers (Mitchell, 1991; Tushman and Anderson, 1986). As suggested by Schumpeter (1939) and Dosi (1982), although large established firms may have developed excellent routines along an existing technological trajectory, new innovators can still pose serious threats by disrupting that trajectory. Established leaders in an industry that have accumulated substantial technological resources and innovation capabilities based on the existing technological trajectory may fall into the "success trap" or exhibit organizational inertia. Thus, they are likely to respond more slowly to emerging opportunities and to perceive the threat of paradigm shift inadequately (Levinthal and March, 1993; Nelson and Winter, 1982; Sorensen and Stuart, 2000; Zucker and Darby, 1997).

By contrast, laggards have less to lose. Thus, they are more willing than incumbent leaders to grasp emerging opportunities, perceive paradigm shifts, and adopt radically new technologies quickly, thereby enhancing catch-up probability (Cho et al., 1998; Christensen and Bower, 1996; Sorensen and Stuart, 2000; Tushman and Anderson, 1986; Lieberman and Montogomery, 1998). Laggards catch up especially when there is a technological paradigm shift because the disadvantages of late entry become unimportant (Cho et al., 1998; Lee and Lim, 2001).

Everybody starts in the same place along the emerging technological trajectory (Perez and Soete, 1988). Khanna, Song, and Lee (2011) discussed the catch-up of Samsung with Sony in television technology and sales when the electronics industry underwent a paradigm shift from analog to digital technology. To catch up with Sony, Samsung concentrated its innovation efforts on digital television early on, whereas Sony, the incumbent leader, stuck to analog for too long. This is an example of how a technological laggard successfully caught up with an industry incumbent.

Technological Opportunity and Technological Catch-up

Existing literature has emphasized the importance of technological opportunity in determining innovation activities, especially during paradigmatic changes in technological environments (Jaffe, 1986; Klevorick et al., 1995; Scherer, 1965). Jaffe (1986: 984) defines technological opportunity as "exogenous variations in the cost and difficulty of innovation in different technological areas due to characteristics of the technology or the state of exogenous scientific knowledge". Different technological fields provide different technological opportunities (Henderson and Cockburn, 1994). These differences influence patenting activities (Ahuja and Katila, 2004) and technological catch-up activities.

When technological opportunities are abundant, new technologies appear frequently. Laggards are more likely to seize emerging technological opportunities and occupy new technological niches in global markets (Park and Lee, 2006; Song, 2006). Research has shown that like new firms, such as the venture capital firms in the Silicon Valley, laggards who are ambitious enough to play catch-up with industry incumbents are more likely to explore new technologies in emerging niche fields (Utterback and Abernathy, 1975; Khanna et al., 2011). Focusing on emerging niche technologies offers strategic benefits for laggards for three reasons. First, markets for new technologies are often too small to attract established firms. As a result,

laggards avoid direct competition with established firms in these markets. Second, laggards have limited resources and capabilities (Madhok and Osegowitsch, 2000; Mathews, 2002). Concentrating their limited resources on certain niches can help them overcome resource constraints, allowing them to develop and maintain a leadership role in emerging technologies (Kohn, 1997). Third, as an industry becomes more stable and mature over time, capital intensity and economies of scale become more important, often in favor of industry incumbents (Pavitt and Wald, 1971). Hence, by focusing on emerging technologies, laggards can overcome competitive disadvantages due to diseconomies of scale.

To summarize, abundant technological opportunity in emerging niche fields allows laggards to catch up with incumbent leaders in an industry. Therefore, we hypothesize that:

Hypothesis 1: Technological laggards are more likely to succeed in catching up when technological opportunities are abundant.

Technology Life Cycle and Technological Catch-up

The phrase "technology life cycle" refers to the amount of time until an existing technology is replaced by a new technology in a given technological field (Jaffe and Trajtenberg, 2002; Narin, 1999). When the technology life cycle is short, incumbent firms have difficulty switching quickly from the existing technology to the new technology (Dosi, 1982; Schumpeter, 1939; Sorensen and Stuart, 2000; Tushman and Anderson, 1986; Zucker and Darby, 1997). By contrast, laggards have the flexibility to adopt new technologies more quickly than incumbents, thereby gaining competitive advantages that help them catch up. However, when the technology life cycle is short, the cumulativeness of knowledge in a technological field is low and existing knowledge in the field becomes obsolete quickly. Thus, knowledge amassed over time in a field

dominated by incumbents becomes less important (Park and Lee, 2006). In this situation, laggards can overcome the learning curve advantages enjoyed by incumbent leaders and catch up with incumbent firms more easily by focusing their learning on newly emerging technologies. Hence, we hypothesize that:

Hypothesis 2: Technological laggards are more likely to succeed in catching up in a technological field with a short life cycle.

Organizational Capabilities and Technological Catch-up

Though a change in technological trajectory within an industry gives laggards the opportunity to enter new and potentially profitable technology areas, firms need adequate organizational capabilities in order to identify and take advantage of favorable technological opportunities. Among various capabilities that contribute to organizational survival and performance, predictive and combinative capabilities are the most critical for successful technological catch-up.

Predictive capability and technological catch-up

Barney (1986) argued that earning above-normal economic returns occurs when a firm can forecast the future value of its resources more accurately than its competitors in the resource market. A firm that misses or underestimates favorable environmental changes cannot keep up with market demand and technological evolution; therefore, it misses out on competitive opportunities. Predictive capabilities are essential to an organization's success and performance (Barney, 1986; Makadok and Walker, 2000). Recent studies suggest that managerial foresight about the emergence of new opportunities leads to competitive advantages (Ahuja, Coff, and Lee, 2005). Such technological foresight can help laggards catch up with incumbents. The external

environment must be scanned constantly in order to detect and take advantage of changing technological trends.

Firms that search for and build on recent technologies are better able to predict technological advances over time (Katila, 2002). Lukewarm investments in the latest technologies may prevent firms from innovating in those technologies in the future (Cohen and Levinthal, 1990; McGrath, 1997; Yates et al., 1978). Therefore, the technological predictive capabilities of a laggard firm, developed over time through its efforts to search for emerging technologies, improve its chances of catching up successfully. Hence, we hypothesize that:

Hypothesis 3: The degree to which a technological laggard searches for emerging technologies is positively related to its success in catching up technologically.

Combinative capability and technological catch-up

An organization with dynamic capabilities can recognize and respond to opportunities and threats in rapidly changing environments by extending, modifying, and combining existing resources and capabilities both inside and outside the organization (Eisenhardt and Martin, 2000; Helfat and Peteraf, 2003; Teece, Pisano, and Shuen, 1997). For a firm to become a dynamic force within the market, it must learn new skills by recombining existing resources and capabilities (Kogut and Zander, 1992). Such combinative capabilities can be a source of competitive advantage. Organizational combinative capabilities contribute to the development of dynamic capabilities and play an important role in the organizational learning and innovation process. Such technological combinative capabilities help laggards move from one product generation to another quickly (Mathews and Cho, 1999; Teece et al., 1997). In the process, they become more flexible and adaptable to rapidly changing technological trends than industry incumbents that

stick to existing successful trends or routines.

Generally speaking, organizations that acquire diverse knowledge through explorative searching are more likely to improve their combinative capabilities over time. Diverse learning helps firms succeed in their innovation efforts. Explorative learning exposes firms to new ideas and solutions to technological problems. However, for effective innovation, a firm must have strong absorptive capacity to absorb and assimilate the technologies identified during explorative searching (Cohen and Levinthal, 1991). Moreover, the firm must be able to integrate externally sourced knowledge with its own knowledge for successful innovation. Thus, a firm's combinative capabilities consist of both absorptive capacity and the ability to integrate internal and external knowledge.

Generally speaking, stronger combinative capabilities of a firm lead to a better chance for the firm to succeed in innovation. However, most laggards have mediocre combinative capabilities at best, due to relatively weak absorptive capacity, and inadequate internal knowledge. Thus, they are not in a position to explore extensively before enhancing their combinative capabilities. In order to do so, they must strike a good balance between explorative learning and exploitative learning (Gupta et al., 2006; Levinthal and March, 1993; March, 1991). Though searching for diverse knowledge may help laggard firms increase flexibility in the changing environment, excessive exploration for diverse knowledge without integration with or exploitation of existing knowledge is likely to lead to innovation failure, weak absorptive capacity, and fragile internal knowledge bases (Levinthal and March, 1993; March, 1991). Hence, we hypothesize that:

Hypothesis 4: The degree to which a technological laggard searches for diverse technologies has a curvilinear (inverse U-shaped) relationship with its success in catching up

technologically.

DATA AND METHODOLOGY

Sample and Data

Chinese, Korean, and Taiwanese firms were used in this study as representative technological laggards. The sample consisted of all Chinese, Korean, and Taiwanese firms that were granted at least one patent by the USPTO between 1977 and 2004. Patent data have been widely used in organizational research in recent years to study technological innovation (e.g., Ahuja and Katila, 2001; Benner and Tushman, 2002; Rosenkopf and Nerkar, 2001; Sorenson and Stuart, 2000). Prior studies have suggested that patents can be useful indicators of knowledge creation and innovative capability (Ahuja and Lampert, 2001; Nerkar, 2003; Song et al., 2003). Thus, a technological laggard's patent stock can be used to evaluate its technological capabilities and catch-up performance. The USPTO database is useful for analysis of innovative behaviors, as each patent document contains detailed information on the assignee, inventor, technology type, and citations (i.e., the prior technologies and background knowledge upon which the patent builds).

In total, 4,004 Chinese, Taiwanese, and Korean firms were granted at least one patent by the USPTO between 1977 and 2004. Because catch-up success in this study was determined by comparing the innovative output of a firm with that of other firms belonging to the same technology class, the primary technology class of a firm was defined as the class in which the firm had been granted the highest number of patents among all technology classes to which it belongs. All variables in this study were measured based on patent data from the primary technology class of each firm. Firms with more than two primary technology classes were excluded from the sample. The final sample was thus composed of 3,439 firms, including 204

Chinese firms (5.93%), 941 Korean firms (27.36%) and 2,294 Taiwanese firms (66.71%). These firms were distributed across 365 primary technology classes (using 3-digit Standard Industrial Classification codes) of the U.S. Patent Classification System. All patenting activities of each firm were tracked year-by-year and unbalanced panel data including 5,301 observations in total were constructed.

Measures

Dependent variable and subtypes

The dependent variable in this study was catch-up success. A laggard was considered to be catching up if it managed to reduce the technological gap between itself and incumbents in the industry by innovating at a faster rate or producing innovations of higher impact than the average level in the corresponding technological field. As mentioned earlier, three types of technological catch-up were recognized: quantitative, qualitative, and comprehensive catch-up. Quantitative catch-up emphasizes innovation speed as measured by the rate of increase of the number of patents granted to a firm. In the existing literature on catch-up strategies at the country or industry levels, catch-up occurs when a poorer economy/firm grows at a faster rate than a richer economy/firm, effectively reducing the gap between the two (Dowrick and Nguyen, 1989; Kumar and Russell, 2003; Baumol, Nelson, and Wolff, 1994; Nelson, 2004). For example, Park and Lee (2006) operationalized catch-up economies as countries whose patent registration growth rates are higher than the average rates of the representative advanced economies. Therefore, catching up is mainly characterized by relative growth speed. In this study, technological catch-up depends on the relative innovation speeds of laggards and incumbent leaders.

Quantitative catch-up was measured in this study by comparing the average annual patent

growth rate of a firm with that of the same technology class during the same observation period (Park and Lee, 2006). Quantitative catch-up was operationalized as a dummy variable, which was coded as 1 if a firm had a higher average patent growth rate than that of other firms in the same technology class, and as 0 otherwise. In this study, the average patent growth rates at both the firm level and the technology class level were calculated in terms of the compound annual growth rate (CAGR). The CAGR of firm i or technology class i is $\mathrm{CAGR_{iN}} = (\frac{\mathrm{P_{tf}}}{\mathrm{P_{ts}}})^{\frac{1}{\mathrm{N}}} - 1$, where $\mathrm{P_{ts}}$ is the number of patents of firm i (or technology class i) at year *ts* (*first patenting year for firm i*), $\mathrm{P_{tf}}$ is the total number of patents granted to firm i (or technology class i) during the time period between year *ts* and year *tf*, and N is the total number of years being considered, which equals *tf – ts+1*. Given that the innovative outcomes of a firm often fluctuate substantially from year to year, a CAGR calculator is a useful tool for measuring the annual patent growth rate as an indicator of performance, as its value fluctuates widely from one period to the next. To solve the problem of patenting fluctuation, the CAGR based on three- and four-year moving averages of the number of patents granted was also calculated.

Not only can laggards catch up with industry leaders by striving to increase their patent stocks and accelerating innovation, they can also become market leaders by developing radical/breakthrough innovations. Whereas quantitative catch-up focuses on the patent growth rate, qualitative catch-up emphasizes the technological impact and importance of the innovations initiated by a laggard firm. A firm is said to have achieved qualitative catch-up if it has developed technologies with greater technological impacts than the average technological impacts of all patents in the same technology class. Prior research has suggested that patents that receive more citations by other patents are more important and valuable than those that receive fewer citations (Ahuja and Lampert, 2001; Trajternberg, 1990). Lanjouw and Schankerman

(2004) found that the number of patent citations was related to the quality of the invention associated with the patent.

In this study, forward citations data was used to identify technologically important innovations initiated by laggards. The number of forward citations received by each patent of a laggard firm over the 5-year period was counted and compared with the average number of forward citations received by all patents in the corresponding technology class in the same observation period.[1] In this research setting, a patent was defined as technologically important if it received more forward citations than the average number of forward citations received by all patents in the same technology class in the same observation period. The total number of technologically important patents held by each laggard firm was the measure for qualitative catch-up. The larger the number of technologically important patents granted to a laggard firm, the more successful its qualitative catch-up was deemed to be.

The third subtype of the dependent variable used in this study was comprehensive catch-up. Successful completion of both quantitative and qualitative catch-up was necessary to have achieved comprehensive catch-up. A dummy variable was used to measure comprehensive catch-up. The variable was coded as 1 if a firm had achieved the first two types of catch-up, and 0 otherwise.

Explanatory variables

The phrase *technological opportunities* refers to "the variations in the cost and difficulty of innovation in different technological areas due to characteristics of the technology or the state of exogenous scientific knowledge" (Jaffe, 1986). The abundance of technological opportunities was measured at the technology class level using two distinct variables that reflect the static and

[1] Self-citations were excluded when computing the number of forward citations.

dynamic aspects of technological opportunity. First, the total number of patents (*'avg_cnt'*) issued in the technology class in which a firm was granted patents in a given year was computed in order to capture the time-invariant differences of the richness in technological opportunity across technology classes (Ahuja and Katila, 2004). All else being equal, a technology class in which more patents were issued implies that it offers richer technological opportunities than other technology classes. Second, following prior research, technological opportunity was measured in terms of the average annual growth rate of patents granted in each technology class j (*'pat_gr_tc'*) (Park and Lee, 2006). This measure captures the time-variant differences in the level of technological opportunity. By using both patent stock and patent growth rate as measures of technological opportunity, both time-invariant and time-variant aspects of technological opportunity can be captured.

Technological life cycle was defined as the time span between the predecessor technologies and the successor technologies. It was calculated as the time difference between the application year of the citing patent and that of each of the cited patents in each technology class j (Jaffe and Trajtenberg, 2002; Narin, 1999). Prior studies also suggested that the median age in years of the U.S. patent references cited can be used as an indicator of technological life cycle (Oriani and Sobrero, 2008). When both measures were calculated, they were found to be equal. Therefore the first indicator (average citation lag in technology class j and year t) was used to measure technological life cycle in this study. The longer the average citation lag in a technology class, the longer the life cycle of a given technology.

The number of new technologies searched was measured as the citation lag between patents cited by a laggard. Prior studies suggested that if a firm cites recent patents, it can be viewed as working within current technological domains rather than mature technological domains (Ahuja

and Lampert, 2001; Sorensen and Stuart, 2000). Patents that cite outdated patents tend to generate less impact (Sorensen and Stuart, 2000), indicating that the firm may have fallen into a competence trap (Rosenkopf and Nerkar, 2001). Thus, the average citation lag between the issue years of cited patents and application years of citing patents was used to evaluate the extent to which a laggard firm learned from new knowledge. The citation lag of a cited patent was calculated as the time elapsed since it was issued until the application year of the citing patent. Because citation lags can be influenced by knowledge characteristics in the different technological sectors in which a firm operates, this measure was standardized by dividing the average citation lag of a firm by that of the corresponding technology class. The smaller the resulting number, the more intensively a laggard searched for emerging technologies.

The degree of diversity of technologies searched was measured by determining the diversity of patent citations in terms of technology classes. Previous studies suggested that if a firm cites many different technology classes in its patents, it can be regarded as building upon different technological bases and combining many relatively disparate technologies successfully (Ahuja and Katila, 2004; Rosenkopf and Nerkar, 2001; Shane, 2001). Thus, following prior studies, the Blau index (1- Herfindahl) of patent classes cited by the patents of a firm was used as the measure for the degree to which a laggard combines diverse knowledge in its patents (Hall et al., 2001). The Blau index is calculated as $1 - \sum_{j=1}^{n} q_{ij}^2$, where q_{ij} is the proportion of patents in technology class j cited by patent i, and n is the total number of technology classes. Thus, the larger the Blau index value, the more diverse the range of technologies for which a laggard firm searches.

Control variable

At the firm level, we controlled for the average number of citations (‘*no. of citations’*) made by

each firm in each patenting year. In addition, year dummies were used to control for the time effect on patenting. At the macro level, country dummies reflecting Chinese firms (‘*cnx_dum’*) and Korean firms (‘*krx_dum’*) were used to control for country effects. The dummy variable *‘patent intensity’* was used to reflect the four high-tech industries, which together make up 52.94% of the sample. These include the electronics industry (23.15%), the machinery industry (18.78%), the professional and scientific instruments industry (6.31%), and the transportation industry (4.7%).

Model Specification

For the binomial dependent variables (quantitative and comprehensive catch-up), logistic regression analysis was used to test the hypotheses. The logit model was used to estimate the probability of successful technological catch-up as a linear function of a series of explanatory variables. The function is $P_{i,t} = \frac{e^{\beta X_{i,t}}}{1+e^{\beta X_{i,t}}}$, where $P_{i,t}$ is the probability of firm i catching up successfully during t number of years, $X_{i,t}$ is the vector of the exploratory variables, and β is the vector of the logit coefficients. The measure of qualitative catch-up was a count variable with non-negative integer values. A Poisson regression approach is usually used for such data. A Poisson regression assumes that the response variable Y has a Poisson distribution, and that the logarithm of its expected value can be modeled by a linear combination of unknown parameters. However, a characteristic of the Poisson distribution is that its mean is equal to its variance. In this data setting, the observed variance of the dependent variable (number of technologically important patents) (std. dev. = 6.61) is greater than the mean (= 1.26). This overdispersion problem can be solved by adopting a negative binomial distribution. Thus, the following negative binomial regression model was used to test the hypotheses on qualitative catch-up:

$\Pr(Y = yj) = \frac{e^{-\lambda_j}\lambda_j^{Y_j}}{Y_j!}$, where $\lambda_j = \exp(\sqrt{B_i X_{ij}}\exp(\mu_j)$ and $e^{\mu_j} \sim \text{Gamma}(1/\alpha, 1/\alpha)$ for the number of technologically important patents. Therefore, this study used both panel logistic regressions and panel negative binomial regressions to test the hypotheses.

Since forward citations to measure qualitative catch-up were computed within a 5-year window and the data covered patents registered by the year 2004, patents granted after the year 2000 were excluded from the analysis in order to avoid the right-censoring problem when computing forward citations. Thus, 3,439 firms were used to test quantitative catch-up, 1,901 firms were used to test qualitative catch-up, and 1,712 firms were used to analyze comprehensive catch-up. In this study, 366 firms (9.3%) succeeded in achieving quantitative catch-up among the 3,439 technological laggards. Among the 1,901 firms included in the qualitative catch-up analysis, 601 firms (31.4%) registered at least one technologically important patent. In addition, 105 firms (6.13%) achieved comprehensive catch-up (both quantitative and qualitative catch-up) among the 1,712 cases that were used to analyze comprehensive catch-up.

Both fixed effect and random effect models were employed to test the hypotheses. The Breusch-Pagan LM (Lagrangian multiplier) test and Hausman test were also employed to evaluate model fits. Results of the Breusch-Pagan LM test ($p < 0.01$) suggested that the random effect model was more appropriate than the pooled regression model (Greene, 2003). However, results of the Hausman test ($p < 0.01$) suggested that the fixed effect estimation was more suitable than the random effect estimation in this study. However, in fixed-effect models of the logistic regressions and the negative binomial regression, the STATA analysis indicated that over 90% of the full sample should be dropped due to collinearity problems, lack of within-group variance, and all-positive or all-negative outcomes for some variables. The results in the fixed effect models were therefore deemed unreliable. Thus, random effect estimations are reported in

this study.

RESULTS

Empirical Findings

Tables 1-1, 1-2, and 1-3 show descriptive statistics and correlations for analysis of quantitative, qualitative, and comprehensive catch-up, respectively.

Insert Table 1-1, Table 1-2 and Table 1-3 here

Table 2 summarizes the results of the panel logistic regression and panel negative binomial regression analyses, which tested quantitative (Model 1), qualitative (Model 2), and comprehensive catch-up (Model 3). In Table 2, Models 1a, 2a, and 3a contain the control variables only, serving as the baseline models. Models 1b, 1c, 2b, 2c, 3b, and 3c are full specifications which include the linear and squared terms of all of the independent and control variables. To assess the potential bias from multicollinearity, variance inflation factors were estimated and some collinearity was found between two technology class-level variables: technological opportunities and technology life cycle. Thus, these two variables were placed in separate regression models to avoid the multicollinearity problem.

Insert <Table 2> here

Hypothesis 1 predicted that abundance of technological opportunity would have a positive relationship with the technological catch-up of laggard firms. Results in Models 1b, 2b, and 3b show that the coefficients of technological opportunity are positive and significant, thereby supporting hypothesis 1. Hypothesis 2 suggested that technological laggards are more likely to catch up in technological areas where the technology life cycle is short. The coefficients of technology life cycle in Models 1c ($p < 0.01$), 2c ($p < 0.01$), and 3c ($p < 0.01$) were negative and significant. These results provide evidence of a negative relationship between the length of the technology life cycle and technological catch-up, in support of hypothesis 2.

For firm-level variables, hypothesis 3 suggested that laggards that learn more from new technologies can improve their technological predictive capabilities, thus making them more likely to catch up. The negative and significant coefficients of this measure in Models 1b, 1c ($p < 0.01$), 2b, 2c ($p < 0.01$), 3b, and 3c ($p < 0.01$, $p < 0.05$) support hypothesis 3 for all three types of catch-up. As for hypothesis 4 regarding the degree of diversity of technologies searched, the positively significant coefficients ($p < 0.01$) for the Blau index in Models 1b, 1c, 2b, 2c, 3b, and 3c and the negatively significant coefficients ($p < 0.01$) for the squared terms of the Blau index in these models indicated that laggards can maximize their catch-up success only when they learn technologies from diverse areas to a moderate degree. These results are consistent with hypothesis 4.

Robustness Checks

Additional measures for quantitative catch-up

The growth rate of total patents in each technology class was used to evaluate quantitative catch-up in this study. However, considering that the U.S. and Japan are the two leading countries in most technological fields, alternative measures for quantitative catch-up were used

by comparing the average patent growth rate of each laggard firm with the average patent growth rate of U.S. patents only and of Japanese patents only, and with the sum of U.S. and Japanese patents issued by the USPTO. Then panel regressions were run to check if the hypotheses were sensitive to these different benchmarks. All hypotheses were still supported regardless of benchmarks.

Additional measures for qualitative catch-up

To check the robustness of the results for qualitative catch-up, qualitative catch-up was operationalized by computing the forward citations received by a firm's patents using two different time windows: four years and six years. All hypotheses were still supported.

Panel data analysis using time-lagged independent variables

The effects of all independent variables on the three types of catch-up were examined using independent variables lagged by between t − 5 and t years at the firm level. A time-lagged independent variable was computed as the average value for the variable spanning the previous two, three, four, and five years. The signs of the coefficients remained consistent, as predicted.

Sub-sampling high-tech sectors

Panel regressions were run again on firms in the four high-tech sectors, which account for 52.94% of the full sample. These high-tech sectors include the electronics (23.15%), machinery (18.78%), professional and scientific instruments (6.31%), and transportation industries (4.7%). The results were still consistent with our predictions.

Cross-sectional data analysis

Cross-sectional data was also used to test the hypotheses. In the cross-sectional data analysis, data covering the entire observation period of each firm (from the first patenting year to the last patenting year) were used to evaluate the firms in terms of the three types of technological catch-

up. In the case of quantitative catch-up, a threshold condition when comparing patent growth rates was also added to operationalize quantitative catch-up, because the absolute number of patents was still important (Trajtenberg, 2001) in evaluating technological performance. Since no exact cutoff value can be established for determining catch-up success, different cutoff values (total number of patents granted to a firm = 2, 3, 4, and 5) were used as thresholds. In the cross-sectional data analysis, relations among independent and dependent variables remained consistent regardless of the cutoff value.

DISCUSSION AND CONCLUSIONS

While first-mover advantages have been stressed in the strategic management literature, the catch-up strategies of laggard firms have received little attention. Few studies have investigated this phenomenon empirically at the firm level. Given this research gap in the literature, a major contribution of this study is the systematic and rigorous examination of the catch-up strategies of laggards using large-sample firm-level data. Although findings from this study could be generalized to all contexts, we paid special attention to the catch-up strategies of laggard firms from three emerging countries: China, Korea, and Taiwan. Another contribution of this study is its overarching conceptual framework encompassing the effects of both technological environments and organizational capabilities on technological catch-up success.

In this study, we highlighted the importance of emerging technological opportunities, especially in relation to paradigm changes and laggards' capabilities to seize such opportunities. Specifically, we showed that laggards were more likely to catch up with incumbent leaders when there exist abundant technological opportunities that create emerging niches, and when the technological life cycle was short. The abundance of technological opportunities enhanced catch-up probability because laggards can occupy new technological niches more quickly and flexibly

than incumbents, who tend to stick to existing technologies. The results also suggested that laggards should choose technological fields with short life cycles in order to catch up with incumbent firms. When technological life cycles are short, laggards can overcome the learning curve advantages enjoyed by incumbent leaders and found shortcuts in their efforts to catch up. However, laggards that ignored or underestimated emerging technological opportunities could not catch up successfully. These findings have significant practical implications for managers of laggard firms who want to identify better environmental conditions for catching up.

Findings in this study also suggest that in order to take advantage of emerging technological opportunities, laggards should opt for recent or emerging technologies rather than old technologies in order to improve their technological predictive capabilities over time. Striking a good balance between exploitative and explorative learning by searching for diverse technologies at a moderate level can help laggard firms with underdeveloped combinative capabilities to become more flexible in the changing technological environment, thereby enhancing catch-up probability. The findings of this study also have significant managerial implications for managers of laggard firms. To facilitate catch up, managers of laggard firms need to plan for development and improvement of their firms' predictive and combinative capabilities early on.

While this research sheds light on the technological catch-up strategies of laggard firms by proposing an overarching conceptual framework and then providing systematic and rigorous empirical evidence about the technological catch-up of laggards at the firm level, it has some limitations that should be overcome in future studies. First, this study focused on firms from three Asian countries only (China, Taiwan, and Korea). Although the findings of this study may be generalizable to the catch-up behavior of firms in other countries, future research should

examine the catch-up phenomenon in other contexts to confirm the generalizability of our findings. Second, this research uses the number of patents granted to a firm as a measure of technological catch-up. However, this measure is imperfect. Thus, provided sufficient data are available, more sophisticated indicators should be employed to measure technological catch-up and determine whether the effect of the independent variables on catch-up success would be different if technological catch-up were measured in terms of those other indicators. Third, future studies should investigate the linkage between technological catch-up and financial performance. Finally, in-depth comparison of the catch-up efforts in emerging Chinese companies as opposed to those of Korean and Taiwanese companies is warranted. Future research should examine the similarities and differences in catch-up behaviors and patterns between the two groups, as the number of Chinese patents in the U.S. has begun to grow exponentially in the 21st century.

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Figure 1. Utility Patents Granted by the USPTO from 1963 to 2009 (China, Korea, Taiwan)

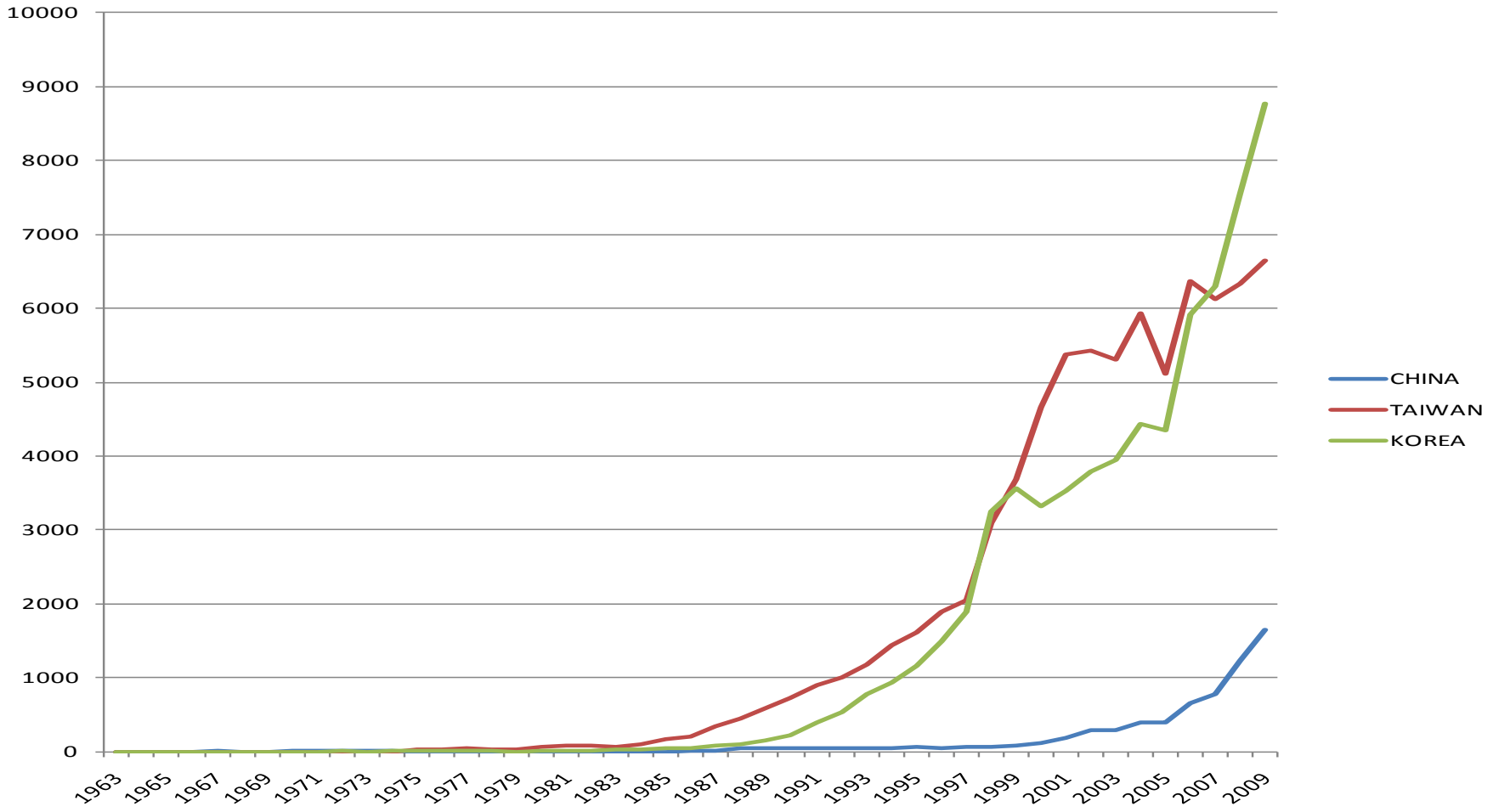

Table 1-1. Descriptive Statistics and Correlations (Quantitative Catch-up)

Variables	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1. Quantitative Catch-up	0.19	0.39	0.00	1.00	1.00										
2. Tech opportunity (avg_cnt)	861.16	922.36	1.00	5402.00	0.19	1.00									
3. Tech opportunity (pat_gr_tc)	0.38	0.16	0.00	1.65	0.13	0.15	1.00								
4. Tech life cycle	6.47	1.81	1.00	13.00	-0.10	-0.32	-0.32	1.00							
5. Predictive capa	0.84	0.58	-1.50	5.33	-0.10	-0.10	0.00	0.04	1.00						
6. Combinative capa	0.25	0.24	0.00	0.91	0.02	0.14	-0.03	0.03	0.01	1.00					
7. (Combinative capa)^2	0.12	0.16	0.00	0.83	-0.06	0.10	-0.07	0.06	0.03	0.95	1.00				
8. no. of citations	4.43	5.04	1.00	158.75	0.10	0.13	-0.01	-0.05	-0.02	0.32	0.30	1.00			
10. krx_dum	0.27	0.44	0.00	1.00	0.02	0.05	0.00	0.08	0.02	0.09	0.08	0.09	1.00		
11. cnx_dum	0.05	0.21	0.00	1.00	-0.07	-0.05	-0.03	0.03	0.05	0.02	0.04	0.04	-0.14	1.00	
12. patent intensity (high_tech)	0.62	0.49	0.00	1.00	0.08	0.26	0.00	0.06	-0.05	0.14	0.13	0.08	0.11	0.01	1.00

N=3401. Year dummies are included, but not shown.

Table 1-2. Descriptive Statistics and Correlations (Qualitative Catch-up)

Variables	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1. Qualitative Catch-up	1.26	6.61	0.00	177.00	1.00										
2. Tech opportunity (avg_cnt)	760.99	863.98	2.00	5402.00	0.13	1.00									
3. Tech opportunity (pat_gr_tc)	0.45	0.13	0.03	1.65	0.36	0.10	1.00								
4. Tech life cycle	5.92	1.65	1.00	12.33	-0.12	-0.26	-0.16	1.00							
5. Predictive capa	0.87	0.60	-1.50	5.33	-0.04	-0.09	0.00	0.02	1.00						
6. Combinative capa	0.23	0.24	0.00	0.91	0.03	0.18	0.05	0.01	0.01	1.00					
7. (Combinative capa)^2	0.11	0.15	0.00	0.83	-0.01	0.15	0.02	0.03	0.03	0.95	1.00				
8. no. of citations	4.08	3.16	1.00	41.00	0.07	0.18	0.08	-0.06	-0.02	0.38	0.35	1.00			
10. krx_dum	0.28	0.45	0.00	1.00	0.00	0.09	0.00	0.07	0.01	0.08	0.07	0.13	1.00		
11. cnx_dum	0.04	0.20	0.00	1.00	-0.03	-0.05	-0.03	0.02	0.06	0.01	0.02	0.04	-0.13	1.00	
12. patent intensity (high_tech)	0.60	0.49	0.00	1.00	0.08	0.28	0.09	0.08	-0.04	0.13	0.13	0.10	0.14	0.05	1.00

N=1901. Year dummies are included, but not shown.

Table 1-3. Descriptive Statistics and Correlations (Comprehensive Catch-up)

Variables	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1. Comprehensive Catch-up	0.11	0.31	0.00	1.00	1.00										
2. Tech opportunity (avg_cnt)	760.99	863.98	2.00	5402.00	0.13	1.00									
3. Tech opportunity (pat_gr_tc)	0.45	0.13	0.03	1.65	0.20	0.15	1.00								
4. Tech life cycle	5.92	1.65	1.00	12.33	-0.16	-0.26	-0.17	1.00							
5. Predictive capa	0.87	0.60	-1.50	5.33	-0.08	-0.08	-0.01	0.02	1.00						
6. Combinative capa	0.23	0.24	0.00	0.91	0.02	0.16	0.05	0.02	0.02	1.00					
7. (Combinative capa)^2	0.11	0.15	0.00	0.83	-0.06	0.12	0.02	0.04	0.04	0.95	1.00				
8. no. of citations	4.08	3.16	1.00	41.00	0.12	0.19	0.09	-0.06	-0.03	0.40	0.36	1.00			
10. krx_dum	0.28	0.45	0.00	1.00	0.13	0.10	0.00	0.07	0.00	0.09	0.07	0.15	1.00		
11. cnx_dum	0.04	0.20	0.00	1.00	-0.08	-0.05	-0.04	0.00	0.06	0.02	0.04	0.04	-0.14	1.00	
12. patent intensity (high_tech)	0.60	0.49	0.00	1.00	0.09	0.27	0.10	0.07	-0.03	0.11	0.11	0.11	0.15	0.07	1.00

N=1712. Year dummies are included, but not shown.

Table 2. Results of Regressions on Technological Catch-up of Laggards

Hypotheses	Variables	Measures	Quantitative Catch-up			Qualitative Catch-up			Comprehensive Catch-up		
			Model 1			Model 2			Model 3		
			Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3a	Model 3b	Model 3c
H1	Technological Opportunity	avg_cnt		5.01(0.00)***			5.21(0.11)***			2.29(0.00)**	
		pat_gr_tc		7.15(0.97)***			2.09(0.19)**			3.26(1.12)***	
H2	Technology Life Cycle	cit_lag_tech			-4.24(0.08)***			-5.72(0.02)***			-4.21(0.11)***
H3	Tech Predictive Capa	cit_lag_firm		-2.71(0.23)***	-2.76(0.25)***		-4.04(0.06)***	-4.11(0.06)***		-2.69(0.34)***	-2.51(0.32)**
H4	Tech Combinative Capa	blau		6.40(1.76)***	6.92(1.93)***		5.73(0.46)***	5.69(0.46)***		4.90(2.58)***	5.06(2.54)***
		$(blau)^2$		-6.93(2.98)***	-7.44(3.26)***		-6.90(0.76)***	-6.74(0.76)***		-5.40(4.72)***	-5.51(4.62)***
Controls	no. of citations	cit_cnt	2.97(0.03)***	2.83(0.03)***	3.04(0.03)***	5.31(0.01)***	5.20(0.01)***	4.68(0.01)***	3.18(0.05)***	3.35(0.05)***	2.92(0.05)***
	Country dummy	krx_dum	-2.41(0.30)**	-1.80(0.29)*	-1.74(0.31)*	-2.45(0.08)**	-2.38(0.08)**	-1.88(0.08)*	0.86(0.37)	1.40(0.37)	1.66(0.37)*
		cnx_dum	-2.79(0.89)***	-2.48(0.75)**	-2.60(0.81)***	-2.65(0.19)***	-2.09(0.19)**	-1.84(0.19)*	0.00(40176.95)	0.00(23385)	0.00(8394.57)
	Patent intensity	high_tech dum	1.86(0.27)*	1.33(0.27)	2.27(0.28)**	-1.04(0.07)	-2.24(0.08)**	-0.53(0.07)	0.97(0.36)	0.02(0.00)	1.19(0.36)
	Year dummy	year_1977	0.00(9236.42)	0.00(176045.3)	0.00(10830.49)	0.58(1.17)	0.59(1.17)	-0.15(1.16)	0.00(28772.70)	0.00(114134.8)	0.00(61552.06)
		year_1978	0.00(9005.07)	0.00(234648.9)	0.00(10198.68)	0.00(21619.03)	0.00(5868.26)	0.00(4664.65)	0.00(311571.30)	0.00(346647)	0.00(69642.37)
		year_1979	0.00(9026.83)	0.00(235084.8)	0.00(10547.58)	0.27(1.16)	0.52(1.15)	-0.21(1.14)	0.00(31319.40)	0.00(191181)	0.00(66658.01)
		year_1980	0.00(12764.42)	0.00(347402.1)	0.00(13909.35)	1.37(0.91)	1.97(0.89)**	1.05(0.89)	0(445561.00)	0.00(288813)	0.00(101877.1)
		year_1981	0.00(7352.35)	0.00(196291.3)	0.00(8172.396)	0.47(0.82)	0.93(0.81)	0.02(0.81)	0(254851.50)	0.00(160736)	0.00(57339.42)
		year_1982	-1.56(2.59)	-1.75(2.40)*	-1.72(2.59)*	0.02(0.64)	0.44(0.64)	-0.64(0.64)	0.00(162599.00)	0.00(103427.1)	0.00(36315.54)
		year_1983	-0.01(4777.351)	0.00(124900.8)	-0.01(5419.543)	1.63(0.51)	1.95(0.50)*	0.76(0.50)	0.00(161128.20)	0.00(99892)	0.00(35326.38)
		year_1984	-0.01(4493.50)	0.00(118335.8)	-0.01(5252.42)	-0.63(0.53)	-0.25(0.54)	-1.29(0.54)	0.00(153198.00)	0.00(90500)	0.00(33275.49)
		year_1985	-0.01(3880.22)	0.00(99088.5)	-0.01(4579.205)	1.09(0.37)	1.70(0.34)*	0.09(0.37)	0.00(117442.10)	0.00(70394)	0.00(25789.27)
		year_1986	-3.72(2.18)***	-4.17(2.20)***	-3.76(2.19)***	1.06(0.28)	1.69(0.28)*	-0.12(-0.12)	-1.00(1.77)	-0.71(2.00)	-1.35(1.78)
		year_1987	-3.12(1.46)***	-4.23(1.42)***	-3.44(1.45)***	1.07(0.22)	1.83(0.22)*	-0.31(0.22)	1.07(1.02)	1.23(1.00)	0.27(1.02)
		year_1988	-4.15(1.95)***	-5.01(1.84)***	-4.36(1.88)***	0.55(0.24)	0.97(0.24)	-0.76(0.24)	-1.23(1.42)	-1.08(1.00)	-1.72(1.35)
		year_1989	-4.90(1.65)***	-6.01(1.54)***	-5.00(1.61)***	1.04(0.20)	2.02(0.19)**	0.10(0.20)	-1.19(1.07)	-0.82(1.00)	-1.49(1.06)
		year_1990	-4.64(1.41)***	-5.93(1.31)***	-4.90(1.36)***	2.13(0.19)	2.85(0.18)***	1.12(0.18)	-0.55(0.91)	-0.16(1.00)	-0.92(0.88)
		year_1991	-4.77(1.28)***	-6.10(1.18)***	-5.01(1.24)***	2.86(0.16)	3.96(0.15)***	2.04(0.15)**	-0.07(0.71)	0.39(1.00)	-0.58(0.72)
		year_1992	-4.84(1.19)***	-6.41(1.09)***	-5.10(1.14)***	0.55(0.16)	1.45(0.15)	-0.10(0.15)	-1.07(0.69)	-0.76(1.00)	-1.50(0.68)
		year_1993	-4.95(1.16)***	-6.32(1.05)***	-4.95(1.10)***	2.18(0.15)	3.19(0.14)***	1.87(0.14)*	-1.13(0.60)	-0.56(1.00)	-1.15(0.60)
		year_1994	-5.60(1.16)***	-7.21(1.05)***	-5.72(1.10)***	0.71(0.13)	1.51(0.13)	0.27(0.13)	-1.26(0.56)	-0.96(1.00)	-1.46(0.55)
		year_1995	-5.06(1.10)***	-6.81(0.99)***	-5.17(1.04)***	0.39(0.13)	0.99(0.31)	-0.09(0.12)	-1.03(0.48)	-0.74(0.00)	-1.04(0.55)
		year_1996	-5.26(1.09)***	-7.15(0.97)***	-5.38(1.02)***	2.92(0.11)	3.67(0.11)***	2.84(0.11)***	-0.16(0.42)	0.03(0.00)	-0.22(0.43)
		year_1997	-5.51(1.08)***	-7.49(0.97)***	-5.63(1.01)***	2.72(0.11)	3.38(0.10)***	2.76(0.10)***	-0.97(0.41)	-0.84(0.00)	-0.78(0.41)
		year_1998	-5.25(1.06)***	-7.28(0.92)***	-5.33(0.99)***	1.73(0.11)	2.17(0.10)**	1.70(0.10)*	0.72(0.36)	0.77(0.00)	0.87(0.36)
		year_1999	-5.09(1.05)***	-7.12(0.92)***	-5.20(0.98)***						
		year_2000	-4.95(1.04)***	-6.74(0.90)***	-4.97(0.96)***						
		year_2001	-4.86(1.03)***	-6.54(0.88)***	-4.84(0.95)***						
		year_2002	-4.19(1.03)***	-5.25(0.87)***	-4.00(0.94)***						
		year_2003	-2.62(1.02)***	-2.68(0.84)***	-2.34(0.93)**						
		intercept	-1.22(1.03)	-3.19(0.90)***	0.61(1.10)	1.78(0.14)	0.39(0.17)	5.62(0.22)***	-10.12(0.61)***	-0.87(1.00)***	-3.17(0.88)***
N			3401	3401	3401	1901	1901	1901	1712	1712	1712
Chi-square			127.31***	217.20***	148.35***	59.35***	164.34***	170.27***	24.42***	62.54***	67.50***
Likelihood-ratio test of rho			1209.85***	873.53***	928.19***	1179.30***	1011.33***	1126.46***	131.17***	198.98***	177.98***

Notes: * if $p < 0.10$, ** if $p < 0.05$; *** if $p < 0.01$; Standard errors are in parenthese.
Sample sizes are reduced from 3439 to 3401 because of some missing values.