이성훈 석사학위논문

Cycle Time of Technology, Sector Specialization, and Firm Performance

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Abstract

Cycle Time of Technology, Sector Specialization, and Firm Performance

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Technology cycle time is a technological variable that has been used fairly often to explain firm performance. Based on the mean backward citation lag proposed by Hall et al. (2001), technology cycle time is usually seen as a measure of the qualitative aspect of a firm's technology. Taken at the sector level, however, technology cycle time can also be an indicator of the level of the entry barrier of the sector. This is particularly useful since the idea of the sectoral system of innovation highlights the existence of technological heterogeneity between industrial sectors, implying that technological factors must be examined at the sector level in order to analyze firm performance fully. However, while technology cycle time at the level of technological classes has been used before and the sectoral effects themselves have often been discussed, the technology cycle time at the level of industrial sectors has been used less often, especially in a direct manner. In addition, with the exception of studies such as Lee (2013), many studies tend to focus only on the advanced countries.

This paper attempts to address this gap by calculating the technology cycle time at the sector level and then incorporating this into the empirical model and testing two hypotheses. The first hypothesis is that in general, firms in sectors with relatively long technology cycle time tend to show better performance. This is in accordance with the idea that long technology cycle time acts as an entry barrier to latecomers, due to the relatively long time

span of the prior technology that need to be learned. The second hypothesis is that this is not true for firms in emerging countries, of which those in sectors with shorter technology cycle time tend to perform better instead. The results of the analysis, based on a panel analysis using US firms in 1992-1995 and 2007-2013 in addition to Korean firms in 1992-1995, confirm these hypotheses.

Keywords : Technology cycle time, sectoral system of innovation, entry barrier

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1 Introduction

Technology has always been seen as an important part of the economy at every level. Compared to its generally perceived importance, however, the analysis of technological factors had been relatively lacking for a long time. One reason, perhaps, is that until about the 1990's there seemed to be little data that were readily available for use in measuring any aspect of technology. For example, while the idea to use patent data was suggested at least since Schmookler (1966), as Hall et al. (2001) points out, the sheer size of the data and the fact that they were not computerized at the time meant that it was difficult to use.

Once it became easier to use patent data, however, empirical analyses on technology became more viable. In particular, the availability of citation data meant that many dimensions of technology could be investigated. Griliches (1998), for example, suggested using them to study knowledge spillovers or the quality of the technology embodied in a patent. This was particularly useful since citations in patents are not made solely by the applicants, but also the examiners, allowing them to be a sufficiently objective measure.

One of the variables from the data, suggested by Hall et al. (2001), is the backward citation lag or technology cycle time. In qualitative terms, for each patent this measures how recent a knowledge the technology is based on, and is an indicator of how fast the technology develops when taken for a firm or a sector. This was used in several studies such as Hirschey and Richardson (2001) and Lee (2013), in relation to firm performance.

Traditionally, the firm-level technology cycle time was used as one of the indicators describing a firm's technological characteristics, which proved useful as an explanatory variable. In many cases, however, the analyses were centered on advanced countries, overlooking the possibility that the impact of technology on firms can be different for those in emerging countries due to differences in their knowledge base. In addition, they tend to overlook the idea put forth in several studies such as Malerba (2002) that technological heterogeneity exists

across industrial sectors, which can potentially lead to varying effects on firms in different countries. One exception is Lee (2013), which embraces this idea to assert that firms in emerging countries have a better chance of catching up in sectors with short cycle time, although the sectoral effects were inferred rather than directly shown in the study.

In order to address this gap, this paper investigates the effect of the sector level technology cycle time on firm performance. In doing so, it will verify the hypothesis that technological cycle time of the sector can have an impact on firm performance, which can differ depending on where the firm operates. This study will achieve this by comparing Korean firms to US firms in 1992-1995, a period in which Korea was still very much an emerging country while the US was already an advanced country. The US firms in 2007-2013 will also be analyzed as well in order to verify that results hold regardless of the time period. The conclusion of this paper should serve as a guideline into which industries firms in emerging countries should enter not only in order to survive, but to achieve the best possible performance.

To this end, this paper will first review some of the related literature in Section 2 and then go on to construct some hypotheses based on this insight in Section 3, explaining the theoretical framework behind the hypotheses. Then, in Section 4, the variables that will be used in the analysis will be presented, along with the definition of the variables. In Section 5, a description of the datasets used in the analysis will be provided, including the summary statistics of the final dataset used in the analysis, whose results will be reported and discussed in Section 6. Then Section 7 will give some concluding remarks and state some limitations of this paper.

2 Literature Review

Patent data were initially recognized as useful indicators of technological development by studies such as Acs and Audretsch (1989) and Griliches (1998). These

studies not only emphasized the information that can be gained from looking at the number of patents, but also noted that patent documents contain other useful information in the form of citations data. This insight was what motivated Hall et al. (2001), who collected data on not only the basic aspects of patent data, but also on which patents were cited by others. The database was later updated to include patents that were granted from 1976 to 2006, and is perhaps one of the most widely used datasets in the field[1].

The data proved to be useful, particularly in addressing the multidimensionality of technology noted by several theoretical discussions, as is demonstrated by Bessen and Maskin (2009). For example, Bloom and Van Reenen (2002) took the number of citations into account to address the fact that not all patents have the same impact on firms. Hall et al. (2001) also makes this point, stating that since an innovation only needs to satisfy two conditions, novelty and non-obviousness, in order to be patented, not all patents have the same value. So, the fact that a firm has more patents than its competitor does not necessarily mean that it has better technological capabilities. Citations data provide a suitable way to address this problem by adding in qualitative aspects of each patent such as how many times a patent was cited by others.

One aspect that has been shown to be important is the technology cycle time, which is a measure of the pace of technological development as was noted, for example, by Kayal and Waters (1999). As Park and Lee (2006) notes, shorter technology cycle time in a sector implies that there is less need to learn older technology, since the trending technology is changing so rapidly that it would be obsolete by the time a firm manages to find a use for it. Conversely, in sectors with long cycle time, familiarity with past innovations is more desirable, which makes it difficult for new firms to enter. This is, in fact, one of the insights that form the basis of the analysis in Lee (2013) where the effects of different technological indicators on the performance of Korean and

[1]This was done in the NBER patent data project, and the data are provided in this website: https://sites.google.com/site/patentdataproject/Home

US firms were compared. The results showed that technology cycle time has a negative effect on the performance of Korean firms while it did not have a significant effect on that of the US firms.

The importance of technology cycle time is also shown in how it can be related to other aspects of the firm's capabilities as well. For example, Bierly and Chakrabarti (1996) showed that firms that generate new knowledge internally tend to have a shorter cycle time than those that obtain their knowledge from external sources. The sample in this study is limited to US pharmaceutical companies. This does not necessarily show how technology cycle time can affect firm performance, but this still provides some insights as to what a firm's technology cycle time indicates about the firm's capabilities.

Another example of a study using technology cycle time is Hirschey and Richardson (2001), where high-tech firms in Japan and the US were analyzed. Here, technology cycle time is actually shown to have a negative effect on firm performance, or in other words, shorter cycle time is found to be more desirable for firms. This is in direct contrast to the results from Lee (2013), despite the fact that the two studies cover a similar time period[2]. This difference may have stemmed from the fact that only high-tech firms, defined as firms that have at least 10 patents granted per year, were included in the sample in Hirschey and Richardson (2001), which was not the case in Lee (2013). In other words, the analysis of the former was based on a more homogeneous group of firms than the latter. In addition, Hirschey and Richardson (2001) perform a pooled regression whereas Lee (2013) uses panel regression, the choice between the fixed and random effects model being determined by the Hausman test, which would have contributed to the differences.

[2]Lee (2013) looks at the years 1988 to 1995, whereas Hirschey and Richardson (2001) looks at the years 1989 to 1995.

3 Theoretical Framework

Most of the studies mentioned in the previous section that use technology cycle time usually calculate it at the firm level. Unfortunately, given the idea of the sectoral innovation system described in papers such as Malerba (2002) and Lee (2013), firm level technology cycle time is not sufficient to analyze firm performance. The sectoral innovation system emphasizes the importance of technological heterogeneity between sectors, which calls for the use of sector level technology variables, such as the technology cycle time in this paper. Note that the term "sector" in this case means the industrial sector, not the technological sector[3]. However, technology cycle time at the level of industrial sectors has received very little attention, if at all, despite the fact that the need to account for sectoral differences has been supported by some studies such as Scherer (1983) or Cohen et al. (2000) in terms of characteristics such as propensity to patent.

The use of sector technology cycle time is of great importance, because technology cycle time can play a very different role depending on the level at which it is observed. At the firm level, this variable can indicate a firm's technological capability as was shown in Bierly and Chakrabarti (1996). At the sector level, however, the cycle time can now be taken as a measure of how high the entry barrier to a sector is. As was mentioned in the previous section, the length of the technology cycle time determines the average amount of research on prior innovations necessary for a firm in the sector to successfully innovate on its own. Therefore, in a sector with long technology cycle time, a latecomer firm has greater difficulty catching up to the incumbents, since it needs to

[3]Taken more broadly, the technology cycle time has been calculated at the level of technological classes or sectors based on the IPC (International Patent Classification), for example in Park and Lee (2006). The reason that industrial sectors are used instead is because patents are often classified into multiple IPC classes and the sectoral system of innovation is usually not focused on patent classes.

absorb more of the older technology than it needs to in short cycle sectors. Achieving this goal tends to involve an increase in R&D and other investments according to Griffith et al. (2003), so this translates to the latecomer firms being forced to endure higher costs than the incumbent firms in the form of imitation costs. In other words, long technology cycle time can act as an entry barrier to latecomer firms by raising the required level of investment for them to compete effectively, which was also noted in studies such as Mansfield et al. (1981)[4].

In addition, the actual costs involved in learning prior innovations can differ significantly for each firm depending on their knowledge base. As Bierly and Chakrabarti (1996) noted, high absorptive capacity can only be achieved when the firm has a certain level of technological capability. Latecomers to a sector tend to be less effective than the incumbents when it comes to learning older technology of that sector, assuming that the incumbent even needs to learn them by the time the latecomer has begun to do so. This is a particularly important factor in long cycle sectors due to the time span of the set of technologies that needs to be absorbed. On the other hand, this is also a blessing for incumbent firms since, as a result, they face less competition than they would in short cycle sectors. In fact, a similar observation was made in Mansfield et al. (1981), albeit in terms of imitation costs. Therefore, the following hypothesis can be made.

> Hypothesis 1 : In general, firms in sectors with long technology cycle time show better performance.

However, one cannot immediately assume that this holds for firms in all countries, considering the heterogeneity of the technological environment at the

[4]These tend to explain the advantage of technological leaders through the imitation costs, which according to Mansfield et al. (1981) includes licensing costs, costs of inventing around the existing patents, etc. In the context of technology cycle time, imitation costs can be taken to include the licensing costs and the investment needed to absorb previous technology.

national level. In particular, one can note that a firm in an emerging country is almost always a latecomer in any sector since the country was probably struggling to simply make ends meet before any firm could emerge at all. This means that these firms are already at a disadvantage in long cycle sectors just as is the case with latecomers in advanced countries.

In addition, however, they are also cursed with even lower technological capability than the latecomers in advanced countries, which means that they have lower absorptive capacity as well. As noted previously, this means that the disadvantage in costs is even higher compared to most firms in advanced countries. One may also note that according to Jaffe et al. (1992), knowledge spillovers tend to show a tendency of geographical localization, which in this case would mean that latecomer firms in advanced countries are more likely to benefit from existing knowledge than those in emerging countries. Thus, a second hypothesis can be formed for firms in emerging countries as follows.

> Hypothesis 2 : In emerging countries, however, firms in sectors with short technology cycle time show better performance.

4 Method

In order to verify the hypotheses, panel regression analysis is performed with the following variables.

4.1 Dependent Variables

Two dependent variables will be used as a measure of firm performance. The first variable is the return on assets (ROA), which is calculated as the ratio of net income to total assets. This measure is used because this is often used in studies on technology such as Artz et al. (2010). This measures profitability as how well the company is using the assets it currently has.

Another measure used is the return on equity (ROE), also a measure used to measure firm performance in studies such as Aghion et al. (2008). This is the ratio of the firm's net income to its equity, and as such has a close relationship to ROA. The results for ROE provides a means to check for robustness.

4.2 Independent and Control Variables

In accordance with the hypotheses and the framework on which they are based, two independent variables will be used in this paper. The first of which forms the basis of these variables is the sector technology cycle time (TCT), which is a measure of the pace of technological development of a sector. This is calculated as

$$\text{Sector TCT}_{S,T} = \frac{\sum_{t=T-2}^{T} \sum_{p} (\text{MBCL of Patent } p \text{ in Sector } S \text{ granted at time } t)}{\sum_{t=T-2}^{T} \text{Number of Patents in Sector } S \text{ at time } t}$$

where MBCL refers to the mean backward citation lag, another name for technology cycle time, and is based on the definition used in Park and Lee (2015). In essence, mean backward citation lag is the difference between the application year of the patent and the average of the application years of the cited patents. For example, if the application for patent A was made in 2000 and it cited patents B and C, which were applied for in 1990 and 1987, respectively, then the mean backward citation lag is 11.5 years.

Thus, the sector TCT in year T is the average of the lags of patents granted at most 2 years before T, in effect a 3 year average. This paper does not calculate TCT using only the patents granted that year, because of the general consensus that patents and the technology they embody have long-lasting effects due to the monopoly rights from patents and the effect on the flow of profits.

It should be noted that as sector, the paper simply takes the industry classification for each country, taking the first two digits of the SIC for US firms and the letter with the first two digits of the KSIC for Korean firms[5]. There were several reasons for this choice, the first of which was that it is usually a fruitless exercise to try and link two different industrial classifications, the SIC and KSIC in this case, mainly because the classifications tend to be tailored to each country's specific economic conditions. A viable alternative may have been to use the patent classification instead, but this is also faced with the problem that in many cases, patents are assigned multiple classes, which makes it difficult to use.[6].

The discussion in Section 2 implies that relative length is important, since TCT acts as an entry barrier and the latecomer's entry is determined by how high this is in one sector relative to the other. Therefore, the annually normalized version of sector TCT, or relative sector TCT, is used as the first independent variable, defined as

$$\text{Relative Sector TCT}_{s,t} = \frac{\text{Sector TCT}_{s,t}}{E\left[\text{Sector TCT}_{s,t}\right]}$$

Another variable used in the analysis is the relative firm technology cycle time. The firm TCT is defined similarly as the sector TCT, except that the average is taken over the patents owned by the firm. The relative firm TCT is essentially the ratio of the firm's technology cycle time to that of the sector, and is calculated annually. In other words, the variable is defined as follows

$$\text{Relative Firm TCT}_{i,t} = \frac{\text{Firm TCT}_{i,t}}{\text{Sector TCT}_{s,t}}$$

[5]For example, the US firms with the SIC number that starts with 26 were grouped in the same sector. For Korean firms, an example of a group was that of firms with the KSIC number starting with D15.

[6]Some attempts have been made to link the IPC (International Patent Classification) with industrial classification systems such as the NAICS, as was done in Kortum and Putnam (1997), but a variety of issues presents itself. One such problem is that all such methods are heavily dependent on the time period at which the analysis was done.

where s is the sector in which firm i operates. So, the relative firm TCT represents how much faster the firm's pace of technological development is than that of the sector. For both the relative TCTs, the decision to use the ratio is based on the analysis by Park and Lee (2006).

The control variables will include the capital-labor ratio, debt-equity ratio, investment propensity, firm size as measured by the number of employees, based on the analysis in Lee (2013), and market share. Capital-labor ratio is defined as the ratio of tangible assets, represented by property, plant and equipment, to the number of employees, while investment propensity is defined as the rate of increase of tangible assets. Debt-equity ratio is defined as the ratio of total liabilities to stockholders' equity, and firm size is measured by the number of employees.

The market share will be calculated by taking the ratio of the firm's sales to the sum of the sales of all firms in the same sector. This variable is included because several studies have tended to consider this one of the main determinants of firm performance. Some examples of such studies include Wernerfelt and Montgomery (1988) and Hansen and Wernerfelt (1989). The use of this variable should be able to provide some interesting implications, since market share represents the firm's market power and other competitive advantages. As noted by Hansen and Wernerfelt (1989), although the market share is generally seen as a positive contributor to firm performance in itself, it can also serve as an indicator of the level of the entry barrier. Given this paper's premise that the sector TCT can serve as a measure of entry barrier, taking market share into account should provide some points for comparison.

A model that includes the R&D expenditure will also be estimated, but only for US firms. The main reason for this is that R&D expenditure is often missing for some data points. This is not necessarily a serious problem for US firms due to the relative abundance of data, but it is a serious blow for Korean firms, especially because of the calculations necessary to obtain the data, describe in the next section. The variable is added for the US firms mostly in order to check

for robustness, and because R&D expenditure is considered to be an important factor in determining a firm's technological capability, as the case, for example, in Bierly and Chakrabarti (1996). Overall, however, the comparison between the US and Korean firms will be based on the models that do not include R&D expenditure.

5 Data

In this section, a description of the datasets used and the descriptive statistics of the final datasets are given. Note that the descriptive statistics are for the datasets with the outliers removed, where outliers are defined as data points that are more than four standard deviations away from the mean for any of the variables involved[7]. For the TCTs, the descriptive statistics for the non-relative versions are given in order to provide a better picture of the differences between the two countries.

5.1 US Firms : 1992-1995

For US firms, two separate datasets were used in order to perform the analysis. The first dataset is the patent data from the NBER Patent Database, which is based on Hall et al. (2001) and covers the citations data for patents from 1976 to 2006. The dataset originally contained information such as the application and grant year of the patents, their assignees, their classification according to the International Patent Classification system, and so on.

The second dataset used is Compustat for North America, which contains financial information for all North American firms. Most of the data on firms was obtained from this dataset, including information such as the total assets, number of employees, and so on. In addition, only the firms in the SIC ranging

[7]For some variables, such as the number of employees, the distribution of the log value was used instead because the values could only take positive values.

between 2000 and 6000 were taken, which includes the manufacturing, transportation, and trade industries.

In order to merge the two datasets, the *pdpass* from the patent dataset were assigned to the firms in the Compustat data based on the names of the firms. The names in the patent dataset are often subject to a fair number of variations, which was fortunately accounted for in Hall et al. (2001). For example, "PepsiCo Inc." is sometimes also written as "Pepsico Inc.", both of which have been given the same *pdpass* number. This, in practice, causes little trouble in merging the data for 1992-1995 as the names used in the Compustat data is always one of such variations since Hall et al. (2001) based their matching scheme on the same dataset.

After the merge, firms that were found to have a market share of 1 were removed. This was done in order to avoid a potential problem that did not need to be considered in Lee (2013), which is that a situation where for some data points the relative firm TCT is systematically equal to 1 can arise. Note that this was done for both the US and Korean data before the removal of outliers, as the relative firm TCT were calculated beforehand as well and the issue is in systematically obtaining the value of 1 for the variable rather than simply having only one firm in the sector in the final dataset[8]. After this, the dataset was made into a balanced panel dataset by taking out firms that did not have data for all four years.

The descriptive statistics of the resulting data for US firms from the year 1992 to 1995 is given in Table 1, for observations that do not have missing values in any of the independent variables. The data consists of 293 firms over 4 years, leading to a total of 1172 observations.

[8]Of course, having the value of 1 for relative firm TCT is also not, in itself, an issue. The procedure is simply to avoid a situation where for some firms, 1 is the only value the relative firm TCT can take due to the fact that they are the only firm in the sector. While one might assume that the particular sector is a monopoly, this is by no means guaranteed, which is why such data were removed instead.

Variables	N	Median	Mean	S.D.
ROA	1172	0.06	0.02	0.14
ROE	1172	0.12	0.05	0.44
Sector TCT (years)	1172	10.07	10.06	1.69
Firm TCT (years)	1172	8.08	8.37	2.59
Capital-Labor Ratio (million $ per person)	1172	0.03	0.05	0.07
No. of Employees (thousands)	1172	2.51	14.59	41.20
Investment Propensity	1172	0.04	0.10	0.27
Debt-Equity Ratio	1172	0.90	1.26	2.58
Market Share	1172	0.00	0.04	0.09
R&D Expenditure (billion $)	1172	0.01	0.12	0.43

Table 1: Descriptive Statistics for US Firms : 1992 - 1995

5.2 US Firms : 2007-2013

In order to be sure that Hypothesis 1 holds, estimates are also made based on the data from 2007 to 2013. Since the original patent dataset only contains information for patents up to 2006, additional data needed to be collected. The additional data for patents granted in the years from 2007 to 2013 were obtained from USPTO Bulk Data, which can be downloaded from Google. The raw data was formatted in order to match the format of the dataset from the NBER Patent Database. To obtain the information on the cited patents, such as the application and grant year, the datasets were merged sequentially by year to the one that contains the information for patents up to that year. For example, in order to obtain the data for patents cited by those granted in 2008, the data for patents up to 2008 were first created, which was then merged to the dataset of patents granted in 2008.

The merging of this new dataset involved first assigning the existing *pdpass* number to new variations of the firms that were included in the dataset for 1976-2006. In addition, new firms were given new *pdpass* numbers starting from 1, since the existing numbers were larger than 10,000,000 which was certainly

much larger than the number of new firms. Once this was done, the same process used for the merging of the datasets for 1992-1995 was undertaken.

The descriptive statistics of the data for US firms from the year 2007 to 2013 is given in Table 2, only for observations that do not have missing values in any of the independent values. The data consists of 284 firms over 7 years, leading to a total of 1988 observations.

Variables	N	Median	Mean	S.D.
ROA	1988	0.05	-0.01	0.22
ROE	1988	0.10	0.01	0.53
Sector TCT (years)	1988	8.99	9.06	1.97
Firm TCT (years)	1988	9.99	10.04	3.17
Capital-Labor Ratio (million $ per person)	1988	0.05	0.08	0.13
Number of Employees (thousands)	1988	3.99	14.33	29.58
Investment Propensity	1988	0.03	0.08	0.31
Debt-Equity Ratio	1988	0.81	1.12	1.39
Market Share	1988	0.00	0.03	0.08
R&D Expenditure (billion $)	1988	0.05	0.33	1.05

Table 2: Descriptive Statistics for US Firms : 2007 - 2013

5.3 Korean Firms : 1992-1995

Although the patent data come from the same source as that for the US data, the relevant financial data for Korean firms are taken from KISValue, a database that contains financial and performance data of Korean firms. This data is the reason why the years 1992-1995 was taken rather than a more recent time period, since the theoretical framework requires a comparison between countries in differing stages of development. Korea is not really an emerging country from the year 2000, which makes it quite pointless to make any comparisons with the US firms according to the hypotheses.

It is necessary to note that no balancing of the data was performed for the Korean firms, due to the fact that the size of the dataset was already quite

limited and such a procedure left even less data to work with. Nevertheless, the data has undergone some cleaning procedures. First, Samsung Electronics was removed from the dataset, as was the case in Lee (2013), in order to be able to make more direct comparisons with the previous results. In addition, sectors that only contained a single firm were removed, just as was the case for the US data.

The data for the R&D expenditure was also not used in the analysis, due to the fact that this led to the discarding of too many data points. This is mostly because unlike the Compustat dataset, the KISValue database does not provide a single measure of R&D expenditure. Instead, as was explained in Yu (2010), it requires adding up the data from several parts of the financial statement, including that from the statement of financial position, income statement, and the cost of goods. Although the cases where all three parts were missing was relatively few, at least one of them are missing for many data points, making the final result for the R&D expenditure rather unreliable. Unfortunately, taking only the data points that includes all three parts reduces the size of the dataset to 88 firm years, making it too small for any meaningful analysis.

Variables	N	Median	Mean	S.D.
ROA	216	0.02	0.02	0.03
ROE	216	0.06	0.09	0.10
Sector TCT (years)	216	10.06	10.68	2.90
Firm TCT (years)	216	9.67	11.18	6.21
Capital-Labor Ratio (billion ₩ per person)	216	0.07	0.12	0.15
Number of Employees (thousands)	216	3.35	5.58	7.99
Investment Propensity	216	0.04	0.08	0.21
Debt-Equity Ratio	216	2.81	3.01	1.43
Market Share	216	0.08	0.18	0.24

Table 3: Descriptive Statistics for Korean Firms : 1992 - 1995

The descriptive statistics of the data for Korean firms from 1992 to 1995 is given in Table 3, only for observations that do not have missing values in any

of the independent values. The data consists of 216 observations comprised of 74 firms.

6 Results and Discussion

Tables 4 through 9 show the results of the panel regression on the data described in the previous section. All tables for the US data contain the results for six models, while those for the Korean firms contain only three. The first three models for both countries differ in terms of whether the TCTs at only one or both levels were used. The same can be said for models 4-6 for the US firms, but these also contain the coefficient for R&D expenditure. Note that the results were chosen based on the Hausman test, using a p-value of 0.1 as the cutoff point.

6.1 Results for US Firms

Tables 4 and 5 show the results of the regression for US firm from 1992-1995, while Tables 6 and 7 show the same for the years 2007-2013. The results all agree that US firms in sectors with relatively long TCT tend to perform better, confirming the first hypothesis. This is reinforced by the fact that the estimated coefficient for the relative sector TCT is consistently positive at 1 % level or better. In other words, since the results are consistent regardless of the time period at which it is observed, one can state that the positive relationship between sector TCT and firm performance holds in general.

Although this seems to contradict the previous results from Lee (2013) and Hirschey and Richardson (2001), one should note that the results are based on a period that is more than 20 years later, which implies a different economic environment. In addition, as none of the previous studies use sector-level variables directly, any conclusions on sectoral effects made with analyses using only firm-level variables should be interpreted as an implication rather than

actual results.

In fact, the results imply that when it comes to technology cycle time, the sector level is more important than the firm level. This is supported further by the fact that Models 3 and 6 show no significant effect from the relative firm TCT, even though the sector TCT is not included. On the other hand, Models 2 and 5 show that the relative sector TCT has a significant impact on firm performance regardless of whether the relative firm TCT is taken into consideration.

6.2 Results for Korean Firms

Tables 8 and 9 show that among Korean firms, those that operate in shorter cycle sectors tend to perform better, confirming the second hypothesis. One may note, however, that compared to the US, the effects are shown to be less significant, usually at the 10% level. Some of this may be attributed to the relatively small size of the dataset, but one may also suppose that this is because in this particular time period, Korea was on its way to become an advanced country, even if it ended up stumbling in 1997.

It is also noteworthy that, while not directly related to the hypotheses, the effect of the relative firm TCT is found to be insignificant, which goes against the result from Lee (2013). However, the analysis in this paper is also quite different from that in Lee (2013) in that the latter uses the TCT based only on the patents of a single year and is also not normalized on an annual basis. In other words, while TCT used in this paper is taken relative to the sector TCT for each year, the same cannot be said for TCT in Lee (2013).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Relative Sector TCT	0.0903***	0.0845***		0.0911***	0.0852***	
	(0.0226)	(0.0224)		(0.0227)	(0.0224)	
Relative Firm TCT	0.0364		0.0224	0.0368		0.0225
	(0.0224)		(0.0223)	(0.0224)		(0.0223)
Capital-Labor Ratio	−0.4642	−0.4594	0.0026	−0.4425	−0.4404	0.0128
	(0.3242)	(0.3245)	(0.3049)	(0.3274)	(0.3277)	(0.3098)
No. of Employees	−0.0005	−0.0005	−0.0003	−0.0004	−0.0004	−0.0003
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Inv. Propensity	0.0702***	0.0698***	0.0681***	0.0702***	0.0698***	0.0681***
	(0.0123)	(0.0123)	(0.0124)	(0.0123)	(0.0123)	(0.0124)
Debt-Equity Ratio	−0.0042**	−0.0041**	−0.0042**	−0.0043**	−0.0041**	−0.0042**
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Market Share	0.0048	−0.0111	−0.0771	0.0220	0.0037	−0.0706
	(0.2292)	(0.2292)	(0.2302)	(0.2320)	(0.2320)	(0.2329)
R&D Expenditure				−0.0212	−0.0184	−0.0084
				(0.0435)	(0.0435)	(0.0437)
R^2	0.0616	0.0587	0.0444	0.0618	0.0589	0.0445
Adj. R^2	0.0458	0.0437	0.0331	0.0459	0.0438	0.0331
Num. obs.	1172	1172	1172	1172	1172	1172

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 4: Regression Results : US, ROA, 1992-1995

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Relative Sector TCT	0.3490^{***}	0.3268^{***}		0.3488^{***}	0.3262^{***}	
	(0.0890)	(0.0879)		(0.0892)	(0.0882)	
Relative Firm TCT	0.1398		0.0857	0.1396		0.0849
	(0.0879)		(0.0875)	(0.0880)		(0.0876)
Capital-Labor Ratio	-2.1846^{+}	-2.1661^{+}	-0.3802	-2.1915^{+}	-2.1837^{+}	-0.4485
	(1.2740)	(1.2751)	(1.1979)	(1.2867)	(1.2879)	(1.2168)
No. of Employees	-0.0013	-0.0012	-0.0006	-0.0013	-0.0013	-0.0008
	(0.0031)	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0033)
Inv. Propensity	0.1641^{***}	0.1626^{***}	0.1560^{**}	0.1641^{***}	0.1626^{***}	0.1560^{**}
	(0.0483)	(0.0484)	(0.0487)	(0.0484)	(0.0484)	(0.0487)
Debt-Equity Ratio	-0.1046^{***}	-0.1041^{***}	-0.1044^{***}	-0.1046^{***}	-0.1041^{***}	-0.1044^{***}
	(0.0054)	(0.0054)	(0.0054)	(0.0054)	(0.0054)	(0.0054)
Market Share	0.1438	0.0827	-0.1729	0.1384	0.0689	-0.2162
	(0.9007)	(0.9006)	(0.9044)	(0.9118)	(0.9115)	(0.9147)
R&D Expenditure				0.0067	0.0172	0.0558
				(0.1708)	(0.1708)	(0.1717)
R^2	0.3145	0.3125	0.3024	0.3145	0.3126	0.3025
Adj. R^2	0.2340	0.2328	0.2253	0.2338	0.2325	0.2251
Num. obs.	1172	1172	1172	1172	1172	1172

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 5: Regression Results : US, ROE, 1992-1995

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Relative Sector TCT	0.0724^{***}	0.0708^{***}		0.0768^{***}	0.0749^{***}	
	(0.0210)	(0.0206)		(0.0211)	(0.0207)	
Relative Firm TCT	0.0090		−0.0062	0.0103		−0.0059
	(0.0228)		(0.0224)	(0.0228)		(0.0224)
Capital-Labor Ratio	−0.1737	−0.1746	−0.1252	−0.1669	−0.1680	−0.1179
	(0.1062)	(0.1062)	(0.1056)	(0.1062)	(0.1062)	(0.1058)
No. of Employees	−0.0005	−0.0005	−0.0003	−0.0002	−0.0002	−0.0000
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Inv. Propensity	0.0360^{**}	0.0362^{**}	0.0333^{**}	0.0366^{**}	0.0368^{**}	0.0336^{**}
	(0.0125)	(0.0125)	(0.0125)	(0.0125)	(0.0125)	(0.0125)
Debt-Equity Ratio	-0.0094^{*}	-0.0093^{*}	-0.0092^{*}	-0.0091^{*}	-0.0091^{*}	-0.0090^{*}
	(0.0043)	(0.0043)	(0.0044)	(0.0043)	(0.0043)	(0.0044)
Market Share	0.0770	0.0755	0.0416	0.0775	0.0759	0.0404
	(0.1894)	(0.1893)	(0.1897)	(0.1893)	(0.1892)	(0.1897)
R&D Expenditure				-0.0310^{+}	-0.0307^{+}	−0.0234
				(0.0176)	(0.0176)	(0.0175)
R^2	0.0143	0.0142	0.0074	0.0161	0.0160	0.0084
Adj. R^2	0.0122	0.0121	0.0063	0.0137	0.0137	0.0072
Num. obs.	1988	1988	1988	1988	1988	1988

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 6: Regression Results : US, ROA, 2007-2013

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Relative Sector TCT	0.1526^{**}	0.1514^{**}		0.1540^{**}	0.1527^{**}	
	(0.0530)	(0.0520)		(0.0534)	(0.0524)	
Relative Firm TCT	0.0068		-0.0253	0.0072		-0.0253
	(0.0576)		(0.0566)	(0.0576)		(0.0566)
Capital-Labor Ratio	-0.5787^{*}	-0.5793^{*}	-0.4765^{+}	-0.5765^{*}	-0.5772^{*}	-0.4782^{+}
	(0.2689)	(0.2687)	(0.2671)	(0.2691)	(0.2690)	(0.2675)
No. of Employees	0.0002	0.0002	0.0007	0.0003	0.0003	0.0006
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Inv. Propensity	0.0373	0.0374	0.0315	0.0375	0.0376	0.0314
	(0.0316)	(0.0316)	(0.0316)	(0.0316)	(0.0316)	(0.0316)
Debt-Equity Ratio	-0.2677^{***}	-0.2677^{***}	-0.2674^{***}	-0.2676^{***}	-0.2676^{***}	-0.2674^{***}
	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0110)
Market Share	0.1127	0.1116	0.0382	0.1129	0.1118	0.0385
	(0.4794)	(0.4792)	(0.4797)	(0.4795)	(0.4793)	(0.4799)
R&D Expenditure				-0.0099	-0.0097	0.0054
				(0.0446)	(0.0445)	(0.0443)
R^2	0.2631	0.2630	0.2595	0.2631	0.2631	0.2595
Adj. R^2	0.2245	0.2247	0.2216	0.2244	0.2246	0.2215
Num. obs.	1988	1988	1988	1988	1988	1988

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 7: Regression Results : US, ROE, 2007-2013

	Model 1	Model 2	Model 3
Relative Sector TCT	-0.0114^{*}	-0.0110^{*}	
	(0.0053)	(0.0050)	
Relative Firm TCT	-0.0008		0.0021
	(0.0039)		(0.0037)
Capital-Labor Ratio	-0.1652^{**}	-0.1664^{**}	-0.1631^{**}
	(0.0555)	(0.0550)	(0.0562)
No. of Employees	-0.0040^{**}	-0.0040^{**}	-0.0040^{**}
	(0.0015)	(0.0015)	(0.0015)
Inv. Propensity	0.0013	0.0013	0.0001
	(0.0076)	(0.0076)	(0.0077)
Debt-Equity Ratio	-0.0076^{**}	-0.0075^{**}	-0.0078^{**}
	(0.0028)	(0.0028)	(0.0028)
Market Share	-0.0376	-0.0375	-0.0447
	(0.0289)	(0.0288)	(0.0291)
R^2	0.2007	0.2005	0.1737
Adj. R^2	0.1254	0.1262	0.1094
Num. obs.	216	216	216

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 8: Regression Results : Korea, ROA, 1992-1995

	Model 1	Model 2	Model 3
Relative Sector TCT	-0.0433^{+}	-0.0434^{*}	
	(0.0224)	(0.0210)	
Relative Firm TCT	0.0001		0.0110
	(0.0164)		(0.0156)
Capital-Labor Ratio	-0.6673^{**}	-0.6672^{**}	-0.6592^{**}
	(0.2343)	(0.2321)	(0.2366)
No. of Employees	-0.0124^{*}	-0.0124^{*}	-0.0123^{*}
	(0.0062)	(0.0061)	(0.0062)
Inv. Propensity	-0.0045	-0.0045	-0.0092
	(0.0322)	(0.0321)	(0.0325)
Debt-Equity Ratio	-0.0183	-0.0183	-0.0193
	(0.0117)	(0.0117)	(0.0118)
Market Share	-0.2139^{+}	-0.2139^{+}	-0.2409^{+}
	(0.1218)	(0.1214)	(0.1222)
R^2	0.1578	0.1578	0.1345
Adj. R^2	0.0986	0.0994	0.0847
Num. obs.	216	216	216

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 9: Regression Results : Korea, ROE, 1992-1995

6.3 Discussion

The results confirm the observations in several studies such as Park and Lee (2006) and Lee (2013) for both the advanced and emerging countries. The empirical results here are particularly valuable because unlike the previous studies, this paper incorporates the TCT at the level of industrial sectors directly in the model, allowing for a more direct conclusion with regards to which industrial sector a firm in an emerging country should choose to enter. Specifically, the results support the policy recommendation that firms in emerging countries need to enter sectors with short TCT in order to successfully catch up to the firms in advanced countries.

One may also note that, by the discussion in the theoretical framework, the results also imply that the sector TCT is a good measure of the entry barrier. In many studies such as Hansen and Wernerfelt (1989), Wernerfelt and Montgomery (1988), or Karakaya and Stahl (1989), market share is usually seen as one of the main indicators of the entry barrier. This work shows that technological factors such as the TCT is just as important if not more so, an idea that has been suggested several times in studies such as Park and Lee (2006) and Lee (2013).

The results do not seem to agree with Hirschey and Richardson (2001) as operating in sectors with longer TCT is found to be beneficial to the firm. However, one crucial difference is that Hirschey and Richardson (2001) only uses firms that were issued more than 10 patents per year over the period 1989-1995. Since the same cannot be said of the firms analyzed in this paper, this leads to a much narrower set of firms, and thus a narrower set of sectors[9].

[9]This can be particularly important, since the effects of firm-level TCT is less clear in theoretical terms. While the analysis of Bierly and Chakrabarti (1996) implies that shorter TCT means higher technological capability, shorter TCT can also mean that the firm is relying on technology that becomes obsolete more quickly, which can have adverse effects on firm performance. In fact, it is not even certain that firm-level TCT generally has a linear effect on firm performance, as is evidenced by the lack of significance of its effects in this

In addition, they do not use a moving average of the technology cycle time, and they also use the median rather than the mean backward citation lag, which may have contributed to the differences in the results. Their control and dependent variables are also different, using the ratio of market value of common equity to assets, the ratio of the book value of common equity to assets, and so on.

On the other hand, there is a general agreement with the results from Lee (2013). For the Korean firms, however, while the results may support the same conclusion, there are some differences as the effect from the firm level TCT is found to be insignificant in this analysis while the same cannot be said for the results from Lee (2013). The differences here, however, seem to stem from the fact that the analysis in Lee (2013) uses the TCT calculated for each year, while this analysis is based on the TCT calculated on patents over 3 years and then normalized. In addition, the additional removal of data as described in Section 5 also would have contributed to the difference, especially since this also led to a change in the number of firms.

7 Conclusion

This paper shows that technology cycle time is an important determinant of firm performance. In particular, it confirms that in general, firms perform better in sectors with long TCT. In addition, it also shows that an exception can be made for firms in emerging countries, for which specializing in short TCT sectors tend to be better. Taken together, then, they support the argument that sector TCT acts as an indicator of the level of the entry barrier, with longer sector TCT corresponding to higher levels. This shows that TCT should be among the major variables to examine in analyzing how difficult it is for latecomers to enter a sector along with the more traditional measures such as market share.

paper and in Lee (2013).

The results do not, however, offer insight as to what the firms need to do once they actually enter such sectors, which is what emerging countries really need to know. To address this, additional work will be necessary to verify the effect of firm or relative cycle time on firm performance in conjunction with the impact of sector cycle time. One of the most prominent results from Bierly and Chakrabarti (1996) is that firms that tend to develop its technology internally rather than obtain them from external sources usually have a shorter cycle time. However, the existence of joint ventures and R&D alliances implies that reliance on internally advanced technology does not necessarily lead to the firm having a high technological capability. So, if there has been an overall increase in the number of R&D alliances or other joint projects, this may have contributed to the inconclusive results concerning the impact of relative firm TCT.

The estimates themselves also need to consider some other factors. First of all, other technological variables such as the self-citation ratio may need to be considered, especially given that the previous studies have shown their importance. Originality of the patents or technological diversity may also be worth considering. This is even more important since, as was already mentioned, technology has many aspects that cannot be safely ignored.

Another possible course of action is to take other characteristics of the sector such as the average age of the firms or the competitive environment into account. The role of the relative cycle time may be more obvious when these are considered, especially given that the idea of sectoral innovation system also considers the interaction between the agents involved in the sector. For example, if the sector is highly competitive, it may be more important to keep a fast pace of technological development in order to stay ahead of the other firms. The inherent characteristics of the technology of the sector will likely limit the extent to which a firm can change its cycle time, but it may still play an important role.

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국문초록

기술발전주기, 산업특화와 기업성과

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기술발전주기는 기업성과를 설명할 때 자주 사용되는 기술 관련 변수이다. Hall et al. (2001)에서 제시한 평균후방인용시차(mean backward citation lag)를 이용해 계산하는 이 변수는 보통 기술의 정성적 측면을 나타낼 때 사용한다. 그러나 산업이나 기술 분야의 차원에서 봤을 때 기술발전주기는 진입장벽을 나타내는 척도가 될 수 있다. 산업혁신시스템 (sectoral innovation system)에서 주장하는 산업 간 기술적 이질성(technological heterogeneity)을 받아들일 경우, 기업성과를 분석할 때 산업적 차원의 기술적 요인들에 주목해야 할 필요성이 있다는 점을 감안할 때 이러한 해석은 상당히 유용하다. 그러나 기술발전주기를 기술분야 차원에서 계산하거나 산업 차원에서의 영향을 논의한 연구들은 존재하는데 비해 산업 차원에서 이를 직접 계산해 사용하는 경우는 상대적으로 적다. 또한 Lee (2013) 등을 제외한 대부분의 연구들은 주로 선진국들에 초점을 맞추는 경향이 있다.

이 논문은 이러한 부분들을 보완하기 위해 산업 차원에서의 기술발전주기를 계산해 계량모형에 포함하고 두 가지 가설들을 검증한다. 첫 번째 가설은 일반적으로 기술발전주기가 긴 산업에 있는 기업들이 더 좋은 기업성과를 보이는 경향이 있다는 것이다. 이는 기술발전주기가 길면 더 오랜 기간에 걸친 이전 기술들을 배워야 하기 때문에 후발기업들에게 진입장벽으로 작용할 수 있다는 점에 착안한 것이다. 두 번째 가설은 신흥 국가의 경우는 반대로 기술발전 주기가 짧은 산업의 기업들이 더 좋은 성과를 보인다는 것이다. 1992-1995년의 미국과 한국 기업들, 그리고 2007-2013년의 미국 기업들을 이용한 패널 분석의 결과들은 이 가설들을 지지한다.

주요어 : Technology cycle time, sectoral system of innovation, entry barrier
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