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On the measurement of patent stock as knowledge indicators

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Abstract

Most of the conventional indicators for measuring the amount of technological knowledge (TK) have so far been input-based indicators. Hence, there is growing need to develop output-based indicators, and accordingly some studies have been conducted thereon. However, previous research has adopted patent count or patent stock by simple count in measuring the amount of TK as output-based indicators. The principal problem with using this variable is that the value of individual patent is too heterogeneous. That is a large portion of these patent databases are either of little value or nothing at all. As a result, patent count or patent stock by simple count cannot be seen as a suitable measure of TK.

In this study, we attempted to resolve the value-heterogeneity problem in measuring patent stock. The notion of citation-based patent stock (CPS) and valuation-based patent stock (VPS) is proposed in this paper and the calculation method is described in detail. In CPS, the economic value of individual patent is assumed to be proportional to the number of citations received from other patents. And in VPS, the economic value of individual patent is derived from the value distribution of patents registered in some cohort by manipulating the patent renewal data. We validated the indicators by comparing them with the usual input-based indicators and by analyzing the relationships between them and the productivity growth empirically.

Keywords: Technological knowledge; Measurement; Indicator; Patent stock; Citation-based; Valuation-based

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1. Introduction

Technological knowledge (TK) is known to be the key factor in maintaining competitiveness of a firm and innovation capability of a country. Accordingly, great interest has been drawn to measuring the amount of TK. Unfortunately, it has long been an acknowledged fact that the task of gauging the amount of TK is relatively difficult, in fact almost impossible as compared to the relative easiness of measuring economic variables such as fixed capital or labor [1,2]. The inherent difficulty of measuring the amount of TK may be attributed to the following factors. First, TK encompasses heterogeneous and multi-disciplinary components that are difficult to standardize [3]. Second, TK embraces embodied and tacit knowledge that is not easy to separate or quantify [4–7]. Third, TK is subject to idiosyncratic differences across industrial sectors [8], and thus, is difficult to generalize. This explains why in past researches, various proxy indicators had to be employed for measurement of the amount of TK.

Under the guidance of the OECD, several TK indicators have been developed and manipulated since the 1990s. These include R&D expenditure, R&D stock, the number of researchers, the number of R&D employee and the number of patents [2]. Most of these indicators, with the exception of patent, are input-based indicators for creating TK. In recent years, the number of analyses using patent database have been growing rapidly, especially in techno-economic analysis, due to the construction of the patent database and the easiness of public access to these databases [9,10].

Patent can be regarded as a typical output-based indicator of TK. In conventional analyses using patent data, patent count or patent stock by simple count has been adopted to measure the amount of TK [2,11]. But, as has been acknowledged by many economists, a principal problem with the use of patent data on this analysis is that there are too many patents, a large portion of might be worth little or nothing [12,13]. As a result, patent count and patent stock by simple count are very inaccurate measures of the amount of TK.

We examined previous researches and attempted to identify the various shortfalls in those researches. Thus, the main objective of the current research can be summarized as follows. First, the concept of patent stock for measuring the amount of TK is proposed. As mentioned above, the existing patent stock has been calculated by using simple patent counts which means that the value of individual patent is equal to. This implies that the aspect of heterogeneity of a patent value had not considered in these conventional analyses. In this paper, we propose the concept of citation-based patent stock (CPS) and valuation-based patent stock (VPS) to resolve such value-heterogeneity problem, and present practical empirical methods for measuring these patent stocks. Second, validation of the indicators proposed in this study is performed empirically. CPS and VPS are output-based indicators of TK. In the validation part, we compared the conventional indicators, such as R&D stock, R&D researchers, patent counts, patent stock by simple counts with CPS and VPS.

This paper is organized as follows. First, data source for constructing CPS and VPS is briefly described. Then, the concept of CPS is introduced and the procedure for measuring CPS is described in detail. And the empirical study on measuring CPS of all the patents registered in USPTO is performed. Next, the notion of VPS is introduced and the concrete process for estimating VPS is presented. In addition, the method of estimating VPS is also presented. Then, the validation of the output-based indicators proposed in our study is performed empirically. Finally, some implications of current research and prospective issues of future research are discussed.

2. Data source

We measured CPS using the NBER patent-citations data files which comprise of detailed information on 2,923,922 U.S patents granted between 1963 and 1999, and all of the citations made to these patents between 1975 and 1999 totaled 16,522,438 citations. (For a description in detail of these data, see Hall et al. [10]).

To examine the difference across industries, U.S. patent 3-digit technology classes were incorporated into the international standard industrial classification (ISIC) rev. 3.1 from United Nations Statistics Division. In this study, we referred to the 4-digit classes of ISIC for matching. Some classes overlap with a couple of other industries. In such cases, we excluded those cases as it adulterates the technological homogeneity within an industry. Based on the same rationale, we narrowed our analysis down to the manufacturing industry. Our classification is given in Appendix A. A constructed variable, namely the industry code, was generated in this process.

In the calculation of VPS, the renewal history data of a patent was needed. But, this was not available in the NBER database. Hence, we collected the detailed information about the renewal history of a patent from the U.S. Patent and Trademark Office (USPTO: www.uspto.gov) database. Other information for comparing the indicators of TK was obtained from OECD database. And the productivity data of U.S. manufacturing industries were collected from the database provided by the U.S. government. Further details of this dataset will be discussed in a later section.

3. Method for measuring CPS

Patent citation is defined as the count of citations of a patent in subsequent patents, and citations per patent represent the relative importance of that patent. Accordingly, a patent citation analysis executes a bibliometric analysis on patent documents. In that respect, the methodology applied here is fundamentally a citation-based technique in that it attempts to link patents in a patent database in the same way as science citation analysis links references in a scientific paper database [14]. Ultimately, patent citation analysis produces technological indices such as citation per patent, highly cited patents, technical impact index, technology cycle time, etc [15]. These indices have been used as measures of quality of technical assets [16], negotiation power between firms [17], economic value of innovative outputs in market value equation [18], or domestic or cross-border technology linkages and knowledge flows [19,20]. Although patent citations have been deployed as weights for evaluating economic importance of patents in some previous studies [21–26], the focus of previous research had been centered on a more micro-level, that is, firm-level analysis.

In measuring CPS, the value of individual patent is assumed to be proportional to the number of citations received. Similarly to the construction of R&D stock, CPS can be measured in the following manner.

3.1. Overall procedure for measuring CPS

In general, technological knowledge stock (TKS) reflects the cumulative amount of technological knowledge that a firm or an industry possesses at a certain point in time [27]. Several past studies employed the notion of R&D stock, as a proxy measure for TKS, and gauged the cumulative amount in an attempt to estimate the rate of return to R&D investment [28,29]. Similarly in the construction of R&D stock, CPS of an industry i can be defined as follows:

$$\mathrm{CPS}_{i,t} = \mathrm{CPF}_{i,t} + (1-\delta_i)\mathrm{CPS}_{i,t-1} \tag{1}$$

where $\mathrm{CPS}_{i,t}$ is the CPS of industry i in year t, and $CPS_{i,t}$ is the supply of a new technological knowledge of industry i in year t, and δ_i is the depreciation rate of CPS in industry i. TKS becomes obsolete over time as a new TK is supplied and the depreciation rate, δ_i, reflects this. In order to calculate CPS using Eq. (1), the CPS of base year should be measured beforehand. Applying a perpetual inventory method in the construction of R&D stock, we obtained the CPS of base year (tb) as follows:

$$\mathrm{CPS}_{i,tb} = \mathrm{CPF}_{i,tb}\frac{1+g_i}{g_i+\delta_i} \tag{2}$$

where g_i is the average growth rate of CPS in industry i. Hence, the estimation of both $\mathrm{CPF}_{i,t}$ and δ_i is needed to measure the $\mathrm{CPF}_{i,t}$. In the following sub-section, the procedure for estimating the depreciation rate of TK is briefly described.

3.2. Estimation of depreciation rate of TK

The depreciation rate of TK is closely related with the notion of pace of technological progress or technological development [5,30,31]. A number of patent-based technology indicators have been developed over the last decade. These indicators included technology cycle time (TCT) indicator for a new measure of technological progress [32].

There are two ways to look at patent citation lags: backward and forward [10]. Backward lags focus on the citation made by a particular patent. Thus, if patent A cites patent B, the backward citation lag can be calculated by the time difference between the application year of the citing patent and that of the cited patent. Forward lags focus on the citation received to a particular patent and the forward citation lags can be calculated similarly to backward citation lags. Citation received may indicate the importance of the cited patent and as mentioned before, may be used in the valuation of an individual patent for measuring CPS. Backward citation reflects the knowledge flow between the citing patent and cited patents. Hence, it is closely related with the obsolescence of TK and can be used for estimating the depreciation rate of TK.

Original TCT is defined as the median of backward lags and the TCT indicator has been used in assessing the pace of progress for different technologies or different nations in the same technology [23,32–34]. Unlike the original TCT that is defined as the median backward citation lags since they hope to exclude the influence by very old cited patents, the TCT introduced in this paper is defined as the mean backward citation lags. But, it can be eliminated by excluding the cases of which case the backward citation lags extend beyond 20 years. The criterion, i.e., 20 years, which is derived from U.S. patent law, is the maximum term of a patent beyond which such patent is deemed to have expired. That is, we assume that a citation that extends beyond 20 years has little economic importance since the cited patent has already expired. In that regard, the TCT of a specific industry can be computed by taking the lag of each citation to be an observation and calculating the mean for all of the citations. Maintaining the homogeneity of technologies within an industry, we removed the inter-industry citations by comparing the industry code between the citing patent and the cited patent.

The depreciation rate of TK in a specific industry can be calculated by simply taking the inverse of the TCT. The underlying assumption is that the value of TK declines at constant exponential decay rate and the lifetime distribution of TK can be represented in the similar manner as that of the citation lag. This assumption is in accordance with that of the existing methods for measuring depreciation rate of TK [35].

This approach for estimating the depreciation rate based on the concept of TCT is easy to understand and easily applicable. By calculating the TCT of each industry, the depreciation rate of TK of each industrial sector can be estimated separately. Furthermore, if applied into different cohort, we could estimate the time-variant depreciation rate of TK. The depreciation rates across industries are shown in Table 1. As expected, traditional industries such as food, tobacco, and paper industries show a low value of depreciation rates. On the contrary, the depreciation rate of new and high-tech industries such as computing machinery, and communication equipment industries are relatively high.

3.3. Estimation of the forward citation-lag distribution

Note that $\mathrm{CPF}_{i,t}$ is the sum of the value of all the patents that belong to industry i, and as mentioned before, the value of individual patent is assumed to be proportional to the number of citations received. Hence, in order to obtain the supply of a new technological knowledge of industry i in year t, we need to determine the value of each patent. In doing so, truncation problem is unavoidable since patent data can only be observable by the current time, and in our research, 1999. That is, the number of citations received by any given patent is truncated in time because we only know about the citations received so far. More importantly, patents of different ages are subject to differing degree of truncation [10]. For example, a patent A registered in 1990 has a 9 years' chance period of citation by 1999. On the contrary, a patent B registered in 1995 has only 4 years by 1999. Hence, the truncation problem should be resolved first before attempting to construct a CPS.

Hall et al. [10] proposed two approaches namely, the fixed-effects approach and quasi-structural approach, for resolving this problem. In the fixed-effects approach, citation counts are scaled by dividing them by the average citation count for a group of patents to which the patent of interest belongs. And in quasi-structural approach, forward citation-lag distribution is derived via econometric estimation. These two approaches have their own advantages and disadvantages, respectively. But, discussions on these two approaches have been excluded from this paper due to the following reasons. The fixed-effects approach assumes that all sources of systematic variation over time in citation intensities are artifacts that

Table 1
Depreciation rates across industries

Industry code	Depreciation rate (%)	Industry code	Depreciation rate (%)	Industry code	Depreciation rate (%)
1	11.88	9	12.63	17	14.39
2	11.86	10	13.11	18	16.08
3	13.09	11	12.52	19	13.93
4	13.85	12	12.84	20	13.72
5	12.69	13	12.61	21	13.21
6	12.29	14	12.52	22	12.44
7	12.02	15	12.76	23	13.35
8	13.97	16	17.89		

should be removed before comparing the citation intensity of patents from different cohort. Hence, this approach purges the data of any systematic movements over time in the importance or impact of patent cohorts. And, in the estimation of forward citation-lag distribution by quasi-structural approach, only the information about the average number of citations collected in year t is used. Thus, it is only natural that there is information loss when using this approach. For these reason, we have excluded these two approaches from our study.

Instead of adopting the existing methods, we derived the forward citation-lag distribution by using the lag of each forward citation as an observation and by estimating each point estimate of forward citation lag. Similarly to the estimation of the depreciation rate of TK, we excluded the cases where the forward citation lags were over 20 years based on the same rationale. And such exclusion of data is partly due to the fact that NBER citation database goes back to 1975.

To implement this approach, let N_{tk} be the total number of forward citations of patents which belong to industry k in year t. And among them, f_{tk1} denotes the number of forward citations of lag l. Then, the forward citation-lag distribution of industry k and year t can be estimated as follows:

$$Pr\{L = l\} = \frac{f_{tkl}}{N_{tk}}, \; t = 1975, \cdots, 1979, \; k = 1, \cdots, 23, \; l = 0, 1, \cdots, 20. \tag{3}$$

Using Eq. (3), we obtained the year-wise and industry-wise forward citation-lag distributions. To examine the difference across industries and dynamic stability of these distributions, we performed parametric (one-way ANOVA) and non-parametric (two-sample Kolmogorov–Smirnov test) statistical tests. Test results show that the forward citation-lag distributions are different across each industry, whereas the dynamic stability of these distributions in each industry is relatively ambiguous across industries. This ambiguity is partly due to insufficiency of dynamic data of these distributions. From the pool of yearly data for the period between 1975 and 1979, we estimated the industry-wise forward citation-lag distributions.

3.4. Estimation of the supply of a new technological knowledge in CPS

As mentioned before, the truncation problem can be resolved by applying forward citation-lag distribution to the number of citations received. But, like in the study of Hall et al. [10], we imposed additional assumption on the distribution, that is, proportionality. Proportionality means the shape of the lag distribution over time is independent of the total number of citations received, thereby making more highly cited patents to be more highly cited at all lags. With proportionality, the observed citation total at a point in time for any patent can be corrected for truncation, simply by scaling up the observed citation total by dividing it by the fraction of the lifetime citations that were predicted to occur during the lag interval that had been actually observed.

For more detailed description about the correcting the truncation problem, let O_A be the observed citation total of patent A which was granted in year t, and $F_{T,j}$ denote the cumulative probability of forward citation-lag distribution in industry j which embraces the patent A until the citation exposure time T. Since we excluded the cases of which the forward citation lags were over 20 years, the citation exposure time T of patent A satisfies the following condition:

$$T = \min(1999 - t, 20) \tag{4}$$

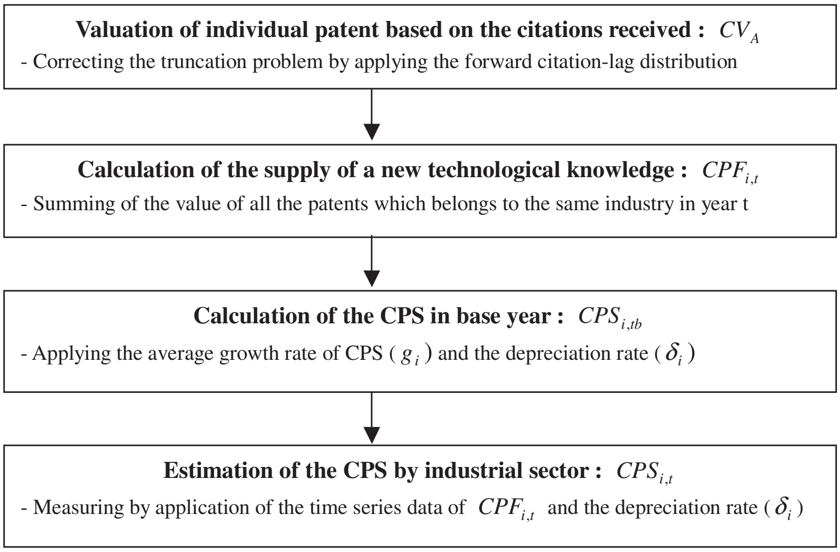

Fig. 1. Overall procedure for measuring CPS.

Then, the value of patent A based on the citations received, CV_A, can be calculated as follows:

$$CV_A = \frac{O_A}{F_{T,j}} \tag{5}$$

Applying Eq. (5) to all the patents of industry *i* in year *t*, the supply of a new technological knowledge of industry i in year t, $\mathrm{CPF}_{i,t}$, can be obtained in a straight-forward manner. Fig. 1 depicts the overall procedure for measuring CPS.

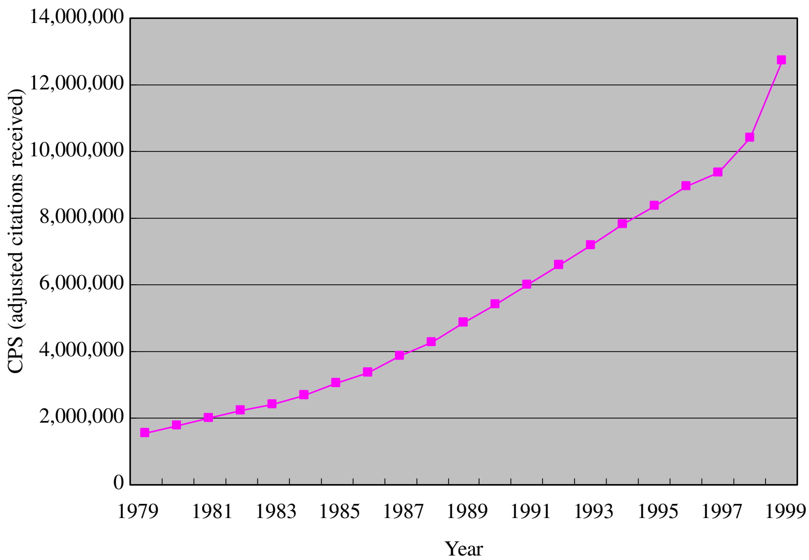

Fig. 2. Trend of CPS over time.

Table 2
Share of each industry in CPS (%)

Industry code	1979	1985	1990	1995	1999	Industry code	1979	1985	1990	1995	1999
1	1.6	1.5	1.4	1.2	1.0	13	5.3	4.3	3.9	3.5	2.8
2	0.2	0.2	0.2	0.1	0.1	14	5.2	5.3	5.1	4.6	4.1
3	1.5	1.6	1.4	1.1	1.0	15	11.2	10.9	9.7	8.3	7.5
4	0.3	0.2	0.2	0.1	0.1	16	3.8	5.8	7.7	10.0	15.9
5	0.5	0.6	0.6	0.6	0.5	17	10.4	10.6	9.8	9.2	9.4
6	0.2	0.2	0.1	0.1	0.1	18	6.5	8.6	11.3	14.1	16.3
7	1.0	0.9	0.9	0.8	0.6	19	10.4	12.2	15.0	16.4	15.5
8	0.8	0.7	0.6	0.5	0.6	20	1.7	1.9	1.9	1.7	1.6
9	2.9	1.9	1.2	0.8	0.6	21	1.7	1.7	1.8	2.0	2.2
10	28.3	24.8	21.4	18.7	14.8	22	3.4	3.2	3.5	3.7	3.2
11	2.4	2.2	1.9	1.9	1.6	23	0.2	0.1	0.1	0.1	0.1
12	0.6	0.6	0.5	0.5	0.5						

Along the procedure given in Fig. 1, we measured the CPS of all the patents registered in USPTO. The trend of the CPS is given in Fig. 2.

As shown in Fig. 2, the CPS grows rapidly. This trend reflects the rapid technological progress in recent years. The average annual growth rate of CPS is about 11.2%. Next, in order to investigate the relative importance of each industry in CPS dynamically, we calculated the CPS of each industry at an interval of 5 years and the share of each industry is given by Table 2. From this table, we can see that the share of chemical industry was the largest in 1979, followed by machinery and electrical machinery. But, this changed dramatically in 1999. The Radio, TV and communication equipment industry's share suddenly seized the largest portion with a share of 16.3%, followed by office, accounting and computing machinery industry with a share of 15.9%, and then by medical, precision and optical instrument industry. These results reflect the changes in the industrial structure in recent years.

4. Method for calculating VPS

In the previous section, we examined the method for calculating CPS. In the CPS, the value of individual patent was estimated relatively by the number of citations received. But, the value of patents was estimated in terms of monetary value, and the amount of TK was assumed to be proportional to such monetary value in VPS.

Monetary value models for the valuation of individual patent can be broadly classified into three basic approaches, namely cost approach, market approach, and income approach [36]. But, since they are based on the valuation of each patent it is not appropriate to be used in this study.

In a recent research, attempts were made to use additional information from the patent system. Studies using patent renewal data exploit the fact that in many countries patentees must pay periodic renewal fees in order to maintain their patents in force. Provided that if more valuable inventions generate patent families with longer life span, we could use the renewal data to attach weights to patents and produce weighted patent count indices that would be a more precise measure of innovative output than raw patent counts [12]. This approach, so called the renewal-based approach, produces a value distribution of all the patents registered at a certain cohort. This approach is suitable for our study in that the focus of our study lies in measuring the amount of TK at a macro level, i.e., the industrial level.

The renewal-based approach was originally proposed by Pakes and Schankerman [37]. They stimulated a broader interest in renewals by showing how to use these data to uncover characteristics of the value of patent protection. Similar studies have been performed along the line of this research for years [13,38–41]. In measuring the VPS, the framework of Pakes and Schankerman [37] was deployed. So, we begin this section by outlining the framework used in the Pakes and Schankerman study.

They conditioned on a patent application having been made, and endowed each application with an initial one period return to patent protection, r_0, which was assumed to decay deterministically at an annual rate of δ thereafter. As mentioned above, patentees must pay a renewal fee to keep their patents in force and this fee increases in age. A patent owner seeking to maximize the expected discounted value of the net returns to patent protection will renew his patent at when the patent reaches the age 'a', if and only if, the current returns, $r_o \exp(-\delta a)$, are greater than the current cost of renewal, c_a. Similarly, the patentees will renew the patent at age a only if $r_0 > c_a \exp(\delta a)$. Assuming a functional form for the initial distribution of patent value, they showed that the parameters of this distribution can be estimated by identifying the parameter values that make the renewal proportions predicted by the theory to be 'as close as possible' to those actually observed in the patent renewal data [12]. And among the functional forms for the initial distribution of patent value, lognormal distribution was analyzed to have the best in terms of explanatory power [39].

In measuring VPS, the value of individual patent can be derived from the patent renewal history data. Similarly in the construction of R&D stock, the VPS to gauge the amount of TK can be measured as follows.

4.1. Overall procedure for measuring VPS

Similarly in the construction of CPS, VPS of an industry i can be defined as follows:

$$\mathrm{VPS}_{i,t} = \mathrm{VPF}_{i,t} + (1 - \delta_i)\mathrm{VPS}_{i,t-1} \tag{6}$$

$$\mathrm{VPS}_{i,tb} = \mathrm{VPF}_{i,tb} \frac{1 + g_i}{g_i + \delta_i} \tag{7}$$

where $\mathrm{VPS}_{\mathrm{i},t}$ is the VPS of industry i in year t, and $\mathrm{VPS}_{i,t}$ is the supply of a new technological knowledge of industry i in year t. δ_i is the depreciation rate of VPS in industry i, and g_i is the average growth rate of VPS in industry i. Hence, the estimation of both $\mathrm{VPF}_{i,t}$ and δ_i are needed to measure the $\mathrm{VPS}_{i,t}$. In our study, δ_i, the depreciation rate of TK was estimated by the inverse of TCT, as discussed in the previous section. So, the estimation of $\mathrm{VPF}_{i,t}$ was sufficient for measuring $\mathrm{VPS}_{i,t}$.

Before explaining the procedure for measuring $\mathrm{VPS}_{i,t}$ in detail, we will describe the patent renewal system of USPTO briefly. In the U.S., the patent renewal system was introduced in 1980. Under this system, an applicant must maintain the patent by paying periodic renewal or maintenance fees in order to hold protection right against its patent for the maximal term of expiration. The renewal fees are paid every four years and the fees escalate progressively. But, the amount of renewal fees varies according to the status of the entity, that is, the status of the applicant. In the U.S., the applicant is classified into two classes, that is, small entity and large entity. Individual inventors, small firms and non-profit organizations belong to the small entity and generally large firms belong to the large entity. For a small entity, the amount of renewal fees is half that of a large entity. In case of a large entity, the renewal fees escalate progressively from $890 after the fourth year, $2,050 after the eighth year, and $3,150 after the twelfth year from the year on which the patent is granted. If the patentee fails to pay the renewal fee by the designated date, the protection right expires. The relatively substantial and escalating nature of these mandatory renewal fee payments has the natural effect of discouraging renewal of less valuable patents.

As mentioned before, we adopted the framework by Pakes and Schankerman in our study. In this model, both the patent renewal distribution and the cost of renewal play a critical role in deriving the value distribution of patents which were registered in a specific year. Thus, patent renewal distribution must be differently estimated by the status of entity. In addition, since the characteristics of each industry affect the patent renewal distribution, an industry-wise estimation of patent renewal distribution is necessary.

4.2. Estimation of patent renewal distribution

The renewal history data of a patent are needed for calculating the VPS. But, the NBER database does not provide this information. Hence, the detailed information about the renewal history data of a patent was collected from the PAIR (Patent Application Information Retrieval) database at USPTO. Then, we found that it was not possible to trace the renewal history of all the patents registered in a specific year practically. Thus, the stratified sampling approach was adopted for estimating the patent renewal distribution in the current research.

With regard to the introduction year of patent renewal system and the maximal time period of the renewal decisions, we sampled patents registered in 1984, 1986, and 1988 to test the stationarity of the distribution. Based on the results of the sampling, the year-wise and industry-wise patent renewal distributions were obtained. Also, the share by each entity status, i.e., small entity and large entity, was estimated. To investigate the difference across industries and the dynamic stability of these distributions, we performed a chi-square test. The test results show that the patent renewal distributions and the share by entity status are different across industries. These distributions and the shares are stable dynamically. From the pool of yearly data for the years 1984, 1986 and 1988, we could estimate the patent renewal distributions by both industry and entity status, respectively.

In terms of the patent renewal distributions, food products and beverage (1), paper and paper products (7), office, accounting and computing machinery (16), electrical machinery (17), Radio, TV and communication equipments (18), medical, precision and optical instruments (19) and motor vehicle (20) industries are such that the percentage of patents that were renewed for a period beyond 12 years exceeded 40% (For your reference, the number in parenthesis denotes the industry code). Based on this, we can conclude that the renewal proportion of high-tech industries is relatively higher than that of traditional manufacturing sector. In terms of the share by entity status, the share of small entity is relatively high in the tanning and dressing of leather (5), furniture (22), wood and wood products (6), other transportation equipment (21) and fabricated metal products (14) industries. On the contrary, the share of large entity is comparatively high in the coke, refined petroleum products (9), Office, accounting and computing machinery (16), chemicals and chemical products (10), Radio, TV and communication equipment (18), electrical machinery (17) industries. From these observations, we can conclude that the share of large entity is relatively high in high-tech and large-scale equipment industries and that of small entity is high in industries where small firms play a critical role among traditional industries.

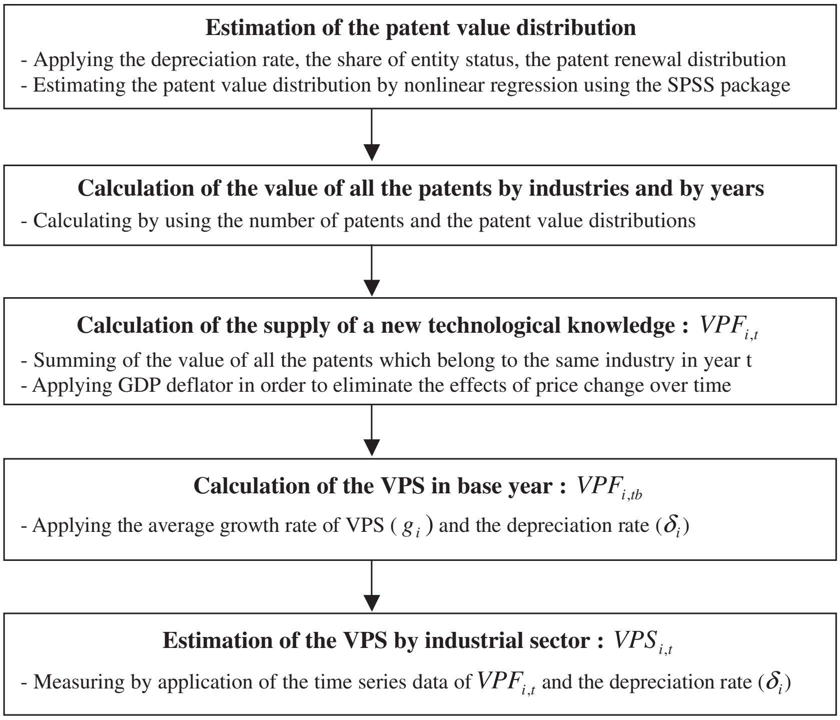

Fig. 3. Overall procedure for measuring VPS.

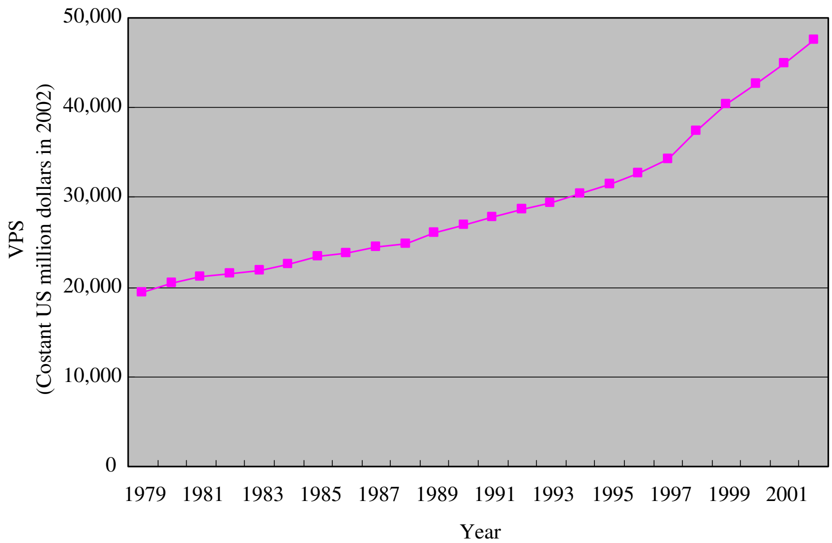

Fig. 4. The trend of VPS over time.

4.3. Estimation of the supply of a new technological knowledge in VPS

With the patent renewal distribution by industry and entity status obtained, the value distributions of patents which were registered for certain cohort can be derived by using the same framework by Pakes and Schankerman. As mentioned before, the initial distribution of patent value was assumed to be a lognormal distribution. By finding the parameter values that make the renewal proportions predicted by the theory to be as close as possible to those actually observed in the patent renewal distributions, we could obtain the value distributions by industries and by years. The statistical package, SPSS ver. 11.0, was used in our analysis.

Now, by combining the patent value distribution and the number of patents registered for some industries, the supply of a new technological knowledge can be obtained in straight-forward manner. And VPS could be measured in a similar way as calculating CPS. However, in measuring VPS, a price deflator such as R&D deflator is necessary because VPS is represented in monetary value. In our study, GDP deflator was adopted as the price deflator in order to eliminate the effects of price change over time. Fig. 3 shows the overall procedure for measuring VPS.

Following the procedure illustrated in Fig. 3, we measured the VPS of all the patents registered in USPTO. The dynamic trend of the VPS is given in Fig. 4. From this figure, the VPS can be seen to grow steadily and more steeply in recent time. This trend could reflect the more rapid technological progress during those periods. The VPS of all the patents registered in USPTO was estimated at $47.5 billion in 2002 constant US dollar which is 2.4 times that for 1979 which was $19.5 billion. Based on these data, the average annual growth rate of VPS was about 4.0% for the relevant period and the average growth rate of VPS in the 1980s was 2.95% and that of 1990s was 4.75%.

In order to investigate the relative importance of each industry in VPS dynamically, we calculated the VPS of each industry for an interval of 5 years and the share of each industry is given by Table 3.

As shown in Table 3, in 1979, the share of chemical industry (10) was the largest, followed by Radio, TV and communication equipment (18) and electrical machinery (17). But, this changed substantially in 1999. Radio, TV and communication equipment industry's share became the largest with a share of 28.5%, followed by office, accounting and computing machinery industry (16) with a share of 18.9%, and then chemicals and chemical products (10), electrical machinery (17) and medical, precision and

Table 3
The share of each industry in VPS (%)

Industry code	1979	1985	1990	1995	1999	Industry code	1979	1985	1990	1995	1999
1	2.4	1.9	1.5	1.2	1.0	13	6.0	5.1	4.6	3.9	3.1
2	0.4	0.3	0.2	0.2	0.1	14	3.5	3.2	3.0	2.6	2.1
3	1.2	1.1	0.9	0.8	0.7	15	9.6	8.8	8.0	6.9	5.6
4	0.2	0.2	0.1	0.1	0.1	16	6.3	8.4	10.8	13.6	18.4
5	0.2	0.2	0.2	0.2	0.2	17	13.5	14.1	13.4	12.3	11.3
6	0.1	0.1	0.1	0.1	0.1	18	15.0	17.9	20.8	23.7	26.5
7	1.0	0.8	0.7	0.7	0.6	19	11.0	11.0	11.2	11.4	10.9
8	0.8	0.7	0.6	0.5	0.5	20	2.3	2.3	2.3	2.0	1.6
9	2.0	1.4	1.1	0.8	0.6	21	1.2	1.1	1.1	1.0	0.8
10	19.8	18.5	16.7	15.5	13.7	22	1.8	1.6	1.5	1.4	1.3
11	1.1	1.0	0.9	0.8	0.7	23	0.0	0.0	0.0	0.0	0.0
12	0.4	0.4	0.3	0.3	0.2						

optical instrument (19) industries. As mentioned before, these results could reflect the change of industrial structure recently.

5. Validation of the indicators proposed in our study

In this section, we will validate the output-based indicators proposed in our study, that is, CPS and VPS, empirically. Firstly, we compared them with the usual input-based indicator such as R&D stock and R&D researchers. Then, we regressed the rate of growth of productivity on the rate of growth of the patent stock since the main aim of measuring the amount of TK is to ultimately analyze how TK had contributed to the productivity growth.

5.1. Comparisons with the usual input-based indicators

The indicators proposed in our study are output-based indicators of TK and which were adopted as alternatives to the conventional input-based indicators, R&D stock and R&D researchers. R&D stock and the number of R&D researchers have been frequently adopted as proxy indicators of TK, particularly in the analysis of macro level [14,27,42,43]. In spite of the different viewpoints, there must be strong correlations among them since they also represent the amount of TK.

To conduct an empirical analysis, we focused on the manufacturing sector of U.S. The relevant dataset on R&D and R&D researchers was extracted from the OECD ANBERD (Analytical Business Enterprise Expenditure on R&D) database [44]. This dataset provides industrial R&D data covering the reference period 1976–1996 for OECD member economies. Since the focus of the analysis is confined to the only U.S manufacturing, the relevant indicators are also restricted within that of U.S. In particular, the measurement of CPS and VPS is also restricted to the patents registered within the U.S. For the concordance between ISIC rev. 3.1 and the industrial classification of ANBERD database, manufacturing industries were reorganized into 16 sectors. The indicators, R&D stock (RDS), R&D researchers (RDH), patent counts (PC), patent stock by simple counts (PSC), CPS, and VPS, were collected or estimated by industrial sectors and by years. PC denotes the number of patents registered within a specific industry and PSC means the patent stock estimated by using only patent counts [11].

In order to investigate the relationships between the input-based indicators and the output-based indicators, we performed a correlation analysis. Table 4 exhibits the summarized statistics and Fig. 5 displays the dynamic trend over time.

As shown in Table 4, the correlation coefficients for all the pairs are statistically significant at the level of 0.01. We can see certain patterns among the indicators in Table 4. Firstly, as a whole, the VPS appear

Table 4
Correlation statistics between input-based indicators and output-based indicators

		PC	PSC	CPS	VPS
RDS	Coefficient	0.6182	0.5285	0.6178	0.7323
	Sig. prob.	0.0000	0.0000	0.0000	0.0000
RDH	Coefficient	0.3896	0.3199	0.3474	0.5303
	Sig. prob.	0.0000	0.0000	0.0000	0.0000

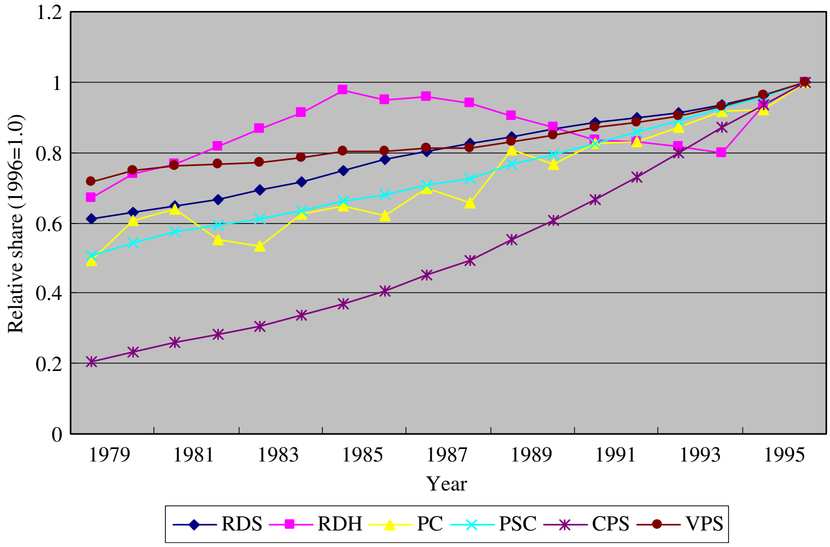

Fig. 5. Dynamic trend among indicators for TK.

to be highly correlated with input-based indicators. Secondly, the degree of correlation among input-based indicators and output-based indicators seem to share the same pattern. When compared with R&D stock, the degree of correlation is the highest in VPS, followed by the patent counts, CPS and PSC. We can see the same pattern in comparison with R&D researchers. This findings, in turn, implies that the two input-based indicators are highly correlated each other. In fact, the correlation coefficient between these two input-based indicators is very high of as much as 0.864. Based on the correlation analysis results, we can verify that there are strong correlations among input-based indicators and output-based indicators as conjectured.

5.2. Contribution of the output-based indicators to productivity growth

As mentioned before, the main reason for measuring the amount of TK is to analyze how TK has contributed to productivity growth as a whole. In this section, we report the usability of the indicators proposed in this study to assess the contribution of TK to productivity growth at the industry level of aggregation.

We followed the standard approach in analyzing the contribution of TK to productivity growth by postulating that technological knowledge, K, is an additional factor of production [11,45–47]. As explained in these papers, we seek to estimate the output elasticity of knowledge, denoted by the parameter γ. This is done by estimating a total factor productivity (TFP) growth equation instead of the full production function, this being one of the approaches used in the literature to estimate the contribution of TK to productivity.

Denoting $\Delta x_{it} = \log X_{it} - \log X_{it-1}$ for any variable X, TFP growth is related to the growth in K by

$$\Delta tfp_{it} = \lambda + \gamma \Delta k_{it} + \Delta \varepsilon_{it} \quad (8)$$

where $\Delta \mathrm{tfp}_{it}$ is the rate of growth of the Solow residual, λ is an exogenous shifter, and $\exp(\varepsilon_{it})$ is a random disturbance multiplying the production function in levels [11].

The data on TFP growth for the manufacturing sector was obtained from the estimates of the U.S. Bureau of Labor Statistics (BLS). This dataset provides TFP growth data for 18 2-digit SIC manufacturing industries for the period between 1949 and 1999. TFP growth was measured by deducting weighted average of the growth rates of each of five inputs: capital, labor, energy, material, and purchased business services inputs from the growth rate of output. For the concordance between ISIC rev. 3.1 and the industrial classification of the BLS, manufacturing industries were reorganized into 16 sectors. The data of 16 U.S. manufacturing industries for the period between 1979 and 1999 was constructed for TFP, PC, PSC, CPS, and VPS, respectively. Eq. (8) is estimated by pooling each industry's 21 observations for the period between 1979 and 1999. Applying PC, PSC, CPS and VPS to the proxy variable for TK respectively, we were able to estimate the output elasticity of TK, γ. The regression model with and without industry/year dummy variable, was classified into 4 models and the results are listed in Table 5.

As a whole, the regression models are statistically significant since the significant probabilities of F-value range from 0.000 to 0.008, with the exception of the PC of model 4. And the adjusted coefficients of determination, $\bar{R}^2$, are higher in model 1 as 0.329–0.349 on the whole. It is the percent of the variation that can be explained by the regression equation and is widely used to determine how well a regression fits. The model 3 will not be discussed here because the estimates of output elasticity of TK are negative for PC, PSC, and CPS. In the model 2, the adjusted coefficients of determination range from 0.099 to 0.213 and those of model 4 vary from 0.000 to 0.067. Based on the above estimates, we can conclude that model 1 is the most appropriate for the investigation of the relationship between TFP and TK. The regressions in model 1 explain about 34% of the changes in TFP growth, but most of the explanation comes from the year dummies. And these results are analogous to the results of the study of [11] which focuses on the estimate of output elasticity of PSC.

The estimates of output elasticity of VPS are higher than the other indicators as 0.219–0.303 for most models and they are statistically significant. The next in ranking is PSC whose estimate range from 0.143 to 0.249, followed by the estimates of CPS which varies from 0.049–0.126. In case of PC, the estimates

Table 5
Estimates of the output elasticity of TK

		PC	PSC	CPS	VPS
Model 1 (year dummy = yes, industry dummy = yes)	γ	0.001	0.157	0.049	0.248
	t (sig.)	0.128 (0.898)	1.951 (0.052)	1.228 (0.220)	2.942 (0.004)
	$\bar{R}^2$	0.329	0.338	0.332	0.349
	F (sig.)	5.463 (0.000)	5.644 (0.000)	5.534 (0.000)	5.876 (0.000)
Model 2 (year dummy = yes, industry dummy = no)	γ	0.012	0.249	0.126	0.303
	t (sig.)	1.069 (0.286)	4.805 (0.000)	4.164 (0.000)	6.690 (0.000)
	$\bar{R}^2$	0.099	0.160	0.145	0.213
	F (sig.)	2.743 (0.000)	4.037 (0.000)	3.698 (0.000)	5.315 (0.000)
Model 3 (year dummy = no, industry dummy = yes)	γ	−0.016	−0.043	−0.001	0.050
	t (sig.)	−1.904 (0.058)	−0.629 (0.530)	−0.027 (0.978)	0.750 (0.454)
	$\bar{R}^2$	0.220	0.212	0.211	0.212
	F (sig.)	6.632 (0.000)	6.363 (0.000)	6.330 (0.000)	6.377 (0.000)
Model 4 (year dummy = no, industry dummy = no)	γ	−0.009	0.143	0.072	0.219
	t (sig.)	−0.945 (0.345)	2.826 (0.005)	2.663 (0.008)	4.904 (0.000)
	$\bar{R}^2$	0.000	0.021	0.019	0.067
	F (sig.)	0.893 (0.345)	7.989 (0.005)	7.094 (0.008)	24.046 (0.000)

are very low. In fact, there are even negative values in models 3 and 4. Based on this, we can conclude that the output-based indicators proposed in this paper, in particular VPS, are more closely correlated with the productivity growth than the conventional indicators, PC and PSC.

6. Conclusions and future research

So far, most of the indicators for measuring the amount of TK have been input-based indicators. Hence, the need to develop output-based indicators has increased over time. Until recently, patent count or patent stock by simple count has been used as output-based indicators to measure the amount of TK. But, the principal problem with this analysis is that the value of individual patent is too heterogeneous. In that respect, the patent count or patent stock by simple count cannot be seen as a suitable measure of TK.

This study attempted to measure the amount of TK by using output-based indicator, that is, patent stock. We have tried to resolve the value-heterogeneity problem related to measuring the patent stock. In this paper, CPS and VPS were proposed and the procedure for calculating them has been depicted in detail. In CPS, the economic value of individual patent was assumed to be proportional to the number of citation received from other patents. But, in the calculation procedure for CPS, the truncation problem occurred because the observation of citation received was truncated by the time axis. In this study, patent citation-lag distribution is adopted to solve this truncation problem. In VPS, the economic value of individual patent was derived from the value distribution of patents that were registered in some cohort. We mentioned before that patentees must pay an annual renewal fee in order to keep their patents in force and that this fee increases with age. A patent owner seeking to maximize the expected discounted value of the net returns to patent protection will renew his patent, if and only if, the current returns are greater than the current cost of renewal. Hence, the patent renewal data implies the value distribution of patents and VPS can be calculated as the similar way for estimating R&D stock if the value of individual patent is obtained from patent renewal data.

And, we performed a validation of the indicators proposed in this paper. We compared them with the usual input-based indicators and then we analyzed the relationships between the indicators and the productivity growth empirically. Based on the correlation analysis results, VPS was found to have a higher correlation coefficients with R&D stock and R&D researchers than CPS, PC and PSC. And the output elasticity of TK hovers around 0.30 in case of VPS, which is greater than the estimates obtained using other patent indicators. These results show that the proposed patent stock, particularly VPS, is a useful indicator for measuring TK. But, in case of CPS, we found that it was less useful in that it was relatively restricted and vague. This might be due to the problem of citation inflation, mentioned in the study of Hall et al. [10]. The number of patents registered has been rising steeply since 1983 and the number of citations made per patent has also increased over time. The combination of more patents making more citations suggests a citation inflation which in turn suggests that later citations are more likely less significant than earlier ones. This could be observed partially in Fig. 2. The CPS of 1999 is estimated by 8.3 times of that of 1979 which we assume to be an outcome of the citation inflation. Hence, in order to use the CPS by the proxy variable for TK, we will need to resolve this problem which will be dealt with in further studies.

By nature, this research represents an exploratory effort toward obtaining a full understanding of the characteristics of TK indicators and measuring the amount of TK. In that respect, it should be noted that the current research is subject to some limitations. First, the set of indicators employed here is by no means exhaustive. An extension of current study is required by including other proxy indicators. Second, as mentioned before, the modification of CPS is necessary. Third, the means of practical use of these indicators have not yet been proposed. Although we investigated the relationships between them and the productivity growth, the application of these indicators has not yet been fully exploited.

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Appendix A. Aggregation of U.S. patent 3-digit technology classes into ISIC rev. 3.1

Industry code	ISIC code	ISIC rev. 3.1	U.S. patent 3-digit technology class
1	15	Food products and beverage	99, 127, 426, 452, 460
2	16	Tobacco products	131
3	17	Textiles	2, 8, 19, 26, 28, 38, 57, 66, 68, 87,139, 442
4	18	Wearing apparel; dressing and dyeing of fur	112, 450
5	19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	12, 24, 36, 54, 69, 150
6	20	Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	142, 144, 212, 217
7	21	Paper and paper products	162, 229, 281, 493
8	22	Publishing, printing and reproduction of recorded media	84, 101, 276, 283, 462
9	23	Coke, refined petroleum products and nuclear fuel	44, 184, 208, 376, 507, 508
10	24	Chemicals and chemical products	23, 48, 55, 71, 95, 96, 102, 134, 137, 149, 201, 203, 204, 205, 239, 250, 401, 416, 422, 423, 424, 427, 429, 430, 435, 436, 501, 502, 504, 510, 512, 514, 516, 518, 520, 521, 522, 523, 524, 525, 526, 527, 528, 530, 534, 536, 540, 544, 546, 548, 549, 552, 554, 556, 558, 560, 562, 564, 568, 570, 585, 800
11	25	Rubber and plastic products	106, 152, 264, 383
12	26	Other non-metallic mineral products	65, 125, 451
13	27	Basic metals	29, 72, 75, 82, 83, 141, 148, 164, 168, 199, 216, 228, 241, 242, 249, 260, 270, 420
14	28	Fabricated metal products, except machinery and equipment	30, 51, 59, 70, 76, 81, 117, 118, 122, 138, 140, 163, 165, 173, 175, 182, 211, 221, 222, 225, 227, 234, 237, 245, 254, 256, 267, 289, 407, 408, 413, 414, 419, 432, 470
15	29	Machinery and equipment n.e.c.	7, 42, 56, 62, 74, 86, 89, 100, 110, 124, 126, 132, 156, 159, 166, 169, 171, 172, 177, 187, 193, 194, 196, 198, 202, 210, 223, 224, 236, 251, 261, 266, 269, 271, 291, 294, 373, 384, 402, 406, 409, 411, 412, 417, 431, 453, 454, 474, 475, 476, 482, 483, 492

(continued on next page)

Appendix A (*continued*)

Industry code	ISIC code	ISIC rev. 3.1	U.S. patent 3-digit technology class
16	30	Office, accounting and computing machinery	235, 341, 345, 347, 360, 365, 369, 380, 382, 395, 400, 700, 701, 702, 704, 706, 707, 708, 709, 710, 711, 712, 713
17	31	Electrical machinery and apparatus n.e.c.	60, 116, 123, 136, 174, 191, 200, 218, 219, 257, 279, 290, 310, 313, 314, 315, 318, 322, 323, 327, 330, 331, 333, 335, 336, 337, 346, 361, 362, 363, 366, 372, 377, 388, 445
18	32	Radio, TV and communication equipment and apparatus	178, 181, 307, 320, 326, 329, 332, 334, 338, 340, 342, 343, 348, 349, 358, 367, 370, 375, 379, 381, 385, 386, 392, 438, 439, 455, 505, 714
19	33	Medical, precision and optical instruments, watches and clocks	33, 73, 128, 324, 351, 352, 353, 355, 356, 359, 368, 374, 378, 396, 399, 433, 494, 503, 600, 601, 602, 604, 606, 607, 623
20	34	Motor vehicles, trailers and semi-trailers	91, 180, 185, 188, 192, 293, 298, 301, 303, 415, 418, 464, 477
21	35	Other transport equipment	104, 105, 114, 157, 213, 238, 246, 278, 280, 295, 296, 305, 410, 440, 441
22	36	Furniture; manufacturing n.e.c.	4, 5, 15, 49, 63, 79, 135, 160, 273, 297, 300, 312, 446, 463, 472, 473
23	37	Recycling	588

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