Passing the European Patent Office: evidence from the data-processing industry

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Abstract

This explorative paper investigates how firms in the global data-processing industry that seek patent protection for their innovations in Europe have coped with the patentability requirements of the European Patent Office. Starting from a continuous research spectrum with basic research on the one extreme and development on the other, the main hypothesis is as follows: firms that carry out more basic research are more successful in passing the patent office than firms that focus more on development. Basic research explores more novel and unknown technical paths, while development aims more at modifying and redesigning existing products. Therefore, the results from more basic-oriented research are expected to fulfill the patentability requirements relatively more often than the results from development. This hypothesis is tested and largely confirmed for the global data-processing industry (with a sample of 44 firms) in the period 1986–1990, using indirect variables for basic research and development. © 1998 Elsevier Science B.V. All rights reserved.

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Keywords: Patent procedure; Patentability requirements; Data-processing industry

1. Introduction

Not all patents applied for are eventually granted by a patent office. Applications must pass a patent granting procedure which examines and selects inventions. In most modern systems, a patent is only granted for an invention that: (i) is new; (ii) involves an inventive step; and (iii) is industrially applicable (Cornish, 1989). This paper is a first and explorative attempt to investigate empirically how firms have coped with these patentability requirements. The analysis focuses on the ‘success ratio’ of an individual firm, which is defined as the proportion of all applications of a firm that are granted a patent. The

The patent-granting procedure, and the way firms have coped with it, has not been studied before. Griliches (1989) provides some estimates of the waiting times between applications and grants in the US patent office. Pakes (1986) and Schankerman and Pakes (1986) use information from the patent procedure (the annual renewal fees) in order to estimate the value of patents already granted. In a sense, the study of Mansfield et al. (1981) is most related to this paper as it examines innovation and imitation strategies in the presence of patent protection.
main hypothesis advanced and tested in this paper is that the success ratio can be explained by the type of research a firm carries out. A firm that carries out more basic research is expected to have a higher success ratio than a firm that carries out development. The patenting performance is studied for firms in one particular industry, the data-processing industry, that have filed applications in one particular patent office, the European Patent Office. Limiting the analysis to a single industry and patent office allows one to make some assumptions about relatively ‘homogeneous’ conditions for all firms. Industry appropriability conditions (Levin et al., 1987), for example, are similar to all firms, and applications are handled by the same group of patent examiners, specialized in the field of data-processing.

The paper is structured as follows. Section 2 explains the main hypothesis tested in this paper. Section 3 describes the two data sets and takes a closer look at the data-processing industry. Section 4 is the core of the paper and presents the estimation results. Section 5 examines the success ratios and the waiting times for different countries in the European Patent Office. Finally, Section 6 offers some concluding remarks.

2. Main hypothesis

The main hypothesis advanced in this paper is that the success ratio can be explained by the type of research of the filing firm. Type of research can be located on the ‘research spectrum’ with at one extreme pure basic research, in the middle oriented basic and applied research, and at the other extreme development. Firms that allocate relatively more resources to the basic research extreme are expected to be more successful with their patent applications than firms that carry out relatively more development.  

\[^2\text{Of course, knowledge from pure basic research (for example, scientific discoveries) is hardly patentable. But this is not the type of research firms usually carry out. What we have in mind are firms that carry out application-oriented research, which can be relatively more directed either towards basic research or towards development.}\]

Innovations that result from it are therefore expected to meet the patentability requirements more often. Development aims more at modifying and redesigning products. Due to the stronger connection with existing products, the innovations are expected to pass the patent office less easily. Assuming a consistent patent office policy, more basic research is thus expected to outperform, with respect to success ratios, development.

3. Description of the data

3.1. The European Patent Office

The European Patent Office (EPO), which performs the administrative tasks of the Munich European Patent Convention (EPC), came into force in the second half of 1978. Since then, firms have been able to apply for a European patent. Rather than applying for separate patents in various European countries, a firm may apply for a European patent, which is valid in all EPC-connected countries the firm chooses. Important parts of national patent laws are still valid for the European patent; there is, as yet, no common European patent law. As expected, the EPO has gradually taken over the work of the national patent offices in Europe. The most important reason for this is that a European patent is often less expensive than various national patents. In practice, patent attorneys suggest following the European route if firms want protection in three or more European countries, in which case a European application is less expensive (see Vanhaverbeke and van Cayseele, 1992 for more evidence on this issue).

The first data set used here contains information on European patent applications. The set is called ‘espace bulletin’ and is published by the EPO six times a year. The CD-ROM used for this study is the fifth of 1993 and contains all patent applications filed in the EPO from June 1978 to August 1993, plus their procedural status. It is possible, for example, to check whether an application has been withdrawn or granted, which firm is the applicant, from which country the applicant originates and to which technical field the invention belongs, according to the International Patent Classification (IPC). A major advantage compared to other sets—for example, that of the US patent office—is that it enables one to
check whether or not an application is approved, and when.

3.2. The data-processing industry

The second data set is on the data-processing industry. The data-processing industry is not synonymous with the computer industry. Although the data-processing industry mainly consists of computer firms, part of the telecommunications industry is also part of it. During the 1960s and 1970s, the market was dominated by IBM and the lead position of IBM has continued to the present. IBM still had the first position in the period 1986–1990, which is the period studied in this study. However, the dominance of IBM decreased in the 1980s. In 1986 IBM had a market share of 28.3% which decreased to 23.5% in 1990. The four-firm revenue concentration ratio was 41.8% in 1986 and 38.4% in 1990. Thus, of the 4.8% loss in market share of IBM, only 1.4% went to the three firms after IBM. This is largely the result of the entrance of Japanese firms (see Duysters and Hagedoorn, 1995 for the internationalisation of the data-processing industry in the 1980s).

The data set used in this study covers the 100 largest firms in the data-processing industry worldwide (by 1990 data-processing revenues) for the period 1986–1990. These data have been collected by a private consulting firm, called the Gartner Group, and are summarized in its report ‘Yardstick Top 100 Worldwide’, September 1991. Table 1 exhibits some key figures of the data-processing industry taken from this data set and the EPO. Combining rows 1 and 2 in Table 1 indicates that the firms active in the market do not tend to concentrate on data-processing: on average, only 31.5% of the corporate revenues originate in the data-processing market. In this data-processing market, the revenues were growing at the high average annual rate of 17.5% in the years 1986–1988, but slowed to 8.2% for the years 1989–1990. The average annual R&D expenditures are 207.7 million. The average R&D intensity (R&D expenditures per revenues) is 9.2%.

4. Determinants of success ratio differences

Having provided some backgrounds of the data sets and the industry, the analysis can now focus on the specific problem posed in the Introduction. As outlined above, the main hypothesis is that firms that carry out relatively more basic research have a higher success ratio than firms that carry out more development. Before presenting the results, first we want to make two comments on the analysis performed. The first comment concerns the explanatory variables used in the estimations. Since the set on the data-processing industry does not contain direct data on the type of research performed by a firm, indirect variables are used that indicate the degree of fundamental research a firm carries out, or is expected to carry out. In Section 4.1, we will explain which variables are included and for what reason.

The second comment involves some assumptions about the patenting behavior of firms. There is no explicit theoretical framework underlying the patenting decision of a firm. This study must be considered as a first and crude attempt to analyse patenting performances. Some assumptions used simplify the analysis considerably and still seem appropriate in a

Table 1
Annual key figures of the top 100 data-processing (DP) firms in 1986–1990 (revenues and expenditures in millions of dollars; employment in # employees)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corporate revenue</td>
<td>7171.1</td>
<td>11,998.3</td>
<td>237.8</td>
<td>59,765</td>
</tr>
<tr>
<td>DP revenue</td>
<td>2259.5</td>
<td>5853.4</td>
<td>207.8</td>
<td>54,891.2</td>
</tr>
<tr>
<td>R&amp;D expenditure DP</td>
<td>207.7</td>
<td>619.7</td>
<td>0</td>
<td>5715</td>
</tr>
<tr>
<td>DP employment</td>
<td>16,563.7</td>
<td>41,136.8</td>
<td>662</td>
<td>375,587.2</td>
</tr>
<tr>
<td>R&amp;D employment DP</td>
<td>1853.1</td>
<td>4181.6</td>
<td>0</td>
<td>35,714.0</td>
</tr>
<tr>
<td># Applications</td>
<td>131.0</td>
<td>327.6</td>
<td>0</td>
<td>1980</td>
</tr>
<tr>
<td># Grants</td>
<td>32.5</td>
<td>91.9</td>
<td>0</td>
<td>619</td>
</tr>
</tbody>
</table>

first exploring study. Firms are, for example, assumed to apply for a patent for any innovation that might be patentable. Because the outcome of the patent procedure is very hard to predict, the probability of success for each firm is assumed to be equal to the unconditional probability of success. Another assumption concerns the legal support for the applicant firm. Patent attorneys or in-house patent departments of large firms are assumed to be equally capable. In other words, we assume a transparent and competitive market for legal support.

Section 4.1 will explain the variables that are included in the estimations. The estimation method and the results are presented in Sections 4.2 and 4.3.

4.1. Variables of specification

The dependent variable is the success ratio of grants to applications for each individual firm in the data-processing industry (‘success’). The success ratio is calculated for EPO applications in the period 1986–1990. We take all applications of a firm in the IPC classes b41*, g06* and h01* (main and supplementary). These classes fairly well describe the data-processing industry. Next, we look at the number of grants until August 1993 resulting from these applications. An application may have been withdrawn by the applicant, disapproved by EPO examiners, or may still be in process. Most of the 1986–1990 applications are still in the examination process. Thus, the success ratio does not give the absolute proportion of applications being awarded a patent. However, the differences between the provisional success ratios are still expected to provide the necessary information on interfirm differences. A priori, there is no reason to believe that the waiting times in the EPO are not identical for each firm. Out of the top 100, 35 firms have not filed an application, so that the success ratio for these firms cannot be calculated. We have carried out regressions including only firms with five or more EPO applications. The sample then reduces to 44 firms. We have taken five applications instead of one in order to reduce the effect of extreme variables (if a firm applies for only one patent and is granted this patent, the success ratio is 1 and a complete outlier compared to the rest).

The available data set does not contain direct data on the type of research. Thus, we are looking for variables that indicate the degree of basic research that firms perform. Most of the explanatory variables presented below are inspired by this notion.

The first explanatory variable proposed is the ratio of patent applications to R&D expenditures, also known as the propensity to patent (Scherer, 1983). This variable, labelled as ‘propens’, is obtained as follows. The total number of applications in the period 1986–1990 is divided by the total R&D expenditures for data processing in that same period. No lag between R&D and patenting is included because there is evidence that most patent applications are filed early in the innovation process (Hall et al., 1986). We thus obtain the number of applications per million dollar of R&D. It should be stressed that the absolute expenditures will not provide information on type of R&D: focussing relatively more on basic research may cost as much focussing more on development. The same argument holds for the R&D intensity, defined as the R&D to revenues ratio. The propensity to patent, however, does provide some information on the type of research performed. Research that is more oriented towards basic research is expected to result in more patent applications per unit expenditure. Think, for example, of a key innovation around which a cluster of improvement patents is possible. More development-oriented research concentrates more on specific products or processes and is therefore expected to generate a smaller number of patent applications. A positive sign is therefore expected for ‘propens’. Notice that besides type of research, the propensity to patent may also reflect learning from and experience with filing patent applications. This reinforces the positive relationship.

The second and third variables are inspired by the notion that diversification induces more basic research. Nelson (1959) and Arrow (1962) have argued that a more diversified firm can spread risks better and is therefore more inclined to do basic research. Moreover, the output of basic research can be used in more, maybe unexpected, market segments, making the payoff of basic research higher. This is
particularly true for companies in the data-processing industry.

In a recent study (Duysters and Hagedoorn, 1995), empirical research on the same set of data-processing companies has shown that the internally generated technological core competencies of these companies can be applied beyond the traditional data-processing industry. Firms with a combination of a strong and coherent technology base and more diversified sales were found to perform significantly better than companies that were more specialized in terms of their sales orientation. This is in line with the increased recognition that technological convergence is one of the major driving forces of technological and economic developments in the data-processing market (Georgiou et al., 1986; de Jonquieres, 1989; Forester, 1993; Duysters and Hagedoorn, 1998). For a very long time, technological development in the various information technology markets has followed very distinct trajectories. Today, the basic design parameters which form the core of technological regimes (Georgiou et al., 1986) have become increasingly similar, not only in terms of the material properties but also with respect to the manufacturing process involved. Technological convergence is therefore gradually removing the sectoral boundaries between the various information technology industry segments. Another recent study (Duysters and Hagedoorn, 1998) has shown that data-processing companies are focusing their basic research in three major fields: computers, telecommunications and micro-electronics. Because of the effects of the convergence process, a basic knowledge base consisting of computer, telecommunications and microelectronic know-how can be effectively applied to three basic industries: the computer industry, the telecommunications industry and the microelectronics industry. Moreover, basic research in one of these areas can be applied to each of these three industries. As mentioned previously, basic research leads to more successful patenting because the novelty requirements are met more easily. In the data-processing industry, technological competition takes place on the level of the sophistication of components (Duysters, 1996). The complex character of these components in combination with the cumulative and path dependent character of technological knowledge (Nelson and Winter, 1982; Dosi, 1988) enhances the need for basic research. An in-depth analysis of the data-processing industry (Duysters, 1996) has shown that the field where most progress can be made is on the level of the individual components. Because of the scientific character of research in this area, basic research is a necessity to innovate. Novelties can hardly be created by merely putting together different sets of components. Therefore, we contend that basic research is more important to generate innovations than system knowledge and complementarities.

In this paper, we distinguish internal from external diversification. By internal, we mean diversification within the data-processing market. A measure for internal diversification is the number of DP market segments in which the firm has been active in the period 1986–1990, divided by the total number of segments during that period. We label this variable as ‘divers’ and expect a positive sign for it. The segments within the data-processing market are mainframes, superminis, minicomputers, microcomputers, CAD/CAM/CAE, peripherals, data communication hardware, software, maintenance, service and other. Over the period (5 years) concerned, the total number of segments was 55. The variable ‘divers’ is thus continuous by approximation. The other variable is associated with the degree of external diversification of a firm. This variable is defined as the total revenues from the data-processing market divided by the total corporate revenues, for the period 1986–1990. Label this variable as ‘specialis’. The same arguments as in the case of internal diversification can be used to justify the inclusion of ‘specialis’. A negative sign is therefore expected. However, it is felt that, since the spill-overs within the market are probably stronger than those coming from outside the market, ‘specialis’ will play a less important role than ‘divers’.

The fourth explanatory variable is proposed to describe the main focus of a firm, which can either be on innovation or on marketing. Define the variable ‘market’ as the ratio of Sales and Marketing employees to R&D employees in data processing. A firm that stresses R&D and wants to compete primarily through innovation is expected to know the technical fields and current patents better and thus to have a higher success ratio. In contrast, a firm that focuses on sales and marketing, as a means to compete knows less of the existing technologies in the
market, has less patenting experience, and is thus expected to achieve a lower success ratio. A negative sign is expected for ‘market’. The next variable is concerned with the personnel in the research department. Let ‘rdequip’ be defined as the R & D expenditures per R & D employee. The idea behind this variable is that researchers involved in basic research have more equipment at their disposal. So a positive sign is expected for this variable.

The final two variables are suggested to catch some fixed effects. The first is a country dummy. Each country has a different national patent system, which may affect the strategies of firms as well as the experience with patent offices in general. Furthermore, the waiting times of processing in the EPO may differ between the countries of origin of the applicants. Some countries may have to wait longer than other countries. The data-processing firms are divided into three groups by region of origin (of their headquarters): United States (‘US’), Japan (‘JP’) and Europe (‘EC’). The regressions will include two of the three dummies (‘US’ and ‘JP’).

The second dummy variable included indicates the primary market segment (by revenue) in which the firm is active. The 11 segments are regrouped into three. The first (‘computer’) contains the core of the data-processing industry with the mainframe, supermini, minicomputer and microcomputer segments. The second group (‘noncore’) contains the CAD/CAM/CAE, peripheral and data communication segments. Finally, the third group contains the software, services and maintenance segments (‘support’). We expect that ‘computer’ and ‘noncore’ play a larger role than ‘support’, because this last group contains such segments as service and software, which rarely can be protected by patents.

4.2. Estimation method

Ordinary Least Squares (OLS) estimations can cause problems in the context studied here because the dependent variable ‘success’ cannot be smaller than 0 or greater than 1 and is thus doubly truncated (see Maddala, 1983 for more details on truncated and censored variables). Instead of OLS, a two-limit (also known as ‘doubly truncated’) Tobit estimation model is more appropriate. The Tobit model deals properly with the lower limit of 0 and the upper limit of 1 of the dependent variable ‘success’. In fact, the two-limit Tobit model provides three estimates: (i) of the chance that the success ratio is zero, i.e., whether or not a firm is granted at least one patent (this is a probit); (ii) of the chance that all applications are granted a patent (another probit); and (iii) of the success ratio, given that it is not equal to 0 or 1 (regression part).

4.3. Results

Three equations have been estimated: one with all the variables outlined above, one with exclusion of the market segment dummies, and finally one with ‘divers’ as the only explanatory variable.

The variable for internal diversification, ‘divers’, performs very well; it has the expected sign and is statistically highly significant. Notice that in the estimation with ‘divers’ as the only explanatory variable (iii), the standard error of the estimation is only a small fraction larger than in the estimations including all explanatory variables (i). So ‘divers’ is the most important variable in the estimations.

Since larger firms are more diversified in general, one might object that firm size does the job rather than the degree of diversification. In order to check for that, we have defined ‘dprev’, the revenues in the period 1986–1990, as an indication of size. The variables ‘divers’ and ‘dprev’ indeed correlate significantly. The two-limit Tobit estimation with ‘dprev’ as the explanatory variable is given by: success = 0.1694 + 5.703q + 5.5318E + 7(1.349)dprev. ‘Dprev’ is statistically not significant at the 5% level, while ‘divers’ is highly significant if it is the only explanatory variable (check (iii) in Table 2). Thus, it can be concluded that diversification has more power than firm size in explaining the success ratios.

The next variable, ‘propens’, performs well in regression (ii); it has the expected sign and is statistically significant at the 0.5% level. Therefore, it can be concluded that a high propensity to patent (applications to R & D expenditures ratio) of a firm in the data-processing industry is indeed an indication of
Table 2
Results of the two-limit Tobit estimations

<table>
<thead>
<tr>
<th>Variable</th>
<th>(i)</th>
<th>(ii)</th>
<th>(iii)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.2068 (2.167)</td>
<td>0.1798 (2.070)</td>
<td>−0.0218 (0.360)</td>
</tr>
<tr>
<td>Divers</td>
<td>0.2922 (2.858)</td>
<td>0.2779 (3.299)</td>
<td>0.3574 (3.394)</td>
</tr>
<tr>
<td>Propens</td>
<td>0.0306 (0.867)</td>
<td>0.0616 (2.819)</td>
<td>−</td>
</tr>
<tr>
<td>US</td>
<td>−0.1728 (−2.554)</td>
<td>−0.2083 (−3.586)</td>
<td>−</td>
</tr>
<tr>
<td>JP</td>
<td>−0.1703 (−2.865)</td>
<td>−0.1794 (−3.015)</td>
<td>−</td>
</tr>
<tr>
<td>Computer</td>
<td>0.0273 (0.307)</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>Noncore</td>
<td>0.0275 (0.412)</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>Specials</td>
<td>−0.0990 (−1.235)</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>Market</td>
<td>−0.0003 (−0.024)</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>Rdequip</td>
<td>−0.1497 (−0.718)</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>Mean log-lik.</td>
<td>21.011</td>
<td>19.54</td>
<td>11.603</td>
</tr>
<tr>
<td>Std. error</td>
<td>0.1113</td>
<td>0.1147</td>
<td>0.1421</td>
</tr>
<tr>
<td># Cases</td>
<td>44</td>
<td>44</td>
<td>44</td>
</tr>
</tbody>
</table>

The dependent variable is ‘success’. Numbers in parentheses are t-statistics. The standard errors used to calculate these t-statistics are heteroscedastic-consistent estimates.

The degree of fundamental research and as such associated with good patenting performance.

The country dummy variables ‘US’ and ‘JP’ perform very well in the (i) and (ii) estimations. They both have a negative sign, statistically significant at the 1% level. So US and Japanese firms have lower success ratios than European firms. Section 5 studies these country differences in more detail. The market segment dummy variables perform rather poorly.

5. National waiting times and success ratios

The results with respect to the country dummies in the above regressions (i) and (ii) indicate that US and Japanese data-processing firms have significantly lower success ratios than European firms for their applications during 1986–1990. There are two possible reasons for this. First, US and Japanese firms may have to wait longer for their grants. Fewer of their 1986–1990 applications are then processed, resulting in lower success ratios. This possibility will be examined in Section 5.1. A second reason may be that US and Japanese firms just perform worse because of their country of origin, while European firms may perform systematically better in the EPO. This possibility will be examined in Section 5.2.

5.1. National waiting times

The waiting times for the data-processing industry are first determined for the year of application 1986 and are calculated as follows. We have taken all applications of a country in 1986 and checked how many of those were granted a patent in the period 1986 to August 1993. Next, we checked how many of these total grants were granted after how many years. The categories of waiting times are: 2 and less, 3, 4, 5, 6 and 7 and more years. We have examined the waiting times for the US, Japan, Germany, France and the United Kingdom. For each of these countries, a cumulative distribution of their waiting times has been constructed. Using the Kolmogorov–Smirnov test, we have tested in pairs whether these lag distributions differ. The null hypothesis is that distributions do not differ. The alternative hypothesis is that m must wait longer than n, where m and n are the total grants of a country. The Kolmogorov–Smirnov test statistic \( D_{m,n} \) is the largest difference between the cumulative distribution of \( m \) and that of \( n \). Given the large samples and the one-tailed test we want to perform, we can use the statistic \( X^2 = 4D^2_{m,n} mn/(m+n) \) which is approximated by the Chi-square distribution with 2 df (Siegel and Castellan, 1988). Table 3 summarizes the results.

From the Kolmogorov–Smirnov tests in Table 3, a country ranking can be constructed for the waiting times.

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The Kolmogorov–Smirnov test is a nonparametric test which can be used to check whether two (or more) distributions have an identical distribution underlying them. For more details, see Siegel and Castellan (1988).
Table 3
National differences in waiting times in the data-processing industry in 1986

<table>
<thead>
<tr>
<th>Countries</th>
<th>Kolmogorov–Smirnov statistic</th>
<th>$X^2$</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m = 315$ French grants $n = 640$ German grants</td>
<td>$D_{m,n} = 0.0997$</td>
<td>8.390</td>
<td>0.02 &gt; $p &gt; 0.01$</td>
</tr>
<tr>
<td>$m = 640$ German grants $n = 127$ UK grants</td>
<td>$D_{m,n} = 0.1268$</td>
<td>6.812</td>
<td>0.05 &gt; $p &gt; 0.02$</td>
</tr>
<tr>
<td>$m = 127$ UK grants $n = 950$ US grants</td>
<td>$D_{m,n} = 0.1938$</td>
<td>16.837</td>
<td>$p &lt; 0.001$</td>
</tr>
<tr>
<td>$m = 950$ US grants $n = 767$ Japan grants</td>
<td>$D_{m,n} = 0.0430$</td>
<td>3.132</td>
<td>0.30 &gt; $p &gt; 0.20$</td>
</tr>
</tbody>
</table>

Source: EPO Espace Bulletin 1993/5.

In order of decreasing waiting time, the ranking which emerges is: (1) Japan; (2) US; (3) UK; (4) Germany; and (5) France. Only the difference between the US and Japan is not significant at the 5% level. The higher speed of processing European applications, as given by the British, German and French applications, might thus partially explain the higher success ratios of European firms found in the regressions in Section 3.

In order to get larger samples and to check whether these differences in processing speed have been existing from the start, we have carried out identical tests for data-processing applications filed in the period 1978–1985. Exactly the same order of waiting times also emerges from these samples. All differences are highly significant (< 0.1% level). We have furthermore checked whether this phenomenon is specific to the data-processing industry. All applications granted (i.e., in all IPC classes) in the period 1978–1985 were incorporated and, again, exactly the same order as before is found with very strong evidence. It can thus be concluded that the difference in waiting times is not specific to the data-processing industry. We should emphasize here that we have only detected the differences in national waiting times. It is outside the scope of this study to examine possible reasons for the differences (maybe they are due to preferential treatment given by the EPO to European applicants or to the organizational structure within the EPO).

5.2. National success ratios

In order to isolate the differences in EPO success ratios of countries from the differences in waiting times, we will focus on the period 1978–1985. The vast majority of applications during that period were processed by August 1993 for each country. Thus, differences in waiting times do not affect differences in success ratios. Table 4 presents the success ratios of countries in the data-processing IPC classes as well as the overall success ratios of countries.

The overall success ratios do not seem to differ much from the ratios in the data-processing classes for each country. The examination of data-processing files thus appears to be not more or less stringent than that of other files. From Table 4, it can furthermore be concluded that the lower success ratio of Japan, which was found in the data-processing industry in Section 4, is a severe misrepresentation. Japanese firms generally perform better than European firms, both in data processing and overall.

How can these differences in EPO success ratios of countries be explained? One possible explanation may be found in the novelty requirements of the national patent offices. If applicants are used to stringent examination, they are more likely to carefully select the inventions they file. In a less stringent system, they would then perform better than applicants who are used to looser national examination. For countries outside the EPC, one might bring forward the argument that their national offices have already screened the applications, because those applicants may be expected to first file in their national

Table 4
EPO success ratios during 1978–1985

<table>
<thead>
<tr>
<th>Country</th>
<th>Data processing</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Japan</td>
<td>0.855</td>
<td>0.833</td>
</tr>
<tr>
<td>France</td>
<td>0.785</td>
<td>0.762</td>
</tr>
<tr>
<td>Germany</td>
<td>0.717</td>
<td>0.731</td>
</tr>
<tr>
<td>US</td>
<td>0.659</td>
<td>0.623</td>
</tr>
<tr>
<td>UK</td>
<td>0.552</td>
<td>0.581</td>
</tr>
</tbody>
</table>

Source: EPO Espace Bulletin 1993/5.
office and then in the EPO. The better the screening (i.e., the higher the novelty requirements), the higher the success ratio for that country in the EPO. We thus expect lower national success ratios to lead to higher EPO success ratios. The national success ratios are taken from the WIPO publication ‘100 Years Protection of Industrial Property’, which contains the total number of applications and patents granted in a country for the period 1883–1982. We assume that the national patent offices treated residents and nonresidents in the same way. The national success ratios then indicate the experience of national applicants with their patent office. The EPO success ratios have been calculated for the period 1978–1985 because, as indicated previously, almost all applications from that period were processed by August 1993. The sample contains 36 countries (all countries we could find data for, both in the EPO and in the WIPO publications). For reasons outlined above, a two-limit Tobit model is used again. With the EPO success ratios (‘eposuccess’) as dependent and the national success ratios (‘natsuccess’) as independent variable, the estimation is given by:

\[
\text{eposuccess} = 0.7392(10.891) - 0.2581(2.648)\text{natsuccess}.
\]

The coefficients of ‘natsuccess’ has the expected sign and is statistically significant at a 0.5% level. It can thus be concluded that national success ratios are indeed of influence in explaining the EPO success ratios.

The argument brought forward above might be called ‘Porterian’ in the sense that stronger domestic screening implies better foreign performance. Another, more indirect and speculative, reason behind the inverse relationship might be found in the type of incentive provided by a patent system. A patent system that sets high barriers for applicants, by means of high novelty requirements, may induce

6 This is also common practice for much European applicants.

7 The following countries have been included: Argentina, Australia, Austria, Belgium, Brasil, Bulgaria, Canada, Cyprus, (former) Czechoslovakia, Denmark, Finland, France, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Malta, Netherlands, New Zealand, Norway, Poland, Portugal, (former) Soviet Union, South Africa, Spain, Sweden, Switzerland, Turkey, UK, US, (former) West-Germany, (former) Yugoslavia.

8 As explained by Porter (1990).

6. Conclusions

This paper provides a first and exploring empirical analysis of the way firms cope with the patentability requirements of patent offices. The main hypothesis is that the proportion of successful applications of a firm depends on the type of underlying research. More basic research leads to more successful applications than more development-oriented research. The argument is that more basic research explores more novel and unknown paths, only weakly related to existing products, and therefore meets the patentability requirements more often. At the other extreme, development aims at modifying and redesigning existing products is more closely connected to these products, and consequently its fruits less easily pass the patent office.

This hypothesis has been tested for the data-processing industry in the period 1986–1990. Since no direct data on basic research vs. development were available, the success ratios of data-processing firms in the EPO are explained by indirect variables indicating the (expected) degree of basic research. One such variable is diversification. As argued by Nelson (1959) and Arrow (1962), more diversified firms are expected to do more basic research because they can better spread the risks and apply the results in more fields. Indeed, the variable for diversification within the data-processing market turns out to be the most important in explaining the success ratios. Another variable, the propensity to patent, also performs well. More basic research does not only result in more patent applications but also in better patenting performance.

Another result is that US and Japanese firms achieved lower success ratios for their applications in the period 1986–1990. However, it is found that this is due to the longer waiting times between applications and patents granted in the EPO for US and Japanese firms, compared to European firms. Without this difference in waiting times, Japanese applicants in general have higher success ratios than European and US applicants. Moreover, we have found some evidence that national patent offices act
as screening institutes for the EPO. Countries without stringent screening, visualized by low novelty requirements, perform worse in the EPO than countries that apply more stringent screening.

Finally, it must be stressed that this paper has a strongly explorative nature. Future research must develop a theoretical model for patent application decisions of firms. Other industries besides the data-processing industry should be studied to check for the robustness of the results (preferably using data sets with direct variables about the type of research). The reason behind the longer waiting times for Japanese and US firms should be studied more carefully.

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References


