

**Passing the European Patent Office: Evidence
from the Data-Processing Industry**

Theon van Dijk

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EVIDENCE FROM THE DATA-PROCESSING INDUSTRY**

by

Theon van Dijk
MERIT, University of Limburg
P.O. Box 616, 6200 MD, Maastricht

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ABSTRACT

This paper argues that firms pursuing pioneering innovation strategies are more successful in obtaining patent protection than firms pursuing imitative innovation strategies. A pioneering strategy requires more basic research, which explores novel and unknown technical paths. The novelty requirements of the patent office are therefore met more easily. An imitative strategy aims at modifying and redesigning products with applied research and development. Due to the stronger connection with existing products, imitative research outcomes pass the patent office less easily. This hypothesis is tested for the global data-processing industry (100 firms) in the period 1986-1990. My goal is to explain the grants-to-applications ratios of individual firms in the European Patent Office (EPO) using instrumental variables, such as diversification, that indicate the degree of fundamental research. The hypothesis is confirmed. Another result is that, compared to European firms, US and Japanese firms have to wait longer before their EPO applications are processed (*JEL Codes L63, O19, O34*; *Key words*: patent procedure, innovation strategies, data-processing industry)

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1. Introduction and Theoretical Backgrounds

Not all patents applied for are eventually granted. Applications must pass a granting procedure which examines and selects inventions. In most systems a patent is only granted for an invention (i) that is new; (ii) involves an inventive step; and (iii) is industrially applicable. This paper analyzes the success ratio, defined as the proportion of all applications granted a patent, of individual firms in a particular sector: the data-processing industry. What factors determine the success ratio of a firm? As this question is examined for one specific industry, the limitation of analyzing one single industry must be acknowledged. Limiting the analysis to a single industry allows one to make some assumptions about relatively "homogeneous" conditions for all firms. I will not try to answer the question using juridical variables. Thus, interfirm success ratio differences are not, for example, looked for in patent attorneys which may differ in quality. On this point I assume a transparent and competitive market for legal support. The same holds for in-house patent departments of large firms. These departments are assumed to be equally capable.

This paper examines whether the success ratio can be explained by the type of innovation strategy of the applicant firm. The basic theory underlying this analysis has been described Van Dijk (1993) and will only be roughly sketched here. There are similarities between types of product differentiation and innovation strategies. As Comanor (1967) has pointed out, an important goal of research and development (R&D) is to achieve product differentiation. A firm which differentiates itself from competitors thereby creates some market power. Although the prospect of market power provides some incentive to perform R&D, the incentive is stronger in the case of patent protection. As explained in Van Dijk (1993), a patent defines a protected region around the product, which competitors are not allowed to trespass with their differentiations. This area of protection might well be larger than the natural distances evolving from free competition. The presence of a patent system therefore provides stronger incentives to invest in product differentiation than would otherwise be the case. The address branch of the product differentiation literature (see Eaton and Lipsey (1989)

for an overview) distinguishes two types of differentiation. The first is horizontal differentiation and is relevant if not all consumers agree on the most preferred variety. For example, some consumers prefer a red car while others prefer the same car in white. The second type is vertical product differentiation. The most obvious form of this type is quality. At equal prices, all consumers will prefer a higher to a lower quality.

There is a parallel between these two types of differentiation and two major categories of innovation strategies that can be observed in business practice. The classification here is a simplification of Freeman (1982) to two basic types of strategies. The first is a *pioneering* innovation strategy. Firms that have adopted pioneering innovation strategies allocate more resources to basic research. Their major goal is to generate new or improved products and processes. These innovations are protected primarily by means of patents. Firms pursuing pioneering strategies can rely on patent protection because most innovations they generate are sufficiently novel to pass the patent office. Improvements, but also new products, can be considered as vertical differentiations of existing substitutes. Each consumer will prefer, at equal prices, an improvement to an older version of the product. The other possible strategy is an *imitative* innovation strategy, where more resources are allocated to applied research and development, rather than basic research. The major goal of defensive firms is not to be first with an innovation, but to keep up with the technological leaders in the industry. Their imitations are not basically different but mainly modifications of original innovations. They might be considered horizontal differentiations.

The patenting performance of the two innovation strategies is examined under a single patent system, in this case the European Patent System. Given a consistent patent office policy, pioneering innovation strategies are expected to outperform, with respect to success ratios, imitative strategies. The argument is that a pioneering strategy requires more basic research, which explores novel and unknown technical paths. The novelty requirements of the patent office are therefore met more easily. An imitative strategy aims at modifying and redesigning products with applied research and development. Due to the stronger connection with

existing products, the fruits of imitative research pass the patent office less easily.

The underlying study is the first to examine the patent-granting procedure in detail. Griliches (1989) provides some estimates of the waiting times between applications and grants in the US patent office in describing the patent procedure. Pakes (1986) and Schankerman and Pakes (1986) use information from the patent procedure, i.e., the annual renewal fees, in order to estimate the value of patents already granted. They do not, however, examine the possible relation between the value of a patent and the underlying research and development. The study of Mansfield, Schwartz and Wagner (1981) is most related to the present study as it examines innovation and imitation strategies in the presence of patent protection.

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

2. Description of the Data

(a) 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 general, 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 1993 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.

(b) The Data-Processing Industry

The second data set used here 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 telecommunication 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 1994 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%.

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)

	Mean	Standard Deviation	Minimum	Maximum
Corporate Revenue	7,171.1	11,998.3	237.8	59,765
DP Revenue	2,259.5	5,853.4	207.8	54,891.2
R&D expenditure DP	207.7	619.7	0	5,715
DP Employment	16,563.7	41,136.8	662	375,587.2
R&D Employment DP	1,853.1	4,181.6	0	35,714.0
# Applications	131.0	327.6	0	1980
# Grants	32.5	91.9	0	619

3. 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. First, I will explain the variables that are included in the estimations. The estimation method and the results are presented in the next subsections.

(a) 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. I 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, I 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 lags in the EPO are not identical for each firm¹ (section 4 will address this issue).

Out of the top 100, 35 firms have not filed an application, so that the success ratio for these firms cannot be calculated. In one series of regressions, I have therefore set the success ratios for these firms equal to zero. The reason for doing so is that the fact itself that a firm does not apply for a patent does provide useful information about its innovation strategy. The absence of applications strongly suggests an imitative strategy. In order to check for the impact of this operation, I have carried out another series of regressions including only firms with 5 or more EPO applications. The sample then reduces to 44 firms. I have taken 5 applications instead of 1 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 basic theory behind the success ratio was explained in section 1. To recapitulate, the hypothesis is that a pioneering strategy, aiming at new or improved products and processes

1. Actually, some country dummies are introduced to deal with possible differences in waiting lags.

using of basic research, has a higher success ratio than a defensive innovation strategy, which is aimed at imitation and keeping up. The available data set does not contain direct data concerning the distinction between basic and applied research expenditures. Thus, I am looking for instrumental variables that indicate the degree of basic research that firms perform, or are expected to perform. Most of the independent variables presented below are inspired by this notion.

The first explaining variable proposed is the ratio of patent applications to R&D expenditures, also known as the propensity to patent (see 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, Griliches and Hausman 1986). I thus obtain the number of applications per million dollar of R&D. It should be stressed that the absolute R&D expenditures will not provide information on the strategies chosen: imitation may cost as much R&D as improvement. 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. Following a pioneering strategy, much R&D results in patent applications. Imitative strategies yield less patentable output, and result in a smaller number of applications per unit of R&D expenditures. A positive sign is therefore expected for '*propens*'.

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 pay-off of basic research higher. As mentioned previously, basic research leads to more successful patenting because the novelty requirements are met more easily. In this study, I distinguish internal from external diversification. By *internal*, I mean the diversification within the data-

processing market. A measure for the 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. Label this variable as '*divers*'. I expect a positive sign for '*divers*'. 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 *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 to 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 explaining 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 lags 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').² 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 3. 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*'). I 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.

(b) Estimation Method

Ordinary Least Squares (OLS) estimations can cause two problems in the context studied here. First, the dependent variable 'success' cannot be smaller than 0 or greater than 1 and is thus doubly truncated: values smaller than 0 must be set equal to 0 and values greater than 1 must be set equal to 1 (see Maddala 1983 for more details on truncated and censored variables). The second problem is caused by the many zero observations for the variable 'success', especially in the large sample series (A). These zero observations can "force" the constant of the estimated OLS line too much toward zero. Instead of OLS, a two-limit (also known as 'doubly truncated') Tobit estimation model is more appropriate for two reasons. First, the Tobit model deals properly with the lower limit of 0 and the upper limit of 1 of the dependent variable 'success'. Second, the Tobit model also takes into account the many zero

2. The US group contains 62 firms (including one Canadian firm), the Japanese group 19 firms (including three Taiwanese firms) and the European group 19 firms.

observations of the 'success' variable (which is particularly important in the (A) series). 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).

(c) Results

Two series of Tobit estimations are carried out. Table 2 summarizes the results: in one series (A in table 2) the success ratio of firms that have not filed any applications in the EPO in the period 1986-1990, is set equal to 0. In the other (B), firms with fewer than 5 applications are expelled. The major difference between the A-series and the B-series of estimations is the constant term. In the A-series, the constant has a negative sign (all significant at a 0.5% level) indicating the presence of a threshold. Since in the B-series the constant has a positive sign, the firms with fewer than 5 applications face the threshold and cause the negative sign of the constant in the A-series. According to estimation A (iv), for example, where 'divers' is the only explaining variable, a minimum level of internal diversification is required (in this case $0.3309/0.7018 \approx 0.47$, i.e, on average a firm has to be active in about 5 of the total 11 market segments) in order to be granted a patent.

Table 2

Results of the two-limit Tobit estimations

Series	A				B		
Variable	(i)	(ii)	(iii)	(iv)	(i)	(ii)	(iii)
Constant	-0.4039 (-3.007)	-0.4751 (-4.546)	-0.3403 (-4.151)	-0.3309 (-5.139)	0.2068 (2.167)	0.1798 (2.070)	-0.0218 (-0.360)
Divers	0.6458 (4.944)	0.6818 (5.321)	0.6692 (7.629)	0.7018 (7.521)	0.2922 (2.858)	0.2779 (3.299)	0.3574 (3.394)
Propens	0.1635 (3.314)	0.1992 (4.029)	0.2165 (3.005)	-	0.0306 (0.867)	0.0616 (2.819)	-
US	0.0450 (0.562)	0.0216 (0.288)	0.0066 (0.089)	-	-0.1728 (-2.554)	-0.2083 (-3.586)	-
JP	-0.0932 (-1.155)	-0.0952 (-1.168)	-0.0664 (-0.759)	-	-0.1703 (-2.865)	-0.1794 (-3.015)	-
Computer	0.1836 (1.569)	0.1056 (0.907)	-	-	0.0273 (0.307)	-	-
Noncore	0.2558 (2.691)	0.2313 (2.472)	-	-	0.0275 (0.412)	-	-
Specialis	-0.1416 (-1.525)	-	-	-	-0.0990 (-1.235)	-	-
Market	-0.0183 (-0.586)	-	-	-	-0.0003 (-0.024)	-	-
Rdequip	-0.2581 (-0.871)	-	-	-	-0.1497 (-0.718)	-	-
Mean log-lik.	-19.055	-20.287	-24.371	-29.091	21.011	19.540	11.603
Std. error	0.2248	0.2282	0.2408	0.2542	0.1113	0.1147	0.1421
# Cases	100	100	100	100	44	44	44

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

I will discuss the estimation results per variable, starting with those that perform relatively badly. The first is 'rdequip'. The equipment per R&D employee does not have the expected effect on the success ratio. Both in A (i) and in B (i), the variable 'rdequip' does not have a positive sign. Since both coefficients are statistically not significant at the 10% level, no conclusions can be drawn about the effects of the R&D expenditures per R&D employee on the success of passing the EPO. The second variable is 'market'. This variable, which was constructed to catch the main focus of a firm, on marketing or on innovation, does not perform well. 'Market' does not have the expected sign in estimation A(i), while it does have it in B (i). In both cases, however, the coefficient is not significant at the 10% level. Firms pursuing pioneering strategies apparently take into account the marketing of their products as much as firms pursuing imitative strategies. Thirdly, the variable 'specialis', included as an indication of the external diversification of a firm, has the expected negative sign in both A (i) and B (i). But this variable is only significant at the 10% level in A (i) and not in B (i). Thus, external diversification, for spreading risks and absorbing spill-overs from outside the data-processing market, does not seem to be very important in explaining the success ratios.

The results concerning the dummy variables for market segments and countries are mixed. The segment dummies 'computer' and 'noncore' in equations A (i) and (ii) have the expected positive sign. But only 'noncore' firms, and not 'computer' firms, have significantly higher success ratios than 'support' firms (at the 5% level). However, this conclusion does not hold for the B (i) estimation: both segment dummies are not significant at the 10% level. The country dummy variables 'US' and 'JP' perform very well in the B (i) and B (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 4 studies these country differences in more detail. The country dummies do not perform well in the A-series; in all of the estimations both dummies are not significant at the 10% level.

The next variable, 'propens', performs well in general; it has the expected sign and is statistically significant at the 0.5% level in all regressions but B(i). 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 the degree of fundamental research and as such associated with good patenting performance.

Finally, the variable for internal diversification, 'divers', performs very well. In each of the seven estimations (A-series and B-series), this variable has the expected sign and is statistically highly significant. Notice that in the estimations with 'divers' as the only explaining variable, i.e., A (iv) and B (iii), the standard error of the estimation is only a small fraction larger than in the estimations including all explaining variables (A (i) and B (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, I 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 (necessary because 'divers' also lies between 0 and 1, inclusive) for the large sample (A-series, 100 cases) is given by: $\text{divers} = 0.3631 (14.840) + 1.5635\text{E-}6 (3.918) \text{dprev}$ (t-values in parentheses). The relation is less strong for the small sample (B-series, 44 cases): $\text{divers} = 0.5052 (13.566) + 2.4178\text{E-}6 (1.849) \text{dprev}$. However, 'dprev' performs worse than 'divers' in explaining the success ratios. For the large sample, the Tobit method results in the following estimation: $\text{success} = -0.1607 (-2.353) + 1.7039\text{E-}6 (5.049) \text{dprev}$. The sign of 'dprev' is the expected one and significant at the 0.1% level. However, compared to estimation A (iv), with 'divers' being the only explaining variable, the t-statistic of 'dprev' in the above estimation is smaller (5.049 compared to 7.521 in A (iv)), and the standard error of the estimation is larger (0.3842 compared to 0.2542 in A (iv)). Therefore, for the large sample it can be concluded that internal diversification has more influence than size in explaining the success ratios. For the small sample this conclusion holds even stronger. The Tobit model yields the following estimation: $\text{success} = 0.1694 (5.703) + 5.5318\text{E-}7 (1.349) \text{dprev}$. 'Dprev' is statistically not significant at the 5% level, while 'divers' is highly significant if it is the only explaining variable (check B (iii)).

Thus, also for the small sample, it can be concluded that diversification has more influence than firm size in explaining the success ratios.

Finally, I have checked whether there is a relation between the success ratio and the profitability of a firm. To correct for the size effect, I have taken as the profitability variable the DP operating income over the period 1986-1990 divided by the DP revenues for that same period. For the sample of all 100 firms, an OLS regression is performed with profitability as dependent and success ratio as independent variable. The coefficient of the success ratio has a negative sign, but is statistically not significant at a 10% level. The adjusted R^2 is very low (about 1%). The same regression is also performed for the smaller sample of 44 firms with 5 and more applications. Again, the coefficient of the success ratio has a negative sign but is now statistically significant at a 5% level. The explained variance of profitability (adj. R^2) is equal to 8.1%. One should, however, be very careful in interpreting these results. It is not necessary so (and even doubtful) that, since the success ratio is inversely related to profitability, pioneering innovation strategies are more profitable than imitative strategies. The country effect can also be important. We saw that US and Japanese firms have lower success ratios in the period 1986-1990. If US and/or Japanese firms are more profitable, we would thus also get a negative sign. For the large sample of 100 firms, I found no evidence for US or Japanese firms being more profitable. For the smaller sample, however, there does seem to be some evidence. US firms are more profitable than European firms (significant at a 5% level), while Japanese firms are not. Thus, there is some evidence that the inverse relationship between success ratio and profitability is related to country differences. In fact, as we will see in the next section, Japanese and US firms have a lower success ratio than European firms over the period 1986-1990 partially because they have to wait longer for their grants.

4. National Waiting Lags and Success Ratios

The results with respect to the country dummies in the above regressions (the B-series) 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 to explain 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 subsection (a). 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 subsection (b).

(a) National Waiting Lags

The waiting lags for the data-processing industry are first determined for the year of application 1986 and are calculated as follows. I 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, I checked how many of these total grants were granted after how many years. The categories of waiting lags are: 2 (and less), 3, 4, 5, 6 and 7 (and more) years. I have examined the waiting lags for the US, Japan, Germany, France and the United Kingdom. For each of these countries, a cumulative distribution of their waiting lags has been constructed. Using the Kolmogorov-Smirnov test³, I 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 I want to perform, I can use the statistic $X^2 = 4D_{m,n}^2 mn / (m + n)$ which is approximated by the Chi-square distribution with 2 degrees of freedom (Siegel and Castellan Jr. 1988). Table 3

3. The Kolmogorov-Smirnov test is a non-parametric 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 Jr. (1988).

summarizes the results.

Table 3

National differences in waiting lags in the data-processing industry in 1986

Countries	Kolmogorov-Smirnov Statistic	X^2	Significance
m = 315 French grants n = 640 German grants	$D_{m,n} = 0.0997$	8.390	$0.02 > p > 0.01$
m = 640 German grants n = 127 UK grants	$D_{m,n} = 0.1268$	6.812	$0.05 > p > 0.02$
m = 127 UK grants n = 950 US grants	$D_{m,n} = 0.1938$	16.837	$p < 0.001$
m = 950 US grants n = 767 Japan. grants	$D_{m,n} = 0.0430$	3.132	$0.30 > p > 0.20$

From the Kolmogorov-Smirnov tests in table 3, a country ranking can be constructed for the waiting times for the data-processing industry in 1986. 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, I have carried out identical tests for applications filed in the period 1978-1985. The results are presented in table 4. Exactly the same order of waiting lags also emerges from these samples. From large to small lags, the ranking is: 1. Japan; 2. US; 3. UK; 4. Germany; and 5. France. All differences are highly significant ($< 0.1\%$ level).

Table 4

National differences in waiting lags in the data-processing industry during 1978-1985

Countries	Kolmogorov-Smirnov Statistic	χ^2	Significance
m = 1725 French grants n = 3466 German grants	$D_{m,n} = 0.1167$	62.782	$p < 0.001$
m = 3466 German grants n = 765 UK grants	$D_{m,n} = 0.1545$	59.848	$p < 0.001$
m = 765 UK grants n = 5961 US grants	$D_{m,n} = 0.1153$	36.054	$p < 0.001$
m = 5961 US grants n = 3779 Japan. grants	$D_{m,n} = 0.0762$	53.132	$p < 0.001$

Is this phenomenon specific to the data-processing industry? Table 5 summarizes the results for all applications granted (i.e., in all IPC classes) in the period 1978-1985. Again, the same order as before is found here with very strong evidence. It can thus be concluded that the difference in waiting times is not specific to the data-processing industry.

Table 5

National differences in waiting lags for all grants during 1978-1985

Countries	Kolmogorov-Smirnov Statistic	χ^2	Significance
m = 14191 French grants n = 33661 German grants	$D_{m,n} = 0.0609$	148.093	$p < 0.001$
m = 33661 German grants n = 9198 UK grants	$D_{m,n} = 0.1636$	773.401	$p < 0.001$
m = 9198 UK grants n = 34785 US grants	$D_{m,n} = 0.1176$	402.416	$p < 0.001$
m = 34785 US grants n = 20660 Japan. grants	$D_{m,n} = 0.0516$	138.045	$p < 0.001$

It should be emphasized here that I have only checked the differences in national waiting lags. It is outside the scope of this study whether these differences are due to preferential treatment given by the EPO to European applicants, for example, or to the organizational structure within the EPO.

(b) National Success Ratios

In order to isolate the differences in EPO success ratios of countries from the differences in waiting lags, I 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 lags do not affect differences in success ratios. Table 6 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 6 it can furthermore be concluded that the lower success ratio of Japan which was found in the data-processing industry in section 3 is a severe misrepresentation. Japanese firms generally perform better than European firms, both in data processing and overall.

Table 6 EPO success ratios during 1978-1985

Country	Data Processing	Overall
Japan	0.855	0.833
France	0.785	0.762
Germany	0.717	0.731
US	0.659	0.623
UK	0.552	0.581

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 office and then in the EPO.⁴ The better the screening (i.e., the higher the novelty requirements), the higher the success ratio for that country in the EPO. I 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" (Geneva, 1983), which

4. This is also common practice for much European applicants.

contains the total number of applications and patents granted in a country for the period 1883-1982. I assume that the national patent offices treated residents and non-residents 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 I could find data for, both in the EPO and in the WIPO publications).⁵ For reasons outlined above, a two-limit Tobit model is used again. With the EPO success ratios ('epo-success') 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 t-ratios are given in parentheses. The coefficient 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. The choice between the two innovation strategies, pioneering or imitative, may depend on the dimensions of the patent system, as explained in Van Dijk (1993). If a patent system sets high barriers for applicants, by means of high novelty requirements, the pioneering strategy might become more costly, but provides more protection against further improvement in return. Firms that pursue pure pioneering strategies benefit from the advantage of high protection without investing more in basic research (because they will meet the novelty requirements anyway). Therefore, stringent

5. The following countries have been included: Argentina, Australia, Austria, Belgium, Brasil, Bulgary, Canada, Cyprus, (former) Czechoslovakya, 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.

novelty requirements can be thought to encourage pioneering strategies. Indirectly, strong domestic novelty requirements then lead to better patenting performance in the EPO, by inducing pioneering innovation strategies.

5. Conclusions

This paper has argued that firms which pursue pioneering innovation strategies are more successful in obtaining patent protection than firms which pursue imitative innovation strategies. A pioneering strategy aims at profits resulting from new or improved products and processes. This strategy requires more basic research, which explores novel and unknown paths that are only weakly related to existing products, and therefore its fruits are better patentable. The novelty requirements are met more easily. An imitative strategy, on the other hand, aims at modifying and redesigning existing products and makes more use of applied research and development. Due to the stronger connection with existing products, the fruits from applied research and development pass the patent office less easily.

This theory has been tested for the data-processing industry in the period 1986-1990. Since no direct data on basic vs. applied research were available, the success ratios of data-processing firms in the EPO are explained by instrumental variables which indicate the degree of basic research. One such variable is diversification. As argued in 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. Pioneering 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 lags, Japanese applicants in general have higher success ratios than European and US applicants. Furthermore I 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.

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