The Longitudinal Nature of Patent Value and Technological Usefulness Exploring PLS Structural Equation Models

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Abstract

The purpose of this paper is to investigate the evolution of patent value and technological usefulness over time using longitudinal structural equation models. The variables are modeled as endogenous unobservable variables which depend on three exogenous constructs: the knowledge stock used by companies to create their inventions, the technological scope of the inventions and the international scope of protection. Two set-ups are explored. The first longitudinal model includes time-dependent manifest variables and the second includes time-dependent unobservable variables. The structural equation models are estimated using Partial Least Squares Path Modelling. We showed that there is a trade-off between the exogenous latent variables and technological usefulness over time. This means that the former variables become less important and the latter more important as time passes.

Keywords: Patent value, longitudinal structural equation models, partial least square, PLS path modelling

1 Introduction

In this paper we explore a predictive dynamic model that considers patent value as an unobservable variable. The patent value model has been previously presented as a first and a second-order structural equation model (Martínez-Ruiz & Aluja-Banet, 2008, 2009). The structural equation model (SEM) was based on the theoretical background and an extensive review of the literature. The patent value was modeled as an endogenous unobserved variable depending on the following four exogenous constructs: the knowledge stock used by a firm to create the invention, the technological scope of protection, the international scope of protection and the technological usefulness of the inventions. The latter is also an endogenous latent variable depending on the first three exogenous constructs. Each latent variable was estimated using a set of manifest variables or indicators constructed mainly from the information contained in patent documents.

Now we introduce the dynamic aspects of the model, since patent value has an intrinsic life cycle. This means that over time, the value first increases and then reaches a stage where the size of the increments become smaller and smaller. We attempt to capture this phenomenon and to estimate the evolution of the value over time. We explored two models. The first one considers time-dependent indicators for technological usefulness; this allows us to obtain a global estimation of the patent value as a weighted sum of the manifest variables at different time points. In the second model, technological usefulness is modeled as an unobservable variable which changes over time (time-dependent latent variable); and each of these constructs is estimated by a group of measured manifest variables within the corresponding time period. Both models allow the analysis of loadings and path coefficients over time, but the second also measures the changes of the lagged endogenous latent variable. This approach has been followed by Jöreskog & Wold (1982) to model longitudinal data in structural equation models, and we use it in a PLS Path Modelling framework.

2 Patent Value

Patents are intellectual assets that do not necessarily have an immediate return. A patent may protect a product that can be manufactured and sold. But a patent may also protect technologies which, together with other technologies, enable the manufacture of a final product. In both cases, obtaining an economic value of patents may be extremely difficult. In studying patent value, different approaches have been taken throughout the literature. Some of the approaches focus on the private value of a patent while others concentrate on a patent's social value. Lanjouw *et al.* (1998, p. 407) defined the private value of a patent in terms of "the difference in the returns that would accrue to the innovation with and without patent protection." The magnitude of this difference would be crucial in applying or renewing the protection. Reitzig (2004) also focused on the private value of patents, and specifies the need to consider the patent value as a construct. Technical experts were surveyed and, according to them, the research showed that the factors that determine patent value are: state of the art (existing technologies), novelty, inventiveness, breadth, difficulty of inventing, disclosure and dependence on complementary assets. Additionally, Trajtenberg (1990) showed that patent data was highly correlated with some indicators of the social benefits of innovations. Guellec & van Pottelsberghe (2000) presented a value scale proposing that technology increases its own value as it passes through different stages: from invention to application, examination, publication and decision to grant, and finally to the high value stage if the patent is granted. The distinction is made between the intrinsic value of the patent simply for being granted (and thereby having proven novelty, inventive activity and applicability) and the potential value of technology (dependent on its potential for generating future returns). On the other hand, Lanjouw & Schankerman (2004) constructed an index for patent quality, emphasizing "both the technological and value dimensions of an innovation" (p. 443). Using factorial analysis, the researchers model patent quality as an underlying construct that explains a set of patent indicators (forward citations, backward citations, family size and number of claims). The latent variable is computed as a "linear combination of the set of indicators, where weights depend on the factor loadings" (p. 449). One of the main results of this research is that the use of a latent variable model significantly reduces the variability of the construct.

Some patent indicators have been used to directly infer the patent's value, such as forward citations or family size. Even though this may be useful and may give an approximation of the patent value, many elements may affect the invention and protection process. We consider some of these factors based on the background, and represent their interactions proposing a multidimensional analysis of the problem. It is worth noting that this research does not seek to determine the value of an individual patent or to obtain a monetary value of the assets. Rather, the patent value is proposed in terms of the technological usefulness of the inventions. This model, however, allows us to compare and rank the value of a company's patent portfolio. We addressed the question of what variables determine the patent value and how they relate to each other. These variables are modeled as unobserved variables. So, they and their relationships set up a structural model. Little research has reported on the structural relationship among latent variables which influence patent value using a multidimensional approach. The recent investigations of Harhoff *et al.* (2003), Harhoff & Reitzig (2004), Reitzig (2003), and Reitzig (2004) used a large number of indicators of patent value which were aimed mainly at estimating the probability of opposition to a patent. In most cases, analytical approaches have been based on standard econometric analysis techniques (probit or logit models) or survey analysis. One reason that could explain why a multidimensional and structural approach has not been applied to technology/patent value is that the more general structural models are based on maximum likelihood estimation and the multivariate normal distribution of data. Patent indicators are very heterogenous and asymmetric, and, in general, they exhibit a large variance and skew. Consequently, assuming that this type of data has a multivariate normal distribution may lead to biased results. PLS Path Modelling overcomes this drawback because it is an iterative algorithm that makes no assumptions about data distribution.

3 Longitudinal Nature of Patent Indicators

A fundamental feature of longitudinal data is that the same measurement is obtained on different occasions for the same individuals. So, the aim of a longitudinal study is to assess the changes between occasions and explain these changes based on theoretical grounds. It is important to emphasize that the patent indicators described above have a temporary nature. The number of inventors, applicants, cited patents, claims and IPC codes are determined at the time of the patent filing or during the patent examination process. We may assume that they are determined at the instant zero. However, this assumption is not valid for forward citations and family size. Both, the family size and the forward citations, are variables with a longitudinal character. Usually, the companies first protect their inventions in their local countries and then in others within a period of time. So, the family size is an indicator that may change over time. Harhoff *et al.* (2003, p. 1360) said that this indicator "may be available around the time of application."

In addition, it is known that the number of forward citations is an indicator that may vary over time, since a patent may receive citations over a long period.

As a first attempt –and given the complexity of recovering some data– we retrieve the number of yearly citations received for patents belonging to the sample. This allows us to assess the implications on the results by considering the longitudinal nature of the data in the estimated models. We are also aware that longitudinal data have an intrinsic autoregressive nature. So, in this way, we also explore the robustness of the proposed structural models.

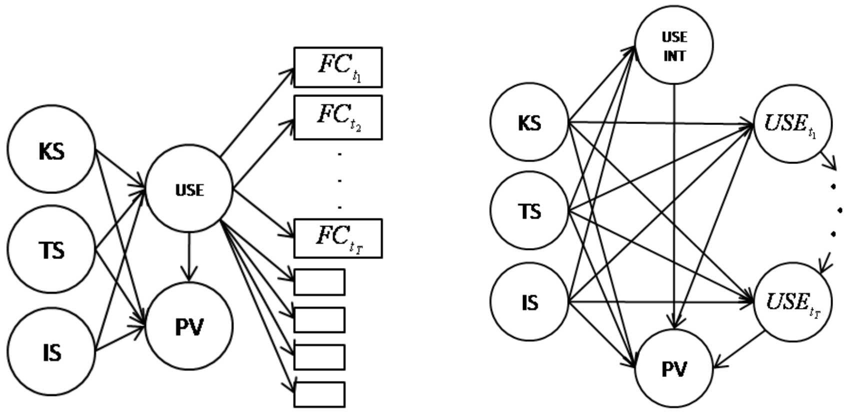
4 Patent Value Models for Longitudinal Data

In order to model the patent value over time, we explore two longitudinal models (see Figure 1). The first longitudinal model A (Figure 1(a)) considers three exogenous constructs –knowledge stock (KS), technological scope (TS) and international scope (IS)– at time point zero. The knowledge stock represents the base of knowledge that was used by the applicant to create an invention. This would be the content domain. This existing knowledge encourages the inventive activity and may come from within or outside the company. Since we are considering the patent document as the main data source, the applicants and inventors, who have contributed their knowledge to the creation of the invention, may be considered as having formed this construct. The same applies to backward citations. The previous works, cited in the patent document, are the scientific and technical knowledge units that must exist before the creation of an invention, and they may be used as knowledge inputs within the invention process (Narin *et al.* , 1997). Moreover, backward citations represent the prior art, and demonstrate that the invention has not previously been protected. These three indicators have been related to the patent value by other authors (see for instance Reitzig (2004)). However, they still have not been used to estimate an unobserved variable as they are in a structural equation model[1]. The technological scope of the invention is related to the potential utility of an invention in some technological fields. So, the manifest variables for this construct are the number of four-digit IPC classes where the patent is classified (Lerner, 1994), and the number of patent claims (Tong & Frame, 1994). The IPC classes allow us to know the technical fields related to the invention, and therefore the number of potential application fields. This does not mean that an invention's ultimate use is restricted to a determined area. A company may protect an invention for strategic purposes, for example to prevent its being used by a competitor. Here, the underlying issue is that a larger number of classification codes corresponds to a larger number of

[1]See Martínez-Ruiz & Aluja-Banet (2009) for a discussion on the reflective and formative nature of measurement models.

potential application fields, and hence, the technological scope of the patent is greater. On the other hand, and according to Tong and Frame (Tong & Frame, 1994, p. 134), "each claim represents a distinct inventive contribution, so patents are, in effect, bundles of inventions". Moreover, it has been shown that patents with a large number of claims have a higher likelihood of being litigated, so they can be considered more valuable Harhoff & Reitzig (2004); Lanjouw & Schankerman (2001); Reitzig (2004). Claims are a description of what the inventors actually claim to have invented and describe the potential application of the invention. As seen in the literature review, the number of claims should reflect the inventive activity of the invention. So, under the assumption that a highly sophisticated invention will require much inventiveness, the patent will also have a considerable amount of claims. Thus, this variable will also give information about the technological scope of the patents. It is arguable that this is not always so. Probably there are sophisticated inventions that have not required a large number of claims to be protected. But this may be unusual in the field of renewable energy. For instance, as seen in Table 4 below, the number of claims is a skewed variable (skewness = 2.25, kurtosis = 8.64, sample 1), with median 10. International scope refers to the geographic zones where the invention is protected. Inventions are usually protected in the local country first and then in others, as part of the companies' patenting strategy. All the patents considered in the sample are granted in the U.S. So, we defined two dummy variables that consider whether the invention had been protected in Japan (priority JP) or in Germany (priority DE) during the priority period. Japan and Germany are large producers of renewable energy technologies. Hence, it is interesting to examine whether these variables affect the patent value. Variables indicating whether inventions have been protected through the European Patent Office (EPO) or by the World Intellectual Property Organization (WIPO) have been excluded from the analysis because they provide little information. This means that for the international scope, not all the variables that could form the construct are being considered.

The endogenous latent variable, technological usefulness (USE), is measured by time-dependent manifest variables. The indicators of this variable are the number of forward citations per year. So, by capturing the longitudinal nature of forward citations through an unobservable variable, we "average" the contribution of the longitudinal indicators. For USE, we also consider the previously defined dummy variables (JP, DE and EP). The patent value (PV) is modeled as an endogenous latent variable formed by the weighted contribution of knowledge stock, technological scope, international scope and the technological



(a) Model A: Time-dependent manifest variables

(b) Model B: Time-dependent latent variables

Figure 1: Patent value structural models for longitudinal data. In model A, the forward citations measured at different time points (FC_{t_i}), the family size and the dummy variables (JP, DE, EP) are manifest variables of the latent variable, technological usefulness. In model B, technological usefulness is a time-dependent latent variable, each measured by a set of indicators.

usefulness. Hence, this model gives an overall measure of the patent value.

The second longitudinal model B (Figure 1(b)) considers: (1) the same aforementioned exogenous constructs, (2) an auxiliary endogenous construct[2] (USE-INT) clustering the family size and the dummy variables JP, DE and EP, and (3) the technological usefulness (USE) as a set of time-dependent latent variables, each one measured by blocks of observed variables at different time points. We modeled seven different time periods: 1992-1993, 1994-1995, 1996-1997, 1998-1999, 2000-2001, 2002-2003, and 2004-2005. In model B, the patent value (PV) is also formed by the weighted sum of all the constructs and latent variables, but now the model allows for the analysis of changes in the technological usefulness over different time periods.

5 The Patent Sample

In order to analyze whether it is possible to find a pattern in the parameter estimates, the proposed models were estimated with time-period data. We established some criteria for retrieving data from the Delphion database. We used the International Patent Classification (IPC) codes for renewable energies listed by Johnstone *et al.* (2007). Hence, patents are classified in codes related

[2]This latent variable groups the measures related to family size and the international protection of patents. Initially, when the model did not consider variations in time, the variables were considered as indicators of technological usefulness. However, it is now necessary to rethink this formulation.

to wind, solar, geothermal, wave/tide, biomass and waste energies. All patents were granted in the U.S. We arbitrarily chose: (1) a set of 359 patents applied for in the years 1989-1990-1991 (sample 1), (2) a set of 129 patents applied for in the years 1995-1996 (sample 2), and (3) a set of 179 patents applied for in 2000 (sample 3). According to the Delphion database, these data sets represent 41.74%, 35.15%, and 51.29% of all patents applied for in the U.S. in the field of renewable energy during the selected time periods, respectively. Due to the manner in which the sample was selected, the sample is homogenous in terms of technological area and the country where the patents were granted. At any rate, it is worth noting that at this stage, the patent value model is being tested in general at the level of renewable energy technologies.

Table 4 in section 9 provides descriptive statistics for patent indicators for each patent data set. The results indicate that some variables are very heterogeneous and asymmetric, and they also exhibit large variance. So, normality is not a recommended assumption. Positive values of skewness indicate positive/right skew (notice how the medians are always smaller than the means). Likewise, positive kurtosis indexes show distributions that are sharper than the normal peak.

All forward citations received by patents per year were retrieved from the United States Patent and Trademark Office (USPTO) database from 1992 to 2005. Figures 2 and 3 show the number of citations received by year and the accumulated citations received by year, respectively, for patent applications in 1989, 1990, 1991, 1995, 1996, and 2000. These figures show an increase in the number of citations over time. Figure 2 shows that the number of citations reaches a peak then decreases. The patents applied for in 1989 are the most cited. The patents less cited are those applied for in 1991 and 1996.

6 PLS Path Modelling for Longitudinal Data

PLS Path Modelling is a component-based procedure for estimating a sequence of latent variables developed by the statistician and econometrician Herman Wold. During the last few years, it has proved to be useful for estimating structural models, in marketing and information systems research in particular, and in the social sciences in general. Some of its features have encouraged its use, such as: (1) it is an iterative algorithm that offers an explicit estimation of the latent variables and their relationships, (2) it works with fewer cases and makes no assumptions about data distribution, and (3) it overcomes the identification problems when formative measurement models are included.

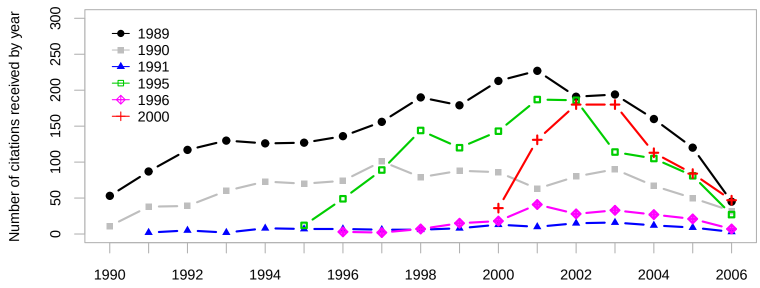


Figure 2: Number of citations received by year, patents applied for in 1989, 1990, 1991, 1995, 1996 and 2000

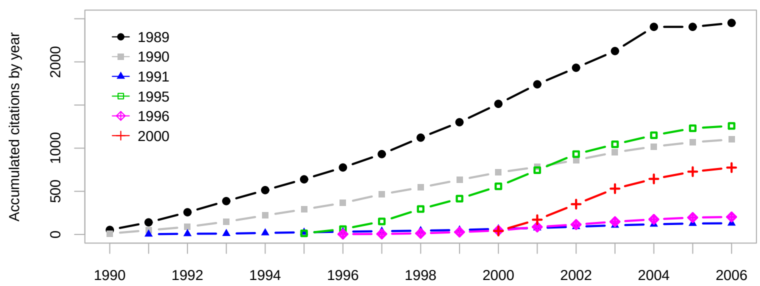


Figure 3: Accumulated citations received by year, patents applied for in 1989, 1990, 1991, 1995, 1996 and 2000

Wold's basic-design of PLS Path Modelling does not consider higher-order latent variables. Therefore, in Wold's algorithm each construct must be related to a set of observed variables in order to be estimated. However, Lohmöller (1989) proposed a procedure for the case of hierarchical constructs; that is to say, for cases where there is a construct with no block of manifest variables, or more simply: it is only related to other constructs. In hierarchical component modelling, manifest variables of first-order latent variables are repeated for the second-order latent variable. So, a set of "auxiliary" variables is introduced for estimation purposes. After that, the model is estimated using PLS Path Modelling in the usual way.

In a more traditional way, structural equation models with longitudinal data consider the repetition of the structural and measurement models in each of the years under study. Therefore, when the model is tested, the whole model is estimated at the same time. So, both background variables and initial measures, as well as the final status are included in the model. Wold (1982) and Scepi & Esposito Vinzi (2003) followed this approach, but the latter also introduced multi-table analysis with an aim toward identifying temporal components in the data structure. We addressed the more traditional approach in order to estimate the longitudinal patent value models. As a PLS Path Modelling procedure is used, the aforementioned autoregressive process is also implemented.

7 Results

Model assessment. We first assess the internal consistency of reflective outer models by using Cronbach's alpha coefficient (should be > 0.7). All reflective measurement models are unidimensional. Cronbach's alpha coefficients of technological usefulness are 0.91, 0.94 and 0.82 for models A with samples 1, 2, and 3, respectively. Cronbach's alpha coefficient for the auxiliary latent variable in model B is 0.80 and Cronbach's alpha range is from 0.94 to 0.99 for the different time points of technological usefulness. We computed the average variance extracted (AVE) to assess the extent to which measures of a given construct differ from measures of other constructs (discriminant validity). As suggested by Fornell & Larcker (1981), the percentage of variance captured by the construct in relation to the variance due to random measurement errors should be greater than 0.5. The AVE of technological usefulness is 0.58, 0.65, and 0.53 for samples 1, 2, and 3, respectively, in models with time-dependent manifest variables. Thus, the latent variable is capturing on average more than 50% of the variance in relation to the amount of variance due to measurement error. For the model with time-dependent latent variables, the AVE of technological usefulness ranges from 0.95 to 0.99 at the different time points.

Tables 5 and 6 in section 9 report the cross loadings –or correlations between manifest variables and constructs– for a reflective block of variables in models A and B in the three analyzed time-periods. As shown, each observed variable is correlated more with its corresponding construct. Thus, for instance, in the longitudinal model with time-dependent latent variables, the family size and the dummy variables JP and DE are more related with the auxiliary variable USE-Int than with the technological usefulness in the different time-periods. This empirical evidence supports the relationships between latent and manifest variables as proposed in the models.

Loading estimates for reflective models A and B are reported in Tables 7 and 8 in section 9, respectively. Loadings indicate how much variance each indicator shares with the latent variable (reliability). A rule of thumb generally accepted is 0.7 or more (Hulland, 1999). A low value in a loading factor suggests that the indicator has little relation to the associated construct. As shown in the tables, all loading estimates are significant at the 0.01 level[3]. For models A, the loadings of time-dependent manifest variables, that is, the forward citations for the different time periods, range from 0.776 to 0.955. Thus, the technological usefulness is reflected in reliable time-dependent indicators, and the latent variable explains the correlations among the manifest variables. Although significant, the loadings for the family size and the dummy variables (Germany and Japan) are less than 0.7. This situation changes when the time-dependent latent variable model is considered. For model B, loadings are always greater than 0.7. In this case, the family size and the dummy variables (DE and JP) are reliable indicators of the auxiliary latent variable USE-Int, and the construct explains the correlation among the indicators. We have not given a definitive name to this latent variable. "International patenting strategy" would describe the concept formed by the family size and the dummy variables JP and DE. These indicators measure whether the inventions have been protected internationally, particularly in the major countries which produce renewable energy technologies. Hence, these variables may change over time. This is what makes the construct different in regards to an international scope.

The reliability of formative outer models –knowledge stock, technological scope, international scope– was assessed by examining weight estimates and the correlations between the constructs and their corresponding manifest variables. Manifest variables in formative measurement models do not have to be intercorrelated. In fact, Pearson correlations between patent indicators are small and medium,[4] ranging from 0.04 to 0.25[5]. However, the indicators should be correlated with the constructs which are related, because the manifest variables are supposed to contribute to the formation of the unobservable variable. Tables 5 and 6 show the correlations between knowledge stock, technological scope and international scope, along with their corresponding manifest variables (models A and B, and samples 1, 2, and 3). Tables 7 and 8 in section 9 show the estimates for outer relationships. For models A, of which there are three, the weight estimates are in line with the correlations between constructs and indica-

[3]The t-values were computed by bootstrapping with 200 bootstrap resamples; t-value > 1.65 significant at the 0.05 level; t-value > 2 significant at the 0.01 level.

[4]Cohen (1988) suggests that correlations of 0.1, 0.3, and 0.5 express small, medium and large effect sizes, respectively.

[5]Correlations between the number of inventors, backward citations, the number of IPC codes, the number of claims, and the dummy variables.

tors. For samples 1 and 2, there are medium and large correlations between the knowledge stock and its indicators. The weight estimates are positive, and the number of inventors indicates a significant relationship with the construct. The same happens with the technological scope and international scope. For model A with sample 3, the weight estimates are negative as well as the correlations between the constructs and their corresponding indicators. Thus, weight estimates and correlations between each formative construct and its corresponding indicators vary in the same way, validating the formative constructs. Negative correlations are attributed to the fact that the sample corresponds to patents applied for in 2000. As discussed below, forward citations influence the model estimates in a meaningful way. These variables are less informative for sample 3, affecting the estimation of the unobservable variables for that year. The results for model B suggest that a model with time-dependent latent variables may reveal significant relationships in the formative outer models. The number of IPC codes, the number of claims, and the dummy priority variables JP and DE are strongly and significantly related to their constructs. The same was found in Martínez-Ruiz & Aluja-Banet (2009). The relationship between knowledge stock and the number of inventors is also significant.

Since multicollinearity is a problem in multiple regression –and the basic design of PLS Path Modelling uses multiple regression to estimate inner relationships– we calculated the correlations between the estimated constructs and the variance inflation factor[6] so as to perform a collinearity diagnostic. The variance inflation factors for the regression coefficients of the technological usefulness range from 5.18 to 89.88 from 1992-1993 to 2002-2003, respectively. Moreover, we calculated the mean communalities to test for the discriminant validity of unobservable variables. Tables 9 and 10 in section 9 report the results. The mean communalities of each construct are larger than the correlations between the construct and other unobservable variables (models A and B, samples 1, 2, and 3). So, the constructs share more variance with its block of indicators than with another construct representing a different block of manifest variables. In addition, there was no evidence of collinearity between knowledge stock, technological scope, and international scope, nor between these constructs and the auxiliary latent variable USE-Int and technological usefulness. However, and as expected, technological usefulness for the different time periods is highly correlated. Therefore, we estimated the inner relationships by

[6]The square root of the variance inflation factor tells you how much large the standar error is, compared with what it would be if that variable were uncorrelated with the other independent variables in the equation. A common rule of thumb is that if VIP(regression coefficient) > 5 then multicollinearity is high.

using multiple regression and PLS regression. The latter is recommended to avoid multicollinearity problems among inputs.

Multiple regression to estimate structural relationships. Once the latent variables were obtained with PLS Path Modelling, we estimated the structural relationships by using multiple regression in the usual way. Tables 1 and 2 show the standardized path coefficients of the longitudinal model with time-dependent manifest variables for the three-analyzed samples, and with time-dependent latent variables for sample 1, respectively. These tables also report the significance of each estimate.

The relationships between patent value and the exogenous constructs are all significant at the 0.01 level (models A and B, samples 1, 2, and 3). The magnitude of the regression coefficients and the t statistic reveal the contribution of each variable to the patent value. Path coefficients of model B show how technological usefulness is reflected over time ($\beta_{92-93} = 0.131$ $t - value = 23.16$,...,$\beta_{04-05} = 0.145$ $t - value = 19.73$) while the regression coefficient in model A ($\beta_{sample3} = 0.856$, $t - value = 18.53$) is "averaging" the contribution of the change in forward citation over time. In addition, when considering forward citations as longitudinal manifest variables of technological usefulness, the regression coefficient between technological scope and technological usefulness is 0.049 ($t - value = 2.28$, sample 1). However, this value changes when the technological usefulness is modeled as a time-dependent latent variable. In model B, the regression coefficient between technological scope and USE 92-93 is 0.210 ($t - value = 2.08$). This relationship is smaller in subsequent years. So, this result suggests that the relative contribution of the technological scope of protection –determined when the invention is classified in some IPC codes and the number of claims– is larger in the first stage of the life cycle of patents, and then it declines. The knowledge stock and the international scope also appear to add more to the patent value in an early stage. The inner relationship between the auxiliary latent variable USE-Int and the patent value is also significant.

These results are similar to those obtained in Martínez-Ruiz & Aluja-Banet (2009). However, the effects captured by the structural model are smaller, mainly among the formative constructs and the technological usefulness. This may be due to the fact that considering the longitudinal nature of forward citations helps to reveal the relative weight that this variable has on the estimate of patent value. Figure 4 shows the evolution of loadings, which describes the relationship between forward citations and patent value for model A and samples 1, 2 and 3. The Figure clearly shows how the patent value increases, stabilizes and

Table 1: Standardized path coefficients of the A-structural model (longitudinal model with time-dependent manifest variables) for samples 1, 2, and 3; t-values in parenthesis, ** at the 0.01 significance level, * at the 0.05 significance level.

	Sample 1: 1989-1990-1991		Sample 2: 1995-1996		Sample 3: 2000	
Construct	**Technological Usefulness**	**Patent Value**	**Technological Usefulness**	**Patent Value**	**Technological Usefulness**	**Patent Value**
Knowledge stock	0.140	0.146	0.239	0.121	0.193	0.192
	(1.4605)	(4.952**)	(2.299**)	(7.638**)	(1.860*)	(3.148**)
Technological scope	0.049	0.133	0.214	0.117	0.041	0.201
	(2.283**)	(4.944**)	(2.721**)	(7.494**)	(0.554)	(3.390**)
International scope	0.251	0.131	0.106	0.0779	0.169	0.166
	(0.637)	(4.267**)	(0.908)	(4.491**)	(1.921*)	(2.346**)
Technological usefulness		0.888		0.897		0.856
		(26.851**)		(52.024**)		(18.538**)

Table 2: Standardized path coefficients of the B-structural model (longitudinal model with time-dependent latent variables) for sample 1; t-values in parenthesis, ** at the 0.01 significance level, * at the 0.05 significance level.

	Sample 1: 1989-1990-1991								
Construct	**USE-Int**	**USE 92-93**	**USE 94-95**	**USE 96-97**	**USE 98-99**	**USE 00-01**	**USE 02-03**	**USE 04-05**	**PV**
Knowledge stock	0.095	0.111	0.050	0.001	-0.040	0.003	-0.002	-0.005	0.028
	(1.110)	(1.303)	(1.348)	(0.032)	(1.328)	(0.155)	(0.151)	(0.387)	(3.710**)
Technological scope	0.186	0.210	0.022	0.054	-0.020	-0.029	-0.007	-0.011	0.034
	(1.990*)	(2.082**)	(0.607)	(1.396)	(0.758)	(1.289)	(0.427)	(0.737)	(4.017**)
International scope	0.340	-0.022	-0.031	0.032	0.007	-0.018	-0.019	-0.019	0.018
	(2.989**)	(0.320)	(1.071)	(0.750)	(0.189)	(0.912)	(1.147)	(1.376)	(2.390**)
Auxiliary construct USE-Int									0.069
									(3.612**)
Technol. Usefulness 92-93			0.883						0.131
			(35.097**)						(23.167**)
Technol. Usefulness 94-95				0.911					0.146
				(32.888**)					(25.194**)
Technol. Usefulness 96-97					0.952				0.160
					(51.654**)				(21.377**)
Technol. Usefulness 98-99						0.968			0.154
						(68.869**)			(14.214**)
Technol. Usefulness 00-01							0.980		0.163
							(93.416**)		(14.649**)
Technol. Usefulness 02-03								0.985	0.154
								(118.539**)	(15.350**)
Technol. Usefulness 04-05									0.145
									(19.738**)

then decreases over time. Figure 5 shows the evolution of the standardized path coefficient, which describes the relationship between knowledge stock, technological scope and international scope, and technological usefulness, as well as between the latter and the patent value for model B. The results suggest a trade-off between exogenous constructs and technological usefulness. This means that the knowledge stock, the technological scope and the international scope contribute more to the patent value at time equal to zero while the technological usefulness determines the patent value in subsequent time-periods.

Finally, the determination coefficients R^2 for technological usefulness in models A are 0.09, 0.15, and 0.06 with samples 1, 2, and 3, respectively. The R^2 in model B is close to 0.8 for technological usefulness and 0.17 for the aux-

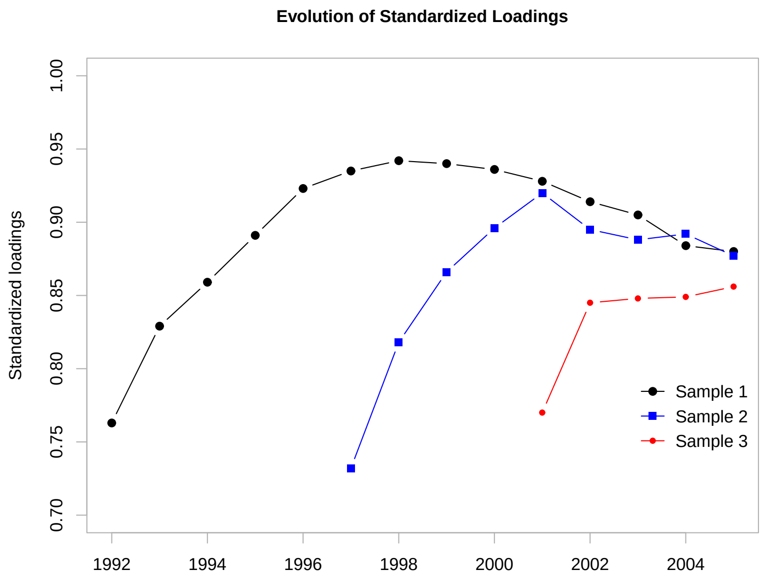


Figure 4: Evolution of standardized loadings of the longitudinal model with time-dependent manifest variables (model A) and samples 1, 2 and 3. The loadings describe the relationships between forward citations and patent value.

iliary latent variable. So, this suggests that the data is better explained by a longitudinal model with time-dependent latent variables.

PLS regression to estimate structural relationships. Since there is multicollinearity between the technological usefulness for the different time-periods, we also estimated the structural relationships by using PLS regression. The number of significant components t_h were determined by leave-one-out cross validation. The marginal contribution of each PLS component t_h to the predictive power of the regression model was estimated using the Q_h^2 index and redundancies[7].

The patent value was regressed on the knowledge stock, the technological scope, the international scope, the technological usefulness for the different time periods and the auxiliary variable USE-Int, a total of 11 regressors. By default,

[7]For each h-component, the Q_h^2 index is defined as $Q_h^2 = 1 - \sum_{k=1}^{q} PRESS_{kh} / \sum_{k=1}^{q} RSS_{k(h-1)}$, where PRESS is the Predicted REsidual Sum of Squares, and RSS is the Residual Sum of Squares of the latent variable Y_k when the regression model is estimated considering $h-1$ components. The rule is to retain the h-component when $Q_h^2 \geq 0.0975$. The redundancy coefficient measures the amount of explained variance in the indicators for the endogenous construct, explained by the set of manifest variables of the exogenous constructs. It is defined as, $Rd(Y, t_h) = \frac{1}{q} \sum_{k=1}^{q} cor^2(y_k, t_h)$, where q is the number of endogenous variables.

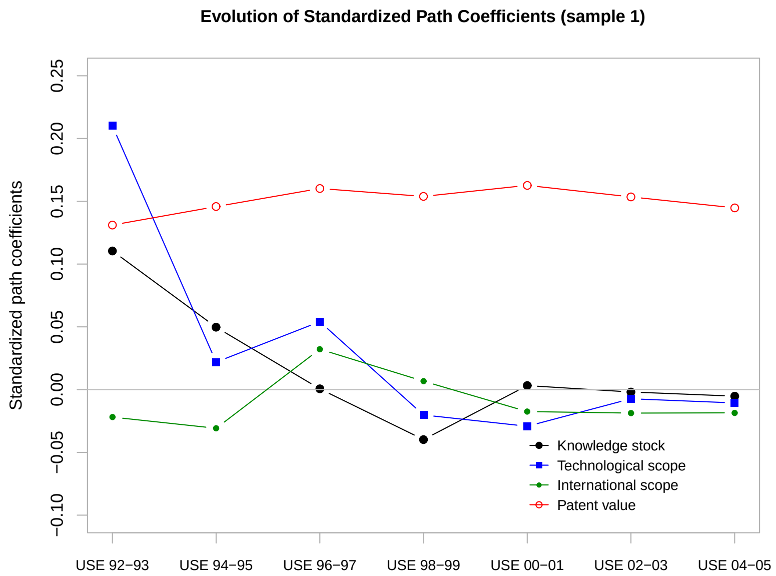


Figure 5: Evolution of standardized path coefficients of the longitudinal model with time-dependent latent variables (model B) and sample 1 (1989-1990-1991). The path coefficients describe the relationships between knowledge stock, technological scope and international scope, and the technological usefulness (USE), and between the latter and the patent value.

the PLS regression holds as many components as there are independent variables in the model. For patent value PLS regression, however, two components can predict about 68% of the variation of the regressors (see Table 11 in section 9). Thus, a two-component model would be sufficient to describe the patent value in terms of the exogenous latent variables and constructs. Nonetheless, we report the results for models with one, two, three and four components. Figures 6 shows the correlations between latent variables and the first four PLS components. As shown in Figure 6(a) for instance, the patent value, the technological usefulness for the different time periods and the technological scope are highly correlated with the first component whereas the international scope and the auxiliary latent variables USE-int are correlated more with the second component. The knowledge stock and also the technological scope are correlated with the third component. The forth component helps to explain the auxiliary latent variable USE-Int and the international scope.

Table 3 shows the PLS-regression coefficients considering one, two and three component models and the variable importance in the projection (VIP index)

Table 3: PLS-regression coefficients for 1-component, 2-component and 3-component models, and variable importance in the projection (VIP index) for model B and sample 1.

	PLS Regression Path Coefficients			**Variable Importance in the Projection (VIP)**		
Construct	1 Comp	2 comp.	3 Comp.	1 Comp	2 comp.	3 Comp.
Knowledge stock	0.029	0.033	0.027	0.241	0.241	0.242
Technological scope	0.044	0.040	0.034	0.364	0.364	0.364
International scope	0.007	0.023	0.020	0.059	0.084	0.085
Auxiliary latent variable USE-Int	0.040	0.062	0.067	0.324	0.335	0.336
Technological usefulness 92-93	0.133	0.132	0.132	1.092	1.092	1.092
Technological usefulness 94-95	0.147	0.145	0.145	1.201	1.200	1.200
Technological usefulness 96-97	0.157	0.156	0.156	1.283	1.282	1.282
Technological usefulness 98-99	0.159	0.159	0.159	1.302	1.301	1.301
Technological usefulness 00-01	0.157	0.157	0.158	1.288	1.287	1.287
Technological usefulness 02-03	0.154	0.153	0.154	1.257	1.256	1.256
Technological usefulness 04-05	0.149	0.148	0.148	1.219	1.219	1.219

for model B and sample 1[8]. As shown, and according to the results of the 2-components PLS model, the regression coefficients are very similar to those obtained with multiple regression. However, the technological usefulness in the different time points is the variable that most contributes to the prediction of the patent value.

8 Final Remarks

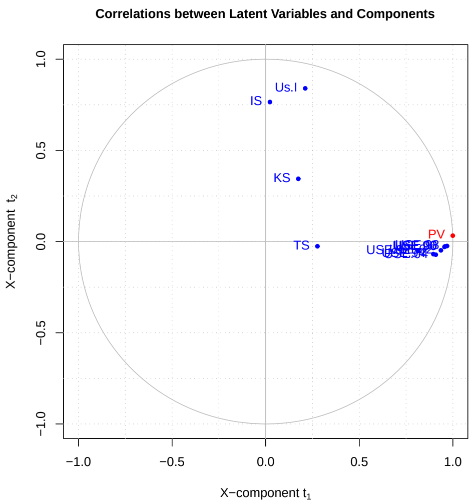
It seems reasonable to think that if a company has invested a lot of knowledge in the creation of an invention, this invention will tend to have a larger value. In the same way, a technology with multiple potential applications would be more valuable than one that can only be applied in a more limited area. The same applies for the international scope of protection. An invention with broader protection is presumably more valuable than one without it. The estimation results of the patent value models for longitudinal data suggest that the contribution of the knowledge stock used by companies to create their inventions, the technological scope of the inventions and the international scope of protection are variables that contribute little to the patent value when compared to the technological usefulness. As expected, this is more evident in model B than in model A. Based on the PLS regression findings, for the model with

[8]The VIP index reflects the influence of the explanatory variables in the h-component model. For a jth independent variable, the $VIP_{hj} = \sqrt{(\frac{p}{Rd(Y;t_1,\ldots,t_h)} \sum_{l=1}^{h} Rd(Y;t_l)w_{lj}^2)}$. The contribution of variable j to the construction of the component t_l is measured by the weights w_{lj}^2. The variables that have larger VIP (> 1) are more important for predicting the dependent variable.

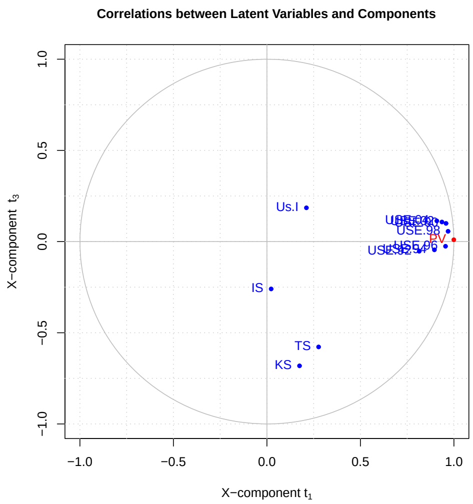
time-dependent manifest variables (model A), about 56.97% of the patent value is explained by the technological usefulness of patents and 43.03% by the other exogenous constructs (sample 1), whereas in the model with time-dependent latent variables (model B), these percentages are 89.40% and 10.60%, respectively.

Forward citations are the most widely used measures for assessing the importance or value of patents. This variable can be used as an indicator for a construct whose contribution to the patent value can be weighted –as was done in the case of technological usefulness. However, the value provided by this indicator is a later value or *a posteriori* value, which can be estimated once time has elapsed; and this could be too late if technology decisions must be made immediately. The benefit of using longitudinal models is that considering the time factor and the longitudinal nature of forward citations help to reveal when each of the construct and latent variables is important. Hence, exogenous constructs may be good indicators of value in the first stage of the life cycle of patents.

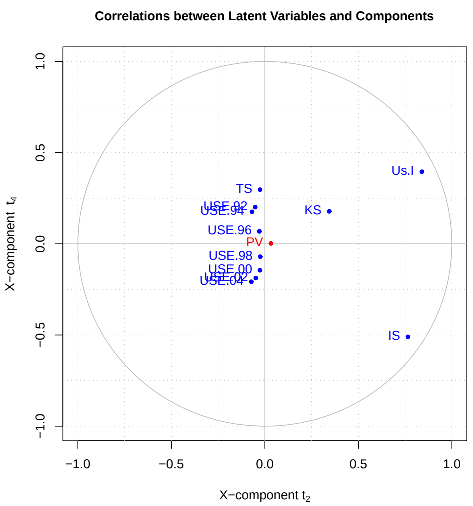
From a statistical standpoint, there are some aspects that have to be considered. First, these models were estimated with small samples. PLS Path Modelling is known for its ability to build a set of unobservable variables and estimate the structural relationships between them when small samples are available (Chin & Newsted, 1999; Tenenhaus & Hanafi, 2010). However, estimating the models with a larger sample, or even considering the population, would help to confirm the exploratory results presented here. In addition, it is well known that for consistency at large, PLS Path Modelling requires three or more indicators per construct –for reflective outer models at least. Simulation studies support this claim (Chin & Newsted, 1999). However, recent investigations have shown that the estimates of formative relationships with few indicators are fairly robust. On the other hand, considering longitudinal data requires caution when assessing results. As expected, the forward citations per year are highly correlated indicators; that is, the value of the variable at time t_i will influence the value of the variable at time t_{i+1}. This may not affect the estimates of the relationship in the outer model –because these models are modeled in a reflective mode– but this can affect the stability of the estimates of the structural relationships. This problem is solved using PLS regression instead multiple regression in the second stage of the PLS Path Modelling procedure.



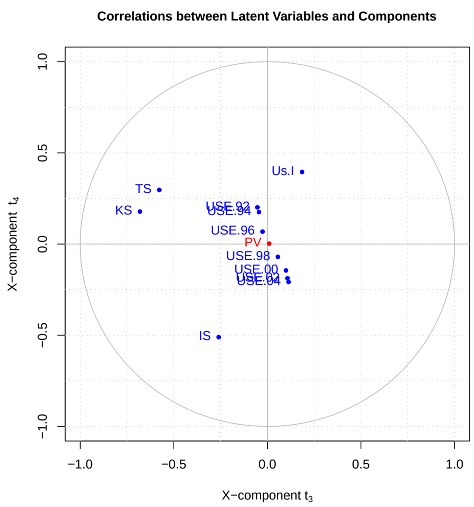
(a) X-components t_1 and t_2



(b) X-components t_1 and t_3



(c) X-components t_2 and t_4



(d) X-components t_3 and t_4

Figure 6: Correlations between latent variables and PLS components. The patent value (PV) is regressed on the knowledge stock (KS), the technological scope (TS), the international scope (IS), the technological usefulness (USE) for the different time periods and the auxiliary variable USE-Int (USE-Int).

9 Appendix: Tables

Table 4: Descriptive statistics of patent data.

	Sample 1: 1989-1990-1991							Sample 2: 1995-1996							Sample 3: 2000						
Manifest Variable	Mean	Standard Deviation	Minimum	Mediam	Maximum	Skewness	Kurtosis	Mean	Standard Deviation	Minimum	Mediam	Maximum	Skewness	Kurtosis	Mean	Standard Deviation	Minimum	Mediam	Maximum	Skewness	Kurtosis
Number of applicants	1.02	0.13	1	1	2	7.57	55.64	1.07	0.47	1	1	6	9.35	95.89	1.06	0.25	1	1	3	4.90	25.98
Number of inventors	1.74	1.17	1	1	8	2.11	5.78	2.04	1.35	1	1	6	1.09	0.04	2.26	1.64	1	2	9	1.62	2.75
Backward citations	8.44	6.25	1	7	32	1.51	2.35	12.58	11.71	1	10	89	3.42	17.05	14.10	13.06	1	11	88	3.09	12.42
Number of IPC	5.12	3.13	1	4	22	1.47	3.34	5.00	3.20	1	4	19	1.89	4.72	6.21	4.45	1	5	21	1.17	0.87
Number of claims	12.78	9.89	1	10	79	2.25	8.64	18.29	15.38	1	16	87	2.18	5.89	16.60	18.03	1	12	156	3.95	22.80
Priority JP	0.17	0.38	0	0	1	1.74	1.03	0.16	0.36	0	0	1	1.93	1.75	0.20	0.40	0	0	1	1.55	0.40
Priority DE	0.06	0.25	0	0	1	3.58	10.84	0.03	0.17	0	0	1	5.48	28.42	0.09	0.29	0	0	1	2.90	6.50
Forward citations	9.29	11.53	0	6	81	3.12	12.79	10.40	17.55	0	6	158	5.84	42.89	3.52	4.91	0	2	42	3.37	20.56
Family size	6.15	6.77	1	3	52	2.32	8.63	8.47	14.87	1	4	120	5.06	30.87	8.71	9.79	1	7	82	3.91	22.81
Dummy EP	0.30	0.46	0	0	1	0.87	-1.25	0.41	0.49	0	0	1	0.37	-1.90	0.51	0.50	0	1	1	-0.06	-2.02
Dummy JP	0.41	0.49	0	0	1	0.36	-1.88	0.41	0.49	0	0	1	0.37	-1.90	0.49	0.50	0	0	1	0.03	-2.02
Dummy DE	0.27	0.44	0	0	1	1.04	-0.92	0.31	0.46	0	0	1	0.83	-1.33	0.36	0.48	0	0	1	0.60	-1.66
Forward citations 1990	0.18	0.57	0	0	5	4.75	30.24	0.00	0.00	0	0	0	-	-	0.00	0.00	0	0	0	-	-
Forward citations 1991	0.53	1.06	0	0	7	3.10	12.26	0.00	0.00	0	0	0	-	-	0.00	0.00	0	0	0	-	-
Forward citations 1992	0.98	1.72	0	0	11	2.82	9.71	0.00	0.00	0	0	0	-	-	0.00	0.00	0	0	0	-	-
Forward citations 1993	1.52	2.41	0	1	18	2.92	11.26	0.00	0.00	0	0	0	-	-	0.00	0.00	0	0	0	-	-
Forward citations 1994	2.10	2.98	0	1	24	2.91	12.82	0.01	0.09	0	0	1	11.36	129.00	0.00	0.00	0	0	0	-	-
Forward citations 1995	2.66	3.62	0	1	28	2.80	11.92	0.11	0.34	0	0	2	3.15	9.98	0.00	0.00	0	0	0	-	-
Forward citations 1996	3.27	4.23	0	2	34	2.81	12.07	0.51	0.87	0	0	4	1.79	2.74	0.00	0.00	0	0	0	-	-
Forward citations 1997	4.00	5.20	0	2	38	2.95	12.14	1.22	2.56	0	0	24	5.92	49.09	0.00	0.00	0	0	0	-	-
Forward citations 1998	4.77	6.25	0	3	45	3.02	12.14	2.39	4.39	0	1	32	4.52	25.72	0.01	0.07	0	0	1	13.38	179.00
Forward citations 1999	5.53	7.30	0	3	48	3.04	11.49	3.43	5.48	0	2	39	4.15	21.90	0.02	0.15	0	0	1	6.52	40.94
Forward citations 2000	6.40	8.58	0	4	54	3.13	11.88	4.68	7.50	0	3	61	4.51	27.40	0.22	0.55	0	0	3	2.81	8.57
Forward citations 2001	7.24	9.46	0	4	65	3.14	12.30	6.45	9.71	0	4	75	4.19	23.06	0.96	1.53	0	0	7	2.15	4.90
Forward citations 2002	8.03	10.32	0	5	75	3.18	13.03	8.11	12.93	0	5	97	4.75	27.72	1.96	3.70	0	1	40	6.57	62.95
Forward citations 2003	8.87	11.32	0	6	81	3.13	12.65	9.25	14.31	0	5	102	4.36	23.60	2.97	4.64	0	2	45	4.72	37.34
Forward citations 2004	9.87	12.36	0	6	93	3.24	14.05	10.27	15.10	0	6	105	4.14	21.58	3.60	5.14	0	2	46	3.81	25.45
Forward citations 2005	10.03	12.63	0	6	93	3.30	14.78	11.06	15.97	0	7	117	4.18	22.31	4.07	5.61	0	2	49	3.59	22.68
Forward citations 2006	10.26	12.86	0	6	99	3.34	15.32	11.33	16.36	0	7	122	4.24	22.91	4.33	5.93	0	2	50	3.38	19.59

Table 5: Cross loadings of indicators for A-measurement models and samples 1, 2 and 3.

	1989-1990-1991				1995-1996				2000			
Indicator	**KS**	**TS**	**IS**	**USE**	**KS**	**TS**	**IS**	**USE**	**KS**	**TS**	**IS**	**USE**
Backward citations	0.277	0.107	-0.127	0.056	0.156	0.189	-0.088	0.044	-0.992	-0.162	0.048	-0.193
Number of inventors	0.932	0.088	0.364	0.142	0.992	0.283	0.133	0.316	-0.034	-0.210	0.031	0.009
Number of IPC codes	0.098	0.817	0.103	0.195	0.147	0.434	0.024	0.120	-0.178	-0.997	-0.111	-0.096
Number of claims	0.080	0.606	-0.154	0.159	0.278	0.936	-0.010	0.271	-0.168	-0.157	0.089	0.003
Priority JP	0.302	-0.008	0.994	0.048	0.181	0.038	0.772	0.091	0.139	-0.015	-0.055	-0.045
Priority DE	0.014	0.011	-0.013	0.002	-0.044	-0.049	0.574	0.094	0.023	-0.098	-0.978	-0.153
Family size	0.125	0.179	0.194	0.223	0.312	0.339	0.029	0.371	-0.241	-0.236	-0.089	-0.243
Dummy JP	0.252	0.186	0.365	0.316	0.401	0.241	0.370	0.462	-0.012	-0.147	-0.133	-0.198
Dummy DE	0.121	0.148	0.151	0.148	0.365	0.228	0.276	0.413	-0.112	-0.001	-0.297	-0.347
Forward citations 1992	0.130	0.217	0.030	0.755								
Forward citations 1993	0.127	0.222	-0.004	0.831								
Forward citations 1994	0.157	0.223	-0.011	0.866								
Forward citations 1995	0.160	0.227	0.008	0.900								
Forward citations 1996	0.178	0.257	0.030	0.931								
Forward citations 1997	0.140	0.260	0.043	0.947	0.157	0.112	0.133	0.766				
Forward citations 1998	0.116	0.232	0.025	0.958	0.175	0.180	0.084	0.855				
Forward citations 1999	0.108	0.210	0.016	0.957	0.184	0.211	0.071	0.906				
Forward citations 2000	0.098	0.187	0.010	0.954	0.191	0.213	0.079	0.936				
Forward citations 2001	0.112	0.182	0.012	0.943	0.234	0.250	0.083	0.952	0.149	0.084	0.092	0.820
Forward citations 2002	0.097	0.171	-0.006	0.930	0.214	0.223	0.057	0.932	0.175	0.042	0.054	0.921
Forward citations 2003	0.094	0.172	-0.014	0.920	0.218	0.226	0.030	0.927	0.155	0.017	0.084	0.928
Forward citations 2004	0.084	0.158	-0.028	0.899	0.257	0.232	0.020	0.925	0.120	0.021	0.120	0.929
Forward citations 2005	0.079	0.157	-0.032	0.896	0.262	0.249	0.001	0.907	0.103	0.067	0.141	0.925

Table 6: Cross loadings of indicators for B-measurement models and sample 1.

Indicator	KS	TS	IS	USE-Int	USE 92-93	USE 94-95	USE 96-97	USE 98-99	USE 00-01	USE 02-03	USE 04-05	PV
Backward citations	0.342	0.112	-0.149	-0.004	0.045	0.067	0.076	0.063	0.039	0.036	0.045	0.061
Number of inventors	0.905	0.087	0.343	0.222	0.120	0.141	0.138	0.093	0.095	0.085	0.068	0.171
Number of IPC codes	0.098	0.785	0.097	0.265	0.182	0.183	0.222	0.173	0.124	0.092	0.068	0.206
Number of claims	0.088	0.647	-0.136	-0.012	0.138	0.142	0.148	0.148	0.149	0.171	0.179	0.186
Priority JP	0.287	-0.018	0.824	0.284	0.014	0.001	0.040	0.022	0.013	-0.007	-0.026	0.056
Priority DE	0.008	0.011	0.464	0.193	-0.014	-0.026	-0.029	-0.008	-0.025	-0.026	-0.030	-0.005
Family size	0.125	0.172	0.252	0.895	0.095	0.094	0.126	0.121	0.108	0.085	0.059	0.187
Dummy JP	0.242	0.174	0.373	0.886	0.180	0.158	0.188	0.201	0.218	0.198	0.176	0.293
Dummy DE	0.121	0.146	0.265	0.746	0.009	0.028	0.076	0.077	0.059	0.047	0.028	0.118
Forward citations 1992	0.132	0.217	0.034	0.138	0.974	0.820	0.736	0.658	0.606	0.567	0.545	0.757
Forward citations 1993	0.126	0.221	-0.023	0.121	0.976	0.922	0.833	0.743	0.684	0.647	0.620	0.832
Forward citations 1994	0.157	0.223	-0.022	0.127	0.905	0.989	0.886	0.788	0.729	0.688	0.657	0.866
Forward citations 1995	0.162	0.227	-0.005	0.122	0.866	0.989	0.939	0.845	0.780	0.738	0.705	0.896
Forward citations 1996	0.180	0.256	0.008	0.158	0.825	0.944	0.988	0.901	0.836	0.789	0.753	0.925
Forward citations 1997	0.142	0.259	0.030	0.170	0.767	0.878	0.987	0.957	0.894	0.843	0.804	0.935
Forward citations 1998	0.118	0.232	0.021	0.174	0.733	0.838	0.951	0.994	0.939	0.896	0.857	0.948
Forward citations 1999	0.109	0.211	0.008	0.168	0.698	0.802	0.918	0.993	0.973	0.934	0.897	0.953
Forward citations 2000	0.099	0.188	0.001	0.180	0.671	0.772	0.886	0.970	0.996	0.966	0.932	0.955
Forward citations 2001	0.112	0.185	-0.005	0.163	0.649	0.748	0.860	0.947	0.996	0.985	0.957	0.950
Forward citations 2002	0.098	0.175	-0.018	0.152	0.628	0.727	0.834	0.926	0.983	0.998	0.975	0.940
Forward citations 2003	0.094	0.177	-0.024	0.145	0.616	0.712	0.816	0.911	0.970	0.998	0.988	0.932
Forward citations 2004	0.085	0.163	-0.038	0.123	0.602	0.691	0.790	0.885	0.949	0.984	0.999	0.913
Forward citations 2005	0.081	0.162	-0.043	0.124	0.595	0.686	0.786	0.880	0.947	0.983	0.999	0.910

Table 7: Standardized weights and loadings of the A-measurement models according to the type of constructs and for samples 1, 2, and 3; t-values in parenthesis, ** at the 0.01 significance level, * at the 0.05 significance level.

Construct	Indicator	Sample 1 1989-1990-1991		Sample 2 1995-1996		Sample 3 2000	
Knowledge stock	Backward citations	0.269	(0.914)	0.125	(0.639)	-1.004	(3.225**)
	Number of inventors	0.987	(4.225**)	0.988	(11.432**)	-0.131	(0.402)
Technological scope	Number of IPC	0.872	(3.427**)	0.353	(1.549)	-0.991	(3.304**)
	Number of claims	0.459	(1.563)	0.905	(6.145**)	-0.081	(0.271)
International scope	Priority JP	0.984	(4.170**)	0.821	(3.078**)	-0.211	(0.682)
	Priority DE	0.330	(1.098)	0.637	(2.164**)	-1.011	(3.062**)
Technological usefulness	Forward citations 1992	0.776	(10.285**)				
	Forward citations 1993	0.837	(15.605**)				
	Forward citations 1994	0.867	(21.051**)				
	Forward citations 1995	0.886	(25.339**)				
	Forward citations 1996	0.912	(56.225**)				
	Forward citations 1997	0.942	(73.476**)	0.766	(17.085**)		
	Forward citations 1998	0.954	(101.785**)	0.855	(26.683**)		
	Forward citations 1999	0.955	(96.355**)	0.906	(35.718**)		
	Forward citations 2000	0.954	(91.283**)	0.936	(53.855**)		
	Forward citations 2001	0.944	(80.711**)	0.952	(66.227**)	0.819	(16.468**)
	Forward citations 2002	0.933	(66.253**)	0.932	(57.330**)	0.921	(23.904**)
	Forward citations 2003	0.924	(58.308**)	0.927	(56.315**)	0.928	(22.558**)
	Forward citations 2004	0.905	(41.677**)	0.925	(66.034**)	0.928	(21.922**)
	Forward citations 2005	0.902	(40.289**)	0.907	(51.682**)	0.925	(22.181**)
	Family size	0.355	(2.426**)	0.371	(4.065**)	-0.243	(1.742*)
	Dummy JP	0.439	(2.894**)	0.462	(4.634**)	-0.198	(1.377)
	Dummy DE	0.256	(1.929*)	0.413	(3.457**)	-0.347	(2.455**)
Patent value	Backward citations	0.046	(0.435)	0.076	(0.871)	-0.381	(2.549**)
	Number of inventors	0.361	(3.029**)	0.447	(4.299**)	-0.029	(0.179)
	Number of IPC	0.357	(2.377**)	0.183	(1.681)	-0.333	(2.377**)
	Number of claims	0.177	(1.496)	0.384	(5.268**)	-0.070	(0.512)
	Priority JP	0.259	(2.147**)	0.177	(1.783*)	0.018	(0.121)
	Priority DE	0.045	(0.493)	0.106	(0.998)	-0.317	(2.295**)
	Forward citations 1992	0.763	(14.561**)				
	Forward citations 1993	0.829	(18.958**)				
	Forward citations 1994	0.859	(22.806**)				
	Forward citations 1995	0.891	(30.297**)				
	Forward citations 1996	0.923	(46.023**)				
	Forward citations 1997	0.935	(54.846**)	0.732	(13.267**)		
	Forward citations 1998	0.942	(63.915**)	0.818	(20.821**)		
	Forward citations 1999	0.940	(61.484**)	0.866	(25.174**)		
	Forward citations 2000	0.936	(55.249**)	0.896	(30.605**)		
	Forward citations 2001	0.928	(49.439**)	0.920	(40.372**)	0.770	(7.959**)
	Forward citations 2002	0.914	(41.874**)	0.895	(36.354**)	0.845	(8.707**)
	Forward citations 2003	0.905	(37.838**)	0.888	(35.426**)	0.848	(9.107**)
	Forward citations 2004	0.884	(29.482**)	0.892	(41.528**)	0.849	(8.682**)
	Forward citations 2005	0.880	(28.566**)	0.877	(36.892**)	0.856	(8.126**)
	Family size	0.375	(2.526**)	0.406	(4.146**)	-0.299	(1.950*)
	Dummy JP	0.498	(2.926**)	0.519	(5.076**)	-0.194	(1.177)
	Dummy DE	0.277	(1.973*)	0.456	(3.655**)	-0.354	(2.382**)

Table 8: Standardized weights and loadings of the B-measurement models according to the type of constructs and for sample 1; t-values in parenthesis, ** at the 0.01 significance level, * at the 0.05 significance level.

Construct	**Indicator**	**Sample 1: 1989-1990-1991**
Knowledge stock	Backward citations	0.427
		(1.344)
	Number of inventors	0.943
		(3.411**)
Technological scope	Number of IPC codes	0.763
		(3.110**)
	Number of claims	0.619
		(2.172**)
International scope	Priority JP	0.893
		(3.107**)
	Priority DE	0.570
		(1.892*)
Usefulness Int.	Family size	0.895
		(5.129**)
	Dummy JP	0.886
		(4.382**)
	Dummy DE	0.746
		(2.606**)
Technological usefulness	Forward citations 1992	0.974
1992-1993		(100.067**)
	Forward citations 1993	0.976
		(146.971**)
Technological usefulness	Forward citations 1994	0.989
1994-1995		(275.169**)
	Forward citations 1995	0.989
		(301.685**)
Technological usefulness	Forward citations 1996	0.988
1996-1997		(159.570**)
	Forward citations 1997	0.987
		(158.284**)
Technological usefulness	Forward citations 1998	0.994
1998-1999		(447.793**)
	Forward citations 1999	0.993
		(437.170**)
Technological usefulness	Forward citations 2000	0.996
2000-2001		(806.005**)
	Forward citations 2001	0.996
		(818.647**)
Technological usefulness	Forward citations 2002	0.998
2002-2003		(1564.357**)
	Forward citations 2003	0.998
		(1559.498**)
Technological usefulness	Forward citations 2004	1.000
2004-2005		(8624.720**)
	Forward citations 2005	1.000
		(8526.497**)

Table 9: Correlations among constructs and mean communalities; longitudinal model with time-dependent manifest variables (model A) and samples 1, 2, and 3.

	1989-1990-1991				1995-1996				2000			
Construct	**KS**	**TS**	**IS**	**USE**	**KS**	**TS**	**IS**	**USE**	**KS**	**TS**	**IS**	**USE**
Knowledge stock	1	0.116	0.323	0.185	1	0.303	0.121	0.318	1	0.190	-0.052	0.192
Technological scope	0.116	1	0.021	0.269	0.303	1	0.000	0.287	0.190	1	0.103	0.095
International scope	0.323	0.021	1	0.100	0.121	0.000	1	0.134	-0.052	0.103	1	0.164
Technological usefulness	0.185	0.269	0.100	1	0.318	0.287	0.134	1	0.192	0.095	0.164	1
Mean Communalities (AVE)	0.480	0.516	0.469	0.583	0.504	0.532	0.463	0.654	0.492	0.509	0.480	0.540

Table 10: Correlations among constructs and mean communalities; longitudinal model with time-dependent latent variables and sample 1 (1989-1990-1991).

Construct	**KS**	**TS**	**IS**	**USE-Int**	**USE 92-93**	**USE 94-95**	**USE 96-97**	**USE 98-99**	**USE 00-01**	**USE 02-03**	**USE 04-05**
Knowledge stock	1	0.129	0.260	0.208	0.132	0.161	0.163	0.115	0.106	0.096	0.083
Technological scope	0.129	1	-0.010	0.195	0.225	0.227	0.261	0.223	0.187	0.176	0.163
International scope	0.260	-0.010	1	0.363	0.005	-0.014	0.019	0.015	-0.002	-0.021	-0.041
Usefulness-Int	0.208	0.195	0.363	1	0.133	0.126	0.166	0.172	0.172	0.149	0.123
Technological usefulness 92-93	0.132	0.225	0.005	0.133	1	0.895	0.806	0.720	0.662	0.623	0.599
Technological usefulness 94-95	0.161	0.227	-0.014	0.126	0.895	1	0.923	0.825	0.763	0.721	0.689
Technological usefulness 96-97	0.163	0.261	0.019	0.166	0.806	0.923	1	0.941	0.876	0.827	0.789
Technological usefulness 98-99	0.115	0.223	0.015	0.172	0.720	0.825	0.941	1	0.962	0.921	0.883
Technological usefulness 00-01	0.106	0.187	-0.002	0.172	0.662	0.763	0.876	0.962	1	0.979	0.948
Technological usefulness 02-03	0.096	0.176	-0.021	0.149	0.623	0.721	0.827	0.921	0.979	1	0.984
Technological usefulness 04-05	0.083	0.163	-0.041	0.123	0.599	0.689	0.789	0.883	0.948	0.984	1
Mean Communalities (AVE)	0.468	0.518	0.447	0.714	0.950	0.978	0.975	0.987	0.993	0.996	0.999

Table 11: Percentage of variation accounted for by partial least squares components, both individual and cumulative, and Q_h^2 index. The patent value is regressed on the knowledge stock, the technological scope, the international scope, the technological usefulness for the different time periods and the auxiliary variable USE-Int.

		Redundancy	
Component	Q_h^2 **index**	**Individual**	**Cumulative**
1	0.999	55.327	55.327
2	0.869	12.973	68.300
3	0.632	8.570	76.870
4	0.041	6.517	83.387

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