CERNA WORKING PAPER SERIES

Essential patents in pools : Is value intrinsinc or induced ?

Henry Delcamp

Working Paper 2010:04

Cerna, Centre d'économie industrielle
MINES ParisTech
60, boulevard Saint Michel
75272 Paris Cedex 06 – France
Tél. : 33 (1) 40 51 90 00

May 2010

Essential patents in pools: Is value intrinsinc or induced ?*

Henry Delcamp†

29, march 2010

Working Paper

Abstract

This paper analyzes empirically the value - as measured by patent citations - of a set of 1363 essential patents belonging to 9 different patent pools. We find that pooled patents receive more cites than control patents having the same characteristics but not included in a pool. This difference stems only partly from the pools' ability to select the most cited patents. Indeed we show that being included in a pool also tends to increase the value of patents. This induced effect reflects the incentive for patent owners to join a pool. We analyze it in details in order to better understand the drivers of enhanced patent value.

* I am greatly indebted to Timothy Simcoe without whom this article would not have been written. François Lévèque, Yann Ménière and Jan Eilhard provided invaluable supports and comments. All errors are my own.

† Mines ParisTech, CERNA

1. Introduction

The first patent pool appeared in the early 19th century but these organizations become again a major topic of discussion lately especially in the telecommunications sector. A patent pool is an agreement between patent owners in order to grant a single license for more than one patent. Patent pools could help to reduce the patent thicket problem. A patent thicket is a “dense web of overlapping intellectual property rights that a company must hack its way through in order to actually commercialize new technology” (Shapiro, 2001). This problem of patent thicket is particularly true for economic sectors such as telecommunications. Patent pools could help to reduce this problem by reducing the number of licenses that a company wishing to use a new technology must sign.

The litterature generally identifies two main economic benefits of patent pools. They reduce the transaction costs by decreasing the number of licenses needed to use a technology. They avoid or reduce the multiple marginalization problem. The multiple marginalization concept, first defined by Cournot (1838), was adapted to intellectual property by Shapiro (2001) indicating that the total amount of royalties, for a technology, claimed by patent owners of complementary patents will be too high and therefore may reduce the standards’ diffusion. This also implies that patent owners could increase their revenues by coordinating their licensing behaviours. There are two known solutions for this multiple marginalization problem. One of them is the concentration of patent owners through mergers or acquisitions. The other one, which seems more realistic, is the gathering of patent owners through patent pools. From a global perspective, the creation of a pool is beneficial for the dissemination of the technology.

But, in practice, problems related to pools creation and stability are important issues. Indeed, patent holders have strong incentives not to participate to the pool in order to free ride by taking advantages of the opportunity to charge higher royalties for their patents (Aoki & Nagaoka, 2004). The aim of this paper is to analyze a possible incentive for patent holders to participate in a pool. In fact, one advantage of the pool may be to “strengthen” the patents. After introduction, patents are considered as essential for the dissemination of the technology and consequently can not be circumvented. It is, for instance, much easier for the patent holder to enforce its patent rights after introduction in a pool. This incentive, for patent holders, is a new research path almost unexplored in the litterature. Only, the International Telecommunications Standards User Group (1998) stressed that : “[…] when a patent is essential to a standard, it is converted into the equivalent of a ‘master patent’, even if it covers a relatively minor and unimportant innovation”.

This paper analyzes the possible link between value and essentiality. The debate beyond patents’ value in pools is to determine if patents are of better value when they are introduced or if the patents submitted are of lesser value initally but the pool reenforce them. We will use the patent number of citations as a proxy of the patents’ value. We will analyze if patents incorporated in pools generally receive more citations. We will identify the part of patent citations coming from the “intrinsinc value” effect (the pool selects patents with more citations) or from the “induced value” effect (when a patent is introduced in a pool, the number of citations increase). In order to do so, we follow the method used in the paper “Patents and the performance of Voluntary Standard Setting Organizations”, Rysman and Simcoe (2008).

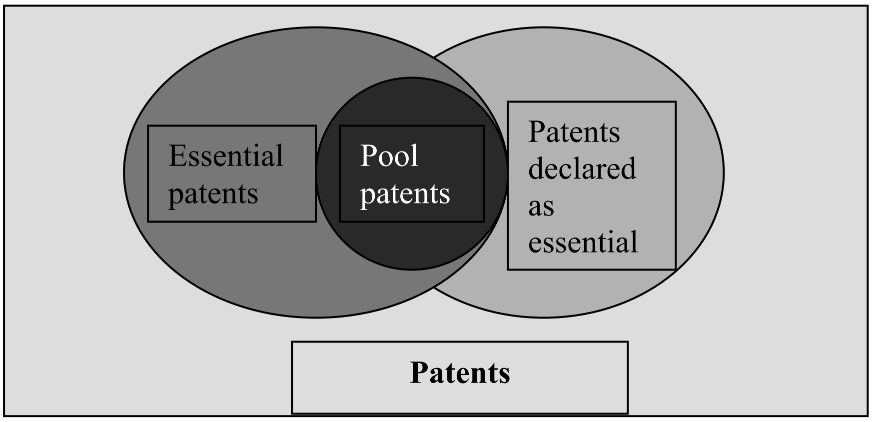
The remainder of this paper is organized as follows. Section 2 presents a literature review around essentiality and patents’ value. Section 3 presents descriptive statistics of the data and explains the collection process of these data. Section 4 deals with the citation age profile of control and pool patents. Section 5 deals with the marginal effect and intrinsinc value effect of the patent introduction in a pool. Section 6 discuss and analyze the link between the patent disclosure in an SSO and the selection by a pool.

2. Litterature review: what is a standard and an essential patent ?

The standardization can be defined as the creation of a common and documented repository to harmonize the activities of a sector. Standardization is conducted by formal or informal standardization bodies such as consortias or standard developing organizations. The creation of a technological standard has many advantages for the consumer. The standardization allows consumers to benefit inter alia from network effects. The creation of standards can also engender adverse effects such as reducing the consumers' choice or enhancing a firm market power. A pool is sometimes constituted after the creation of a technology. The pool includes patents essential to the dissemination of technology and allows user to sign only a single license for all pool patents. A patent holder may choose to bring or not its patent to the pool. The patent holders have, in practice, little incentive to bring their patents to the pool. The pools are constituted by patent holders or by pool administrators such as MPEG LA or Sisvel whose principal business is the creation and administration of pools.

The only criterion for introducing a patent in a pool is the essentiality. In order to be introduced in a pool, a patent has to be essential to the standard. Gilbert (2009) states that there are two main interpretations of the "essentiality" criteria. The definition and debates around the definition of essentiality goes beyond the scope of this paper and we will only present the core definition. The technical essentiality considered as essential any patent that has no close substitutes or substitutes so inferior that makes them very distant alternatives. The Department of Justice (DOJ) in the 1997 business review letter for the MPEG 2 patent pool has adopted this interpretation: "there is no technical alternative to any of the portfolio patents within the standard". In order to ensure the essentiality of the patents, pools usually have a third party evaluator that establishes essentiality reports. This third party evaluator is either an individual patent expert or a panel.

In practice, it is difficult to precisely identify all the essential patents related to a technology. Indeed, all pool patents are essential but all essential patents are not in the pool. Another possible approach would be to use the lists of patents declared as essential in the Standard Setting Organizations. Indeed, many Standard Setting Organizations require their members to make public any patent which may be essential to a standard. However, these lists contain patents that should not really be essential because no controls are conducted and all patent holders do not disclose their patents in SSOs so these lists are not exhaustive and partially wrong. The following graph summarizes the situation.



In their article (2008), Rysman and Simcoe studied the effect of patents' disclosure into Standard Setting Organizations (hereafter SSOs). They show that patents disclosed in SSOs, and then declared as essentials, receive more cites than other patents with the same characteristics (application year, citing year and technology class) and receive their citations later. They highlight that SSOs identify and endorse important technologies and that the disclosure of a patent in an SSO significantly increase the number of citations. They estimate that this marginal effect of disclosure accounts for roughly 20% of the difference in citation rates between SSO and control patents. They use patents declared as essential as a sample of essential patents.

In this article we will work on pool patents consisting of patents declared as essential and essential patents not disclosed. We will compare them to non essential patents with the same characteristics. We will also work on the link between pool patents and SSO patents comparing essential patents to patents declared as essential. For pool patents, the "induced value" effect can be a way to assess the legal and economic strengthening of the patents. Indeed, as stated in the introduction, the patent introduction in a pool is a way to "reinforce" the patent that can not be circumvented anymore. This strengthening of patents by introduction into a pool is almost unexplored in the economic literature but confirmed by discussions with professionals.

In order to assess the value of patents, we will use the patents' number of citations. The patents' number of citations is one of the measures in order to assess the economic and technological significance of a patent. These citations allow to identify prior art for an invention and thus are carefully controlled by patent offices because they help to define the claims' scope of the patent. For example, Layne-Farrar and Lerner (2008) in their empirical assessment of patent pools use forward cites as an indicator of patent value.

Rysman and Simcoe (2008) in their article dedicated to patents within Standard Setting Organizations also use patent citations as an indicator of value. Harhoff and all. (1999) highlighted a positive correlation between the number of citations and a subjective estimate of patents' value determined by patent holders. Hall and all. (2005) show that cited patents are more correlated with the patent holders' market value than non cited patents. Giummo (2003) highlights, on a sample of german patents, that patents with more citations generate more royalties and thus that the citations could be an indicator of the economic value of patents. Given the literature on cites, we can therefore affirm that the link between patents' economic value and number of cites has been proved. Nevertheless, a further dicussion on the relevance of this indicator to assess the economic and technological significance of a patent goes beyond the scope of this paper.

3. The data

We work with 1363 patents from 9 pools. We choose these pools because they publish online their list of essential patents. All these pools are administered by MPEG LA[‡] or Sisvel[§]. This necessarily generates sample selection bias because these pools are all quite large and only partly reflects an *average pool*. Today, pools are generally created and managed by companies holding patents or by specialized firms whose business is the management of pools such as MPEG LA and Sisvel. The data were collected in july 2009. Table 1 presents the number of patents per pool:

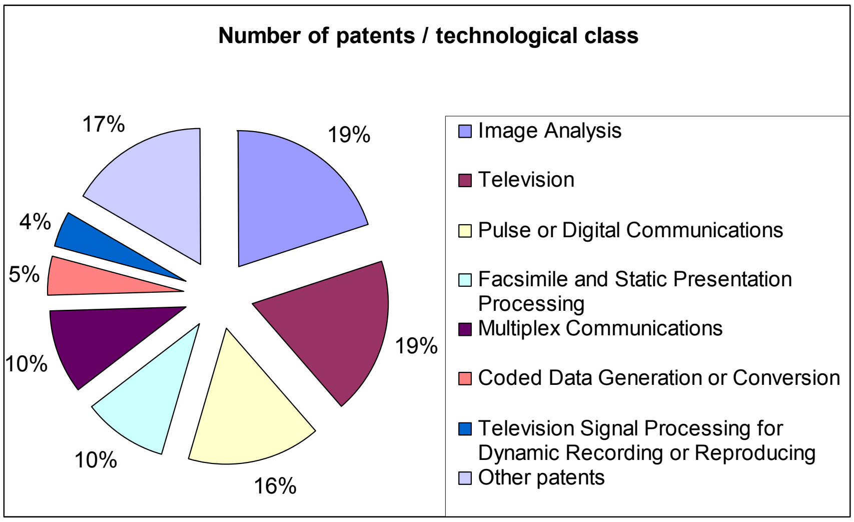
Pool	Number of patents	Number of american patents	Percentage of american patents in the pool
1394	104	62	59.62%
ATSC	50	31	62.00%
AVC	311	60	19.29%
MPEG 4 SYSTEMS	13	7	53.85%
MPEG 4 VISUAL	366	123	33.61%
MPEG AUDIO	102	15	14.71%
MPEG-2	149	90	60.40%
MPEG-2 Systems	27	19	70.37%
VC-1	241	60	24.90%
Total	**1,363**	**467**	**34.26%**

Table 1 : Pool patents

In order to obtain the number of citations for a patent, we connect the patents of our pool database to the 1976/2006 U.S. patents database available online using the patent number. This operation allows us to obtain a valuation of the patents' value of each U.S. patent. Nevertheless, this operation also creates an important selection bias for our sample. Table 1 presents the number of U.S. patents in each pool. Graph 1 highlights the application years for these 467 patents. As we can see, the majority of these applications date from the 1990s.

[‡] http://www.mpegla.com/index1.cfm
[§] http://www.sisvel.com/english

Graph 1 presents the percentage of patents per technology class based on the U.S patent classes as of 31 december 1999[**]. All the patents of our pool database are related to High Technology because of our pools' choice.



Graph 1 : Number of patents / technological class

In order to analyze the pool patents, we created a control database with patents from the NBER database having the same characteristics (application year and technology class) than the pool patents.

It is very important to create a control database with patents having the same characteristics than the patents analyzed because the number of cites could vary based on these characteristics (application year or cohort effect, technology class…). We also constituted a "matched control" sample based on a randomly selected one to one match (the joint distribution of application year and technology class is identical to the pool sample). The sample matched control presents the same characteristics than the pool sample from which we removed all the duplicate patents. This should allow us to identify patents with close characteristics to pool patents and therefore explain the citations difference by the presence in the pool. Hereafter are the main characteristics of each sample. The sample "all controls" is constituted by all the patents with the same characteristics included in the 1976/2006 NBER U.S. patents database. The number of citations corrected *allnscites* represents the patents' number of citations minus the citations made by the patent holder on its own patents.

[**] http://www.nber.org/patents/list_of_classes.txt

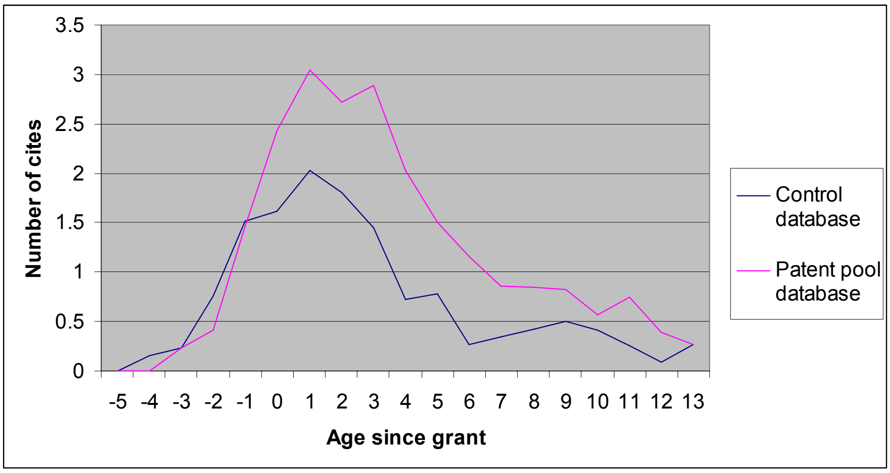
	Patent pool sample	Patent Pool sample without duplicates	Matched controls	All controls	NBER patents
Number of observations	467	383	382	135370	3209376
Mean Allcites	25.188	26.007	16.925	20.693	11.781
Mean Allnscites	21.457	22.006	15.641	19.056	10.946
Application Year	1996.465	1996.731	1996.736	1996.5	1992.094
Age since grant	7.154	6.893	6.38744	6.480	11.766
Cites/year	3.680	3.878	3.270	3.193	1.762
Number of claims	17.161	17.744	17.301	17.709	12.083

Table 2: Samples presentation

The pool patents seem to receive more citations than other patents from the control database. The average number of citations per year is higher for pool patents than for matched control patents and therefore also for all control patents. We can also check with the number of claims which is also sometimes used as an indicator of value than pool patents seem to be of better value than other NBER patents. However, although this ascertainment is useful, it is more interesting for our research to have a closer look at the citation age profile of the pool patents in order to highlight if these patents are usually cited earlier or later than the control patents.

4. Citation age profile

To get a first idea of the citation age profile, we look at the average citation age; conditionnal on patent age. This citation age profile can be highlighted by the graph 2 for the pool and the control sample. The same graph is available in annex for the biggest pool, the 1394 pool. On these graphs we can see that pool patents receive more citations than control patents. The other important information in this graph is that pool patents receive in general their citations later than the control patents. This finding is interesting because it could mean that these late citations are triggered by an event that does not affect control patents such as the inclusion in a pool.



Graph 2 : Citation age profile all pools

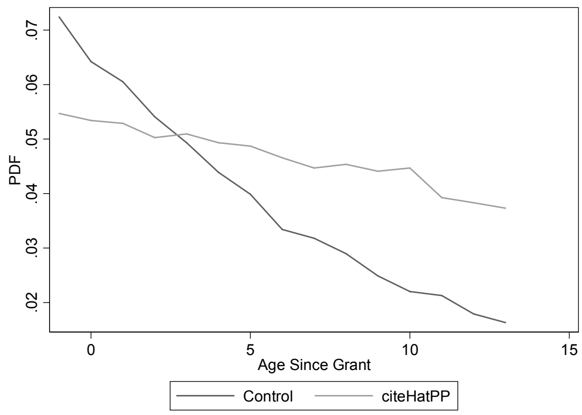
To explain the differences in the citation age profile between the control patents and the pool patents, we also employ the method developed by Mehta, Rysman, Simcoe (2008) using a full set of application, citing year and technology class effect to control for various cofounding factors. This new method makes the asumption that the citation age process begins when the patent is granted by the patent office and not at the date of application. The patent age is, in this case, defined by the difference between the citing year and the grant year of the patent. This method allow to control in the same regression for the birth year effect, the age effect and the citation year effect and overcomes the collinearity between these three effects. To do this, the lag between application and grand year is used as as source of exogeneous variation.
We will not discuss this assumption in this paper but for a better understanding of this hypothesis, you can refer to Mehta, Rysman, Simcoe who examine the potential bias if this

surmise is incorrect and test their method by reexamining prior results[††]. The details for the regression made and a table of coefficients are available in annex 1. However, it is difficult to make predictions on the shape of the age distribution based on these coefficients, we use predictions conditionnal on age to obtain an average citation age for the control sample and the patent pool sample. Then, we compare these results to the results based on raw data. Table 3 summarizes these results for the pool and control sample.

	Raw data	**Estimations**
Patent pool database	2.46 (0.05)	4.10
Control database	1.70 (0.06)	2.01
Standard error in parentheses		

Table 3: Average citation age

As we can see on the above table, the average citation age of pool patents is higher than the average citation age of the control sample. This confirms that pools patents receive their citations later than control patents. This result appears clearly on graph 3 that shows the predicted cites flows for pool and control database.



Graph 3 : Predicted cites flows

This first part of our research shows that pool patents receive more citations than control patents and have a different citation age profile, receive citations later. We will now work on the effects of patent pools in order to separate the induced value effect of the intrinsinc value effect.

[††] For a discussion of this hypothesis, see : Mehta, Rysman, Simcoe, «Identifying the age profile of patent citations», Journal of Applied Econometrics

5. The pools' effect

In this part, we will analyze the link between the patents' citations and the patent pool in order to differentiate between the intrinsinc and the induced value effect. Indeed, the precedent part shows that pool patents receive more citations than control patents and receive their citations later. But this situation can arise from several effects. The number of citations can increase because the patent is incorporated in a pool or the pool can select patents with a higher number of citations. The aim of this part is to answer the following question : Are patents selected because they are more cited or are they more cited because they are selected ?

It would be obviously impossible to establish a causal interpretation of our results because we can not reject the hypothesis that the pools' selection is correlated with another unobserved variable that causes citations. In order to test our hypotheses, we will work with two different methods that will give close results. First of all, we identify the date of creation of our pools. Our pools were created between 1997 and 2007. In some cases, to avoid a truncation problem (because we only have the citations until 2006), we will work on pools created before or during the year 2003.

5.1 The pools' marginal effect

The first method is based on the pool sample. The aim is to study induced value effect of the patents' introduction in the pool. In order to do so, we will work on a panel database of pool patents and control for the introduction in the pool through a dummy "patent pool introduction". Then, we estimate a poisson model on the pool sample with the following specifications:

$$C_{py} = f(\alpha_{py}^{PP}, \beta_a, \chi_y, \delta_p, \varepsilon_{py}) \quad [1]$$

With :

C_{py} = Number of citations for a patent p at year y

α_{py}^{PP} = Post declaration dummy

β_a = Patent age effect

δ_p = Patent fixed effect

χ_y = Truncation effect

$f()$: is a poisson process

The main results are presented in the following table. We also present the most significant results per pool. For this regression, we eliminated the pools that were created after 2003 due to our lack of information on citations after 2006.

Allcites	Patent pool sample	Pool sample with pools created before or in 2003	Pool sample with pools created before 2003	Pool sample with pools created before 2002
Model 1 : Induced value effect starts at disclosure year (N=1551)				
Induced value effect	0.3052*** (0.073)	0.3430*** (0.075)	0.3540*** (0.091)	0.4990*** (0.105)
Patent age effect	0.2085*** (0.014)	0.2002*** (0.014)	0.1860*** (0.019)	0.1886*** (0.026)
Truncation effect	-0.5619*** (0.021)	-0.5619*** (0.022)	-0.5327*** (0.028)	-0.5445*** (0.034)
Model 2 :Induced value effect starts at disclosure year – 2 (N=1551)				
Induced value effect	0.2215** (0.072)	0.2563*** (0.073)	0.4711*** (0.09)	0.8103*** (0.131)
Patent age effect	0.2062*** (0.015)	0.1968*** (0.015)	0.1555*** (0.021)	0.0998** (0.034)
Citing Year effect	-0.5487*** (0.021)	-0.5459*** (0.022)	-0.4901*** (0.027)	-0.4099*** (0.04)

Legend: * p<0.05; ** p<0.01; *** p<0.001. Standard error in parentheses. Results based on the fixed effect poisson specification in equation 1.

Table 4 : Equation 1 results

These results show that the induced value effect requires further analysis and can not be interpreted at a first sight. First of all, we have to manage issues related to our data especially the pools' age because most of our pools are recent. In order to do that, we made several regressions separating the aggregate sample, a sample with all pools created in or before 2003, a sample with all pools created strictly before 2003, a sample with all pools created strictly before 2002. As we can see the coefficients are higher when we only take into account older pools such as pools created in 1997 or 1999. In this case, the induced value effect with a coefficient of 0.4990 seems important and significant. We also control for a "pre-disclosure" effect in order to check for the possibility that patents have been made public before the creation date of the patent pool. In order to do that, we artifically advanced the date of disclosure by two years and compare the results with the standard model. As we can see in table 5, that seems to have an effect on all sample, results for the second model are in general higher than for the model 1.

If we take into account all the sample except pools with a creation date equal to 2006 or 2007 (due to our data on citations), we can say that the patent introduction in a pool increase the number of citations from around 35% to around 50%. To conclude, we can say that the induced value effect is positive and significant.

5.2 The intrinsinc and induced value effects

In order to make the comparison with the induced value effect, we will work on a cross-sectional regression with the entire sample including both the pool and the control patents. The aim of this approach is to compare the two effects; we will therefore introduce a dummy for the patents' presence in the pool and keep the dummies "disclosure" of the precedent regression. We also control for the application year, technology class and age effects. We estimate the following poisson regression on cross-sectional data:

$$C = f(\alpha^{disc}, \beta_p^{Sel.}, \varphi_y, \lambda_c, \varpi_a, \phi_{y,} \varepsilon_{py}) \qquad [2]$$

With :

C = Number of citations for a patent p

α^{disc} = Post declaration dummy / patent

$\beta_p^{Sel.}$ = Selection dummy (1 if selected, 0 otherwise)

φ_y = Application year effect

λ_c = Technology class effect

ϖ_a = Age effect

$\phi_{y,}$ = Citing year effect

$f()$: is a poisson process

The results of this regression are:

Number of citations	Matched control sample (N=782)	Matched control sample with pools created before or in 2003 (N=507)
Model 1 : Control for application year and technology class		
Intrinsinc value effect	0.5268***	0.2162
	(0.131)	(0.118)
Induced value effect	-0.2948	0.7710***
	(0.157)	(0.132)
Application year effect	Y	Y
Technology class effect	Y	Y
Model 2 : Control for application year, technology class and patent age		
Intrinsinc value effect	0.4473***	0.3246*
	(0.124)	(0.139)
Induced value effect	-0.039	0.3971**
	(0.138)	(0.151)
Application year effect	Y	Y
Technology class effect	Y	Y
Patent age effect	Y	Y
Model 3 : Control for application year, technology class, citing year and patent age		
Intrinsinc value effect	0.4592***	0.3427*
	(0.123)	(0.136)
Induced value effect	-0.0508	0.3602*
	(0.137)	(0.142)
Application year effect	Y	Y
Technology class effect	Y	Y
Patent age effect	Y	Y
Citing year effect	Y	Y

*Legend: * p<0.05; ** p<0.01; *** p<0.001. Robust standard error in parentheses. Results based on the poisson specification in equation 2.*

Table 5 : Equation 2 results

We can see that the results for the matched control sample appear to be different from our previous findings on the induced value effect. Indeed, the induced value effect seems to have a negative impact on the number of citations. If we correct the sample and take only into account the pools with a creation date inferior or equal to 2003, the results seem consistent with our previous findings. The pool intrinsinc value effect has a positive and very significant coefficient and the induced value effect is still positive and significant but lower than in our previous findings. Our findings suggest that the intrinsinc value effect is almost as large as the induced value effect at 0.3427 and 0.3602 if we take into account this sample. Thus, our results indicate that around 50% of the difference in the number of citations between the pool and the control patents is due to the intrinsinc value effect and around 50% is due to the induced value effect.

6. The link between patent pools and Standard Setting Organizations

Patent pools are created after the standardization of a technology. Thus, a patent usually is disclosed first in a Standard Setting Organization and then introduced in a pool. Consequently, we have to analyze the impact of the link between SSOs and patent pools on the number of citations. Indeed, Rysman & Simcoe (2008) show that patent disclosure into a Standard Setting Organization increases the patents number of citations by around 35/40%. Thus, it could be argued that the higher number of citations of pool patents is a consequence of the patent disclosure in the Standard Setting Organization. The link between SSO and pool patents could be an interesting argument to explain the pools intrinsinc value effect because of the SSO disclosure effect. The assumption behind this idea would be than pool patents are all previously disclosed in an SSO and then subject to an increase in their number of citations due to this disclosure.

First of all, we have to discuss the possibility to link pool patents to SSO patents. This link is very difficult to establish because SSO patent disclosures are often very vague (the patent number or title is not always given…). In order to do that, we link the database available online at www.ssopatents.org to our pool database. This allows us identifying 25 patents in our database that were previously disclosed in an SSO. We also control directly for the AVC project if some patents are both pool and SSO patents. The result is surprising : only 29 american patents were disclosed in the SSO disclosure database (complete disclosure with patent number…) and none of them are included in the pool. In order to control for the link between pools and SSO patents and given the difficulties explained above, we use the following method. We run the same regression than in equation2 adding a dummy for patents held by firms disclosing in the dedicated SSO.

Another problem could be related to the use of cites in a standardization context. Indeed, Lampe & Moser (2009) show evidence of strategic patent files and highlight that the creation of a pool increase the number of patent filing. Baron & Delcamp (2010) show that patents included late in patent pools are more focused on the standard than patents included at the beginning of the pool creation process. Thus, if the creation of a pool increase the number of patent files on the technological area concerned, it could be problematic to use the number of cites as an indicator of patents' value.

Indeed, it would be quite normal in this case to find a higher number of cites for pool patents than for non pool patents of the same technological class. The difference in this case could not be explained by a difference in value but only by the increase in the number of patent files and therefore by an increase in citations between pool patents. In order to manage this potential problem on cites, in this part, we run all our regressions both on all citations and external cites. The number of external cites can be defined as the number of forward cites that are not self cites or that does not come from patents in the same pool. Using external cites instead of the number of cites (excluding self cites) should resolve the problem of citations in a standardization context.

6.1 Identification of SSO patents

The aim of this method is to control if the pool intrinsinc value effect is still positive and significant when we take into account the patents earlier disclosed in an SSO. As we already explained in the precedent subsection, it is almost impossible to link directly patent disclosures in Standard Setting Organizations and pool patents. To try to circumvent this problem, we use in this section a dummy for pool patents held by firms that make disclosures in the dedicated SSO making the hypothesis that a firm can not disclose only a part of its patent portfolio to an SSO.

This means that we make the assumption that a firm disclosing its patents in an SSO discloses its entire portfolio and not just some patents. With this method, we identified 229 patents (out of 417 in our pool sample) that may have been subject of a disclosure. Afterward, we run the same regression than in equation 3. We perform the regression on the entire pool sample and not only on pools created before 2003 because we are no longer interested in analyzing the induced value effect. Therefore, the induced value effect coefficients will not be interpreted in the results. Then, we estimate the following poisson regression :

$$C = f(\beta_p^{Sel.}, \varphi_y, \lambda_c, \varpi_a, \phi_{y,} \delta_{p,} \varepsilon_{py}) \qquad [3]$$

With :

C = Number of citations for a patent p

$\beta_p^{Sel.}$ = Selection dummy (1 if selected, 0 otherwise)

φ_y = Application year effect

λ_c = Technology class effect

ϖ_a = Patent age effect

$\phi_{y,}$ = Citing year effect

δ_p = SSO presence dummy

$f()$: is a poisson process

The results of this regression are :

Number of citations **Matched control sample (N=782)**	**Matched control sample Allnscites**	**Matched control sample external cites**
Intrinsinc value effect	0.40246** (0.151)	0.42619* (0.183)
Induced value effect	0.14036 (0.157)	0.06575 0.176
Disclosure SSO dummy	-0.19056 (0.127)	-0.29660* 0.137
Application year effect	Y	Y
Technology class effect	Y	Y
Patent age effect	Y	Y
Citing year effect	Y	Y

*Legend: * p<0.05; ** p<0.01; *** p<0.001. Robust standard error in parentheses. Results based on the poisson specification in equation 3.*

Table 6 : Equation 3 results

We can see that the pool intrinsinc value effect is still positive and significant even if the results are lower and less significant than for the precedent regression. The results of this regression are interesting because this mean that even when we control for the SSO induced value effect, the pool patents are still of better value than our control sample.

Conclusion

In this article, we compare the value of patents introduced in a pool to patents with the same characteristics (application year, technology class…) not included. We succesively analyzed the induced value effect of the introduction and then, simultaneously, the intrinsinc and the induced value effect. We also discuss and analyze the link between the marginal effect, on the number of citations, of patents disclosed in an SSO and the pool intrinsinc value effect. Our results show that the patents' introduction in a pool increase the number of cites (induced value effect) but also that pools, in general, select patents with a higher number of citations (intrinsinc value effect). The induced value effect is as important as the intrinsinc value effect on the number of citations. When we take into account, the possible link between Standard Setting Organizations and patent pools, these results seem remain robust.

Indeed, when we take into account the SSO disclosure effect on the patent number of cites, the previous results showing that pools select patents receiving more citations remains true under our assumption that a firm can not disclose only a part of its patent portfolio to an SSO. So, we can say that pool patents have a higher intrinsinc value than patents with similar characteristics not included in a pool.

These results are important in the current debate about the pools and their economic efficiency. Indeed, they show that although the term of essentiality is not directly related to patents' value and therefore to the number of citations, patents selected by pools are generally of better value than similar patents not incorporated in a pool. It shows that essential patents are generally of better value based on the number of citations. This also seems to prove that pools are not used to dismiss poor values' patents that could therefore have a negative impact for consumers on the downstream market.

References

- Aoki, R., Nagaoka, S. (2004), "The Consortium Standard and Patent Pools", *The Economic Review*, 55(4)

- Baron, J., Delcamp, H. (2010), "Strategic inputs into patent pools", *CERNA Working Paper*

- Brenner S. (2008), "Optimal formation rules for patent pools", *Economic Theory*, Vol.40, N. 3, pp. 373-388

- Cournot A.A. (1838), *Recherches sur les principes mathématiques de la théorie des richesses*

- Hall, B. H., A. B. Jaffe, and M. Tratjenberg (2001), "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools.", *NBER Working Paper 8498*

- Gilbert R. (2009), "The essentiality test for patent pools", forthcoming in Rochelle Dreyfuss, Diane Zimmerman and Harry First (eds.), *Working within the Boundaries of Intellectual Property*, Oxford University Press

- Giummo J. (2003), "Should All Patentable Inventions Receive Equal Protection? Identifying the Sources of Heterogeneity in Patent Value", *Discussion Paper*, University of California, Berkeley

- Hall Bronwyn H., Jaffe A., Trajtenberg M. (2005), "Market value and patent citations", *RAND Journal of Economics*, Vol. 36, pp. 16-38

- Harhoff D., Narin F., Scherer F.M., Vopel K. (1999), "Citation frequency and the value of patented inventions", *The Review of Economics and Statistics*, Vol. 81, pp. 511-515

- Lampe, R., Moser, P. (2009), “Do Patent Pools Encourage Innovation? Evidence from the 19th-Century Sewing Machine Industry”, *Working Paper*

- Layne-Farrar, A., Lerner, J. (2008) , “*To Join or Not to Join : Examining Patent Pool Participation and Rent Sharing Rules*”, Working Paper

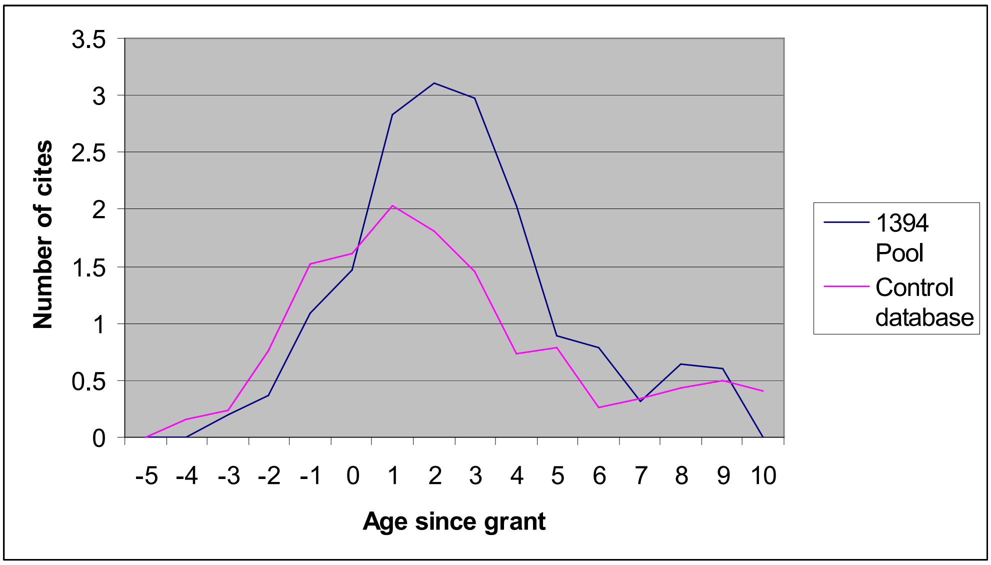
- Mehta A., Rysman M., Simcoe T., “Identifying the age profile of patent citations: New estimates of knowledge diffusion”, *Journal of Applied Econometrics*, forthcoming

- Rysman M., Simcoe T. (2008), “Patents and the Performance of Voluntary Standard Setting Organizations”, *Management Science*, Vol. 54, N 11, pp. 1920-1934

- Shapiro C. (2001), “Navigating the Patent Thicket: Cross Licenses, Patent Pools, and Standard-Setting”, *Innovation Policy and the Economy* (Vol. I), pp. 119–150, MIT Press

- Lerner J., Tirole J. (2004), “Efficient Patent Pools”, *American Economic Review*, Vol. 94, pp. 691-711

Annex 1 : Citation age profile



Graph 4 : Citation Age Profile for the 1394 pool

We estimate a citation age profile based on the following model :

$$C_{py} = f(\alpha_y, \beta_c, \phi_{y,} \delta_a^{PP}, \varphi_a^{cp}, \varepsilon_{py}) \qquad [4]$$

With :

C_{py} : Number of citations for the patent p at year y

α_y : Application year effect

β_c : Technology class effect

$\phi_{y,}$: Citing year effect

δ_a^{PP} : Age effect for the patent pool patents

φ_a^{cp} : Age effect for the control patents

$f()$: is a poisson process

We consider that the age effects could be different in the two samples but the technology class, citing year and application year effects identical. We estimate this equation on the patent pool and control sample. The results are presented in the table 7. In order to control for the truncation of our sample, we stop our analysis to patents with an application year earlier than 2002. These coefficients seem to confirm that there is a difference in the age effect between the pool sample and the control sample.

Age	Control patents	Pool patents
-3	0.23	0.23
-2	0.76	0.41
-1	1.52	1.46
0	1.62	2.43
1	2.03	3.04
2	1.81	2.72
3	1.45	2.88
4	0.73	2.02
5	0.79	1.50
6	0.27	1.16
7	0.34	0.86
8	0.43	0.85
9	0.50	0.83
10	0.41	0.57
11	0.26	0.75
12	0.09	0.39
13	0.27	0.27

Table 7: Age effect for the pool and control patents

Annex 2 : Regressions results with Negative Binomial

Allcites	Patent pool sample	Pool sample with pools created before or in 2003	Pool sample with pools created before 2003	Pool sample with pools created before 2002
Model 1 : Induced value effect starts at disclosure year (N=1551)				
Induced value effect	0.04361	0.19567	0.20934	0.34124*
	(0.101)	(0.127)	(0.131)	(0.154)
Patent age effect	0.16417***	0.14806***	0.14770***	0.16843***
	(0.016)	(0.020)	)0.021)	(0.029)
Truncation effect	-0.49145383***	-0.49727***	-0.49119***	-0.52308***
	(0.026)	(0.033)	(0.035)	(0.041)
Model 2 :Induced value effect starts at disclosure year – 2 (N=1551)				
Induced value effect	0.08819	0.41512***	0.50442***	0.72311***
	(0.093)	(0.118)	(0.124)	(0.168)
Patent age effect	0.16152***	0.13020***	0.12380***	0.12194***
	(0.016)	(0.020)	(0.021)	(0.031)
Truncation effect	-0.49147***	-0.49293***	-0.48400***	-0.46675***
	(0.025)	(0.031)	(0.033)	(0.041)

Legend: * p<0.05; ** p<0.01; *** p<0.001. Standard error in parentheses. Results based on the fixed effect poisson specification in equation 1.

Table 8 : Equation 1 results with negative binomial

Number of citations	Matched control sample (N=782)	Matched control sample with pools created before or in 2003 (N=507)
Intrinsinc value effect	0.37490***	0.30942*
	(0.104)	(0.128)
Induced value effect	-0.05079	0.33393*
	(0.130)	(0.142)
Application year effect	Y	Y
Technology class effect	Y	Y
Patent age effect	Y	Y
Citing year effect	Y	Y

*Legend: * p<0.05; ** p<0.01; *** p<0.001. Robust standard error in parentheses. Results based on the poisson specification in equation 2.*

Table 9 : Equation 2 results using negative binomial

Number of citations Matched control sample (N=782)	Allnscites Matched control sample	External cites Matched control sample
Intrinsinc value effect	0.32699* -0.132	0.41391** -0.133
Induced value effect	0.20576 -0.13	0.27254* -0.132
Disclosure SSO dummy	-0.07768 -0.125	-0.13424 -0.122
Application year effect	Y	Y
Technology class effect	Y	Y
Patent age effect	Y	Y
Citing year effect	Y	Y

*Legend: * p<0.05; ** p<0.01; *** p<0.001. Robust standard error in parentheses. Results based on the poisson specification in equation 3.*

Table 10 : Equation 3 results using negative binomial