THE
CRITERION
JOURNAL ON INNOVATION

VOL. 1 2016

The Value of Patents in Pools and Its Implications for Competition

Henry Delcamp[*]

A patent pool is an arrangement that serves the purpose of obtaining a single license for a package of patents that belong to different owners. Since the late 1990s, patent holders have used patent pools to facilitate chiefly the adoption of technology standards, such as the Digital Versatile Disc and the MPEG video compression format, which embody a large number of patented elements. A patent pool provides a "cooperative marketing agreement"[1] between competitors by reducing the transaction costs of licensing and preventing excessive royalty stacking due to coordination failure between licensors.[2]

Despite those advantages, patent pools also raise questions, especially about their practical functionality. First, the creation of patent pools often generates problems in practice. A patent holder might not join a patent pool to keep the freedom of charging high royalties for its own patents.[3] On the basis of that reasoning, many economists suspect that patent pools include

* Associate Research Fellow, Mines ParisTech; Adjunct Professor, ESCP Europe, Paris. Email: henry.delcamp@ensmp.fr. I am indebted to Timothy Simcoe without whom this article would not have been written. Richard Gilbert, Dan Spulber, Aija Leiponen, Thomas Hoehn, Marc Bourreau, François Lévèque, and Yann Ménière provided support and comments. This article has also benefitted from comments by the participants of the 2010 EURAS conference and the participants of the T.U. Berlin seminar.

1 The "cooperative marketing agreement" was first introduced in Josh Lerner, Jean Tirole & Marcin Strojwas, *Cooperative Marketing Agreements Between Competitors: Evidence from Patent Pools* 1 (National Bureau of Economic Research, Working Paper No. 9680, 2003).

2 Such failure in coordination is also known as the multiple-marginalization problem. Royalty stacking arises when multiple patents affect a single product. In this case, to bring a product to market, the manufacturer takes licences from all the patent holders that affect the final product. If the patent holders do not coordinate their behaviors, the royalty payments cumulate and the licensee faces the risk of an unprofitable product.

3 *See, e.g.*, Vianney Dequiedt & Bruno Versaevel, *Patent Pools and Dynamic R&D Incentives*, 36 INT'L REV. L. & ECON. 59 (2013) (analyzing theoretical models of pool formation and their impact on incentives to invest in research and development).

only low-quality patents. Furthermore, patent pools might have a negative antitrust effect as they could be used as a price-fixing mechanism.[1]

This article seeks to inform the debate surrounding patent pools by assessing empirically the value of pool patents. For many reasons—for example, because patent pools could have an impact on the market size of a standard—one might expect patents to become more valuable once they are pooled. It is therefore important to differentiate the intrinsic value of a patent included in a pool (which is reflected by the number of citations to that patent *before* its inclusion in a pool) from the induced value of the patent that the pool generates (which is reflected by the number of citations to that patent *after* its inclusion in a pool). Working with a database of patents from nine patent pools and a control database composed of the same number of patents that have the same characteristics (application year and technological class) but are not in a pool, I use the number of forward citations of a patent—that is, the number of citations to that patent in subsequent patents—as a proxy of its value. I analyze whether pool patents receive, on average, more citations. I then identify the portion of patent citations resulting from the intrinsic-value effect and the portion stemming from the potential induced-value effect.[2]

Choosing an appropriate control dataset is crucial to differentiating correctly between the intrinsic and the induced-value effects. Because it is impossible to create a control database of essential patents that are not included in a pool, I select randomly patents with similar characteristics from the National Bureau of Economic Research (NBER) dataset and check that the identified effects are robust for patents that are already disclosed as essential in a standard-setting organization (SSO). I devote an entire part of this article to the discussion of the link between pool patents and patents disclosed as essential in an SSO and the potential impact of that link on the different aspects of the value of analyzed patents. My results indicate that, at the time of its inclusion in a pool, a pool patent has a higher intrinsic value than a patent that is not in a pool but has similar characteristics. I also underline that a patent's inclusion in a pool increases the number of forward citations to that patent—that is, there is an induced-value effect. Although I find that the induced-value effect remains stronger than the intrinsic-value effect, the induced-value effect does not appear uniformly across pools and is lower for patents that are already disclosed in an SSO. In particular, I find that the induced-value effect originates primarily from my sample of patents in the pool relevant to the IEEE 1394 interface standard.

1 *See, e.g.*, Jay Pil Choi, *Patent Pools and Cross-Licensing in the Shadow of Patent Litigation*, 51 Int'l Econ. Rev. 441 (2010); Josh Lerner & Jean Tirole, *Efficient Patent Pools*, 94 Am. Econ. Rev. 691 (2004).

2 I partly follow the method in Marc Rysman & Timothy Simcoe, *Patents and the Performance of Voluntary Standard-Setting Organizations*, 54 Mgmt. Sci. 1920 (2008) (examining the disclosure of patents within standard-setting organizations).

Part I of this article reviews the literature on essentiality and the value of patents. Part II explains the data collection process and presents descriptive statistics. Part III examines the intrinsic and induced-value effects of the pool. Part IV analyzes thoroughly both the intrinsic and induced-value effects using data on the standardization process to increase the robustness of the results.

I. What Is a Standard and an Essential Patent?

The creation of a technological standard offers many advantages to consumers. On the one hand, standardization allows consumers to benefit inter alia from network effects. On the other hand, the creation of standards can also have adverse effects such as a reduction in consumers' choices or increase in a firm's control over a market. Generally, consortia or standard-setting organizations conduct the standardization process.

Once a standard has been defined, either a group of patent holders or pool administrators such as MPEG LA and Sisvel initiate a call for patents. There is a priori no relationship between the creator of a pool and the corresponding standard-setting organization. For example, it is not uncommon for a single standardization project to result in the creation of multiple pools. The pool includes patents that are essential to the standardized technology and affords users the convenience of obtaining a single license for all patents in the pool. The literature generally identifies two main economic benefits of patent pools: (1) reducing the transaction costs and (2) avoiding the problem of multiple marginalization.

Patent pools might nevertheless also have perverse economic effects. In particular, patent pools can be used as a price-fixing mechanism by including patents that are substitutes for each other or even fragile legally.[3] To avoid such behavior, some authors indicate that a pool must contain only complementary essential patents and allow patents to be licensed independently outside the pool.[4]

After the creation of a pool, a patent holder will choose whether to submit its patent to the pool. In practice, patent holders have little incentive to put their patents in a pool, as they can maintain a higher level of royalties than those included in a pool.[5] Against this background, many people suspect that pools include only low-quality patents. A part of this article tests directly

[3] *See* Richard J. Gilbert, *Antitrust for Patent Pools: A Century of Policy Evolution*, 2004 Stan. Tech. L. Rev. 3.

[4] *See, e.g.*, Josh Lerner, Marcin Strojwas & Jean Tirole, *The Design of Patent Pools: The Determinants of Licensing Rules*, 38 RAND J. Econ. 610 (2007); Daniel Quint, *Economics of Patent Pools When Some (But Not All) Patents are Essential* (Stanford Institute for Economic Policy Research, Discussion Papers No. 06-028, 2006).

[5] Reiko Aoki & Sadao Nagaoka, *The Consortium Standard and Patent Pools*, 55 Econ. Rev. 346 (2004).

this hypothesis by using the intrinsic-value effect, which offers information about whether patents that are eventually selected into pools were initially more valuable or less valuable than similar patents that are not included in a pool.

The only criterion for including a patent in a pool is essentiality. The usual definition of an essential patent is one that has no close substitutes, or substitutes so inferior that it makes them very distant alternatives to that patent.[6] To ensure the essentiality of a patent, pools usually have a third-party evaluator—either an individual patent expert or a panel of experts—who verifies the claims of the patent's essentiality.[7] In practice, it is difficult to identify precisely all the essential patents related to a technology. Indeed, all pool patents are essential but not all essential patents are in a pool.

It is especially difficult, if not impossible, to identify essential patents that are not included in a pool. Rysman and Simcoe study the effect of a standard on the number of patent citations using the patent's disclosure in an SSO as a proxy of its essentiality.[8] They underline the fact that essential patents receive more citations than those with similar characteristics that are not disclosed in SSOs.[9] They also find that a patent's disclosure in an SSO significantly increases the number of citations to that patent—they estimate that such an effect accounts for more than 20 percent of the difference in citation rates between SSO and control patents.[10] In this article, I focus on pool patents and compare them to nonessential patents with the same characteristics. In the last part, I also analyze the link between pool patents and SSO patents.

For pool patents, the induced-value effect captures the increase in the commercial value of the standard due to the patent pool. The induced-value effect provides a way for assessing the reduction of the multiple-marginalization problem or the reduction of transaction costs that result from the pool and, therefore, the impact of the pool on the market of the standard.[11] That effect benefits not only the pool members but also the holders of essential patents that are not included in the pool.[12] Thus, although I use a similar

[6] *See* Letter from Joel I. Klein, Acting Assistant Attorney General, Department of Justice Antitrust Division, to Gerrard R. Beeney, Esq., Sullivan & Cromwell 9 (June 26, 1997), https://www.justice.gov/archive/atr/public/busreview/215742.pdf ("[T]here is no technical alternative to any of the Portfolio patents within the standard.").

[7] In some pools such as MPEG 2, patent holders "need not consult the expert if they agree unanimously in good faith that a submitted patent is an Essential Patent . . . or that a portfolio patent is not essential." *Id.* at 5 n.15.

[8] Rysman & Simcoe, *supra* note 5.

[9] *Id.* at 25.

[10] *Id.* at 38.

[11] Assuming that the Compulsory Individual Licensing rule is unable to prevent perfectly the risk of collusion through patent pools, the induced-value effect could also capture the increase in value of the collusion's pool patents.

[12] It could also be argued, however, that the number of citations to a patent will decrease after its

method, I analyze a different underlying effect than that analyzed in previous literature.

To assess the value of a patent, I use the number of forward citations to that patent. This is one of the measures necessary for assessing the economic and technological significance of a patent. Forward citations allow for the identification of the prior art for an invention. Patent offices therefore monitor carefully those citations because they help define the scope of the patent's claims. For example, in their empirical assessment of patent pools, Josh Lerner and Anne Layne-Farrar use the number of forward citations as an indicator of patent value.[13] Dietmar Harhoff, Francis Narin, F. Scherer, and Katrin Vopel highlight a positive correlation between the number of citations and the subjective estimate of a patent's value determined by the patent holder.[14] Bronwyn Hall, Adam Jaffe, and Manuel Trajtenberg also demonstrate a positive correlation between the number of citations to a patent and the patent holders' market value.[15] The literature thus indicates a strong relationship between the value of a patent and its number of forward citations.

II. The Data

I analyze 1,363 patents from nine pools, all of which publish their list of essential patents online and are managed by a pool administrator.[16] Patent pool managers regularly update the list of pool patents on their websites. Using the *Internet Archives* website and comparing the current list of pool patents with previous ones, I identify the date on which a patent was first listed in a pool.[17] As Justus Baron and Henry Delcamp show, it is important to account for the exact date of entry as a vast majority of pool patents enter a pool upon its creation.[18]

inclusion in a pool because of the concern that citing those patents would invite license payments even to only vaguely related technologies.

13 Josh Lerner & Anne Layne-Farrar, *To Join or Not to Join: Examining Patent Pool Participation and Rent Sharing Rules*, 29 Int'l J. Indus. Org. 294 (2011).

14 Dietmar Harhoff, Francis Narin, F.M. Scherer & Katrin Vopel, *Citation Frequency and the Value of Patented Inventions*, 81 Rev. Econ. & Stat. 511 (1999).

15 Bronwyn H. Hall, Adam Jaffe & Manuel Trajtenberg, *Market Value and Patent Citations*, 36 RAND J. Econ. 16 (2005).

16 *See, e.g.*, *MPEG-2 Patent List*, MPEG LA, http://www.mpegla.com/main/programs/M2/Documents/m2-att1.pdf; *LTE Listed Patents*, SISVEL, http://www.sisvel.com/images/2016/20160511-LTE-Listed_Patents-v15.pdf.

17 Internet Archive, www.archive.org.

18 Justus Baron & Henry Delcamp, *The Strategies of Patent Introduction into Patent Pools*, 24 Econ. Innovation & New Tech. 776 (2015).

Table 1. Number of Patents Per Pool

Pool Name	Date of Pool Creation	Number of Patents	Number of American Patents	Percentage of American Patents in the Pool
1394	1999	104	62	59.62%
ATSC	1997	50	31	62.00%
AVC	2004	311	60	19.29%
MPEG 4 SYSTEMS	1999	13	7	53.85%
MPEG 4 VISUAL	2004	366	123	33.61%
MPEG AUDIO	1999	102	15	14.71%
MPEG-2	1997	149	90	60.40%
MPEG-2 Systems	2006	27	19	70.37%
VC-1	2006	241	60	24.90%
Total		1,363	467	34.26%

Source: Bill Geary, *Patent Pools in High-Tech Industries*, 37 Intell. Asset Mgmt. 98 (2009).

To obtain the number of citations for each patent, I used data from 1976 to 2006 from the NBER U.S. Patent Citation Database. Note that selection bias exists in my sample as I worked with only U.S. patents.

To analyze how the number of forward citations varies for pool patents, I also created a control database using patents from the NBER database that shared the same characteristics as the pool patents. I constructed the control dataset through a randomly selected one-to-one match, on the basis of the application year and technology class of the patents. The joint distribution of the application year and technology class is identical to that of the pool sample. Table 2 reports the main characteristics of each sample. In their article, Baron and Delcamp present evidence that the creation of a pool motivates patent filing and can affect the overall number of citations in a standardization context.[19] Thus, I also run all my regressions on the number of external citations, which are the number of forward citations that are not self-cited or that do not come from patents in the same pool. I find that those regressions produce results that are similar to those presented in Table 2, confirming the robustness of my findings.

19 *Id.*

Table 2. Patent Pool Sample and Control Sample Data

Data Type	Patent Pool Sample	Matched Controls	All Controls
Number of Observations	383	383	135,370
Mean Allcites*	26.01	16.93	20.69
Standard Deviation Allcites	32.778	29.54	31.76
Min Allcites	0	0	0
Max Allcites	202.46	183.78	1,185.26
Mean Allnscites**	22.01	15.64	19.06
Standard Deviation Allnscites	29.86	28.83	30.24
Min Allnscites	0	0	0
Max Allnscites	196.88	183.78	1,185.26
Application Year	1996.73	1996.74	1996.5
Age Since Grant	6.89	6.39	6.48
Number of Claims	17.74	17.30	17.71

Notes: * *Allcites* uses the number of forward citations; ** *Allnscites* uses the number of forward citations minus the citations by the patent's own patent holder.

As Table 2 illustrates, pool patents receive more citations than comparable patents from the control database, indicating that pool patents have a higher value than NBER patents with similar characteristics. Although that finding is useful, it is more interesting for my research to look more closely at the citation-age profile of pool patents to see whether those patents are usually cited earlier or later than the control patents.

To get an initial idea of the citation-age profile, I investigate the average age of a citation conditional on the age of a patent by using the method developed by Aditi Mehta, Marc Rysman, and Tim Simcoe—that is, by controlling for patent applications, citation year, and technology-class effects—to generate predictions conditional on age.[20] I thus obtain the average citation ages of the control sample and the patent pool sample. The results show that pool patents have an average citation age of 4.10 years and that control patents have an average citation age of 2.01 years—that is, pool patents are cited later than control patents. That result indicates that an event that does not affect control patents—for instance, the inclusion in a pool—triggers citations to pool patents.

20 Aditi Mehta, Marc Rysman & Tim Simcoe, *Identifying the Age Profile of Patent Citations: New Estimates of Knowledge Diffusion*, 25 J. Applied Econometrics 1179 (2009).

III. The Link Between Pools and the Value of Patents

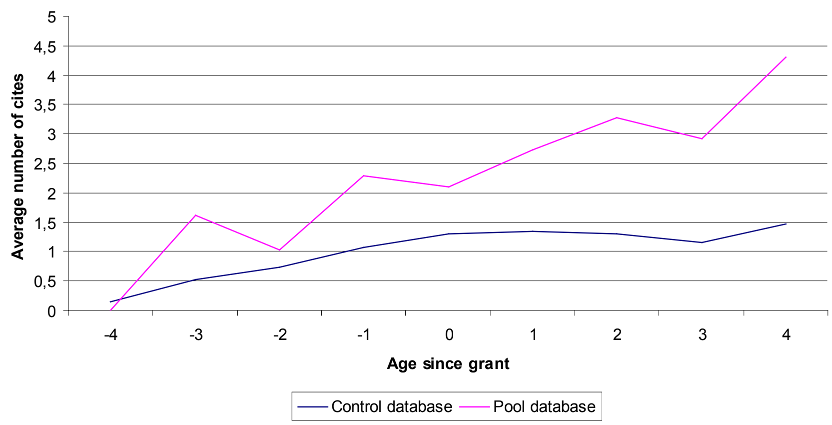
In this part, I analyze the relationship between the number of citations and whether a patent is in a pool. In particular, I differentiate between the intrinsic-value effect (a pool selects patents with more citations) and the induced-value effect (the number of citations to a patent increases after entering a pool) of patent pools. Part I indicates that pool patents receive more citations than control patents and receive their citations later. That result might stem from several factors. The number of forward citations to a pool patent might have increased due to its inclusion in a pool or because the pool selects patents with a higher number of citations. This part addresses the following question: Are patents selected into a pool because they are cited more or are they cited more because they are selected into a pool?

A. Specification

To test my hypotheses, I work with two different methods, each of which provides detailed results. I base all regressions on a Poisson specification, using classical count data on citations. I also test whether my findings are robust to linear estimations. I control for a possible truncation effect using two different methods: (1) I conduct a regression analysis that uses only observations with citation years up to 2004 with patents granted before or in 2002 (and applied before or in 2000)—thereby excluding pools that were created in or after 2004—and (2) I use citing year effects as control variables in all my models. The first method is a very conservative approach that maximizes the robustness of the results. However, its main drawback is a significant reduction in the sample size. I also run alternative regressions that include, for example, pools that were created in 2004 and account for citing years through 2006—the ultimate year for which I have information on citations in the NBER patent database. With a number of pool patents that is close to 360, I obtain results similar to those presented in Table 4, Table 6, and Table 7. However, I present results of the most conservative approach in this article.

To separate the intrinsic-value effect from the induced-value effect, I adopt a counterfactual approach. Taking such an approach is especially difficult for my analysis due to the lack of data on essential patents that do not belong in a pool. To circumvent this difficulty, I use two different approaches. My first panel approach uses data on citations before a patent's inclusion in a pool to estimate the citation pattern after it. Controlling for any other patent characteristics using a fixed-effect model should allow us to capture only a pool's induced-value effect. In the other model, I use a cross-sectional approach to estimate both the intrinsic-value effect and a pool's induced-value effect. (In Part IV, I also take a meticulous approach in selecting the samples, work with different control samples, and perform complementary analyses using data on the standardization process.) Figure 1 shows the number of citations for both the matched control sample and the pool sample before the patents are included in pools. It helps to illustrate not only that pool patents receive more citations than control patents but also that the trend over time is similar generally between the two samples.

Figure 1. Citation Age Profile Since the Grant of a Patent



Note: The negative values underline the fact that some patents receive citations before they are officially granted, as the citation process starts at the time of a patent's application.

However, each of those two approaches has drawbacks. The first is a possible selection-bias problem. As Part II explains, pool patents are certainly not assigned randomly from the sample of essential patents. Using a panel fixed-effect approach and thus comparing the citation pattern of pool patents before and after their inclusion in pools (taking into account any other intrinsic characteristics) should limit that selection-bias problem. Another possible problem is that I do not take into account a possible endogeneity of pool creation. For example, pools might be created only in technological fields that have a high expectation of importance, and therefore have a higher number of citations. It is impossible to account perfectly for that endogeneity problem because I do not have a sample of essential patents that are not in pools. If that endogeneity problem is not controlled completely, it could alter the estimation of the intrinsic-value effect by attributing the difference in the number of citations to a selection effect when, in fact, those differences are due to the endogeneity of the pool creation. However, I use alternative methods to control for that potential endogeneity. For example, I verify that my results are robust using a control database of patents that have the same joint distribution in assignee type, application year, technological class, technological subclass, and HJT subcategory on the basis of the 36 U.S. subclasses.[21] That sample of patents not only is the best control sample that can be created using the NBER U.S. patent database, but also controls, at least in part, for any endogeneity problems that might exist. Such a method ensures that the only difference between the pool sample and control sample is whether a patent belongs to a pool. My robustness tests underline that the endogeneity problem is trivial. Thus, I exclude those results from this article.

To conclude, I note that both models have drawbacks. However, the joint approach, the stability of the results presented in the following parts, and a couple of robustness tests using different control samples raise confidence in my findings on the intrinsic and induced-value effects.

B. The Pools' Induced-Value Effect

To study the value effect induced by the patents' inclusion in a pool, I first use a method based on the pool sample. I work on a panel database of pool patents and control for inclusion in the pool through the *Induced_effect* dummy variable. My empirical framework is thus similar to a regression discontinuity design, regarding patent inclusion in a pool as a treatment that could increase the number of citations. To check for possible discrepancies between the exact date of patent inclusion in a pool and the date on which the list of essential patents on the website is updated—for example, due to a public disclosure of a new patent's inclusion before an official update happens online—I control for a pre-inclusion effect. I then create the *Pre_induced_effect* variable for citations that occur two years before or after the patents' effective inclusion in a pool.[22]

I then estimate a fixed-effect Poisson model with the number of forward citations in year y for a patent p as an explanatory variable, and control for the pools' induced effects, pre-induced effects, patent age effects, and possible truncation effects. I estimate the baseline model using Equation 1 and define its variables in Table 3.

Equation 1. Baseline Model

$$\text{Citations}_{py} = a_0 + a_1\text{Induced\_effect}_y + a_2\text{Pre\_induced\_effect}_y + a_3\text{Age\_effect}_p + a_4\text{Citing\_Year} + \varepsilon_{py}$$

[21] *See* Bronwyn H. Hall, Adam B. Jaffe & Manuel Trajtenberg, *The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools* (National Bureau of Economic Research, Working Paper No. 8498, 2001) (developing the 36 subcategories on the basis of the level of homogeneity of patents).

[22] I follow the method of Rysman & Simcoe, *supra* note 5.

Table 3. Variables in the Baseline Model

Variable	Definition
$Citations_{py}$	Number of citations for patent p in year y
$Induced\_effect_{y}$	Dummy variable that equals 1 after the patent's inclusion in a pool and equals 0 otherwise
$Pre\_induced\_effect_{y}$	Dummy variable that equals 1 either after or two years before the patent's inclusion in a pool and equals 0 otherwise
Age_effect_{p}	Patent linear age effect
Citing_year	Categorical variable for citing year
ε_{py}	Error term

Table 4 reports the main results of the regression using the baseline model. Column 1 reports the results of the baseline model, using the citing year effects as a control variable. Column 2 reports the results of a fixed-effect linear regression.

Table 4. Regression Results of the Panel Fixed-Effect Approach

	(1) Poisson Pool Sample	(2) OLS Pool Sample
Induced-Value Effect	0.005	0.211
	(0.104)	(0.199)
Pre-Induced-Value Effect	0.350***	1.096***
	(0.071)	(0.150)
Patent Linear Age Effect	0.184***	0.324***
	(0.016)	(0.036)
Citing Year Effect	−0.509***	−0.938***
	(0.023)	(0.047)
Number of Observations	1,350	1,350
Number of Groups	136	136
Likelihood	−2,603.54	

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Values in parentheses indicate robust standard errors. Both samples use the number of citations per year as the dependent variable.

As Table 4 reports, the induced-value effect is positive but not statistically significant for either model. Nevertheless, the pre-induced-value effect, with coefficients of 0.35 and 1.10, respectively, is positive and is statistically significant for both models. Those two results suggest that a patent's inclusion in a pool has a positive effect on its value and boosts its number of forward citations. The difference in the coefficients between the induced and the pre-induced-value effects might be due to some discrepancies between the dates on which the website is updated and the actual dates of inclusion in the pool.[23]

I can therefore state that the inclusion in a pool increases the value of an essential patent. In Part IV, I further analyze the induced and pre-induced-value effects using data on the standardization process. The following part is devoted to a joint analysis of the intrinsic and induced-value effects.

C. *The Intrinsic-Value and Induced-Value Effects*

The previous part reveals that the pre-induced-value effect is positive and is statistically significant. A patent's inclusion in a pool has an impact on the number of its forward citations. To analyze jointly the intrinsic and induced-value effects, I run a cross-sectional regression including both the pool and control patents. To compare the two effects, I add a dummy variable to indicate a patent's inclusion in a pool. I also control for the application year, technological class, citing year, and age effects of patents. For some regressions, I also control for the number of claims of the patent. As a baseline model, I estimate a cross-section Poisson model using Equation 2 and define its variables in Table 5.

Equation 2. Cross-Section Poisson Model

$$\text{Citations} = a_0 + a_1\text{Intrinsic\_effect} + a_2\text{Induced\_effect} + a_3\text{Pre\_induced\_effect} + a_4\text{Application\_year} + a_5\text{Techno\_class} + a_6\text{Age\_effect} + a_7\text{Citing\_year} + \varepsilon$$

[23] Internet Archive, *supra* note 20.

Table 5. Variables in the Cross-Section Poisson Model

Variable	Definition
Citations	Number of citations in year *y*
Intrinsic_effect	Dummy variable that equals 1 if the patent is or will be a pool patent and equals 0 otherwise
Induced_effect	Dummy variable that equals 1 after the patent's inclusion in a pool; 0 otherwise
Pre_induced_effect	Dummy variable that equals 1 either after or two years before the patent's inclusion in a pool and equals 0 otherwise
Application_year	Categorical variable for application year
Techno_class	Categorical variable for technological class
Age_effect	Patent linear age effect
Citing_year	Categorical variable for citing year
ε	Error term

Table 6 presents the main results. Columns 1 and 2 report the results of my baseline model. In column 3, I present the same results adding a variable that controls for the number of claims of the patent.[24] Column 4 reports the results for a model using a non-linear age effect (with dummy variables) instead of my baseline model.[25] Column 5 presents the coefficients for an OLS regression. Column 6 checks the robustness of my results across different samples. To ensure that my results do not reflect only the characteristics of patents in my matched control sample, I use an alternative one-to-one "matched controls" sample—that is, an alternative one-to-one control sample that is matched on the basis of the application year and technology class of each patent.

[24] Because patent pools have been shown to motivate patent files, it is important to control for the number of claims of the patent. *See* Ryan Lampe & Petra Moser, *Do Patent Pools Encourage Innovation? Evidence from the Nineteenth-Century Sewing Machine Industry*, 70 J. Econ. Hist. 898 (2009); Baron & Delcamp, *supra* note 21. One would imagine that the characteristics of the patents that are included are different for pool and non-pool patents, especially in scope. In my analysis, it is safer to control for the scope of the patent.

[25] I follow the method of Rysman & Simcoe, *supra* note 5.

Table 6. Results of the Cross-Sectional Approach for Intrinsic-Value and Induced-Value Effects

	Poisson Matched Control Samples				OLS Matched Control Sample	Poisson Alternative Matched Control Sample
Sample	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline Model		Alternative Models			
Intrinsic-Value Effect	0.246* (0.117)		0.246* (0.121)	0.391** (0.182)	0.915*** (0.400)	0.339* (0.211)
Induced-Value Effect	−0.213 (0.188)		0.059 (0.173)	−0.021 (0.204)	−0.349 (0.439)	0.394*** (0.127)
Pre-Induced-Value Effect	0.578*** (0.160)		0.815*** (0.175)	0.625*** (0.159)	1.005** (0.503)	0.213* (0.126)
Pre-Induced-Value Effect 1394		0.923*** (0.172)				
Pre-Induced-Value Effect ATSC		−1.020 (0.765)				
Pre-Induced Value AVC		0.306 (0.370)				
Pre-Induced Value MPEG 4 Systems		0.031 (0.417)				
Pre-Induced Value MPEG 4 Visual		−0.324 (0.363)				
Pre-Induced Value MPEG 2		0.119 (0.337)				
Number of Claims			0.020*** (0.004)	0.014** (0.006)	0.021* (0.011)	0.010 (0.007)
Patent Linear Age Effect	Y	Y	Y		Y	Y
Application Year Effect	Y	Y	Y		Y	Y
Citing Year Effect	Y	Y	Y	Y	Y	Y
Technological Class Effect	Y	Y	Y	Y	Y	Y
Patent Nonlinear Age Effect, Dummies				Y		
Obervations	3090	3090	2695	2695	2695	2695
Number of Clusters	272	272	247	247	247	247
Pseudolikelihood	−4335	−4309	−3458	−3523		−2944

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Values in parentheses indicate robust standard errors. All samples use the number of citations per year as the dependent variable.

Table 6 reports a positive and statistically significant intrinsic-value effect across all models, indicating a higher number of forward citations for pool patents at their time of entry into a pool, relative to non-pool patents with the same characteristics. The results suggest that pools are able to attract valuable contributions in terms of technological significance. On the induced-value effect, the result is fairly similar to that of the panel approach. For example, the induced-value effect is not statistically significant except in column 6, but the pre-induced-value effect is both positive and statistically significant. The results confirm my previous finding that patent pools boost the number of forward citations. Using data on pools that are created before or in 2004, I separate the pre-induced-value effect by pools and find that the pre-induced-value effect occurs mainly due to to the IEEE 1394 pool, as column 2 reports. The regression results reported in column 2 are identical to those reported in column 1, except for the pre-induced-value effect that is divided by pools.

In conclusion, it appears that patent pools can attract valuable contributions—that is, patents that are cited extensively. My findings also suggest that the induced-value effect is around twice as large as the intrinsic-value effect, for my baseline model. However, I find the pre-induced-value effect only in the IEEE 1394 pool. Part IV reports a thorough analysis of the relationship between my results and the standardization process.

IV. The Relationship Between Pool and SSO Patents

The creation of a pool follows the standardization of a technology. A patent is usually first disclosed in an SSO and then included in a pool. I therefore have to separate the impact that SSOs and patent pools have on the number of citations. One could argue that the effects that I discuss earlier—especially the induced effect—result from patent disclosure in SSOs.[26]

To separate those two effects, I create the *Induced_effect_SSO* variable between the *Induced_effect* variable and patents that were disclosed previously in an SSO. I also discuss the possibility of an existing relationship between pool and SSO patents. That relationship is difficult to establish because SSO patent disclosures are often very vague. To control for the relationship between pool and SSO patents in the presence of those difficulties, I use a dummy variable for pool patents that are held by firms that make disclosures in the dedicated SSO. I thus make the assumption that a firm cannot disclose only a part of its patent portfolio to an SSO.

The idea behind my method of separating the two effects is that, if the size of the induced-value effect is different between patents that were already disclosed to an SSO and those that were not, the induced value coefficient

[26] *See* Rysman & Simcoe, *supra* note 5 (showing that a patent's disclosure in an SSO increases the number of citations to that patent by between 35% and 40%).

also captures an increase in the value of the patent due to the underlying standard. As in Equation 2, I use a Poisson regression on my cross-sectional sample, adding the *Induced_effect_SSO* variable.

Table 7 reports the main results. Column 1 reports the results for my baseline model. In column 2, I present the same results adding a variable that controls for the number of claims of the patent. Column 3 presents the results of an OLS regression.

Table 7. Regression Results of the Cross-Section Approach, for Intrinsic-Value and Induced-Value Effects

	(1) Poisson Matched Control Sample	(2) Poisson Matched Control Sample	(3) OLS Matched Control Sample
Intrinsic-Value Effect	0.307* (0.158)	0.308* (0.165)	0.437** (0.219)
Induced-Value Effect	−0.066 (0.240)	−0.062 (0.214)	−0.234 (0.312)
Pre-Induced-Value Effect	0.369*** (0.148)	0.611*** (0.156)	0.820*** (0.338)
Induced-Value Effect _SSO Dummy	−0.583*** (0.258)	−0.233 (0.234)	−0.382 (0.281)
Number of Claims		0.019*** (0.004)	
Patent Linear Age Effect	Y	Y	Y
Application Year Effect	Y	Y	Y
Citing Year Effect	Y	Y	Y
Technological Class Effect	Y	Y	Y
Number of Observations	3,090	2,695	3,090
Number of Clusters	272	247	272
Pseudo-R^2	0.213	0.223	0.147
Pseudolikelihood	−4,590	−3,721	

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Values in parentheses indicate robust standard errors. All three samples use the number of citations per year as the dependent variable.

As column 1 reports, the coefficient of the *Induced_effect_SSO* variable is negative and statistically significant, which indicates a statistically significant difference in the size of the induced-value effect between patents that are already disclosed in an SSO and patents that have entered a pool without previous disclosure in an SSO. The induced-value effect is weaker if the patent has already been disclosed in an SSO. However, the coefficient of the *Pre_induced_effect* variable remains positive and statistically significant.

The induced-value effect is thus positive and statistically significant for patents that have already been disclosed in an SSO, although that effect significantly lower than that of other patents. This result is important in practice as it shows that a pool has an impact on the value of the patent, in addition to the effect of the underlying standard that Rysman and Simcoe emphasize in 2008.

V. Conclusion

In this article, I compare the value of pool patents to that of non-pool patents with similar characteristics. I first analyze the induced-value effect of the inclusion and then analyze simultaneously the intrinsic-value and induced-value effects, which are measured on the basis of the number of forward citations. I also discuss and analyze the relationship between the induced-value effect of patents that are disclosed in an SSO and the effect of a patent pool.

My results indicate not only that a patent's inclusion in a pool increases the number of its forward citations (the induced-value effect), but also that pools generally select patents with a higher number of forward citations (the intrinsic-value effect). The induced-value effect proves to be greater than the intrinsic-value effect on the number of citations. However, that effect is quite unstable and, in my sample, is mainly due to the IEEE 1394 pool.

The results of my analysis play an important role in the current debate surrounding patent pools and their economic efficiency. My results reveal that, although essentiality is not related directly to a patent's value, patents that are selected by pools generally have a higher value than similar patents that are not included in a pool. Contrary to the findings reported in the literature, patent holders do not use pools to license poor-value patents.[27] Such a conclusion holds particular importance for debates surrounding the efficiency of pools, as it confirms that the agreements between competitors can attract valuable contributions. Therefore, the economic advantages could outweigh the potential collusion risks of a pool—for example, the risk that a pool is used as a price-fixing mechanism.

Assuming that antitrust rules completely eliminate the risk of collusion, and consequently that the induced-value effect does not capture an increase in the value of patents due to collusion, my results could also help shed light on the advantages and drawbacks of patent pools. That is, the results of my analysis suggest a way to assess empirically the reduction of the

---

[27] *See, e.g.*, Lerner & Layne-Farrar, *supra* note 16.

multiple-marginalization problem of a pool and the consequent increase in commercial value of a standard due to the patent pool.