TRAGEDY OF ANTI-COMMONS, EMPIRICAL EVIDENCE FROM THE PHARMACEUTICAL INDUSTRY

YIYONG YUAN

Department of Agricultural Economics
University of Missouri
Columbia, MO 65211
yy3z5@mizzou.edu

Abstract: An empirical study of U.S pharmaceutical industry was conducted to directly investigate the validity of the once hotly-debated tragedy of anti-commons for the first time. An index based on Theil's entropy measure and the Herfindahl type indices were applied to measure the transaction cost difficulty resulting from fragmental patent right ownership structure in pharmaceutical industry. The empirical analysis has confirmed the existence of the tragedy of anti-commons.

Key words: Intellectual Property Rights, Tragedy of Anti-commons, Fragmentation

JEL Codes: O34, O38

1. INTRODUCTION

In the paper published in Science (1998) by Heller and Eisenberg, the tragedy of anti-commons, as a concept “opposite” to the tragedy of commons was first raised in view of the rapidly increasing fragmentation of biomedical intellectual property rights ownerships. In the paper, the authors expressed a widely shared concern that overly fragmented patent rights structure might do little good to the technology development of an industry, and even stifle the innovation.

The anti-commons refers to the fact that over-dispersed patent rights to excluding others’ use pose a transaction cost difficulty for innovating firms to access the necessary knowledge that otherwise is more conveniently available. As a result, firms may have to choose not to start or even give up certain ongoing R&D lines which are technologically feasible but infeasible due to the prohibitive transaction cost restriction of complicated ownership right structure. This literally leads to either less R&D activities or less innovation rate citrus paribus. Anti-commons does not simply mean more patents rights will necessarily lead to less innovation, it means more fragmented or more dispersed patent rights distribution, a shared holding-up force for the whole industry will impede the innovation rate of the firms across an industry.

It is important to notice that this industry-wide restriction is different from that faced by individual firm. Within an industry, each firm still has its own situation in terms of the holding-up difficulty due to the patent ownership rights structure particular to each firm itself. With multiple strategic choices, firms anticipating this difficulty may have various reactions to this difficulty. In a study by Ziedonis (2004), more aggressive firm patenting propensity has been confirmed to be one of those strategic reactions using Normalized

Herfindahl index. The anti-commons effect, however, is beyond the reach of individual firm's strategic choice to cope with since it influences all firms simultaneously in the industry. This is a critical difference and forms an interesting contrast: individual holding-up risk leads to more aggressive patenting whereas industry-wide holding-up force leads to less innovation productivity for firm, both of them embodied in the same observable firm patents.

The idea of tragedy of anti-commons is conceptually, very appealing, however it has never been corroborated by any empirical research with solid evidence until now. Critics have been calling for empirical evidence of the Tragedy of the Anti-commons for a long time. Unfortunately, until now, most empirical research is either an indirect research or based on the survey of opinions by practitioners. For example, a recent survey by the American Association for the Advancement of Science (AAAS), titled "The Effects of Patenting in the AAAS Scientific Community" (Hansen, Brewster, Asher and Kisielewski, 2006) has found that most scientists do not hold that growth in patenting negatively affects their research. The major reason leading to this situation is the difficulty of obtaining fragmentation measurement of patent ownerships of an industry. Fortunately, the efforts by Bronwyn Hall, Adam Jaffe, and Manuel Trajtenberg in NBER (2001) led to a searchable patent database which links firm patent information with firm financial data in COMPUSTAT. These progresses have made it possible to look into the patent ownership structure of an industry and hence this empirical study concerning the tragedy of anti-commons.

To be close to the original source that triggered the idea of tragedy of anti-commons, it seems compelling to conduct a survey of the pharmaceutical industry, which is the industry "closest" to the biomedical sector discussed in the 1998 "Science" paper.

In the following text, a hypothesis development is presented first, the theoretic model/variable construction follows, and then a detailed description of the data collection task, especially the part concerning establishment of patent ownership distribution is discussed. As the5-th part of the paper, the empirical analysis concludes the paper.

2. HYPOTHESIS DEVELOPMENT

Hypothesis 1: This hypothesis about tragedy of anti-commons is straightforward since it is built on prior researcher's idea.

If the tragedy of anti-commons is true, more fragmental patent ownership structure should lead to decreased innovation rate for firms ceteris paribus.

Like most previous researches on firm innovation, firm innovation will also be modeled in a production function framework, in which firm patent is the output while R&D, firm size, capital expenditure, technological opportunity, and other controls appear as inputs. While all these predictors carry positive effects on innovation, we expect a negative effect of patent ownership fragmentation on innovation.

Hypothesis 2: This hypothesis serves as an extended version of hypothesis 1 to confirm a judgment concerning the change about the effect of fragmented patent ownership structure on firm innovation over time.

R&D input has well-established property of lagged effect on innovation. Firm innovation observed in a given year are based on R&D projects launched in different prior years, depending on the average R&D-patent cycle length of innovations in a particular industry, if we lag all the R&D inputs (except for technological opportunity) together, we should observe a parabolic change of a R&D input's effect on innovation over time. Similarly, although the patent ownership structure of an industry is not an R&D inputs, we should expect it functions together with its contemporaneous R&D inputs in terms of affecting firm innovation. Depending on the reach of previous arts' knowledge importance for a given industry, there should also be an approximate *parabolic change* of the holding-up effect on a given year's firm innovation of the patent ownership fragmentation of the industry over time.

3. ECONOMETRIC MODEL AND VARIABLE CONSTRUCTION

Since the pioneer work of "Econometric models for count data with an application to the patents-R&D relationship" by Hausman, Hall and Griliches (1984), modeling firm patent in a production function framework with a generalized linear model framework has become the standard empirical study approach.

By the assumption of the Poisson model or the Negative Binomial model in a longitudinal model setting, $E(patent_{it}) = \exp(c + X_{it} * B')$ where i indexes year, t indexes firm, $X_{it}' = (\ln emp_{it}, \ln rnd\,\mathrm{int}_{it}, indtotalp_{it}, indices_{it})$ is the explanatory variable vector, and $patent_{it}$ is patent number granted to firm i at year t , and. Inside X_{it} , $\ln emp_{it}$ is the log of firm employee, $\ln rnd\,\mathrm{int}_{it}$ is the log of firm R&D expenditure intensity (the ratio of R&D to employee), $indtotalp_{it}$ is total relevant patent to control technological opportunity, and $indices_{it}$ is the featured fragmentation index. The choice of R&D

expenditure intensity rather than R&D expenditure is to avoid the simultaneity between R&D and firm employee. Previous researches have constructed various variables to control technological opportunity. Jaffe and Trajtenber (2002) once applied counts of U.S. patents in particular sectors, adjusted by subsequent citations to these inventions. In this research, while citation adjustment is not considered, the total relevant patent including both patents granted to pharmaceutical industry and non-profit entities (universities mainly) to dilute the endogeneity between pure industry patent total (sum across all firms) and firm patent.

Suppose we have ideal information about all legally effective patents' ownership distribution across all necessary entities in a given industry over a certain period (this, of course is not the case, further details about establishing the distribution will be discussed in data collection part), and every patent is equal in terms of its knowledge importance to subsequent R&D and its holding-up strength, we can treat the number of patents held by each entity as the income received by individuals in an economy. Conceptually similar to the idea in the research practice of income inequality, industry concentration and corporate diversification, fragmentation of patent ownerships can be measured with a variety of ready indices.

These inequality/fragmentation indices were developed with different intellectual bases. It could be "an extension of welfare criteria"; "an analogy with the analysis of risk"; "a 'Fundamentalist' approaches such as the GINI coefficient", or generalized entropy measurement based on information theory (Cowell, 2002). All the indices generally have to satisfy several desirable axioms such as scale independence, the principle of transfer, etc.

In this study of anti-commons, I not only need this index to be capable of measuring the difficulty of transaction cost due to fragmental ownerships to make one-to-one comparison but also want it to be exogenous to any observable and unobservable predictors of firm innovation. It is necessary to make a discussion of the pro and con of choosing different indices.

In the empirical research of innovation economics, Herfindahl index has been a popular choice. Herfindahl index is appealing not only due to its simplicity but also due to its desired property. For example, despite of its long history in income inequality research, GINI index is inappropriate since it has the drawback of insensitivity to granularity. For instance, the same GINI follows either distribution A: each of the 5 entiteis has 20% of total patents or distribution B: each of the 20 entities has 5% of total patents. However, from the perspective of transaction cost, the extents of transaction difficulty for these two situations are different from one another: distribution A is easier than distribution B, i.e. distribution B's patent rights is more fragmental. In contrast, Herfindahl does not suffer from this.

Furthermore, by Hall (2000), due to the fact that "shares based on count data where the number of counts is small will generally be biased downward", the Normalized Herfindahl index of fragmentation is defined as $NH = H * N/(N-1)$,

where $H = 1 - \sum_{i=1}^{k} S_i^2$ is the Herfindahl index, N is the total relevant patent number, S_i is the share that each entity's patents are accounting for the total relevant patent number, and the factor of $N/(N-1)$ serves to correct the above-mentioned bias. This improvement helps make Normalized Herfindahl a more appealing index. However, in case that researchers might still question if the Herfindahl type index is a sufficiently good measure of transaction cost difficult or if the Herfindahl and Normalized Herifindahl is free of any exogeneity with the "size variable" N (in this case the total relevant patent) [1], one more alternative index as follows is considered.

According to Theil (1967), a measure of inequality, also known as "redundancy" in communication theory is defined as $\log_2(k) - H = \sum_{i=1}^{k} p_i \log_2 k\left(p_i\right)$, where $\log_2(k)$ is the maximum entropy for the system, k is the number of involving entities, $H = \sum_{i=1}^{k} p_i \log_2\left(\frac{1}{p_i}\right)$ is the entropy for a particular state of the system. Therefore we can use $frag = 1 - \sum_{i=1}^{k} p_i \log_2 k(p_i) \Big/ \log_2 k$ as an index to measure the fragmentation of the patent ownership distribution across the industry. Conceptually, this index measures the degree of uncertainty or "lack of order" of a given ownership structure. It is a good measurement of the of transaction cost difficulty due to the dispersed ownership structure. Particularly, this index is relatively farther from the influence of size variable "N", the industry patent total (excluding those patents granted to non-profit organizations) that together with non-profit organization's patent forms the total relevant patent number, a positive predictor of firm innovation since it reflects the technological opportunity. By using multiple indices to measure the fragmentation or dispersion of the intellectual property rights, we are better positioned in our empirical analysis to obtain a stable estimate of the innovation effect of the fragmented IP rights.

4. DATA

4.1. GRANT YEAR V.S. APPLICATION YEAR

The core task of data collection is extracting information of patent ownership distribution of the pharmaceutical industry. There are two choices to determine the patent ownership: based on filling year or grant year. Since granted patent forms factual patent right to exclude others with legal means available while the effectiveness of pending (although we know they are finally granted ex post) patent rights are disputable, the fragmentation measurement might be better based on grant year rather than application year. It is possible that alternatives might be better but this issue should not be a critical one.

4.2. KNOWLEDGE IMPORTANCE AND THE HOLDING-UP CAPACITY

An ideal measurement of the distribution of an industry's patents ownership should be based on all cumulative patent rights with proper knowledge importance credit and proper legally holding-up capacity during a given time interval in a particularly industry. Since patent right can remain legally effective for years while the "knowledge" value of a patent might depreciate within a relatively short time, this of course, will lead to a deviance from the homogeneity of the patents' knowledge importance. Since there is information available about the (external) citation count received by each patent. This may serve as an option of weighting each patent's knowledge importance. However, as suggested by some researchers, it is difficult to determine that a patent receiving two or more citations should be twice as important as or more important than a patent receiving only one citation. This concern is even truer when it comes to weighting legally holding-up capacity. Therefore, before an ideal solution exists on how to weight each patent, for simplicity, I will suppose the patents in pharmaceutical industry are sufficiently uniform in terms of their knowledge importance/holding-up capacity during a short time span, say, several years. Without prior knowledge, this interval will be an arbitrary one that is shorter than the usual length of a typical patent's life of knowledge importance in an industry.

4.3. MARGINAL OR CUMULATIVE IP RIGHTS: THE EFFECT OF ORGANIZATION OWNERSHIP CHANGE

When we choose to address the concern of decaying knowledge importance of patens using the newly granted patents in relatively short interval, it turns out such choice is a relief when it comes to the issue of using marginal or cumulative patent rights. Because patent ownership structure can change due to either incremental IP rights change (newly granted patent and other IP rights change) or firm ownership change, identifying cumulative patent rights for each year each firm entails the task of detailed clarification of all the historical firm ownership change and related IP rights change. This is a very difficulty task if not possible. More importantly, using the cumulative IP rights is also questionable because it is more appropriate to reflect the IP rights structure at a moment and the coming period. Consider an example in which firm A and firm B in year 1 merged in the end of year 2 with the new firm still named A. In terms of the impact on firm innovation during Year 3 of the fragmented IP rights, those IP rights owned by historical firm B should still be counted as independent from those owned by "old" firm A since firm X's innovation project might be held up by the year 1 IP structure rather than the year 2 or year 3 IP structure. The gain of considering detailed historical firm ownership change when we use the newly granted patent might be quite limited. Using the status quo IP structure based on the newly granted patents for a certain interval is largely a viable choice. Of course, if the merged firm A change its name to firm AA, pooling the newly granted patent each year for an interval of several years will treat the patent granted to firm AA in year 3 independent from those granted to firm A in year 1 and year 2. This situation leads to a larger fragmentation measure compared with the situation keeping one firm's name[2]. However, it is pretty clear that the number of mergers/name changes is quite limited during a certain interval of several years and bears limited influence on the IP structure.

4.4 THE DATA COLLECTION PROCEDURES

In terms of the industry that is most possibly exhibiting the tragedy of anti-commons, I selected patents granted to firms with NAICS numbers 3254 325411 325412 325413 325414, i.e. firms from the pharmaceutical industry, and identified pharmaceutical patents granted to non-profit organizations. The pharmaceutical patents granted to these non-profit organizations are defined to be those patens falling into USPTO classifications 424 (Drug, Bio-Affecting and Body Treating Compositions), 435 (Chemistry: Molecular Biology and Microbiology), 436 (Chemistry: Analytical and Immunological Testing), 514 (Drug, Bio-Affecting and Body Treating Compositions), 530 (Chemistry: Natural Resins or Derivatives; Peptides or Proteins; Lignins or Reaction Products Thereof), 800 (Multi-cellular Living Organisms and Unmodified Parts Thereof and Related Processes), 930 (Peptide or Protein Sequence). This is according to patent classification information from NBER patent citation data file documentation (http://www.nber.org/patents/list_of_classes.txt).

Above choice of firms, of course, may form a truncation compared to the "complete and cohesive" firm list of the "biomedical" industry. However, these firms' patents plus the identified biomedical patents belonging to the not-for-profit organizations should offer a good proxy to the dispersion of the “entire” industry. It has to be noted that, to construct the inequality index, we could consider the patent granted to those firms that do not show up in COMPUSTAT but supposedly belong to pharmaceutical industry following previous definition of biomedical patents, the drawback of doing so is the loose biomedical patent definition based on the classification code of USPTO may disproportionably enlarge the patent ownership portfolio. After all, industry patents are more application oriented and especially industry-wisely specialized, while patents of non-profit organizations, mainly of universities are more basic and versatile in terms of their knowledge importance. So it is more convincing to list these non-profit organizations’ pharmaceutical patents rather than those industry pharmaceutical patents into the pharmaceutical industry patent portfolio that has potential holding-up power over subsequent innovations.

In terms of certain time interval, we have no prior information to determine the time length. I will begin with 1 year and continue up to a 4-year pooling. Hence, for instance, with a 4-year pooling, patents granted in each neighboring 4 years will be treated homogeneously, and pooled together to determine the distribution of the patent right ownerships in the industry. Each year will be associated with a status quo industry patent ownership fragmentation index based on the patents granted to the above-defined entities in the 3 prior years and the current year itself.

A search of firms with above-mentioned NAICS numbers from COMPUSTAT North America Industry Annual (with historical part) for year1980 to 2002 returned 821 firms. These firm names were then matched to the company names and assignee names by the “company name dataset” developed by Hall (2004), this returned 190 firms. Each firms’ name is matched to patent assignee names (one firm name may have multiple names appearing as patent assignees) in the patent database to obtain patent number granted to each firm. This step is the heaviest part of the data preparation task for this study. Some firms may have more than one NAICS number in the same year because the firms might change theirs business line (or change its name equivalently), own multi-industry operation themselves, or because COMPUSTAT changed its classification, so certain firms end up with the same CUSIP in COMPUSTAT but different NAICS in the same year. For example, GENZYME CORP and GENZYME TISSUE REPAIR belong to BIOLOGICAL PDS, EX DIAGNSTICS (NAICS 325414) while GENZYME MOLECULAR ONCOLOGY belongs to IN VITRO, IN VIVO DIAGNOSTICS (NAICS 325413) in COMPUSTAT. Another special case, also happened to GENZYME is that it has an NAICS number not belonging to pharmaceutical industry but SURGICAL, MED INSTR, APPARATUS (NAICS 339112). Only pharmaceutical part of GENZYME is retained in the dataset.

The final data set is based on a panel of 190 firms with previously stated NAICS numbers from 1980 to 2002 during which every firm is granted at least 1 patent each year. The fragmentation index is based on 712 entities including both 522 non-profit organizations and 190 firms. For the fragmentation index based on up to 4-year pooling, the panel data set featuring the inequality index is truncated to year 1983 to 2002 but still luckily with the same 190 firms.

5. EMPIRICAL ANALYSIS

5.1. A RETROSPECT OF THE IP RIGHTS FRAGMENTATION

For information purpose, the 4 indices including Theil, Normalized Herfindahl and GINI are shown in Graph 1 based on the distribution information of the 4-year pooling of patents granted in pharmaceutical industry from 1983 to 2002. According to the results, each of the fragmentation indexes experienced a process of increase and decline during the period. All four indices peaked in the middle 1990's. Theil peaked at 0.802 in 1995; Normalized Herfindahl peaked at 0.98 also in 1995; GINI peaked at 0.26 in 1994. It is really not incidental that tragedy of anti-commons became the focus of researchers of innovation policy issues at the time. **(FIGURE 1 around here)**

5.2. EMPIRICAL RESULTS

Since Negative Binomial model is a generalization of Poisson model, I directly applied a Negative Binomial model to the data. Simple pooling is first used, Conditional fixed effect model is secondly considered for which each firm's innovation rate is controlled. Random effect model is then explored to accommodate unobservable predictors' effects. It is noted that all the models confirm above mentioned concern that contemporaneous patent ownerships structure situation (models without lag) has little chance to lead to significant negative effect on firm innovation. Although the index is based on 4-year pooling patents, only part of the patent rights should be binding for current year even if the anti-commons effect is true.

In the empirical model, X_{it} is firm patent number, $\ln emp_{it}$ is the log of firm employee, $\ln rnd\,\mathrm{int}_{it}$ is the log of firm R&D intensity (the ratio of R&D to employee), $indtotalp_{it}$ is total relevant patent number for current year (includes patents granted to both industry and non-profit organizations) controlling technological opportunity, and $indices_{it}$ is the featured fragmentation index. The choice of R&D intensity rather than R&D itself is due to the well-known correlation between R&D and firm size. Considering different longitudinal data handling options, simple pooling, conditional fixed effects and random effects model are explored one by one.

Innovation has the well-known R&D-patent lag relationship. Patents granted at the same year may have their R&D started at different time, therefore, patents granted in a year might carry the knowledge on which patents granted at the same year is built. We do not have good reason to reject the holding-up strength of patents granted very close. It is therefore necessary to explore the effect of dispersion measure based on patents that also includes those granted in the current year. Again, if we do not want to complicate the interaction among various different R&D predictors and their lags, a reasonable first choice is to lag all of them simultaneously. Therefore, I first lagged all the R&D inputs (R&D intensity and firm size) together with the fragmentation index by 1 year in table 1 through table 4 while each of their no-lag versions is also explored.

Each model controlling the total relevant patent is contrasted with one that does not control the industry patent total, and every model also features each of the 3 indices to highlight the behaviors of these indices. **(TABLE 1 around here)**

Table 1 is based on data obtained by simply pooling the longitudinal data together. It can be observed that neither Normalized Herfindahl nor Herfindahl is significant when total relevant patent is not controlled. Both Normalized Herfindahl and Herfindahl are sensitive to total relevant patent: further than being insignificantly negative, they turn out insignificantly positive in the no-lag model when total relevant patent is not controlled. In contrast, the Theil index is negatively significant for 1-year lag model without control of the total relevant patent ($indtotalp_{it}$). **(TABLE 2 and TABLE 3 around here)**

The results of conditional fixed effects models in Table 2and the results of random effects models in Table 3 reveal certain improvement about the stability of Herfindahl type indices' estimates compared to results in Table 1: Normalized Herfindahl and Herfindahl at most change from negative significance to negative insignificance as the control of total relevant patent is removed while the magnitude still varies a lot. These behaviors of the two indices are expected results since they are not fully free of the endogeneity with the total industry patent[3]. In contrast with these two indices, the estimated effect of the Theil index remains negatively significant no matter total relevant patent is controlled or not across the two models. The different behaviors of the two types of indices is because the construction of Theil index is relatively "freer" of possible endogeneity with this cotrol and therefore demonstrates more stability compared to Herfindahl type indices.

It has to be noted that, each above fragmentation indices is based on 4-neighbouring-year pooling of patents; in fact, when fragmentation index based on 1, 2 and 3 neighboring years is computed and analyzed with the same empirical models from Table 1 through Table 3, all the similar results still follow.

These results demonstrate how the relation between Herfindahl type index and the current year total relevant patent through the pooled 4-year total relevant patent (i.e. N in the definition of Herfindahl index) affects the stability of these indices' estimates. It is observed that, when the lag is longer, the change of the estimates of Herfindahl type indices with and without the total relevant patent as control in these models are less dramatic since the correlation between current-year total relevant patent and the longer-lagged 4-year pooled total relevant patent diminishes.

Even if we are not sure that the Theil index is more convincing or not, it is always reassuring to include more indices to draw a reliable empirical conclusion on the existence of “tragedy of anti-commons”. Since estimates of the effect of the Theil index is relatively more stable, it is used to test the second hypothesis raised in previous section. The results of these models considering longer lags are explored in Table 4 (R&D intensity, firm size and the fragmentation index are still lagged simultaneously). **(TABLE 4 around here)**

In Table 4, random effects models with lags up to 8 years are examined to test the parabolic change of the holing up strength. All the firm patent predictors are significant across all the models. It can be seen that the holding-up effect of fragmentation index peaks when it is lagged 5 years, i.e. the patents granted 5 to 8 years before has the strongest holding-up effect on firm innovations that appear as granted patents in current year. Patents granted in nearer and further years has smaller holding up effect. Graph 4 shows the change of the effect of anti-commons from no lag to 8 years lag. For the other 2 data handling options, similar parabolic change of the holding-up effects are also observed. Similar parabolic changes of anti-commons are also observed in above models using Herfindahl and Normalized Herfindahl respectively when industry patent total is controlled. **(FIGURE 2 around here)**

6. CONCLUSION

These empirical results have confirmed the existence of the tragedy of anti-commons in biomedical industry (The NAICS “pharmaceutical industry”) long suspected since the end of 1990’s. The hypothesis that the effect of the holding-up effect follows a parabolic curve when it is further lagged is also confirmed and consistent with the expectation based on the lag relationship between R&D activity and patent grant.

FOOTNOTES

[1] There is some evidence according to the author that the Herfindahl type fragmentation index such defined is positively related to the number of industry total patents used for calculating the index

[2] Whenever such situation is identified it is considered in the data collection process.

[3] While these indexes are only directly related to the 4-year pooled total relevant patent, the correlation between the 4-year pooled total relevant patent (without lag) and current year total relevant patent is over 0.98.

REFERECNES

Bourguignon. F, Decomposable income inequality measures, Econometrica 1979, Vol.47, No.4, 901-20

Cameron, A., C and P. K. Trivedi, 1998, Regression Analysis of Count Data Econometric Society Monograph No.30, Cambridge University Press

Cowell. F. A, 2003, "Theil, inequality and the structure of income distribution", Discussion Paper, No. DARP 67, London School of Economics and Political Science

Grupp, H., 1990, The concept of entropy in scientometrics and innovation research. An indicator for institutional involvement in scientific and technological developments, Scientometrics 18, pp. 219-239

Hall B.H, 200, "A note on the bias in the Herfindahl based on count data", http://emlab.berkeley.edu/users/bhhall/bhpapers.html

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.

Hausman., J, B.H.Hall and Zvi.Griliches,1984, "Econometric models for count data with an application to the patents-R&D relationship," Econometrica, 52, 909-938.

Heller, M. and R. Eisenberg, 1998, "Can Patent Deter Innovation? The Anticommons in Biomedical Research." Science 280, 698-701.

Hansen, Brewster, Asher and Kisielewski, 2006, "The Effects of Patenting in the AAAS Scientific Community",http://sippi.aaas.org/survey/AAAS_IP_Survey_Report.pdf

Jaffe, A.B. and M. Trajtenberg, 2002, "Patents, Citations, and Innovations: A Window on the Knowledge Economy", Cambridge, MA: MIT Press.

Montgomery, C.A, 1994, Corporate diversification, Journal of Economic Perspectives 8(3), pp. 163-178

Murray. F and S. Stern, 2005, “Do formal intellectual property rights hinder the free flow of scientific knowledge? An empirical test of the anti-commons hypothesis”, NBER Working Paper 11465

Mussard, S, F.Seyte, and M.Terraza, 2003, “Decomposition of Gini and the generalized entropy inequality measures”, Economics Bulletin, Vol. 4, No. 7, 1−6

Shorrocks. A.F., 1980, “The class of additively decomposable inequality measures, Econometrica”, Vol.48, No.3., 613-626

Theil, H. 1967, Economics and Information Theory, Amsterdam: North-Holland

Ziedonis. R.H, 2004, “Don’t fence me in: fragmented markets for technology and the patent acquisition strategies of firms” Management Science Vol. 50, No. 6, 804–820

Epstein.R.A and B.Kuhlik, 2004, “Is there a Biomedical Anti-commons?” Regulation, Vol. 27, No. 2, pp. 54-58

APPENDIX: FIGURES AND TABLES

FIGURE 1: Fragmentation Index 1980-2002

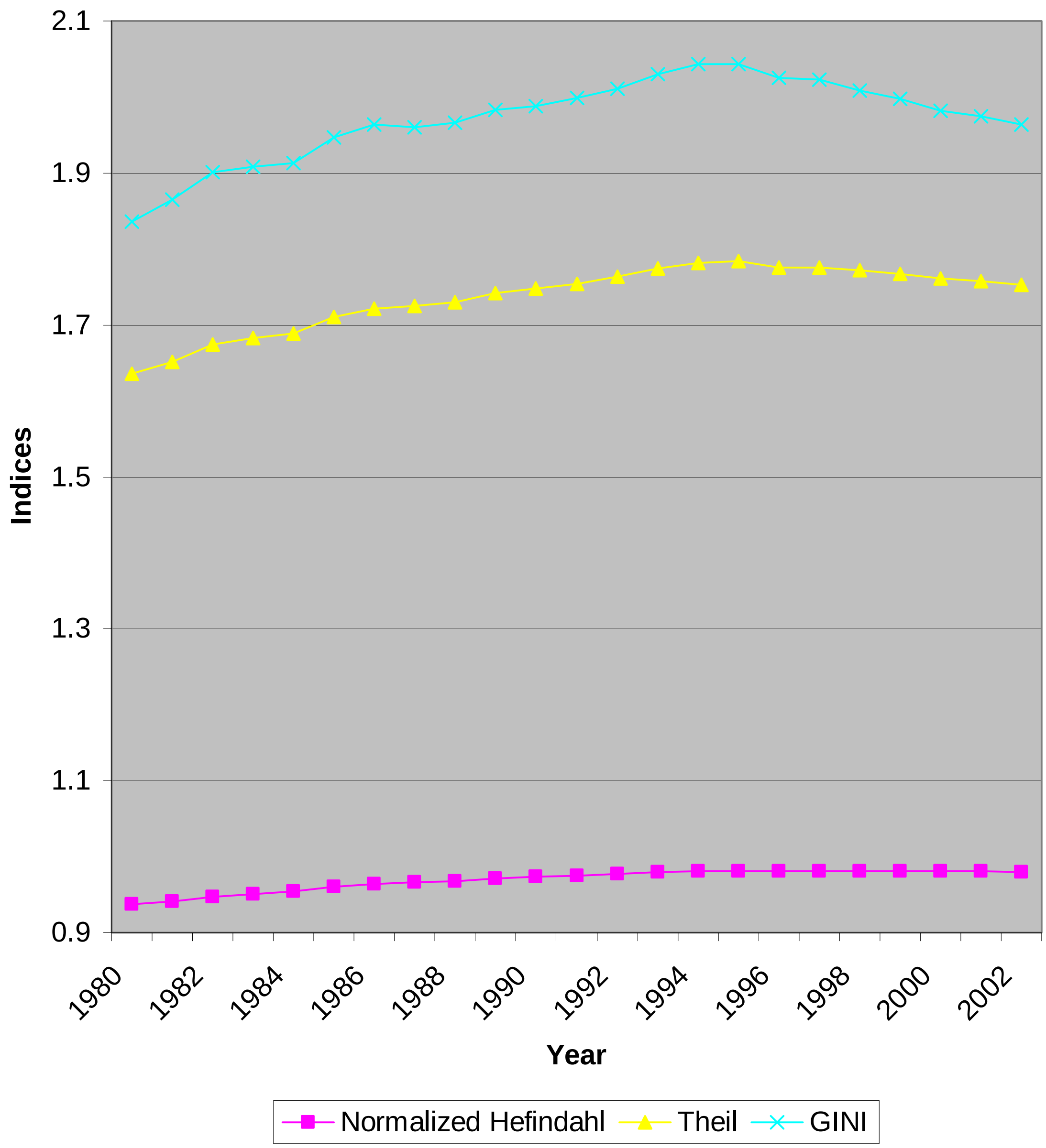

FIGURE 2: Absolute Value of Estimate of the Effect of Theil Fragmentation Index

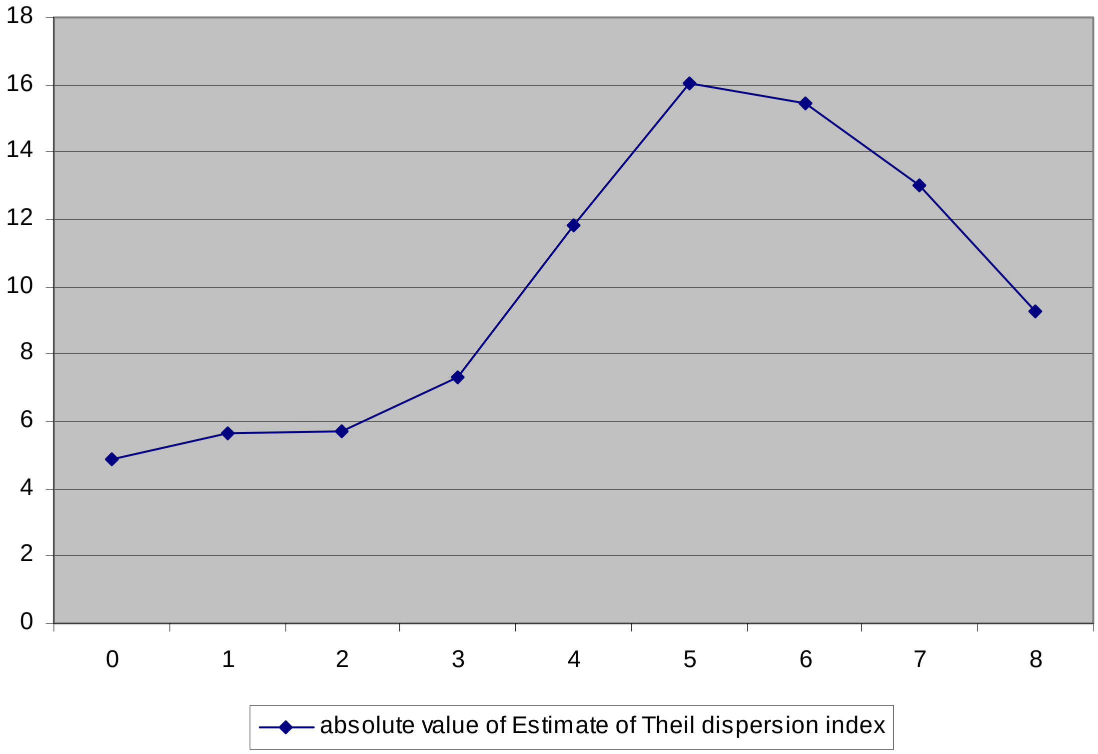

Table 1 Estimates of the Determinants of Firm Patenting With Simple Pooling

Lag of independent variables (except industry patent total) or not	No						I Year Lag						Benchmark Model check(No lag)
control industry patent or not	Yes			No			Yes			No			NA
Featured Index	Theil	Normalized Herfindahl	Herfindahl	Theil	Normalized Herfindahl	Herfindahl	Theil	Normalized Herfindahl	Herfindahl	Theil	Normalized Herfindahl	Herfindahl	NA
Firm size, log of employee: Lnemp	.5258*** (.004692)	.5264*** (.004708)	.5264*** (.004708)	.5341*** (.004631)	.5325*** (.004708)	.5325*** (.004708)	.5112*** (.005356)	.5121*** (.05391)	.5122*** (.05391)	.5174*** (.005252)	.5166** (.005375)	.5166*** (.005377)	.55102*** (.005187)
Log of R&D Intensity: Lnrndint	.1995*** (.01231)	.2035*** (.01253)	.2036*** (.01253)	.02570*** (.009863)	.2444*** (.01162)	.2443*** (.01163)	.1744*** (.01436)	.1794*** (.01470)	.1795*** (.01471)	.2132*** (.01200)	.2089*** (.01378)	.2090*** (.01380)	.1664*** (.01294)
Dispersion Indext	-1.818*** (.6342)	-6.298*** (1.856)	-6.279*** (1.843)	-.9013 (.6170)	1.182 (1.597)	1.198 (1.582)	-2.657*** (.7152)	-7.946*** (2.008)	-7.925*** (1.995)	-1.536** (.6724)	-2.059 (1.596)	-2.037 (1.665)	NA
Technological Opportunity: Industry Patent Total	.0000761*** (.0000102)	.0000912*** (.0000118)	.0000915*** (.0000118)	NA	NA	NA	.0000562*** (.0000118)	.0000711*** (.0000135)	.0000714*** (.0000135)	NA	NA	NA	.0000366*** (.000011)
Intercept(if applicable)	2.779*** (.4771)	7.450*** (1.778)	7.429*** (1.766)	2.027*** (.4618)	.2267 (1.525)	.2112 (1.511)	3.814*** (.5306)	9.432*** (1.916)	9.409*** (1.903)	2.934*** (.4947)	3.766** (1.596)	3.743*** (1.582)	1.863*** (.4052)
Variance Parameter(if applicable)	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	
Log Pseudo-Likelihood	-5048	-5047	-5047	-5076	-5077	-5077	-3313	-3312	-3312	-3324	-3326	-3326	
Wald Chi-square (p-value)	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	

NA:Not Applicable

*: P-Value<0.10; **: P-Value<0.05; ***: P-Value<0.01;

Table 3 Estimates of the Determinants of Firm Patenting With Conditional Fixed Effects

Lag of independent variables (except industry patent total) or not	No						1 Year Lag						Benchmark Model check(No Lag)
control industry patent or not	Yes			No			Yes			No			NA
Featured Index	Theil	Normalized Herfindahl	Herfindahl	Theil	Normalized Herfindahl	Herfindahl	Theil	Normalized Herfindahl	Herfindahl	Theil	Normalized Herfindahl	Herfindahl	NA
Firm size, log of employee: Lnemp	.2441*** (.02650)	.2436*** (.02685)	.2436*** (.02685)	.4604*** (.02347)	.4527*** (.02451)	.4524*** (.02453)	.5369*** (.03015)	.5449*** (.03047)	.5450*** (.03048)	.6501*** (.02641)	.6563*** (.02751)	.6564*** (.02752)	.1981*** (.02502)
Log of R&D Intensity: Lnrndint	.064391** (.02569)	.04515* (.02703)	.04510*** (.02704)	.4085*** (.01622)	.3590*** (.02064)	.3581*** (.02069)	.09492*** (.02648)	.09806*** (.02808)	.09826*** (.02810)	.2357*** (.01884)	.2275*** (.02305)	.2275*** (.02310)	.01345 (.01992)
Dispersion Indext	-3.814*** (.7271)	-5.736*** (2.175)	-5.684*** (2.161)	-4.864*** (.7063)	-1.049 (2.128)	-.9156 (2.114)	-5.631*** (.7944)	-12.43*** (2.285)	-12.36*** (2.270)	-5.164*** (.7829)	-8.556*** (2.218)	-8.461*** (2.203)	NA
Technological Opportunity: Industry Patent Total	.0002756*** (.0000159)	.0002879*** (.0000159)	.0002880*** (.0000159)	NA	NA	NA	.0001329*** (.0000176)	.0001439*** (.0000179)	.0001442*** (.0000179)	NA	NA	NA	.0002933*** (.0000151)
Intercept(if applicable)	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Variance Parameter(if applicable)	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	
Log Pseudo-Likelihood	-2312	-2323	-2323	-2461	-2485	-2485	-1459	-1469	-1469	-1487	-1502	-1502	-2522
Wald Chi-square (p-value)	1653	1616	1616	1301	1211	1210	995	961	961	919	873	873	1885

NA: Not Applicable

*: P-Value<0.10; **: P-Value<0.05; ***: P-Value<0.01;

Models Without lag: 24 groups were droped because only one observation exists for each group.

Models With 1 year lag:13 groups were droped because only one observation exists for each group.

Table 4 Estimates of the Determinants of Firm Patenting With Random Effects

Lag of independent variables (except industry patent total) or not	No						I Year Lag						Benchmark Model check(No Lag)
control industry patent or not	Yes			No			Yes			No			NA
Featured Index	Theil	Normalized Herfindahl	Herfindahl	Theil	Normalized Herfindahl	Herfindahl	Theil	Normalized Herfindahl	Herfindahl	Theil	Normalized Herfindahl	Herfindahl	NA
Firm size, log of employee: Lnemp	.3468*** (.02090)	.3473*** (.02107)	.3473*** (.02107)	.4897*** (.01844)	.4820*** (.01903)	.4818*** (.01904)	.5147*** (.02378)	.5198*** (.02403)	.5199*** (.02403)	.6028*** (.0223)	.6041*** (.02321)	.6042*** (.02323)	.1981*** (.02502)
Log of R&D Intensity: Lnrndint	.08459*** (.02467)	.7179*** (.02586)	.07181*** (.02586)	.3916*** (.01549)	.3447*** (.01976)	.3439*** (.01981)	.1008*** (.02538)	.1044*** (.02676)	.1045*** (.02678)	.2440*** (.01812)	.2325*** (.02216)	.2324*** (.02221)	.01345 (.01992)
Dispersion Indext	-3.955*** (.7219)	-7.020*** (2.149)	-6.967*** (2.136)	-4.638*** (.7016)	-.8532 (2.079)	-.7293 (2.065)	-5.623*** (.7887)	-12.57*** (2.259)	-12.49*** (2.244)	-4.962*** (.7746)	-7.629*** (2.170)	-7.533*** (2.155)	NA
Technological Opportunity: Industry Patent Total	.0002463*** (.0000153)	.0002601*** (.0000154)	.0002603*** (.0000154)	NA	NA	NA	.0001347*** (.0000167)	.0001468*** (.0000171)	.0001471*** (.0000171)	NA	NA	NA	.0002933*** (.0000151)
Intercept(if applicable)	4.0141*** (.5325)	7.806*** (2.040)	7.753*** (2.026)	4.032*** (.5205)	1.456*** (1.972)	1.339*** (1.958)	6.030*** (.5804)	13.87*** (2.141)	13.79*** (2.126)	5.407*** (.5706)	9.042*** (2.055)	8.948*** (2.040)	NA
Variance Parameter(if applicable)	0.6866 (.0836)	.6821 (.08311)	.6821 (.08311)	.5902 (.0718)	.5785 (.07048)	.5785 (.07048)	.5361 (.07558)	.5316 (.07514)	.5316 (.07514)	.5545 (.07941)	.5521 (.07930)	.5521 (.07930)	
Log Pseudo-Likelihood	-2921	-2930	-2930	-3052	-3074	-3074	-1910	-1920	-1920	-1942	-1957	-1957	-2522
Wald Chi-square (p-value)	1774	1738	1738	1484	1401	1401	1133	1100	1100	1011	965.2	965	1885

NA:Not Applicable

*: P-Value<0.10; **: P-Value<0.05; ***: P-Value<0.001;

Table 5 Estimates of the Determinants of Firm Patenting In Random Effects Models With Up To 8 Years Lags

Lag of independent variables (except industry patent total) or not	0	1 year	2 year	3 year	4 year	5 year	6 year	7 year	8 year
Firm size, log of employee: Lnemp	.3468''' (.02090)	.5147''' (.02378)	.5249''' (.02509)	.5130''' (.02747)	.4665''' (.02748)	.4593''' (.02784)	.4391''' (.02899)	.4090''' (.03099)	.3345''' (.03529)
Log of R&D Intensity: Lnrndint	.08459''' (.02467)	.1008''' (.02538)	.1017''' (.02683)	.1070''' (.02799)	.1612''' (.02962)	.2279''' (.03125)	.2374''' (.03304)	.2662''' (.03513)	.2427''' (.03602)
Theil dispersion index	-3.955''' (.7219)	-5.623''' (.7887)	-5.704''' (.8787)	-7.283''' (1.036)	-11.81''' (1.325)	-16.05''' (1.604)	-15.46''' (1.671)	-13.00''' (1.695)	-9.260''' (1.689)
Technological Opportunity: Industry Patent Total	.0002463''' (.0000153)	.0001347''' (.0000167)	.000128''' (.0000174)	.0001401''' (.0000196)	.0002078''' (.0000242)	.0002597''' (.0000297)	.0002536''' (.0000319)	.000202''' (.0000318)	.0001643''' (.0000311)
Intercept(if applicable)	4.0141''' (.5325)	6.030''' (.5804)	6.183''' (.6389)	7.341''' (.7492)	10.42''' (.9476)	13.27''' (1.139)	12.80''' (1.181)	10.94''' (1.193)	8.271''' (1.187)
Variance Parameter(if applicable)	0.6866 (.0836)	.5361 (.07558)	.5600 (.08203)	.6745 (.1007)	.6960 (.1118)	.6909(.1192)	.6737 (.1270)	.7818(.1530)	1.024 (.2134)
Log Pseudo-Likelihood	-2921	-1910	-1773	-1621	-1427	-1228	-1086	-961.1	-884.3
Wald Chi-square (p-value)	1774	1133	965.8	725.9	615	527.8	440.1	341.6	253.4

NA:Not Applicable

*: P-Value<0.10; **: P-Value<0.05; ***: P-Value<0.001;