Patent Assessment Quality

-

Analyzing the consistency of the EPO's ruling on novelty and inventive step in emerging industries

This version: February 2006
Comments welcome!

Paul F. Burke[1]
Markus Reitzig [2]

Abstract:

The increasing number of patent applications worldwide and the extension of patenting to the areas of software and business methods have triggered a debate on "patent quality". While patent quality may have various dimensions, this paper argues that consistency in the decision making on the side of the patent office is one important dimension, particularly in new patenting areas (emerging technologies). In order to understand whether patent offices appear capable of providing consistent assessments of a patent's technological quality in such novel industries from the beginning, we study the concordance of the European Patent Office's (EPO's) granting and opposition decisions for individual patents. We use the historical example of biotech patents filed between 1978 until 1986, the early stage of the industry. Our results indicate that the EPO shows systematically different assessments of technological quality during the granting and the opposition phase. The inconsistency is likely not entirely attributable to additional information revealed after the grant date.

Keywords: Patents, quality, novelty, inventive step, discrete choice, variance decomposition

JEL-Classifications: C25, C51, K41, L00, L20

[1] School of Marketing. The University of Technology ,Sydney, PO Box 123, Broadway NSW 2007/Australia. paul.burke@uts.edu.au.

[2] Corresponding author. RIPE Research Group. The Copenhagen Business School, Kilevej 14a, 2000 Copenhagen-Frederiksberg/Denmark. Reitzig@cbs.dk. Phone +45 38 15 23 81. Fax +45 38 15 25 40.

1 Introduction

This paper is motivated by the ongoing discussion about "patent quality" in both academic circles (Samuelson, 2004) and the popular media as well as among policy makers. Triggered by the explosion of patenting over the last decade (see EPO, 2003) and the increasing number of patents filed in emerging technologies such as biotechnology or software, concerns have been uttered that "patent quality" is decreasing. We try to structure this debate theoretically and summarize some relevant empirical insights of this discussion in Section 2 of this paper. At this point, we would like to take up only one insight central for our work and, to the best we can judge, commonly accepted. While the term "patent quality" has various dimensions, one dimension speaks to the ability of a patent to surmount a validity challenge in court (Thomas, 2002). In other words, quality pertains to the patent's legal sustainability, commonly assumed to be the product of a far-sighted and rigorous granting procedure. In as much as there seems to be a consensus that this dimension of quality is an important one, opinions about the fulfillment of quality granting procedures, especially for patents from emerging technological areas, differ and related empirical evidence is mixed (Allison and Tiller, 2003; Merges, 1996; Quillen and Webster, 2001). Given the various impacts that good or bad quality assessments for patents may have on national innovative activity and, considering the heat at which the debate is currently being carried out, indicate that there is an urgent need for robust empirical evidence shedding light on the question how good or bad patent granting procedures are. In more detail, it is unclear how reliable it is that a patent once granted will survive a validity suit.

In this paper we therefore analyze how reliably the patent granting procedure ensures that a patent survives a subsequent "validity suit". We tackle the question by analyzing the consistency of the EPO (European Patent Office) in assessing the patentability requirements (mainly technological quality) of a patent application during the granting procedure and the subsequent opposition procedure.

For our analysis we use European patents (applications) as the data allows us to observe both granting, opposition, and opposition outcome decisions. For the purpose of this paper we treat the opposition before the European Patent Office (EPO) as a central validity suit (Harhoff and Reitzig, 2004). We confine our sample to biotechnology patents filed between 1977 and 1986. The selection

criteria reflect the major arguments in the aforementioned debate. In the late 1970s and early 1980s biotechnology was an emerging technology from the perspective of the European patent office (Orsigeno, 1989). We model the information about a patent (application)'s technological quality (patentability requirement) available to the EPO using a set of established bibliographic indicators (backward references, family size, forward cites, and others). We estimate a series of discrete choice models and compare the parameter estimates for the bibliographic indicators when explaining patent grant and opposition outcome. To take full account of the complexity of the data we start from simple reduced form probability models and move on to more complex models (Swait and Louviere, 1993) in which we subsequently relax assumptions about the homogeneity of the parameters as well as their variances across the different decision making stages (patent grant and ruling on opposition).

The major findings can be summarized as follows.

Within the general limitations of our research design, particularly our framework of assumptions and for our chosen data, we cannot confirm that the EPO assessed the technological quality of biotech patents consistently in the early 1980s. We do not find convincing evidence on congruent systematic effects driving the assessment of a patent's technological quality during the granting phase and during the opposition procedure, despite the fact that this should be the case from a legal perspective (see 3.2 for details). Moreover, when attempting to identify the sources of inconsistent rulings we did not find compelling evidence that information revealed *after* a patent's date of grant would account for systematically different assessments.

In the following Section 2 we provide clearer definitions of the central term "patent quality" and sketch prior research carried out in the field. Section 3 develops the testable hypotheses and introduces to the research techniques. We present our data and estimation results in Section 4 and discuss them in Section 5. Section 6 concludes and presents new questions for research.

2 Background – related prior research and policy debates

2.1 Patent "quality" – theoretical perspectives

2.1.1 'Classical' patent economics – techno-economic dimensions of patent quality

From a theoretical economic perspective the term "patent quality" denotes the social wealth created through the bestowal of an entitlement to an individual to use a certain type of technology for a limited period of time. In her reflective survey paper, Gallini (2001) summarizes the various arguments that have historically been brought forth for value creation through patent protection and the trade-offs in which they are embedded. The arguments speaking for patent protection relate to the stimulation of research and development (R&D), the encouragement of disclosure of technological knowledge, and – increasingly important in modern times – the facilitation of technology transfer. They all hark back to two fundamental assumptions: (1) the premise that technology contributes to social welfare; and (2) that the economic value of a patent therefore rises with the technological sophistication of the underlying technology[3]. The basic character of these two suppositional principles is reflected in the design of patent laws in virtually all industrialized nations. In order to maximize social welfare through patent protection, legal setscrews were introduced that bring leverage to bear on the protected underlying technology. In more detail, these are the disclosure requirements for technological knowledge, as well as the patentability requirements for a technology's novelty and sophistication (in EU: inventive step; in the US: non-obviousness). The classical patent economics literature is centered on the optimal adjustment of these parameters in the granting process for patent entitlements, with path-breaking theoretical contributions being made by Nordhaus (1967), Scotchmer and Green (1990), Green and Scotchmer (1995), and Barton (2001). For the purpose of this paper, however, it suffices to notice that the amount of technological knowledge a patent protects/discloses constitutes the patent's *technological quality*. The latter has traditionally been assumed to correlate highly with the patent's economic value and is therefore also termed *technological 'merit'* (see Merges, 1988).

[3] For critical discussions of the second assumption see Merges (1988) and Reitzig (2005).

2.1.2 Legal considerations – established normative dimensions of patent quality

When comparing economic and legal approaches to capture the term "patent quality" disciplinary differences become visible. The following definition, though explicitly referring to only one source (Thomas, 2002), seems to be representative for one (dominant) legal school of thought:

> *"'quality patents' are [...] valid patents [which may] be reliably enforced in court, consistently expected to surmount validity challenges, and dependably employed as a technology transfer tool"* (Thomas, 2002: 730)

Interestingly, this definition of the term patent quality focuses exclusively on legal *certainty* or *consistency*. According to the strongly dogmatic underlying perspective, the predictability of legal decisions is almost a self-purpose. For Thomas, as for other lawyers, the *absolute adjustment* of the patentability parameters (disclosure, novelty, and inventive step) and the identification of a related threshold appears to be second-order compared to the requirement of legal certainty; hence, the *relative comparability* of the assessment from one case to another. Merges (1999) appears to share Thomas' (2002) standpoint in general, however, he admits that resource constraints during the granting procedure prohibit calling every patent a bad patent that does not surmount a valid challenge after being granted:

> *"A 'bad patent' is a patent that should have been weeded out after a reasonable investment of effort, but was not"* (Merges, 1999: 581)

In fact, elaborating on Merges' argument of resource constraints, Lemley (2000) goes as far as relaxing the legal consistency criterion for normative legal patent quality. Lemley argues that patent offices would act "rationally" ignorant if they dedicated more resources to subsequent court decisions on a patent's validity than on initial granting procedures. In his opinion, sacrificing legal certainty for the sake of better resource allocations on economically important patents is desirable. We did not find a large set of supporters for this view in the literature, however.

2.1.3 On the relation between techno-economic and legal quality of a patent

In as much as the different disciplines do suggest seemingly different concepts of patent quality, from an overall economic standpoint, their definitions ultimately resemble two sides of the same coin. From a techno-economic standpoint (the concern of traditional patent economics) the value creating potential is predominantly determined by the patent's potential to stimulate R&D, disclose/diffuse technological knowledge, and provides a mechanism for technology transfer. For patents to be able to serve these purposes, however, the "clients" of the patent system must use the latter. Usage of the system requires inventors to have sufficient trust in a patent's efficacy to protect their ideas; that is, inventors must have the confidence that they can rely on the entitlements they receive from the patent offices, and this is why legal certainty (or *consistency*) is as much an economic need as a normative prerequisite. Thus, ensuring sufficiently high thresholds for techno-economic quality (disclosure, novelty, and inventive step) and ensuring their consistent assessment by the patent offices appear to be the two entrenched prerequisites of value creation through patent protection. Obviously, assessments will always be carried out under some resource constraints; the question is what an optimal allocation of resources would look like?

For the reader's general understanding we deemed it important to illustrate the entrenchment of the two dominant notions of patent quality. For the remainder of this paper, however, the divisibility of the two distinct notions will remain pivotal. This is for two reasons. At first it helps to better structure the prior empirical research. Secondly, it enables us to narrow down the existing research gap in a better fashion.

2.2 Perceptions and empirical observations on patent quality – annotations, case-based evidence, and survey data

2.2.1 Perceived trends, annotations, and case-based evidence

Over recent years, patent offices have faced a series of reproaches suggesting that low 'patent quality' is becoming a problem. The vast amount of different annotations can be classified into two major categories that mirror the classically different disciplinary understandings of the term 'patent

quality' (see above). Namely, these categories capture (a) commentaries or case-based annotations stating that inventive step (non-obviousness) was becoming systematically too low as well as (b) comments and casuistic observations about the (increasing) assessment inconsistency by the patent offices with respect to technological quality. The two critical contributions mentioned in the following appear to be representative for a broader set of related papers.

One of the advocates for a reinvigoration of non-obviousness standards is Pamela Samuelson. In her summary paper "Legally speaking: why reform the patent system?" (2004) she lists various reasons why standards should be reinforced. Her firstly mentioned rationale, however, is a *techno-economic* one. Samuelson demands that assessing the commercial success of a patented invention should be made a prerequisite in non-obviousness assessments (in order to ascertain that the threshold value for inventive step is set sufficiently high). The paper's view appears to be representative for a series of contributions that finds patents are (nowadays) granted for trivial inventions that do not add value to society (any more).

Allegations regarding low levels of inventive step on the one hand and inconsistency in the granting procedure on the other seem to be partly entrenched. In his seminal work, Robert Merges (1999) provides theoretical considerations and anecdotal evidence for the problems associated with granting patents for business methods consistently. In his eyes, the potential error rates for patents in emerging industries must be inevitably high as prior art searches will likely be imperfect when much of the relevant information will stem from non-patent sources (Merges, 1999: p. 589).
It appears intuitively understandable that the aforementioned annotations (and observations that led to them) also triggered reactions by empirical researchers. Major findings of these latter works are summarized in the following sub section.

2.2.2 Large-scale empirical evidence

Over the recent years a series of studies have been published that seeks to contribute to a better understanding of the quality of patents. Below, we map the empirical evidence along the dimensions of (lacking) patent quality we delineated above.

Patent quality in terms of technological merit and economic value

A set of different papers seeks to study the effects of 'patent quality' through analyzing the economic value created by patent protection. In their analyses, Harhoff et al. (2003), Hall et al. (2000; 2005), Hirschey and Richardson (2004) and Sampat et al. (2003) 'qualify' patent counts using so-called forward citations to capture the economic merit created by the property right. That is, the authors capture the frequency at which a patent was cited as relevant state of the art in subsequent patent application procedures. The scopes and results of the four different studies differ. Whereas Harhoff et al. (2003), Hall et al. (2000; 2005), and Hirschey and Richardson (2004) seek to refine the understanding between patent quality and a patent's private value, Sampat et al. (2003) trace changes of university patents over time and examine the impacts of the Baye-Dole act (passed in 1980) on patent quality. Their results, however, point in the same direction. The commonly held assumption by all these papers, namely that their quality measure (forward citations) is a valid proxy of a patent's objective technological quality (leading to economic merit) appears unproblematic. Not only does the assumption appear intuitively comprehensible, but recent structural empirical evidence in its support has been published (Reitzig, 2005).

One further contribution appears important in this context, namely a study by Sanyal and Jaffe (2005). In their paper the authors examine several effects that may drive the observable increase in patenting rates. In particular they attempt to disentangle the effects of a potential decrease in patentability standards over time. The major result is that within their framework of assumptions the authors can attribute the increase in filing rates to an increase in overall inventiveness, whereas the evidence for a decrease in patenting standards is rather mixed. The study by Sanyal and Jaffe (2005) that examines the size of the non-obviousness (inventive step) requirement over time nicely shows that existing empirical evidence often relates to both technological value and the consistency related aspects of patent quality, and it naturally leads to the next section.

Patent quality in terms of assessment consistency

Few large-scale empirical studies exist that shed light on the second major aspect in the current discussion about patent quality; namely, on the case-based allegation that patentability

requirements are being assessed inconsistently by the patent offices. As aforementioned, the contribution by Sanyal and Brandeis (2005) also falls into this category; however, their results are mixed. Quillen and Webster (2001) provide interesting evidence on the granting rates at the USPTO (United States Patent Office). Their data indicates that due to internal procedures at the USPTO continued applications have – all else being equal – a higher chance of being granted than original applications. Indirectly, their results therefore support the hypothesis that patent quality was measured along different dimensions in different cases. Another of the few potentially relevant studies in this area is the paper by Graham et al. (2002). In their paper, the authors compare 'twins' of patents in the European and US systems. For a selection of patents with identical priorities[4] the authors track the fate of European oppositions and compare them to US re-examinations. Their findings indicate that the European and US office rule distinctly differently in similar cases, however, the different focus of the paper (consistency is not the study's core topic) and a series of other complications do not allow inferring more details about *inter-institutional* patent assessment consistency.

An important contribution regarding the *inter-industry* consistency of patent granting is presented in a paper by Allison and Tiller (2003). In their study the authors compare business method patents to patents from 'established' patenting areas along a series of bibliographic indicators. Within their framework of assumptions and depending on the indicators' ability to capture patent quality related effects, the authors find no significant differences between business method patents and other patents. The paper can be viewed as a response to Merges (1999) and sheds an unexpectedly positive light on the USPTO. Despite the study's undisputed contribution and the rich underlying data base, however, the rather descriptive character of its results may render it difficult to draw final conclusions. In essence, the authors compare business method patents and other patents along a series of bibliographic indicators without testing whether these indicators actually capture quality related phenomena. The *t*-test comparisons for the means of the variables in the two samples (business methods and other patents) do provide a first indication of whether similarities between the two groups of patents exist. Whether the (dis)similarities as captured by these indicators ultimately relate to quality phenomena of patents in these samples, however, requires more sophisticated tests. Currently,

[4] This means that both patents developed from the same original patent application.

studies employing such tests are missing. Moreover, we know of no study design that analyses the *intra-office* consistency in the patent granting procedure, despites its major political relevance (see 2.3). In our study, we attempt to close this research gap to some extent.

2.3 The policy side – institutional observations and responses to the "patent quality" debate

There are various indications that the current debate on patent quality did not leave policy makers and the patent offices themselves unaffected, either. The following paragraph makes this point clear:

In 1997, the U.S. Department of Commerce published the public report PTD-9977-7-0001 entitled "Patent Quality Controls are Inadequate". The central variable of the report is the potential "error rate" during the granting procedure, measured as the difference between actual patentability assessments provided by the responsible patent examiners and a group of reviewer examiners who – for a sample of patents – were asked to provide a second "pair-of-eyes" check. As the report shows, the potential error rate rose by more than 1000% over the years 1992 until 1996.

Admittedly this figure provides only very limited insight regarding the fundamental question whether patent quality is actually high or low these days, and whether it was higher or lower in the past. This is because, on the one hand, the error rate itself says nothing about the correctness of the adjustment of patentability requirements such as novelty, inventive step, and disclosure (techno-economic dimension of patent quality) in the first place. Moreover, it exclusively refers to the patent office's internal *granting* consistency, without however, providing clear evidence that the patents' reliability of maintenance in *court* had actually suffered. That being said, however, the figure does provide an indication about increasingly lacking trustworthiness in the decision making by the USPTO. Most importantly for this paper, however, it impressively illustrates why consistency in the decision making is of such great practical concern: whereas freezing the (optimal) parameter sizes for novelty, inventive step (non-obviousness) and disclosure is a *one-off* exercise of great concern to patent economists, decision making consistency touches the apparatus of the patent office at its procedural *daily* heart.

Keeping these considerations in mind it is intuitively understandable that not only the USPTO – the addressee of this report – but also other offices around the world as well as practitioner associations started to get in engaged in the "patent quality assurance" debate, focusing hereby mostly on consistency considerations of their own decision making.[5] Different approaches are currently being discussed to assure a qualitatively high patenting procedure, the structural prerequisite for at least one quality element (consistency) of the final product, the patent. According to the EPO (SUEPO, 2002: Summary)

> *"Procedural requirements aim at equal treatment of all stakeholders in the patent system (patent applicants, their competitors, and the public at large); they include procedural fairness, timeliness and affordability). Although there may be certain tradeoffs between these requirements, each of them has a value of its own and produces effects on the economy as a whole. It would therefore be irresponsible to "cut corners" on some of these requirements, but diminishing returns and the need to optimise resource allocation have to be taken into account…"*

and

> *"The most useful framework for sharpening and harmonizing the examiners' judgement is within the examining divisions, provided their composition is varied and their members take the time to effectively fulfill their functions. Crossfunctional teams, delegation of responsibilities, and the involvement of staff in the administration of their units, are further ingredients to foster a true quality culture."*

[5] Various references can be found on the internet. An example for the engagement of the American Intellectual Property Law Association (AIPLA) can be accessed at http://www.aipla.org/Content/ContentGroups/Legislative_Action/108th_Congress1/Testimony2/Testimony_on_the_Patent_Quality_Improvement_Act.htm. The USPTO describes its commitment to a "robust quality assurance program" under the following link http://www.uspto.gov/web/offices/com/strat21/action/q3p17a.htm, the UKPTO here http://www.patent.gov.uk/patent/quality/qassurance.htm. The most comprehensive document describing a patent quality strategy for a patent office is the EPO's SUEPO WP 2005.

Whether it is the second "pair–of-eyes" check, control group assessments, or even creating some kind of diversity in the granting divisions, one observation seems to hold: decision making consistency is high on the policy agenda. And for the executing bodies, namely the patent offices, this normative dimension of patent quality – assessment consistency and resulting legal certainty – appears to be paramount.

3 Empirical research design

3.1 Research gap

While a large amount of evidence exists that patents are valuable assets for their owners (Cockburn and Griliches, 1988; Megna and Klock, 1993; Conolly et al, 1986; Conolly and Hirschey, 1988; Bloom and van Reenen, 2000; Bosworth and Rogers, 2001; Ramb and Reitzig, 2004), empirical evidence about the quality of patents from a social standpoint is scarcer. In particular, as section 2.2.2 highlighted, large-scale empirical data on the patent offices' *consistency of patentability assessments with respect to technological quality* is missing. From a scientific perspective, this knowledge gap is particularly puzzling as the trustworthiness of the PTO's decisions is an essential element of overall patent quality (as was shown in 2.1.3). The intensity of the policy debate and the engagement of various leading patent offices worldwide in quality assurance programs (see 2.3) emphasize the relevance of the research gap.

Focusing on the normative dimensions of patent quality as explicated by Thomas (2002) it is therefore the aim of this paper to shed light on whether patent granting quality procedures can assure that patents may "*consistently* [be] *expected to surmount validity challenges"*. While not a goal in itself, mapping the technological quality of the patents econometrically will be an inevitable interim step in order to facilitate assessment *comparisons* regarding patentability requirements. Finally, recalling Merges' (1999) specific concern that assuring consistency was particularly difficult when most of the prior art stems from non-patent sources, the test should be run for an "emerging" patenting area.

To turn this research aim into testable hypotheses, the following section introduces the decision making logic of the European Patent Office as well as to the set of explanatory variables (bibliographic indicators) used for the later analysis. Section 3.2 will verbally present the fundamental logic of the estimations being performed in the empirical analysis in order to enable the derivation of the hypothesis in 3.3. Section 3.4 will elaborate on the econometric specificities of the estimators chosen for the analysis.

3.2 Modeling the decision making process of the EPO – measuring (in)consistency with indicators

EPO patent data recommends itself for the study of the aforementioned research gap for various reasons. The paramount argument, however, lies in the simultaneous observability of various procedural stages relevant for our analysis; namely, these are the granting procedure and the opposition procedure (including the ruling on the opposition). Essentially, as will be elaborated upon below, mapping the EPO's decision on (a) grant and (b) opposition outcome econometrically allows testing whether EPO patents – once they are granted – surmount the "centralized European validity suit" [6] and provides a good indication whether they live up to the normative understanding of 'quality' patents (Thomas, 2002). Figure 1 reflects a cut-out from the life of a European patent (application) which is explained briefly.[7]

Insert Figure 1 about here

Upon application and examination request, the European Patent Office decides about the patentability of the application. Depending on the fulfillment of the substantial patentability requirements novelty, inventive step (pendant in the US: non-obviousness), disclosure, and susceptibility to industrial commercialization, the application is granted patent status or not (Stage 1). If the patent is granted it can be attacked centrally (i.e. for all designated states) within nine months

[6] For a more detailed elaboration, read Harhoff and Reitzig (2004).

[7] See Reitzig (2004/2005) for more detailed descriptions of the granting and opposition procedures at the EPO.

before the European Patent Office through the so-called opposition procedure (Stage 2). For the purpose of this paper it seems sufficiently correct to say that oppositions resemble first instance validity suits of the patent at the European level. The substantial arguments to be brought forth by an opponent during an opposition procedure again have to relate to the aforementioned patentability requirements. Once the European Patent Office decides about the opposition, the outcome can take the following three forms: either the patent is revoked, or it is amended, or the opposition is rejected (Stage 3).

For the purpose of this paper, the following considerations appear relevant. If the patent office acted in a fully consistent way and if the amount of information based on which granting decisions are made did *not* change from the date of grant until the date of the opposition, then the rejection rate of oppositions should be 100%. This is because the general criteria for the upholding of a patent during opposition and the granting of a patent in the first place are essentially identical. [8] A simple glance at patent statistics across all industries shows, however, that the rejection-of-opposition rate is far from 100%. This allows for three interpretations: Either (A) the patent office acts inconsistently (according to our aforementioned definition) because it does not correctly assess available information in the first place (during the granting phase), or (B) the information difference between the day of grant and the day of the opposition drives the results, or (C) both.

One way to interpret these findings better and decide for one of the potential explanations A through C is to relate the granting decisions (and the opposition outcome decisions) by the EPO to patentability-related information that is available to the examiners (and the members of the opposition division); namely, this would be information that speaks to the novelty, inventive step (non-obviousness), disclosure, and susceptibility of industrial commercialization. Whereas in the real world of the patent offices this information can be very complex (as complex as the actual patent application and prior art documents), in large-scale patent econometric studies it has become a standard procedure to apply a set of widely established bibliographic indicators in order to capture the aforementioned patentability parameters. Indicators such as backward references to the patent and non-patent literature

[8] Note: there appears to be a relatively small percentage of cases where the opposition decision will be

(Narin et al., 1987), the number of designated states (="family size", see Lanjouw et al. 1998), the number of inventors, the number of applicants (Guellec and van Pottelsberghe, 2000; Reitzig, 2004), the PCT (Patent Cooperation Treaty) indicator (Guellec and van Pottelsberghe, 2000; Reitzig, 2004), the accelerated examination request (Reitzig, 2004), and forward citations (Trajtenberg, 1999) do not require further explanation to empirical researchers in the patent arena these days.[9] While the indicators may capture multiple phenomena (such as inventive step and susceptibility to industrial exploitation) simultaneously and may therefore seem a bit blurred (see Reitzig, 2005), in their entity they are regarded as a powerful toolkit to measure the patentability-relevant information available to the office. While most of these indicators remain constant over time (they do not change after the granting date), a difference exists for the forward citations. Their counts for each patent will – on average – rise with the number of years after patent grant.

3.3 Testable hypotheses

Using the decision making logic (see 3.2) of the EPO to shed light on our principal research question (see 3.1), we can now formulate two complementary testable hypotheses. Both hypotheses assume that the EPO – to the best it can – issues patents that are high quality along all dimensions (with H0 stating the opposite). The tests are based on the premise that we are able to proxy parts of a patent's technological merit by using bibliographic indicators[10].

H1 is a comparative interpretation of the observable outcomes for patent grant and opposition outcome. To test H1 we use the observation that opposition divisions (deciding about opposition cases) share partly identical information with the patent examiners (dealing with the prior granting of the patents that are later opposed). This time-invariant information, as reflected in the time-invariant patent indicators (backward references, family size, the PCT indicator, and the number of applicants and inventors) as well as those forward citations received until the date of grant, must similarly

---

based on formal criteria that do not relate to the aforementioned patentability requirements. While we cannot precisely quantify this figure, after talks with a specialist from the EPO's Board of Appeals we are confident, however, that the number is sufficiently small not to distract our findings significantly.

[9] For comprehensive recent reviews, the interested reader may want to take a look at Reitzig (2004/2005).

[10] We critically review this premise whenever appropriate while presenting or discussing our empirical findings.

correlate with rulings of the EPO in Stages 1 (granting) and Stage 3 (opposition outcome) if the EPO cared to carry out proper assessments of technological quality. Consequently we propose:

H1: If the EPO's patent quality assessment decisions are modeled by patent indicators such as backward references, family size[11]*, the PCT indicator, the number of applicants and inventors, and the forward citations received until the date of grant, then there is no significant difference in the role of these predictors in granting and opposition outcome decisions.*

On the other hand, new information may be introduced during the opposition proceedings (e.g. if the opponent provides additional evidence against patentability not considered during the granting procedure). Or, and this may especially be the case in emerging technologies, the assessment of a patent's inventive step may, at second sight during the opposition procedure and in the light of a more mature understanding of the particular technology in question, differ from the very first assessment. In these cases, even if the EPO did its utmost to ensure legal certainty (consistency) by carrying out subtle granting assessments from the beginning, the office may eventually still not succeed in doing so. Intuitively, this "failure" to act consistently must be judged differently than a failure that is attributable to careless granting procedures and should therefore be disentangled. In order to do so, the informational change between the granting and the opposition phase needs to be accounted for. From electronic sources it is very difficult (not to say impossible) to capture the precise informational change, however, an indicator that can potentially capture some of the dynamics (information increase over time) is the forward citation indicator. Particularly forward citations received after the date of grant but before the end of the opposition procedure should correlate with observable inconsistencies if the patent office acted carefully otherwise. Consequently, we propose:

H2: If there is a significant difference in the EPO's rulings for granting and opposition outcome decisions of patents, then this difference should be correlated with the patents' forward citations received after the date of grant.

[11] Family size is a geographic based measure of a patent's impact. For example, it may be captured by the

At this point, a disclaimer appears to be in order. In essence, our hypotheses suggest testing a model of patent quality as being a function of certain observable components (bibliographic indicators) of patent quality. Of course, some of the idiosyncratic nature of each patent on various aspects remains unobservable. To that extent, the model must be somewhat mis-specified due to the exclusion of a number of unobservable components. This however, should be of little concern. Specifically, if the indicators of quality that are observable are significant in determining patent quality (to be seen), then consistency in the use of these aspects in different stages of patent assessment should be stable (i.e., constant), but be observable. That is, consistency should appear on those observable components that are measurable indicators of the patent quality and that systematic assessment should reflect this once differences in variability is taken into account for what has not been observed. In turn, this provides even greater motivation to attend to aspects of differences in the unobservable component of patent assessment which is most often overlooked.

3.4 Methodological aspects – application of variance decomposition discrete choice models

Using the basic axioms of Random Utility Theory (RUT), unobservable (latent) technological quality[12], LQ_i, of patent 'i' can be expressed as an additive function of its systematic/explainable technological quality, Q_i, and some random/unexplainable component, ε_i. That is,

$$LQ_i = Q_i + \varepsilon_i \qquad (1)$$

Systematic technological quality (Q_i) is assumed to be a generalized regression function of various observable and measurable factors. In turn, these factors ultimately determine the overall technological quality of the patent as judged by the patent office and hence its likelihood of being granted upon application or upheld upon challenge. We assume this function to be linear in the parameters (Ben-Akiva and Lerman 1985). We define a matrix $\mathbf{X}_i$ which describes the measurable

---

number of states in which a patent has been applied for.

[12] Note: as discussed in 2.1, the technological quality of the patent is assumed to correlate with the technological merit created through the patent. In the following we refer to technological quality instead of techno-economic quality or technological merit as the patent offices are not concerned with economic aspects in the first place.

technological quality of patent 'i' on various attributes (see Table 1, exogenous variables). We define a set of parameters, $\boldsymbol{\beta}$ which capture the effect that these factors have on changes in mean (systematic) technological quality. In general, the impact that each aspect of the patent application has on its mean technological quality is:

$$Q_{is} = \mathbf{X}_i \boldsymbol{\beta}_s \qquad (2)$$

We use the subscript 's' to suggest that the perceived quality of a patent at different stages of the patent process (initial application; patent opposition) may be different. In particular, while the (observable) patent characteristics may be constant, it is possible that the average impact of these characteristics on its perceived quality may differ from stage to stage; hence, requiring a separate set of parameters, $\boldsymbol{\beta}$, for each stage 's'.

Among the basic empirical models capable of estimating different sets of parameters for similar outcomes using discrete choice data are so-called multinomial models. Essentially, by comparing sets of different parameters, $\boldsymbol{\beta}$, for each stage 's' in our data structure allows inferring about the consistency of the decision making in the different stages. This is why we take the approach using discrete choice models. However, there are various aspects to be taken care off when applying discrete choice modeling to our data.

McFadden (1974) introduces several axioms to construct the (basic) multinomial logit model, including Independence-from-Irrelevant Alternatives (IIA), positivity, and irrelevance of alternative set effect. [13] This implies that the random elements, ε, are iid. By further assuming that this distribution is Gumbel (extreme value type I), the closed-form MNL can be constructed (Ben-Akiva and Lerman

[13] Note: strictly speaking, when we look at the history of an individual patent (application) (see Figure 1) it becomes obvious that data on patent filings and patent opposition (outcomes) are nested in a complicated fashion. Hence, several assumptions of the MNL model are not being fulfilled, and the application of MNL (analog) models introduces potential systematic errors. As will become clearer during the text, the infringement of the MNL relevant assumptions, however, occurs at only one point in our research design (the final pooling of decisions on granting – Stage 1 – and opposition outcome – Stage 3). Here, we treat the samples as if they were truly independent, which is not the case. We will critically review the (minor) limitations of our design at this stage and suggest (even) more sophisticated custom-tailored approaches as potential avenues for future research.

1985)[14]. In the multinomial logit model, one assumes that the error component, ε, is distributed iid Gumbel, with a zero location parameter (without loss of generality) and scale parameter, λ. Applying a multinomial logic to our data[15], from McFadden (1974), the probability that a patent application 'i' ends up in one of 'J' scenarios[16], at observation 't', at stage 's' of the patent application process can then be expressed as:

$$P_{its} = \frac{\exp(\lambda_s Q_{its})}{\sum_{j=1}^{J} \exp(\lambda_s Q_{jts})} \qquad (3)$$

In the first stage (s=1), P_{it} is the probability that patent 'i' will be granted. The technological quality required for the patent not to be granted must be set to some threshold value (e.g. zero) for identification purposes, consistent with a binary logistic regression expression. In the opposition ("challenge") stage, P_{it} is the probability that patent 'i' is upheld. The technological quality threshold of the patent being revoked or amended upon such challenge is set to zero, again resulting in a binary logistic expression. In turn, concerns about IIA violations are not applicable.

In this model, it is not well known that the estimates of vector β, of length 'k', describing the impact of various factors on mean systematic quality, are confounded with scale (Louviere, 2001). In any single data set, the scale parameter of the random component, λ, a scalar, is not identifiable, so the usual procedure is to arbitrarily set its value to 1. By ignoring this parameter, however, one could make erroneous conclusions about the true assessments of technological quality by the patent office in the different stages (Stage 1: grant yes/now; Stage 3: patent revoked/amended/upheld). Specifically,

---

14 Other distributions (e.g., normal), may be assumed to describe the shape of the variance component, giving rise to other model forms (e.g., probit). We have chosen to assume a Gumbel distribution as appropriate although the differences in the estimates from various is often negligible (Louviere, Hensher, and Swait 2000). The value however in assuming that the error component follows a Gumbel distribution is that a closed-form solution is obtained in maximising the likelihood function, which is advantageous when we later model this component as a systematic function of the two patent office assessments.

15 We will comment on the caveats of applying multinomial logits to our nested data whenever necessary.

16 See Figure 1: there are essentially four outcome scenarios, however, at a time we always only compare two binary outcomes with one another (grant and non-grant in Stage 1 and patent revocation or maintenance/amendment in Stage 3)

conclusions about differences between decisions based on estimates of β could be due to differences in the true underlying assessment structure with respect to technological quality, differences in underlying variability or both (Louviere, 2001).

When one estimates a single discrete choice model with a latent dependent variable (including probit, mixed logit), the actual estimates of β are confounded with the scale parameter. In turn, the estimates are in fact ($\lambda\beta$) where λ is the scale parameter associated with that particular set of data. The scale is inversely related to the variance of the random component, σ_ε^2 by the relation:

$$\lambda = \sqrt{\frac{\pi^2}{6\sigma_\varepsilon^2}} \tag{4}$$

In turn, when we compare parameter estimates related to systematic components of technological quality assessments, we actually compare a confounded set of parameters. For instance, estimates describing the impact of patent characteristics on the likelihood of a patent being granted (Stage 1) may be ($\lambda_1\beta_1$). Estimates describing the impact of patent characteristics on the likelihood of a patent being upheld upon opposition (Stage 3) may be denoted ($\lambda_3\beta_3$). In turn, although we often arbitrarily set the value of λ_1 and λ_2 to unity (as most statistical packages do), we cannot be sure that in comparing estimates from two models, say ($\lambda_1\beta_1$) to ($\lambda_3\beta_3$), that differences are due to differences in true underlying technological quality assessments (i.e., heterogeneous β), due to differences in the variance of the random components (i.e., heterogeneous λ), or simultaneously due to differences in both sets of parameters.[17]

[17] In other areas, the issue related to comparing confounded estimates has been noted and used to identify that erroneous conclusions may have often been made in ignoring this statistical truth. For instance, in marketing science several authors have demonstrated empirically that often differences that appear to be occurring in terms of consumer preference observed in real markets relative to preferences obtained in hypothetical settings (e.g., choice experiment) can be dismissed once the differences in variability in consumers choices across the two settings are accounted for (Ben-Akiva et al. 1994; Hensher, Louviere, and Swait 1999; Louviere, Fox, and Moore 1993). For example, the way in which consumers trade-off price (e.g., prefer products with lower prices) and aspects of quality (e.g., prefer higher quality products)

Essentially, the underlying empirical possibilities that require testing are two fold. Firstly, we wish to ascertain whether differences in technological quality assessments by the patent office are the same or different (i.e., $\beta_1 = \beta_2$) and/or differences in the scale parameters (corresponding to differences in variability) are different (i.e., $\lambda_1 = \lambda_2$). Essentially, we wish to test whether assessments related to observable characteristics of the patent being evaluated regarding its technological merit are homogeneous or heterogeneous across two data sets (or populations) and/or test whether the randomness with which choices are observed are heterogeneous or homogeneous across two data sets.

In order to address this issue, Swait and Louviere (1993) propose a nested hypothesis testing procedure.

First, they estimate a model in which complete heterogeneity is imposed on both the scale and assessment components relating to technological quality. That is, essentially, a sample-specific set of parameters is estimated for each stage (Stage 1: all patent applications; Stage 3: opposed patents only). In order to do this, however, the scale parameter cannot be identified and set arbitrarily to one in any one data set. The model log-likelihoods, however, provide a base measure for which subsequent models imposing various aspects of homogeneity can then be compared.

Second, they propose a model of complete technological quality assessment and variance homogeneity, in which the data from the two samples are pooled (Stage 1: all patent applications; Stage 3: opposed patents only). This model is tested against the base model of complete heterogeneity using a likelihood ratio test. Experience shows that in most settings, the hypothesis of complete variance homogeneity is rejected. Hence, assessments and/or scale are heterogeneous.

Third, they introduce a model of complete quality assessment homogeneity while relaxing the assumption of variance homogeneity. To implement this, they manually multiply the independent

---

is often the same whether these evalatuations are made in relation to real products (i.e., revealed preferences) or in relation to hypothetical products (i.e., stated preferences). In turn, once accounting for differences in the variability inherent in these evaluations, it can often be concluded that trade-offs are identical rather than an initial hypothesis that preferences differ.

measurable components of one data set by a scale ratio and assume the alternative data set has a scale ratio of one. The concavity of the likelihood function with respect to the varying scale ratio allows a maximizing scale ratio to be identified under a hypothesis of assessment homogeneity regarding technological quality. Comparing this model's likelihood to the base model of complete homogeneity allows this hypothesis to be formally tested.

Finally, if the model that allows for variance heterogeneity is significantly different from the model of complete homogeneity one interesting question remains. Namely, this is what drives the heterogeneity of the variance. While Swait and Louviere (1993) propose how the models can be estimated using a manual grid search, we use our own purpose written software which allows this to be estimated using a full-information maximum likelihood (FIML) approach in which a Newton-Raphson algorithm is used given a closed form solution.[18] In more detail, we propose to model and test the amount of variation from the assumption of homogeneity exists by estimating two parameters for each of the potentially heterogeneous variables, such that one parameter (homogenous term) describes the average impact across assessment Stages 1 (grant) and 3 (opposition outcome) and another term to test the deviation from this average impact for one assessment stage relative to the other. That is, for those sets of factors, denoted by τ, suspected of being considered in a heterogeneous fashion across the two assessment stages, let the impact of these factors be determined by:

$$\beta_\tau = \beta_\tau^* + \beta_{\tau s} Z_s \qquad (5)$$

where $Z_s = -1$ if initial stage and $+1$ if challenge stage. β_τ^* is the average impact of factor τ, and $\beta_{\tau s}$ provides a test of the degree to which such homogeneity across stages is being violated. That is, the impact of factor τ for the initial stage is given by:

$$\beta_{\tau\, initial} = \beta_\tau^* - \beta_{\tau s} \qquad (6)$$

and the impact of factor τ for the challenge stage is given by:

$$\beta_{\tau\, challenge} = \beta_\tau^* + \beta_{\tau s} \qquad (7)$$

In turn, the t-statistic associated with the mean estimate of $\beta_{\tau s}$ provides a formal test to assess whether an assumption of preference homogeneity is significantly violated (i.e., Ho: $\beta_{\tau s} = 0$). Since each model

[18] This is possible because under the assumption of the error components being Gumbel distributed, the

is also nested within the previous models of homogeneity, appropriate likelihood ratio tests are applicable to further confirm the resulting model.

4 Empirical results

4.1 Data – Stratification criteria and descriptive statistics

For our analysis we chose biotechnology patent data from the 1970s and 1980s. By doing so, we create a "quasi-experimental" set-up that should come close to the one in which Merges (1999) is particularly concerned with the patent office's ability to assess the technological quality of patents consistently; namely, a situation in which due to the novelty of the emerging biotechnological industry (see Orsigeno, 1989) most prior art was likely not documented in patent data bases but in scientific publications and other sources. The selection of the industrial field was based on an updated version of the widely accepted OST INPI ISI classification by Schmoch (1994, personal note on an update from 1998). Biotech patents were identified as showing one of the following IPC subclasses as their main classification: C07G; C12 M, N, P, Q (, R, S)[19]. As of December 2003 (the date of the data extraction) the European patent register contained 36,545 applications and 9,960 granted patents in these areas. At this point, 808 (8.11%) patents in the sample had been opposed. For 558 of these opposed patents, a decision by the *first instance* at the EPO – the opposition division – was observable in December 2003. For the remaining part of the patents, no clear ruling by the opposition division could be identified at that date (pending case either in opposition or appeal). Figure 2 shows the share of unidentified oppositions among the total sample versus the year of patent priority.

Insert Figure 2 about here

Figure 2 shows a steep ascent of unidentified opposition outcomes after the year 1986. Pending a better explanation we take it that this increase can be attributed to the share of opposition cases still to be decided in December 2003 by the first instance at the EPO, namely the opposition

likelihood can be written in a closed-form manner. In turn, the first and second derivates with respect to β and λ are computationally attractive and estimatable.

[19] We did not find patents whose main IPC would belong to the -R or -S group.

division. As this paper primarily focuses on the decision of the opposition division (no further appeals, no subsequent litigation), we cut off the tail of patents applied for from 1987 onwards and obtain a residual percentage of approx. 5.7% of unidentified first ruling opposition cases between 1978 and 1986.[20] Thus, the final data for the analysis comprises 4,726 patent applications, out of which 2,969 were granted. Priority dates lie between 1977 and 1986. A total of 318 granted patents in that period were opposed.

Table 1 contains the descriptive statistics for the sample.

Insert Table 1 about here

The most important findings appear to be the following. At 10.71% the rate of opposition in the biotechnology industry is high, but it is lower than in the even more litigious pharmaceutical or polymer industry (11.91% opposition between 1978 and 1990). In about 33% of all oppositions, third parties manage to invalidate the holders patent during the opposition. In about 32% of the cases the patent is amended, in another 21% of the observations, the opposition is rejected because it is not considered to be substantiated. In the remaining roughly 13% of the oppositions the procedure was either closed (7%) or no outcome can yet be identified (see above, 6%).

Most of the explanatory variables appear to be within the "normal" range when compared to earlier studies, with some biotechnology specificities to be observed. On average, 2.9 references to patents of prior art were made by the EPO examiners during the European search procedure.[21] This figure is slightly lower than for say polymer patents (3.5). More interestingly, however, each patent cites 2.6 non-patent literature references as relevant state of the art. This figure is clearly higher than in other, more mature industries than biotech was in the 1980s. For example, polymer patents with priority dates 1977 and 1990 filed at the EPO quote only 0.5 non-patent references as relevant state of the art. Hence, as expected, the sample shows some of the experimentally desired properties (see

[20] The resulting "imperfection" of the data set appears acceptable considering that with 5.7% unidentified cases the "disturbance" of the opposition outcome variable is negligible.

[21] Note: As Harhoff and Reitzig (2004) and Reitzig (2004) this paper adds the patent references of the international search to the number of references made in the European search if the patent was a PCT patent and the EPO acted as the International Search Authority for the World Intellectual Property Organization.

above) when it comes to the nature of the prior art. The patents were applied for in 9 states on average, and almost three inventors (2.8) were involved in each application. The mean for accelerated examination requests is fairly low. About one percent of all patents are applied for following the *Programme for Accelerated Prosecution of European Patent Applications (PACE)*. The percentage of filings according to Chapter II of the Patent Corporation Treaty (PCT) is roughly 10%, lower than for the entire population of EP patents, but higher than in polymers for the same time period. This finding indicates that applicants delay cost intensive decisions in more than 10% of the applications by choosing the PCT II route. Finally, we computed forward citations for two different periods of time (namely for three-year and seven-year time windows after the application's publication date). The reason for calculating three different measures is Hypothesis 2. We recall that in order to capture alterations in the information status about the patent's technological quality over time we use forward citations as a proxy. Optimally, we would like to distinguish which citations the published patent application received before grant and which it received afterwards. By calculating the forward citations for the different time spans (as described above) we obtain a proxy for this distinction. For the patents in our sample we find an average grant lag (time span from the filing date until the granting date) of 5.4 years and an opposition outcome lag (time span from granting date until date of opposition outcome) of 5.1 years. Since the forward citations were computed from the publication date of the patent this means that the 3-year forward citations capture information that was available for patent examiners during the first 4.5 years after the filing date (3 years + 18 months disclosure period). Hence, for roughly half of the patents *all* information contained in this variable was revealed during the granting phase. Ceteris paribus, the forward citations calculated for the 7-year time frame capture information revealed during the first 8.5 years after patent filing (7 years + 18 months disclosure period). For almost 50% of those patents that were opposed all information contained in this variable was revealed until the end of the opposition proceedings. Finally, the difference between the two citation variables is a reasonably good proxy for information revealed between grant and opposition outcome. As expected, the average number of forward citations in subsequent EPO search procedures rises with the length of the time window. For a three year period it is 0.99 and for a seven-year period 1.77.

4.2 Simple reduced form estimations

In Table 2, the two binary choice models 1a and 2a map the outcomes in Stage 1 (granted; not granted) and, if applicable, in Stage 3 (patent revoked; patent amended or maintained as granted)[22]. The EPO's decisions were modeled using the aforementioned patent indicators (number of references to patent/non-patent literature, number of applicants/inventors, accelerated examination request, PCTI/II indicators, forward citations). As becomes visible from Table 1 we logarithmically transformed some of the explanatory variables when (1) marginal effects of the variables on technological quality were assumed to be decreasing for economic reasons and (2) the distributions of the individual variables were highly left-skewed.

In the first model 1a, the probability of a patent being granted is given by the following expression:

$$P(grant \mid application) = exp(\lambda_1 Q_{i1}) / (1 + exp(\lambda_1 Q_{i1})) \quad (8)$$

where Q_{i1} is the deterministic systematic (observable) component of the technological quality of patent 'i'. The subscript '1' denotes that the technological quality of the patent refers to the EPO's assessment in Stage 1 evaluation (grant yes/no). We assume that Q_{i1} is a linear-in-the-parameters regression function which captures the impact of each factor on patent application success through the estimated vector β_1.

In the model 2a, the probability of a patent being upheld upon being opposed (Stage 3) is given by the following expression:

[22] Note: the coding of the binary outcome for Stage 3 is based on the following consideration. While there is only one technological quality threshold in Stage 1 (non-grant vs. grant) there are in fact 2 thresholds in Stage 3 (patent revocation vs. patent amendment and patent amendment vs. patent maintenance). Since, for econometric reasons, we need to boil down the complexity of Stage 3 to a binary decision we focused on the threshold in Stage 3 that would be most comparable to the granting threshold in Stage 1. Namely, whether there should be some kind of protection or no protection at all. Additionally, we preliminarily tested how our results would change if we coded the outcome in Stage 3 differently. These preliminary analyses suggest that the differences would not be radical, however, we did not inquire this in more detail.

$$P(upheld \mid opposition) = exp(\lambda_3 Q_{i3}) / (1 + exp(\lambda_3 Q_{i3})) \quad (9)$$

The subscript '3' denotes that the assessed technological quality of the patent refers to Stage 3 evaluation, that relating to the office's reassessment of disclosure, novelty and inventive step (technological quality) during opposition. We assume that Q_{i3} is a linear-in-the-parameters regression function which captures the impact of the same factors on patent quality assessment through the estimated vector β_3.

We first estimate both models separately, and hence the scale parameter associated with each decision stage, λ_1 and λ_3, are not identifiable and arbitrarily set to unity. The estimates are provided in Table 2.

Insert Table 2 about here

Consistent with our framework of assumptions, the model 1a reveals that the patent office is systematic in their assessment of a patent application. The model is overall well specified and we obtain individually and jointly significant coefficients for the variables relating to the backward references to the patent literature, the accelerated examination request, the number of inventors, the PCTII variable, and the forward citations received within the first three year after the publication date. Counter intuitively, the family size variable (coded as the ln(1+number of designated states)) correlates negatively with the likelihood of the patent being granted. We can only speculate about this finding; one plausible explanation may be that large and cost-insensitive firms with patenting tactics that cover wider product markets significantly more often file patents for incremental inventions that have a higher likelihood of not be granted. Admittedly, this explanation may be challenged, though.

The model of the opposition outcomes, model 2a, suggests that the factors that were significant for granting initially are no longer significant. Indeed, within our framework of assumptions making simple comparisons of the estimates would suggest that the patent office is not consistent across the two stages – contrary to our expectation as explicated in H1. Moreover, a face

validity test of H2 indicates that the observed inconsistencies are *not* attributable to the informational change regarding the patent's technological quality that occurred from the day of grant until the day of the opposition ruling. We perform this face validity test by comparing the set of parameters in models 1b and 2b. These models are the counterparts to models 1a and 2a, differentiated only by the substitution of the 3-year forward citations by the incremental forward citations received after patent grant. This would mean, however, that the observed inconsistencies would be largely attributable to a misinterpretation of information that was available from the day of patent granting. All this being said there are various caveats to drawing conclusive inferences at this stage, though.

One caveat is that the insignificance of the parameters in the models 2a and 2b may be due to the smaller sample sizes compared to models 1a and 1b. Given the sample size, the *t*-stats are expected to be very small. In order to shed more light on the issue of sample size we compared predicted and observed marginal probabilities exerted by each variable on patent maintenance. The results (not reported in this paper) do show that certain variables (e.g. family size), though not significant in our second model, show a directional effect. The family size variable picks up a non-linear upward and follows the actual marginal probabilities fairly closely. Thus, at this point we do not rule out the possibility that sample size effects drive the results in models 2a and 2b and we will attend to this matter in more systematic fashion at a later point (see below, 4.3 and 4.4).

Another caveat to the interpretation of the estimation results for models 1b and 2b is the selection bias. All patents in Stage 3 of the patent tree (see Figure 1) have been granted initially, and hence, the technological quality distinction to be reflected in the exogenous variables is clearly much finer than in the first stage. If these effects were responsible for the apparent inconsistency, however, we should see that reflected in the scale decomposition (see below).

4.3 Basic estimations of the Swait and Louviere type

The more formal approach using Swait and Louviere (1993) as described in 3.4 is now considered, and implemented using software written in MATLAB. To test H1, we first estimate a model (Model 3a) imposing complete assessment homogeneity regarding technological quality and

arbitrarily setting both scale parameters to unity; hence, an assumption of variance homogeneity is also imposed. Separate models (not reported in the tables) of the two assessment stages (Stage 1: granting stage; Stage 3: opposition outcome stage) provide our comparative log-likelihood, formed by the addition of the disaggregate models (-2993.76 + -195.158 = -3188.92). The disaggregate models fit the data specifically for each assessment stage but do not allow the scale differences to be identified in any one data set. We now assess whether the impact of characteristics of the patent at both assessment stages are comparable (Hypothesis 1), along with an assumption that the variances exhibited at both stages are identical. That is, in order to empirically test Hypothesis 1, we test the assumption that $\boldsymbol{\beta}_1 = \boldsymbol{\beta}_3 = \boldsymbol{\beta}$, given $\lambda_1 = \lambda_3 = \lambda$.

Insert Table 3 about here

The model log-likelihood from the restricted model 3a (in which complete technological quality assessment and variance homogeneity is imposed) is -3287.12. The difference between the log-likelihoods multiplied by two follows a χ^2 distribution, with 'k' degrees of freedom. This arises as a likelihood ratio (LR) test, in which the number of parameters that are estimated in unrestricted and restricted models are 2k and k respectively. The LR is 162.51, greater than the χ^2 value of 18.31. Hence, the hypothesis of complete homogeneous quality assessments in stages 1 (grant yes/no) and 3 (patent revoked, amended, maintained) and homogenous variances across each assessment stage is rejected.

Model 4a serves to determine whether a restriction of homogeneous preferences is still appropriate (Hypothesis 1) but allowing the variance components from the two data sets to differ. That is, we introduce the restriction $\boldsymbol{\beta}_1 = \boldsymbol{\beta}_3 = \boldsymbol{\beta}$ given $\lambda_1 \neq \lambda_3$

Insert Table 4 about here

The estimates are shown in Table 4, column A. It is clear that the successful rescaling procedure is questionable given a negative scale ratio. Specifically, since the scale is inversely related to the variance, in a correct and acceptable model this ratio must be positive. This is confirmed when comparing the proposed model to the unrestricted model. The likelihood-ratio value is 23.49, which is greater than the χ^2 value of 18.31. As a result, we conclude that once differences in variability are accounted for, the model 4a in which we propose that the office shows consistent assessments regarding a patent's technological quality across both granting and opposition stages is rejected.

Again, as in Section 4.2, we wonder whether these inconsistencies are attributable to incremental knowledge created after the day of grant. Using the incremental forward citations as a proxy again, models 3b and 4b provide a test for H2 that is comparable to the test for H1 as delineated before in this Section. And again, even though the analysis is not conclusive, models 3b and 4b in comparison provide growing signs that the inconsistency is not attributable to post-grant information as reflected in the incremental forward citations.

Even though the results presented in 4.3 do still not allow us to draw conclusive inferences regarding Hypothesis 1, the indications for inconsistent rulings on EPO biotech patents applied for in the 1980s increase very strongly. Only under the assumption (to be tested in the next section) that a few of the explanatory variables have heterogeneous variances in Stages 1 and Stage 3 may H1 still be "true" (i.e. its H0 cannot be rejected).

4.4 Proceeding beyond Swait and Louviere – identifying the sources of assessment heterogeneity between the granting and opposition phase

From the above it is clear that some form of assessment heterogeneity with respect to the technological quality exists across the two stages of assessment (grant and opposition) by the patent office, even when allowing differences in variances to exist. It is encouraging to note that the explanatory power of our estimations improved considerably, however, once the model (4a and 4b) permitted such differences in variances. Indeed, the likelihood-ratio test reveals that the rejection of preference homogeneity given variance heterogeneity is only marginal.

With this, we propose, similar to Swait and Bernardino (2000), that there exists some level of assessment homogeneity across the two assessment stages but that only a marginal amount of assessment heterogeneity may exist. In other words: we propose and put up for a test whether the inconsistency in the EPO's ruling – as found in 4.3 – is driven by only few of the informational indicators we use. To do so we estimate, as described in 3.4, a pooled model of the two assessment stages in which some combination of assessment homogeneity and assessment heterogeneity is imposed while still allowing variance heterogeneity to exist. To identify this source of heterogeneity what we did was to test several models and identify several parameters that may be causing the heterogeneity. Table 5 presents the results of two specifications which emerged as the most powerful ones after comprehensive testing. Again, we split Table 5 into columns A (restricted parameter set without incremental forward citations) and B (parameter set including the incremental forward citations received after patent grant).

Insert Table 5 about here

The findings show that distinct variables drive the variance heterogeneity across assessment stages 1 and 3 in both models 5a and 5b. Namely, these are the accelerated examination request and the number of inventors as well as the absolute number of forward cites received within 3 years after publication (in model 5a) as well as the incremental forward citations received between 3 and 7 years after publication (in model 5b). Whereas we do not find rationale explanations why the patent office would interpret information correlated with acceleration requests or the number of inventors differently across the granting and opposition stage, it is, on the other hand, rather intuitive why the incremental forward cites received between three and seven years after publication exhibit variance heterogeneity. We recall that the reason to include the variable was exactly to capture potential informational changes over time. The fact that the forward citations with the 3-year period are also driving heterogeneity, however, is undesired. Theoretically, this variable should not exhibit any variance heterogeneity across assessment stages. A close look at the correlation structure among the independent variables suggests, however, that the rather high correlation between the incremental forward cites and the 3-year time frame forward cites drives the result in part. This high correlation

forces us to revisit the goodness of our measures to pick information status at different stages, and we will take care of this in our discussion.

Before moving on to the discussion, however, we shall briefly note the following. None of the likelihood ratio tests between the covariance heterogeneity models (5a and 5b) and the basic separated models for patent grant (1a, 1b) and patent opposition outcome (2a, 2b) are significant. This means that we do not find that the basic separate models allowing for separate sets of parameters across patent quality assessment stages 1 and 3 show more explanatory power than models 5a and 5b. Of course, we cannot interpret an insignificant test result *per se*. This being said, however, the fact that we do not find a systematic difference between the models in Table 5 and those in Tables 1 and 2 is an indication that the EPO might not have acted as inconsistently as one might think relative to those results suggested in Tables 3 and 4. At least some information on patent quality available from the day of patent filing may be assessed consistently by the office.

5 Discussion

We commence the discussion with a repeated disclaimer as well as some considerations regarding the robustness of our findings. We recall that our results are based on the assumption that the bibliographic indicators we adopt allow operationalizing a patent's technological quality. The assumption is, however, considered unproblematic in general since it is buttressed by an extant literature in the field. Models 1a and 1b indicate that this is a very reasonable assumption for our specific data, too. We do not claim that the indicators we have would capture the entity of the technological quality concept and we are hence aware that our estimations may be systematically underspecified. However, we do not see any reason why at least those indications about the patent's quality we can measure should exhibit different effects in patent quality assessments across different stages (granting vs. opposition procedure). Moreover, we assume that the incremental forward citations received between 3 and 7 years after patent grant are a good proxy for the informational change regarding a patent's technological quality between the day of grant and the day of the opposition outcome. The average time lags for patent granting and opposition decisions as observed for our data render this assumption very plausible. This being said, we cannot rule out that the variable

is blurred and does not exactly capture the informational change for some of the patents. In particular, information on "prior use" of a technology brought up during the opposition phase is likely not reflected in our incremental forward citation measure, however, likely relevant in practice.[23] Finally, by pooling the data from Stage 1 and Stage 3 in models 3a/b, 4a/b, and 5a/b we do infringe on the IIA assumption as we bundle the entity of our data (all patents) with its own sub sample of patent oppositions. We cannot exactly estimate the theoretical impact of this infringement; however, we deem it minor. This is because or efforts to disentangle effects of scale and variance should be suitable to take care of some of the problems arising from infringing IIA in general.

Within the limits of our research design we think that the empirical results contain some very interesting observations offering ample space for discussion. The two fundamental results we obtain are the rejections of both H1 and H2. This means that for the entire sample of biotechnology patents applied for between 1978 and 1986 at the EPO we observe inconsistent rulings by the office in the sense that the EPO seemed to assess the patentability requirements (technological quality) differently at the day of grant and the day of the opposition. The amount of informational change created between the day of grant and the day of the opposition outcome is, to the extent that it is captured by the incremental forward citations, not driving the assessment inconsistencies. Hence, we conclude that other systematic sources of inconsistency exist inside the patent office that drive the result and that have little to do with increasing knowledge regarding the *particular* invention over time.

What could be the sources of such inconsistency?

Even when assuming that there is no informational increase regarding a *particular* patented technology over time (which should be reflected in the incremental forward citations to some extent), there may still be an entire paradigm shift responsible for the inconsistencies. What we did not track were detailed changes in the legislation of the EPO regarding biotechnology patenting between 1978 and 1986. If major changes in the legislation had happened, these might of course drive our results. To the best we know, however, there we no such radical legislative changes in the European patent law during the aforementioned period. Other paradigm shifts – not codified in terms of legislative changes

[23] We thank Dr. Christopher Heath, European Patent Office, for sharing this thought with us. Since evidence on "prior use" of a technology may lead to the revocation of a patent, however, is not common during the patent granting but only during the opposition phase, this type of "surprising" evidence –

– could be caused by a different understanding of the technology as a whole. Whatever the source may be, however, it seems as if the critiques uttered by Robert Merges (1996) are given support by our findings. Whether external, non-codified paradigm shifts regarding the understanding of a technology over time, inter personal differences within the patent office, or simply a lack of vigilance (note: we do not say the EPO was careless but this cannot be ruled out, either) – in retrospect it seems like a bit of a venture for an inventor of the late 1970s/early 1980s to rely on the enforceability of his European biotech patent.

What are the consequences?

Despite all our findings we suggest a more moderate view is suitable rather than one wholeheartedly concluding a lack of faith in the patent system is appropriate due to inconsistency and lack of rigour. For example, as mentioned before our research design is limited to only on industry and has some caveats. For example, we might simply not be able to capture some of the informational change over time (from grant to opposition outcome) that is visible for the EPO in the real world. That as well as the fact that our incremental citation measure may be imperfect reproaches us to be careful when postulating wholesale changes. On the other hand, we find our results convincing enough to make a few suggestions.

On the one hand we believe that the discussion stimulated by Merges (1996) and supported by the findings in this paper should be taken into various directions. One avenue proposed by Lemley (2000) builds on – what we find – the extreme standpoint that inventors' trust in the patent granting system is second order when determining optimal resource allocations for patent grants. With all respect for Lemley's logic we think that in a dynamic world in which patentees repeatedly apply for patent rights the inventors' shaken trust in the system suffered due to a sloppily granted and eventually invalidated patent can surmount the short-term advantages from dedicating fewer resources to the granting procedure. Another avenue we sympathize with requires the consistency in assessment on technological quality as demanded by Thomas (2002) and Merges (1999). But if there is a reasonable chance that patent offices are, for one reason or another, incapable of guaranteeing a high level of consistency – or normative legal quality (Thomas, 2002) – in emerging technologies, what would be

---

from a patent examiner's standpoint – is likely not reflected in incremental forward citations (which are,

the alternatives? Is there value to introducing a "grace period" for granting patents in new technologies? In other words, should society wait and observe a technological area before it jumps in and offers mechanisms for protection? What would be the opportunity costs of such an approach?

Finally, assuming that it is not only information revealed after the granting date that drives the inconsistencies we observe, we wonder whether sufficient resources are dedicated to the patent granting procedure to ensure high quality patents along a normative dimension. While being aware that resources for granting procedures are limited and sympathizing with the rationale of Graham et al. (2002) stating that more resources should be dedicated to the re-examination of economically more important patents in opposition hearings, we still wonder whether the offices must reconsider this issue. Particularly in emerging technological areas, like biotech was in the early 1980s, the lower resource threshold for a patentability assessment might have been too low.

6 Conclusion and further questions

Stimulated by the ongoing discussion about patent quality this paper sought to generate robust empirical evidence on the following question. How reliably do patent granting procedures ensure that a patent survives a subsequent "validity suit"? Using data on European biotechnology patents filed between 1978 and 1986 we show that the EPO's decision making on a patent's technological quality during the granting phase and during the opposition phase ("validity suit") was not consistent to the extent it can be measured using bibliographic indicators. Moreover, we do not find compelling indications that the inconsistency is entirely due to informational increases on the patent's technological quality from the day of grant until the end of the opposition procedure. While there is some indication that subsequently revealed information (i.e. information after patent grant) accounts for some of the differences in patentability assessments over time, we do not have conclusive empirical evidence for this latter finding.

Our results are subject to a number of caveats which we discussed earlier. Here, we recall only briefly that problems of under specification (unobserved contingencies), correlations among exogenous variables as well as specific model assumptions (IIA) may distort our findings.

---

at least in the European System, a reflection of the patent examiners' awareness of prior technology).

This being said we would like to think that our paper makes several contributions and gives occasion to extend the current debate on patent quality.

With all respect for the important contributions carried out in the past we would like to think that this paper provides the first large-scale empirical test of patent assessment quality according to legal definitions in that it compares the consistency of granting and revocation decisions on patentability. Additionally, the tests are carried out within only one office and one industry. Earlier studies do compare different industries to one another, facing additional problems of potentially neglecting important contingencies.

Moreover, we know of no prior study that exploits patent data for the aforementioned research question beyond the level of rather simple comparisons of mean indicator variables. As we laid out in the paper, however, important information regarding the consistency of decision-making of the patent offices may be hidden in (or distorted by) the variances of these indicator variables, and our study is the first to exploit the heterogeneity and richness of patent data to shed more light on the patent quality discussion.

As is likely generated by most research endeavors, our study has left us with more questions than answers. Some of the issues we deemed most important were raised in the discussion. In our eyes they present interesting stimuli for future research.

In order to understand the generality of our findings, a comparison of the biotechnology industry in the 1980s with a mature patenting area (like modern polymers) may promise interesting insights. Such a study, comparable to this one but using patent data from a different technology, could shed light on the question whether Merges criticism is, as a matter of fact, to be limited to new patenting areas, or whether problems may exist in other technological areas, too.

In order to understand the sources of inconsistent rulings, additional qualitative research appears necessary and worthwhile. We do see little space for “squeezing” existing bibliographic data more than has been done in this context, and we would expect good survey data to be more helpful to tackle this question.

Finally, in order to understand the consequences of our findings, we think that a series of further questions need to be answered, however, to appear most pressing. For once we suggest taking a

closer look at existing data in order to estimate what the impact of the inconsistent ruling has on value creation. Secondly, we encourage moving the patent quality debate into a direction where alternative mechanisms to “patenting as usual” are considered for emerging technologies.

Acknowledgements

Thanks go to Ralph Schories (IPECON) for extracting the raw data and assembling the indicators. The usual disclaimer applies. Markus Reitzig furthermore acknowledges financial support from the Danish Social Science Council through grant LOK/BIOTECH/COMBI as well as from the RIPE (Research on Intellectual Property Economics) network funded by the Danish Social Science Council.

References

Allison, J. R. and E. H. Tiller (2003). "The Business Method Patent Myth," Berkeley Technology Law Journal, **18**, Fall.

Barton, J. (2001). Non-obviousness. Manuscript drafted for the Franco-American Conference on Intellectual Property, Berkeley.

Ben-Akiva, M., M. Bradley, T. Morikawa, J. Benjamin, T. Novak, H. Oppewal, and V. Rao (1994). "Combining Revealed and Stated Preference Data," Marketing Letters **5** (4), 335-50.

Ben-Akiva, M. and S. Lerman (1985), Discrete choice analysis (sixth ed.). London, England: The Massachusetts Institute of Technology Press.

Bloom, N. and J. van Reenen (2000). Real Options, Patents, Productivity and Market Value: Evidence from a Panel of British Firms. IFS Working Paper 00/21, The Institute for Fiscal Studies, London.

Bosworth, D. and M. Rogers (2001). ”Market Value, R&D and Intellectual Property: An Empirical Analysis of Large Australian Firms,” The Economic Record, **77**(239): 323-337.

Cockburn, I. and Z. Griliches (1988). "Industry Effects and Appropriability Measures in the Stock Market's Valuation of R&D and Patents." American Economic Review **78**(2): 419-432.

Conolly, R., B. Hirsch and M. Hirschey (1986). "Union Rent Seeking, Intangible Capital, und Market Value of the Firm." Review of Economics and Statistics **68**(4).

Conolly, R. and M. Hirschey (1988). "Market Value and Patents: A Bayesian Approach." Economics Letters **27**(1): 83-87.

EPO (2003). Annual Report. The European Patent Office, Munich.

Gallini, N. (2002). “The Economics of Patents: Lessons from Recent U.S. Patent Reform,”, Journal of Economic Perspectives **16**(2): 131-154.

Graham, S.J.H., B.H. Hall, D. Harhoff, D.C. Mowery. (2002). Post-Issue Patent “Quality Control”: A Comparative Study of US Patent Re-examinations and European Oppositions, NBER WP 8807.

Green, J. R. and S. Scotchmer (1995). "On the Division of Profit in Sequential Innovtion." RAND Journal of Economics **26**(1): 20-33.

Guellec, D. and B. van Pottelsberghe de la Potterie (2000). Analysing Patent Grants. Economics Letters, **69**(1): 109-114.

Hall, B. H., A. Jaffe and M. Trajtenberg (2000/2005). Market Value and Patent Citations: A First Look, NBER WP 7741, and RAND Journal of Economics **36**: 16-38.

Harhoff, D., F. Scherer and K. Vopel (2003). Citations, Familiy Size, Opposition and the Value of Patent Rights. Research Policy **32**: 1343-1363.

Harhoff, D. and M. Reitzig (2004). Determinants of Opposition against EPO Patent Grants: The Case of Pharmaceuticals and Biotechnology, International Journal of Industrial Organization, **22/4:** 443-480.

Hensher, D., J. Louviere, and J. Swait (1999). "Combining Sources of Preference Data," Journal of Econometrics **89**: 197-221.

Hirschey, M. and V.J. Richardson (2004). “Are Scientific Indicators of Patent Quality Useful to Investors?” Journal of Empirical Finance **11**: 91-107.

Lanjouw, J. O., A. Pakes, and J. Putnam (1998) “How to Count Patents and Value Intellectual Property: Uses of Patent Renewal and Application Data,” The Journal of Industrial Economics. **XLVI** (4): 405-33.

Louviere, J. (2001). "What If Consumer Experiments Impact Variances as well as Means? Response Variability as a Behavioal Phenomenon," Journal of Consumer Research **28** (December): 506-11.

Louviere, J., M. Fox, and W. Moore (1993). "Cross-Task Validity Comparisons of Stated Preference Models," Marketing Letters **4** (3): 205-13.

Louviere, J. J., D. A. Hensher, and J. D. Swait (2000), Stated choice methods (1st ed.). Cambridge, United Kingdom: Cambridge University Press.

McFadden, D. (1974), "Conditional logit analysis of qualitative choice behavior," in Frontiers in Econometrics, P. Zarembka, Ed. New York: Academic Press.

Megna, P. and M. Klock (1993). "The Impact of Intangible Capital on Tobin's Q in the Semiconductor Industry." American Economic Review **83**: 265-269.

Merges, R.P. (1988). “Commercial Success and Patent Standards: Economic Perspectives on Innovation,” California Law Review **76**(803): 805-876.

Merges, R. (1999). “As many as Six Impossible Patents Before Breakfast: Property Rights for Business Concepts and Patent System Reform”, Berkeley Tech. L. J. **14**: 577-615

Nordhaus, W. D., 1967, The Optimal Life of a Patent, New Haven.

Orsenigo, L.(1989). The emergence of biotechnology.institutions and markets in industrial innovation, London: Pinter.

Quillen, C., and O. Webster (2001). Continuing Patent Applications and Performance of the U.S. Patent Office, mimeo.

Reitzig, M. (2004). “Improving Patent Valuation Methods for Management – Validating New Indicators by Analyzing Application Rationales”, Research Policy **33** 6/7: 939-957.

Reitzig, M. (2005). On the Effectiveness of Novelty and Inventive Step as Patentability Requirements – Structural Empirical Evidence Using Patent Indicators. SSRN WP 745568.

Sampat, B., D. Mowery, and A. Ziedonis (2003). “Changes in university patent quality after the Bayh–Dole act: a re-examination,” International Journal of Industrial Organization **21**: 1371-1390.

Samuelson, P. (2004). Legally Speaking: Why Reform the U.S. Patent System? Mimeo, University of California at Berkeley.

Sanyal, P. and A. Jaffe (2005). Peanut Butter Patents Versus the New Economy: Does the Increased Rate of Patenting Signal More Invention or Just Lower Standards? WP, Brandeis University.

Schmoch, U. and N. Kirsch (1994). Analysis of International Patent Flows, Karlsruhe, Fraunhofer Institut für Innovationsforschung and Systemtechnik Karlsruhe.

Scotchmer, S. and J. Green (1990). "Novelty and Disclosure in Patent Law." RAND Journal of Economics **21**(1): 131-146.

SUEPO (2002). A Quality Strategy for the EPO. SUEPO WP, Munich.

Swait, J. and A. Bernardino (2000), "Distinguishing taste variation from error structure in discrete choice data," Transportation Research Part B: Methodological **34** (1): 1-15.

Swait, J. and J.J. Louviere (1993), "The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit Models," Journal of Marketing Research **30** (3): 305-14.

Thomas, J. (2002) “The Responsibility of the Rulemaker: Comparative Approaches to Patent Administration Reform,” Berkeley Tech. L.J. **17**: 728-761.

Trajtenberg, M. (1990). "A Penny for Your Quotes: Patent Citations and the Value of Innovations." RAND Journal of Economics **21**(1): 172-187.

Figure 1

Decision Tree: From Application to Opposition Outcome

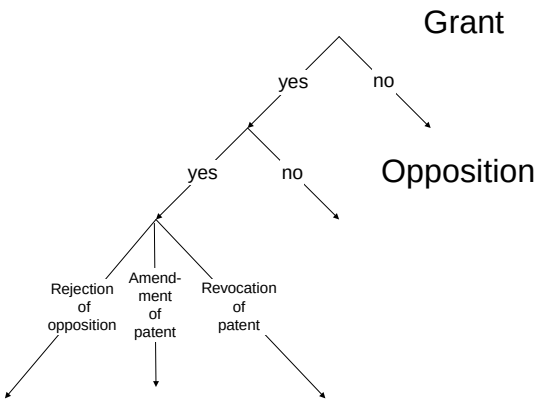
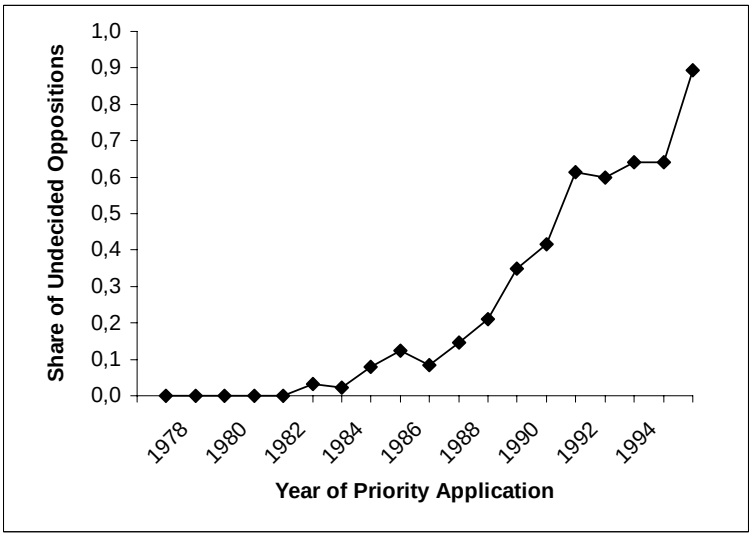


Figure 2

Share of Unidentified Opposition Outcomes[24] among All Opposition Cases in Biotechnology vs. Year of Priority Application



[24] As can be reconstructed from electronic sources. See the text for details.

Table 1
Descriptive statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Left-hand side variables				
Opposition (1: yes, 0: no)[1)]	0.11		0	1
Rejection of Opposition (1: yes, 0: no) [2)]	0.21		0	1
Amendment after Opposition (1: yes, 0: no) [2)]	0.32		0	1
Revocation of Patent after Opposition (1: yes, 0: no) [2)]	0.33		0	1
Opposition Procedure Closed (1: yes, 0: no) [2)]	0.07		0	1
Opposition Outcome not Definable (1: yes, 0: no) [2)]	0.06		0	1
Exogenous variables (right-hand side)				
Number of Backward Citations to the Patent Literature (incl. international search)[1)]	2.89	2.43	0	22
Number of Backward Citations to the Non-Patent Literature (incl. international search)[1)]	2.62	2.85	0	24
Number of Designated States (Family Size) [1)]	8.96	3.01	1	13
Number of Applicants[1)]	1.11	0.42	1	7
Number of Inventors[1)]	2.82	1.72	1	19
Number of Forward Citations (3-year frame) [1)]	0.99	1.88	0	23
Number of Forward Citations (7-year frame) [1)]	1.77	3.00	0	41
Accelerated Examination Request (1: yes, 0: no) [1)]	0.01		0	1
PCT I (1: yes, 0: no) [1)]	0.03		0	1
PCT II (1: yes, 0: no) [1)]	0.10		0	1

Legend: 1): Entire sample comprising N=4,726 patent (application)s.
2): Sample of opposed patents comprising N=318 patents.

Table 2
Reduced form estimates

		Model 1a			**Model 2a**			**Model 1b**			**Model 2b**		
		Stage One: Impact of Patent Quality on Probability of Patent Being Granted relative to Not Granted upon Application			Stage Three: Impact of Patent Quality on Probability of Patent Being Upheld relative to being Revoked or Amended upon Challenge			Stage One: Impact of Patent Quality on Probability of Patent Being Granted relative to Not Granted upon Application			Stage Three: Impact of Patent Quality on Probability of Patent Being Upheld relative to being Revoked or Amended upon Challenge		
		Excluding Information Revealed After Patent Grant			**Excluding Information Revealed After Patent Grant**			**Including Information Revealed After Patent Grant**			**Excluding Information Revealed After Patent Grant**		
k	**parameter**	**Est. B**	**s.e.**		**Est. B**	**s.e.**		**Est. B**	**s.e.**		**Est. B**	**s.e.**	
1	Intercept	-0.0689	0.222		-1.8873	1.3051		-0.1035	0.2227		-1.6332	1.2933	
2	ln(1+patent references)	0.3073	0.0491	**	0.2704	0.2053		0.2338	0.0492	**	0.1634	0.2115	
3	ln(1+non-patent references)	0.0626	0.0432		-0.2073	0.1816		0.0572	0.0433		-0.2107	0.1804	
4	ln(# designated states)	-0.2789	0.0688	**	0.6914	0.4877		-0.282	0.0689	**	0.5835	0.4814	
5	Acc. Exam. Request	0.7014	0.3093	*	-0.9516	0.7963		0.7403	0.3102	*	-0.8948	0.7941	
6	Applicant (=1)	0.1004	0.1106		-0.155	0.463		0.0823	0.1113		-0.198	0.4651	
7	ln(1+ # inventors)	0.4788	0.0773	**	-0.1792	0.3159		0.4967	0.0775	**	-0.2641	0.3127	
8	PCTI (=1)	0.1988	0.1888		0.8453	0.5777		0.3322	0.1887		1.1567	0.5783	*
9	PCTII (=1)	-0.2769	0.1061	**	-0.7925	0.5526		-0.1412	0.1054		-0.507	0.5546	
10	ln(1+3-year cites)	0.2144	0.0552	**	-0.2127	0.1737		-	-		-	-	
	Ln (incremental forward cites)	-	-		-	-		0.5707	0.0650	**	0.0922	0.184	
		Log-Likelihood (0): -3261.26; Log-L (model): -3030.85			Log-Likelihood (0): -205.865; Log-L (model): -175.445			Log-Likelihood (0): -3261.26; Log-L (model): -2997.33			Log-Likelihood (0): -205.865; Log-L (model): -176.081		

* - significant at the α=.05 level; ** - significant at the α=.01 level

Table 3

Models of complete homogeneity

Stages 1 (Patent Grant) and 3 (Opposition Outcome) Pooled

		Model 3a Excluding Information Revealed After Patent Grant					Model 3b Including Information Revealed After Patent Grant				
k	**Parameter**	**Est. B**	**s.e.**	**t-stat**	**p-value**		**Est. B**	**s.e.**	**t-stat**	**p-value**	
1	Intercept	0.1205	0.214	0.563	0.5734		0.1263	0.2142	0.5897	0.5554	
2	ln(1+patent references)	0.3052	0.0471	6.4826	0.0000	**	0.2416	0.0472	5.1194	0.0000	**
3	ln(1+non-patent references)	0.0271	0.0412	0.6576	0.5108		0.0194	0.0411	0.4728	0.6364	
4	ln(# designated states)	-0.2997	0.067	-4.4762	0.0000	**	-0.3108	0.0669	-4.6448	0.0000	**
5	Acc. Exam. Request	0.243	0.2506	0.9697	0.3322		0.2656	0.251	1.0585	0.2898	
6	Applicant (=1)	0.0628	0.1058	0.5932	0.553		0.0474	0.1062	0.446	0.6556	
7	ln(1+ # inventors)	0.3976	0.0735	5.4079	0.0000	**	0.3975	0.0734	5.4127	0.0000	**
8	PCTI (=1)	0.1808	0.1768	1.0225	0.3065		0.303	0.1766	1.7158	0.0862	
9	PCTII (=1)	-0.3104	0.1025	-3.0274	0.0025	**	-0.1878	0.1018	-1.8445	0.0651	
10	ln(1+3-year cites)	0.0939	0.0503	1.8649	0.0622		-	-	-	-	
	Ln (incremental forward cites)	-	-	-	-	-	0.3656	0.0574	6.3658	0.0000	**
		Log-Likelihood (0): -3467.12; Log-L (model): -3287.55					Log-Likelihood (0): -3467.12; Log-L (model): -3268.29				

* - significant at the α=.05 level; ** - significant at the α=.01 level

Table 4

Models of complete homogeneity (with scale/variance heterogeneity)
Stages 1 (Patent Grant) and 3 (Opposition Outcome) Pooled

		Model 4a Excluding Information Revealed After Patent Grant					**Model 4b Including Information Revealed After Patent Grant**				
k	**Parameter**	**Est. B**	**s.e.**	**t-stat**	**p-value**		**Est. B**	**s.e.**	**t-stat**	**p-value**	
1	Intercept	-0.0134	0.1034	-0.1301	0.8965		-0.1887	0.4431	-0.4259	0.6702	
2	ln(1+patent references)	0.1306	0.0226	5.7667	0.0000	**	0.4439	0.0977	4.5453	0.0000	**
3	ln(1+non-patent references)	0.0342	0.0199	1.7192	0.0856		0.1386	0.0857	1.6165	0.106	
4	ln(# designated states)	-0.1322	0.0323	-4.0892	0.0000	**	-0.5599	0.1378	-4.0645	0.0000	**
5	Acc. Exam. Request	0.3585	0.1369	2.6191	0.0088	**	1.6563	0.6074	2.727	0.0064	**
6	Applicant (=1)	0.0507	0.0511	0.9913	0.3215		0.1755	0.2208	0.795	0.4266	
7	ln(1+ # inventors)	0.2229	0.0356	6.2537	0.0000	**	1.0022	0.1535	6.5277	0.0000	**
8	PCTI (=1)	0.0429	0.0842	0.5093	0.6106		0.5117	0.367	1.3943	0.1632	
9	PCTII (=1)	-0.1078	0.0492	-2.1908	0.0285	*	-0.2463	0.2097	-1.1747	0.2401	
10	ln(1+3-year cites)	0.1031	0.0248	4.1527	0.0000	**	-	-	-	-	
	Ln (incremental forward cites)	-	-	-	-	-	1.0919	0.1256	8.6919	0.0000	**
	Scale (Stage 1)	2.1023	0.1034	20.3347	0.0000	**	0.4971	0.0233	21.3233	0.0000	**
	Scale (Stage 3)	-2.0562	0.3528	-5.8275	0.0000	**	-0.3313	0.0642	-5.1582	0.0000	**
		Log-Likelihood (0): -3467.12; Log-L (model): -3218.04					Log-Likelihood (0): -3467.12; Log-L (model): -3188.76				

* - significant at the α=.05 level; ** - significant at the α=.01 level

Table 5

Covariance heterogeneity model with mixture of heterogeneous and homogeneous systematic assessment parameters
Stages 1 (Patent Grant) and 3 (Opposition Outcome) Pooled

		Model 5a Excluding Information Revealed After Patent Grant					**Model 5b Including Information Revealed After Patent Grant**				
K	**Parameter**	**Est. B (lambda)**	**s.e.**	**t-stat**	**p-value**		**Est. B**	**s.e.**	**t-stat**	**p-value**	
	Homogenous parameters										
1	Intercept	-0.7421	0.3711	-1.9995	0.0456	*	-0.7271	0.3862	-1.8825	0.0598	
2	ln(1+patent references)	0.2334	0.0366	6.3839	0.0000	**	0.1896	0.0398	4.7657	0	**
3	ln(1+non-patent references)	0.0344	0.0322	1.0696	0.2848		0.0321	0.0349	0.9187	0.3583	
4	ln(# designated states)	0.0671	0.1463	0.4587	0.6464		0.036	0.1509	0.2386	0.8114	
5	Acc. Exam. Request	-0.0203	0.2694	-0.0753	0.9400		0.0293	0.2818	0.1039	0.9173	
6	Applicant (=1)	0.0632	0.0828	0.7626	0.4457		0.0515	0.0903	0.5708	0.5682	
7	ln(1+ # inventors)	0.1488	0.0998	1.4913	0.1359		0.1447	0.1029	1.4056	0.1598	
8	PCTI (=1)	0.1982	0.1359	1.4583	0.1448		0.3432	0.1469	2.3365	0.0195	*
9	PCTII (=1)	-0.231	0.0797	-2.8974	0.0038	**	-0.1305	0.086	-1.5183	0.1289	
10	ln(1+3-year cites)	0.0199	0.0533	0.3732	0.7090		-	-	-	-	
		-	-	-	-	-					
	Ln (incremental forward cites)						0.2702	0.0587	4.6062	0	**
	Scale (Stage 1)	1.2818	0.063	20.3413	0	**	1.1786	0.0554	21.2872	0	**
	Scale (Stage 3)	1.6417	0.2367	6.9361	0	**	1.5838	0.2301	6.8839	0	**
	Heterogeneous parameters										
1	Intercept	-0.7228	0.3562	-2.0293	0.0424	*	-0.6801	0.3698	-1.8394	0.0659	
4	ln(# designated states)	0.2836	0.146	1.9426	0.0521		0.2744	0.1506	1.8219	0.0685	
5	Acc. Exam. Request	-0.5724	0.2694	-2.1247	0.0336	*	-0.6049	0.2818	-2.1468	0.0318	*
7	ln(1+ # inventors)	-0.2238	0.0995	-2.2499	0.0245	*	-0.276	0.1025	-2.6919	0.0071	**
10	ln(1+3-year cites)	-0.1483	0.0514	-2.886	0.0039	**	-	-	-	-	
	Ln (incremental forward cites)	-	-	-	-		-0.2163	0.056	-3.8601	0.0001	**
		Log-Likelihood (0): -3467.12; Log-L (model): -3208.55					Log-Likelihood (0): -3467.12; Log-L (model): -3175.57				

* - significant at the α=.05 level; ** - significant at the α=.01 level