Misclassification in Patent Office Examinations: Evidence from a Matched Sample of Applications

Paul H Jensen, Beth Webster and Alfons Palangkaraya

The University of Melbourne

1. Introduction

Patents are a mainstay of the global innovation system. Much effort has been expended on getting the balance right between patents' investment-inducing effects and their anti-competitive effects. Research on this issue has considered a wide range of issues including the optimal scope/length of a patent right (Gilbert and Shapiro 1990; Gallini 1992; Merges and Nelson 1992), the optimal size of the inventive step (Hunt 1999) and the efficiency of the examination process (Lemley 2001; Farrell and Merges 2004). However, little is known about whether patent offices make the right decisions about which patent applications to grant and which ones to reject. In this paper, we provide evidence on this issue from a matched sample of patent applications submitted to the European Patent Office (EPO) and the Japanese Patent Office (JPO).

The size of the inventive step is the principal legal mechanism that separates innovations that should be granted a patent from those that should not. In economic terms, the inventive step determines the optimal patent threshold. In recent years, there has been a crisis of confidence about the efficacy of the patent system; the essence of which is that it has become too easy to obtain a patent. The concern is that the ensuing preponderance of 'low quality' patents[1] may be causing friction in the innovation system,

[1] The concept of a "low quality" patent is difficult to define. Many commentators use examples of demonstrably ludicrous patents such as the "peanut butter and jelly sandwich patent" as evidence of low quality patents. In this paper, we use the term "low quality" patent in a similar way to Sampat (2005) and Merges (1999) – it refers to a patent which would not have been granted if the legal threshold of novelty, non-obviousness and usefulness had been properly evaluated. In our terminology, the application has been misclassified.

thereby retarding rather than stimulating innovation.[2] Numerous possible remedies such as raising the height of the inventive step and increasing examination rigour have been proposed (Shapiro 2007; National Academies of Science 2004; Jaffe and Lerner 2004).

In this paper, we take an empirical look at the issue of patent quality. Our particular focus is on "misclassification" of patent applications – that is, applications with a high inventive step that are misclassified by a patent office as a 'refusal' and applications with a low inventive step that are misclassified as a 'grant'. The former can be thought of as a Type I error and the latter as a Type II error. Our interpretation of misclassification, then, is essentially a legal one since we do not consider the economic definition of misclassification: whether the invention would have been created *in the absence of the patent system*. Under this definition of misclassification, granting the patent only serves to create deadweight loss. Of course, this alternative is a very different approach to the one presented here. Although the economic interpretation of misclassification in this way is an interesting avenue to pursue, it is difficult to examine such a counterfactual.

Our empirical model is based on the misclassification model developed by Hausman et al. (1998) which has subsequently been extended and applied to various empirical issues including insurance claims (Artis et al. 2002), language indicators (Dustman and van Soest 2001) and smoking data (Kenkel et al. 2004). As far as we are aware, this is the first application of the concept of misclassification to patent office examination.

Our subject matter is examination decisions made at the European and Japanese Patent Offices between 1990 and 2004 on a matched sample of patent applications. These "twins" are patent applications for the same invention as indicated by the same unique priority number in the applications.[3] We utilize external and *ex post* information about the patent applications – in particular, citation data from the US Patent and Trademark Office (USPTO) – to estimate the probability of grant taking into account the possibility for misclassification. Different outcomes for otherwise identical twin applications indicate misclassification. Citations are used in this manner because other evidence suggests that forward citations are a good measure of the technological value (or

[2] Although it is hard to verify whether innovation is actually slowing down, there is enough anecdotal evidence on undesirable phenomena such as patent thickets, patent trolls and patent submarines to cause serious concern that the patent system is being abused.

[3] See Graham et al. (2003) and Graham and Harhoff (2006) for other studies which use this approach in studying the issues of patent quality.

inventive step) of an invention – the idea being that more highly-cited patents represent a larger technological advance over the prior art (see Karki 1997; Albert et al. 1991).[4]

Using the estimated coefficients of the probability model of grant with misclassification, we then compute a predicted patentability score and a minimum inventive step threshold. We rank order applications according to their estimated inventive step and then use the minimum patentability threshold to determine whether an application should have been granted (a true grant) or should have been refused (a true reject). Misclassification occurs when a true grant is refused or a true reject is granted. We then examine the determinants of misclassification using additional *ex post* information including data on patent renewal at the USPTO, examination duration, the number of claims, the speed of technological change, and a set of other control variables.

The rest of the paper is structured as follows. In Section 2, we briefly discuss common legal patentability criteria used by patent offices and what is meant by patent citation. In Section 3, we specify the empirical model. In Section 4, we explain the data used to estimate the model. In Section 5, we present and discuss the results. In Section 6, we conclude.

2. Background

Patents are temporary legal rights granted to inventors in order to allow them to prohibit others from using their invention. At least since the mid-19th century, patents have played an important role in fostering innovation world in the developed world. From an economic perspective, the fundamental purpose of a patent is to solve the *ex ante* investment problem: that is, in the absence of a legal right to recoup the returns generated by an invention, firms may not invest in the invention in the first place. By attenuating the underinvestment problem, patents create a deadweight loss since they result in patent owners charging monopoly prices for their inventions. In a world of cumulative innovation, they may also impose a tax on subsequent innovators.

[4] Our empirical approach relies on the fact that our sample of patent applications are all granted by the USPTO – thus, we have data on forward citations and renewals for all patents in our sample.[4]

Since issuing patents incurs a social cost, not all inventions are patentable. Following considerable effort at harmonizing international patent examination protocols in the major (trilateral) patent offices in the last 20 years, each national patent office in the developed world uses essentially the same criteria to evaluate patent applications: novelty, non-obviousness and utility. An invention is only eligible for a patent if it is new to the world (i.e. it is novel) and if it represents a non-obvious increment in the state of the art (sometimes referred to as the inventive step). The former is objective (since an invention is either new or it is not), while the latter is subjective (the size of the inventive step is essentially an issue of judgment). The examination process is designed to filter out those applications that should not be granted. In practice, the examination cut-off point is difficult to articulate and it is generally considered that the pivotal examination rule which patent offices use to separate the wheat from the chaff is 'inventive step' or 'non-obviousness'. Examiners base their decision on an application by contrasting with the state of existing knowledge or the 'prior art'.

As part of preparing a patent application, inventors must disclose other published 'art' (which may be contained in previous patents or other (often scientific) publications), which is related to the technology contained in their application. These disclosures of prior art are typically referred to as a 'citation'. While citations play an important legal role in terms of delineating the boundary of the property right associated with the invention, for the disinterested analyst, prior art citations by later applications to an existing patent – forward citations – provide useful information on how inventive the latter is since we expect that standout inventions will be more likely to be cited (Karki 1997; Albert et al. 1991). These forward citations are commonly regarded as good proxies of the size of the inventive step contained in the invention.[5]

3. Empirical Model

Our empirical model of patent outcomes with misclassification is:

$$y_i^* = x_i'\beta + \varepsilon_i \tag{1}$$

[5] Ideally, we should remove self-citations from the analysis since they probably do not provide much information about technological value. However, it was not possible to identify self-citations during the time period we are examining.

where y_i^* is the unobserved inventive step of a patent application i, x_i is an observed characteristic of the application which determines the size of the inventive step, and ε_i is a random error associated with measuring the inventive step. Since y_i^* is a latent variable (unobserved by the econometrician but is observed by patent examiners), Equation 1 can be estimated based on the observed decision of the examiner.

3.1 Estimating the Probability of Misclassification

Suppose we observe the actual patent examination decision y_i (=0 if reject; =1 if grant). If there is no misclassification of patent applications, the observed decision (y_i) is identical with the correct decision and Equation 1 can be estimated in the usual way combining Equation 1 and

$$y_i = 1(y_i^* \geq 0) \tag{2}$$

such that

$$E(y_i \mid x_i) = \Pr(y_i = 1 \mid x_i) = F(x_i'\beta) \tag{3}$$

where $F(\bullet)$ is a common $c.d.f$ of ε_i.

Suppose, however, that patentability is not perfectly or easily observable even to patent examiners. In other words, let us allow for the possibility of misclassification. Here, the observed decision y_i may no longer be related to y_i^* as given in Equation 2. In this case, if we denote the true outcome of the patent application as $\tilde{y}_i$, then:

$$\tilde{y}_i = 1(y_i^* \geq 0) . \tag{4}$$

Following Hausman et al. (1998), we can specify the probability of misclassification as follows. The probability of an incorrectly rejecting a patent application (i.e. a Type I error), α_I , is defined as:

$$\alpha_I = \Pr(y_i = 0 \mid \tilde{y}_i = 1) \tag{5}$$

while the probability of incorrectly granting a patent application (i.e. a Type II error), α_{II} , is defined as:

$$\alpha_{II} = \Pr(y_i = 1 \mid \tilde{y}_i = 0) \tag{6}$$

Thus, the expected value of the observed grant is given as:

$$E(y_i \mid x_i) = \Pr(y_i = 1 \mid x_i)$$

$$= \Pr(\tilde{y}_i = 1 \mid x_i)\Pr(y_i = 1 \mid \tilde{y}_i = 1) + \Pr(\tilde{y}_i = 0 \mid x_i)\Pr(y_i = 1 \mid \tilde{y}_i = 0)$$

$$= F(x_i'\beta)(1-\alpha_I) + (1-F(x_i'\beta))\alpha_{II}$$

$$\therefore E(y_i \mid x_i) = \alpha_{II} + (1-\alpha_I-\alpha_{II})F(x_i'\beta).^6 \tag{7}$$

Notice that Equation 7 collapses to Equation 3 if the probabilities of misclassification (α_I and α_{II}) equal zero.

Hausman et al. (1998) proposed that Equation 7 can be estimated by maximizing the following likelihood function:

$$\begin{aligned} L(\hat{\alpha}_I, \hat{\alpha}_{II}, \hat{\beta}) = n^{-1}\sum_{i=1}^{n}\Big\{ & y_i \ln\left[\hat{\alpha}_{II} + (1-\hat{\alpha}_{II}-\hat{\alpha}_I)F(x_i'\hat{\beta})\right] \\ & +(1-y_i)\ln\left[1-\hat{\alpha}_{II}-(1-\hat{\alpha}_{II}-\hat{\alpha}_I)F(x_i'\hat{\beta})\right]\Big\} \end{aligned} \tag{8}$$

over $(\hat{\alpha}_I, \hat{\alpha}_{II}, \hat{\beta})$, where $\hat{\alpha}_I$, $\hat{\alpha}_{II}$ and $\hat{\beta}$ are estimates of α_I, α_{II} and β respectively.[7] The condition for identification of $(\alpha_I, \alpha_{II}, \beta)$ is shown by Hausman et al. (1998) to be the monotonicity condition:

$$\alpha_I + \alpha_{II} < 1. \tag{9}$$

We estimate Equations 1 and 8 using the normalized ratio of forward citations to backward citations at the USPTO (*CitationRatio*) as our explanatory variable of patentability. We apply Hausman et al.'s approach by maximizing the likelihood function Equation 8 using pooled matched data on patent examination outcomes from the EPO and the JPO and assuming a binary probit specification.[8]

As already argued, citations play an important legal role in terms of delineating the boundary of the property right associated with the invention. Moreover, forward citations provide useful information on how inventive the latter is since we expect that standout inventions will be more likely to be cited (Karki 1997; Albert et al. 1991). However, the

[6] From equations 1, 4, 5 and 6:

[7] Hausman et al. also proposed that the model can be estimated using non-linear least square. Ramalho (2002, 2007) proposed generalized method of moments (GMM) estimators for more general setup. Dustmann and van Soest (2001) extended Hausman et al.'s method into the panel and ordinal discrete dependent variable case.

[8] See Artís et al. (2002), Caudill and Mixon, Jr. (2005), and Kenkel et al. (2004) for recent applications of this approach in the fields of insurance, education and health economics, respectively.

relationship between forward citations and inventive step is most likely quite noisy for a number of reasons. First, citation propensity varies by technology area. Older technology areas have a larger set of prior art and are therefore more likely to both make and receive more citations than other newer technology areas. Second, patents are more likely to be cited in their local patent office since, for example, it is harder for the USPTO to conduct prior art searches in Japanese non-scientific literature than it is to search in American patent databases. Third, more recent patents have had fewer years to accumulate citations and are thus truncated. Moreover, there may be an increasing trend in the likelihood of citation over time. All of these factors make raw citations data an imperfect proxy for inventive step.

To minimise the noise in our proxy, we construct a normalised ratio of forward to backward citations. In other words, our proxy is the ratio of the number of citations received (forward) at the USPTO divided by the number of citations made (backward) at the USPTO, normalised with respect to the average ratio within technology area, US grant year and the presence of a US inventor.[9] To construct this normalised citation ratio, we take advantage a unique characteristic of our dataset: all of the patent applications at the EPO and JPO have been granted by the USPTO. Therefore, they are all equally available for citation regardless of whether they have been granted or rejected at the EPO and JPO.

3.2 The Determinants of Misclassification

Using the estimated coefficients of the model with misclassification, we then compute a predicted patentability score for each application given its citation ratio. This provides an estimate of the true status of the patent application ($\hat{\tilde{y}}_i$):

$$\hat{\tilde{y}}_i = 1(x_i'\hat{\beta} \geq \underline{y}^*) \tag{10}$$

where $\underline{y}^*$ is an unobserved minimum patentability threshold. We estimated $\underline{y}^*$ such that the resulting proportions of misclassification are as close as possible to the estimates of

[9] A newer stream of the literature has shown that the technological importance of the patent is influenced by whether the citations are inserted by the applicant or the examiner (see Sampat 2005; Alcacer and Gittelman 2006). Such data have only been available at the USPTO since 2001, so cannot be utilized here.

α_I and α_{II}. Using the predicted values of $\hat{\tilde{y}}_i$ (the true status) and the observed examination decision y_i (the actual status), we estimate the following models:

1. A binomial logit model of the probability of rejecting an application given the true decision is 'grant' (a Type I error).

2. A binomial logit model of the probability of granting an application given the true decision is 'reject' (a Type II error).

The rationale for estimating Models 1 and 2 is that they enable us to examine whether there is symmetry in the factors affecting the probability of Type I and Type II errors. Although it is possible that some factors shape different types of misclassification uniformly, there is no *a priori* rationale for believing so. Thus, we model each type of misclassification separately and compare the results.

To estimate these two models, we relied on empirical evidence in the literature to develop a set of explanatory variables. For instance, one of the key explanatory variables used in this part of the analysis is examination duration. There is an emerging theoretical and empirical literature exploring the role that the length of time taken to examine an application may be associated with the quality of the examination decision (see Regibeau and Rockett 2007 and Popp et al. 2004). The rationale underlying this is that the more time that is taken to search the universe of prior art, the more likely is the patent examiner to accurately measure the invention's novelty and inventiveness. Ideally, the way to measure this would be hours spent by the examiner in searching the universe of prior art. However, this is unobserved. As a proxy for this, we use the number of days between when the applicant requests and examination and when the patent office makes a final decision whether to grant or reject the application, which we call *ExamDuration*.

Another important potential determinant of misclassification (or the quality of the examination) is the expertise of the patent examiner. Other empirical evidence – such as the work by Cockburn, Kortum and Stern (2003) – has demonstrated that there are systematic differences across individual patent examiners at the EPO. Although we do not observe the individual characteristics of the patent examiners – such as their qualifications or their professional experience – we argue that the amount of R&D expenditure by technology area in a country is a good proxy for the overall expertise of a national patent office in that particular technology area. In other words, given that Japan invests a lot of money into R&D in the automotive industry, Japanese patent examiners should find it easier to identify whether an application for a patent in an automotive-related technology area is in fact novel and non-obvious. To include this in our model, we construct a variable called *Revealed Research Advantage*, which captures the amount of R&D expenditure by technology area in the examiners jurisdiction (Europe or Japan).

There are three other explanatory variables which are of particular interest in understanding the determinants of misclassification: *Years in-force*; *Speed of technology*; and *Past applications*. The first of these is measured by using data from the USPTO on patent renewals. To be precise, it is calculated as the number of years in force as a US patent divided by the mean of years in-force in the same OST. Renewals are well-known to be a proxy for the commercial value of the invention since patent owners will not continue to pay maintenance (i.e. renewal) fees on inventions which do not (or will not in the foreseeable future) generate returns.[10] We use it here to proxy for the fact that applicant may have private information about the potential *ex post* value of the invention. To the extent that this is correct, applicants with potentially valuable inventions may be more persistent in their interactions with the patent office and that this may increase the likelihood that an examiner incorrectly grants an application. Anecdotal evidence suggests that there is less work pressure for examiners if they grant an application rather than reject it, thereby providing an incentive for applicants to be persistent in their interaction with patent offices.[11]

Speed of technology is included in the model since there is evidence suggesting that in newer technology areas (e.g. biotechnology), it is harder to identify the 'inventive step' than it is in older technology areas. If this conjecture is accurate, it may be the case that applications in newer technology areas are more likely to be misclassified. Technology area is grouped at the OST[12] level and data on technological speed has been supplied by

[10] At the USPTO, these maintenance fees must be paid in the 4th, 8th and 12th years after patent issuance and the fees associated increase at each renewal stage – in year 4, the maintenance fee is US$900 which increases to US$3,800 in year 12. Hegde and Sampat (2005) show that less than half (44 per cent) of all patents issued in 1992 by the USPTO were renewed to full term.

[11] Note that since all applications have been granted at the USPTO, this variable is not endogenous to the EPO or JPO decision.

[12] Office of Science and Technology, UK classifications.

CHI Research.[13] Speed of technology is calculated as the inverse of the length of technology cycle divided by mean of the speed of technology in the same OST.

An increase *Past applications* is measured by the number of previous applications the applicant made to that office over the 1990-1995 period. It is included to control for the fact that applicants with many previous applications may have accumulated expertise in the operation of a specific patent office and may therefore submit an application in such a way that it makes it easy for the examiner to make the correct decision.

To capture any trends in the likelihood of misclassification which may be due, for example, to changes over time in patent office budgets we have included the *Decision year.* To represent effects associated with the fact that local applicants are able to use their own language to complete the application which may make examination errors less likely we have included *Local inventor* and *US inventor* dummy variables. The number of claims in the application, normalised by the average number of claims in that year – *Number of claims* – has been included as a proxy for the complexity of the application. In addition, we have included in the model a set of control variables such as the office of the decision and technology area (as defined in the appendix). A complete description of the explanatory variables and descriptive statistics are presented in the Appendix.

4. Data and Descriptive Statistics

4.1 Data Construction

The data for this study were derived from five main sources:

(1) the OECD Triadic Patent Family (TPF) Database;[14]

(2) the EPO's public access online database (*esp@cenet*[15]);

(3) the JPO's public access online Industrial Property Digital Library (IPDL) databases;

(4) the NBER Patent-Citations Data File (Hall et al. 2002);

(5) the USPTO patent renewal data.[16]

[13] The variable for each OST technology group is the average median age of the patents cited on the front page of a patent document over the period 1990-95. The measure assumes that the more recent the age of the cited patents, the more quickly one generation of inventions is replaces another.

[14] http://www.oecd.org/LongAbstract/0,2546,en_2649_33703_30921914_1_1_1_1,00.html.

[15] http://ep.espacenet.com/search97cgi/s97_cgi.exe?Action=FormGen&Template=ep/EN/home.hts.

The first database provides us with a list of triadic patent families defined as a set of patent applications for which the 'priority application must have at least one equivalent patent at the EPO, at the USPTO, and at the JPO' (Dernis and Khan 2004, p.11). To control for the individual invention, we only include patent families with a single priority application.[17] Since the USPTO did not publish patent applications prior to 2001, we consider application outcomes at the EPO and JPO conditional on them being granted by the USPTO. Moreover, we only include non-PCT applications in our matched sample since data on PCT applications at the JPO were not readily available (however, this only represents 10 per cent of the population).

We also constrained the dataset to include patent applications with priority years 1990-95 for two reasons. First, it enables us to minimise the amount of data truncation with regards to the examination decision, since this provides at least eight years to examine the priority application (the data were downloaded in late 2004). Second, it enables us to avoid problems associated with the fact that the JPO had a policy of one claim per application prior to the introduction of the 1988 Japanese Patent Law reforms.[18] The second and third data sources provide information on the status of applications at the EPO and the JPO, while the fourth and fifth datasets provided us with information on patent citations and renewals at the USPTO for our triadic families. These datasets were match-merged on company name.

Originally, there are 70 473 non-PCT applications filed in the trilateral patent offices which meet our criteria above. Of these, 33 880 received a final patent examination decision (i.e. grant or reject) at both the EPO and JPO by the end of 2004. After dropping observations with missing values in any of our variable of interests such as outcomes (grant or reject), citations and duration of examination, we have a cleaned sample of 24 690 twin applications which have been granted by USPTO and have received decisions from the EPO and the JPO.[19]

[16] The renewal data were provided to us directly by the USPTO.

[17] For similar reasons, we also dropped any families involving continuation, continuation-in-parts, or divisional patent applications at the USPTO. About 20 per cent of the Triadic Patent Family involves a US patent with continuation and divisional applications. We expect that these will represent on average a narrower set of claims than its European and Japanese equivalent.

[18] See, for example, Sakakibara and Branstetter 2001).

[19] See Data Appendix for more detailed discussion of the sample construction and possible selection bias.

4.2 Descriptive Statistics

4.2.1 Examination Outcomes

Table 1 provides cross-tabulations of the EPO and the JPO's patent examination outcomes for the full sample and the cleaned sample. The cleaned sample consists of 24 690 applications in which all of the variables of interest are not missing. As can be seen from the table, there is virtually no difference between the cleaned and the full sample in terms of actual decision or examination outcomes. Approximately 78.0 per cent of the applications received a grant decision in both offices and 1.2 per cent received a double rejection.[20]

TABLE 1

Actual Decisions by Patent Office, Full and Cleaned Sample

		EPO Reject *(%)*	EPO Grant *(%)*	EPO Total *(%)*
Full sample				
JPO	Reject	396	6356	6752
	(%)	*1.2*	*18.8*	*19.9*
	Grant	688	26 440	27 128
	(%)	*2.0*	*78.0*	*80.1*
	Total	**1084**	**32 796**	**33 880**
	(%)	***3.2***	***96.8***	***100.0***
Cleaned sample				
JPO	Reject	284	4761	5045
	(%)	*1.2*	*19.3*	*20.4*
	Grant	470	19 175	19 645
	(%)	*1.9*	*77.7*	*79.6*
	Total	**754**	**23 936**	**24 690**
	(%)	***3.1***	***96.9***	***100.0***

4.2.2 Patent Citations and Examination Outcomes

To understand the relationship between examination outcomes and forward citations, Table 2 presents the mean number of normalized forward citations recorded by the USPTO for each patent application in our data set cross tabulated by their outcome status at the EPO and JPO. What is immediately apparent from Table 2 is that while granted

[20] In the appendix, Table A2 provides more descriptive statistics of the pooled sample.

patents in the JPO appear to have a higher inventive step (the normalised forward citations is 1.110) than rejected patents (1.090), the reverse applies for the EPO. In fact, applications that are rejected at the EPO but granted at the JPO had a considerably higher number of normalised citations (1.263) than those that were granted at the EPO but rejected at the JPO (1.079). This suggests some inconsistencies on behalf of the EPO. The second point to notice is that applications that are withdrawn at both offices have, as a group, the lowest level of inventive step. Applications that are still pending – between eight to fourteen years after filing – have the second lowest level of inventive step.

TABLE 2

Mean number of forward citations at USPTO (normalized for technology, us inventor, US grant year), priority years 1990-1995

	EPO				
JPO	*Withdrawn*	*Pending*	*Rejected*	*Granted*	Total
Withdrawn	0.804	0.845	0.857	0.836	0.827
Pending	0.937	0.899	0.902	0.955	0.946
Rejected	1.051	1.227	1.173	1.079	1.090
Granted	1.028	1.043	1.263	1.114	1.110
Total	**0.891**	**0.925**	**1.084**	**1.026**	**1.000**

As already mentioned, our data set is truncated as it does not include applications that were withdrawn, pending or rejected at the USPTO. As a consequence, we can not use this as evidence to compare the quality of USPTO-granted, EPO-granted and JPO-granted patents. Moreover, it does not inform us about whether the JPO or EPO are making Type I or Type II errors since we don't know the optimal examination threshold – all the analysis tells us thus far is that the three patent offices may have different patent thresholds. We turn to an empirical determination of the inventive step threshold – which is not the same as the optimal inventive step threshold – in the next section of the paper.

5. Results and Analysis

5.1 The Probability of Misclassification

The first set of results – on the probability of misclassification – is summarized in Table 3. Since the estimation may be sensitive to the chosen starting values, we used the coefficient estimates obtained from the regular probit model without misclassification and zero misclassification probabilities as the starting values. The identification condition in Equation 9 was imposed. In the first column, we provide the estimation of Equation 1, which assumes that there is no misclassification. As expected *a priori*, the results indicate that citation ratio is positive and statistically significant. In other words, more highly cited applications are associated with a higher probability of being granted. Although we can not rule out of the fact that this result may be driven by some unobservable characteristic of the examination process which is correlated with citations, we do not believe this is the case.

TABLE 4

Determinants of Observed Examination Decision

Dep. Variable: Observed decision Independent variables	**Equation 1**	**Equation 8 (with misclassification)**
Citation ratio	0.045*** (0.006)	0.103*** (0.009)
Constant	1.141*** (0.010)	1.398*** (0.003)
$\hat{\alpha}_I = \Pr(y_i = 0 \mid \tilde{y}_i = 1)$		0.061*** (0.002)
$\hat{\alpha}_{II} = \Pr(y_i = 1 \mid \tilde{y}_i = 0)$		0.098*** (0.008)
LR	-17 835.6	-17 833.0
N	49 380	49 380

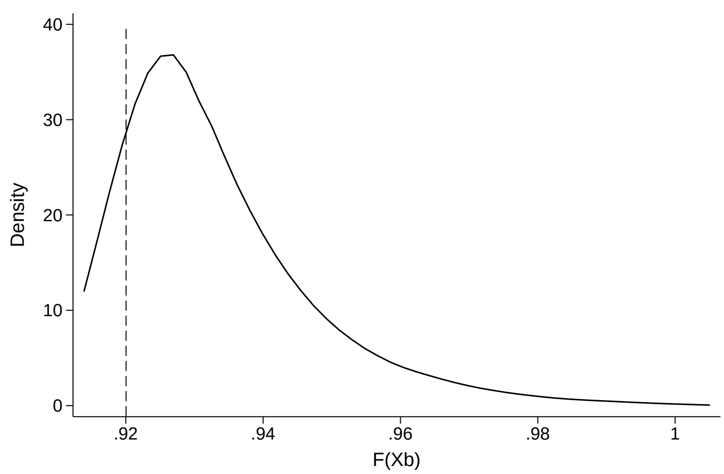
Notes: $y_i = 1$ is observed grant from patent office decision data; $y_i = 0$ is observed reject from patent office decision data; $\tilde{y}_i = 1$ unobserved correct grant; and $\tilde{y}_i = 0$ unobserved correct rejection.

In column 2 of the same table, we provide the estimates of Equation 8, which allows for the possibility of misclassification. Accordingly, we present not only the coefficient on citation ratio (which remains positive and statistically significant), but also our estimates of the likelihood of both types of misclassification (for both offices jointly, since we are using pooled JPO and EPO data). In summary, the joint probability of incorrectly granting an application (a Type I error) is 6.1 per cent, while the likelihood of incorrectly rejecting an application (a Type II error) is 9.8 per cent.

Figure 1 displays the distribution of 'true' grants $\Pr(\hat{\tilde{y}}_i = 1 | x_i)$ if 'truth' is a function of the citation ratio (given the estimated parameters summarised in Table 3). The computed minimum inventive step threshold value for a correct grant decision which minimises the sum of squares of the difference between the resulting decision errors and the estimated decision errors ($\hat{\alpha}_I$ and $\hat{\alpha}_{II}$) is 0.92, which is indicated on the chart as a vertical line.[21] Table 4 provides a cross tabulation of actual decisions and predicted 'true' status.

FIGURE 1

Probability of 'true' grant



[21] The resulting error probabilities are 0.123 and 0.101 as compared to $\hat{\alpha}_I$ =0.061 and $\hat{\alpha}_{II}$ =0.098 respectively. Note also that this figure is not a representation of the optimal inventive step threshold. Rather, it is an attempt to estimate the examination threshold which best fits the observed data and the estimated model of outcomes.

TABLE 4

Actual Decisions and 'True' Status by Patent Office

			'True' Reject	Grant	Total
EPO	Actual	Reject	210	1298	1508
		Grant	6686	41 186	47 872
JPO	Actual	Reject	1402	8688	10090
		Grant	5494	33 796	32 290
		Total	6896	42 484	49 380

5.2 Determinants of Misclassification

To understand the determinants of misclassification, Table 5 presents the estimated average marginal effects for the binomial logit models which provide evidence on the joint probability of both types of misclassification.[22] The marginal effects for our continuous variables have been determined as the change in the probability of an incorrect decision if the independent variable changes from one standard deviation below the mean to one standard deviation above the mean.

Let us consider column 1 in Table 5 regarding the determinants of a Type I error. The factors determining the probability of an incorrect reject can be grouped by whether they have a positive marginal effect (which, as a result of the model specification means that an increase in the variable *increases* the likelihood of error) or a negative marginal effect (which means that an increase in the variable *reduces* the likelihood of error). One factor which causes a large reduction in the likelihood of Type I error is the number of years-in-force at the USPTO. This implies that more valuable patents are less likely to be incorrectly rejected. Although the precise welfare implications of this are difficult to examine, this suggests that patent offices are performing efficiently since most of the social cost associated with Type I errors is associated with the rejection of valuable patents.

[22] The coefficient estimates are presented in Table A3 in the Appendix.

TABLE 5

Average marginal effects of application characteristics on the probability of misclassification

	Marginal Effect on the Probability of:			
Explanatory Variables	Incorrect reject given the true decision is grant (TYPE I ERROR) ‡		Incorrect grant given the true decision is reject (TYPE II ERROR) †	
Examination duration (μ+σ cf. μ-σ)	-0.008	**	-0.023	***
Years in force as a US patent (μ+σ cf. μ-σ)	-0.092	***	0.104	***
Number of claims (μ+σ cf. μ-σ)	-0.001		0.017	**
Speed of technology cycle (μ+σ cf. μ-σ)	-0.017	***	0.018	**
Number of past applications (μ+σ cf. μ-σ)	-0.007	**	-0.013	**
Revealed local research advantage (μ+σ cf. μ-σ)	-0.008		0.022	
Decision year (μ+σ cf. μ-σ)	0.097	***	-0.095	***
Presence of a local inventor (cf. other)	-0.026	***	0.020	**
Presence of a US inventor (cf. other)	0.016	***	-0.017	**
Technology area dummies	Yes		Yes	
Office dummy variable	Yes		Yes	
Sample size	42 484		6896	
Proportion *y*=1	0.118		0.883	
Log likelihood	-12 517		-1997	
Pseudo-R^2	0.186		0.197	

Notes: ***, **, * indicate that the coefficient estimates used to derive the average marginal effects are statistically significant at the 1%, 5%, and 10% significance level. Appendix Table A1 provides the coefficient estimates and their standard errors. The notation μ ± σ refers to one standard deviation above and below the mean, respectively. †Incorrect Grant = 1 if actual decision is a grant and predicted true decision is a reject; 0 if actual decision is a reject and predicted true decision is a reject. ‡Incorrect Reject = 1 if actual decision is a reject and predicted true decision is a grant; 0 if actual decision is a grant and predicted true decision is a grant.

5.2.1 Type I Errors

Other factors which reduce the likelihood of making a Type I error include: examination duration, presence of a local inventor, and the number of past applications. These results accord with our a prior expectations since our hypotheses were that increasing the resources dedicated to examination, familiarity with the culture and language of the domestic patent office, and the experience of the applicant should all improve the likelihood of making the correct decision. In contrast, the result on the speed of technology cycle is difficult to interpret: it suggests that Type I errors are less likely in fast-moving technologies. One plausible interpretation of this is that patent examiners err on the side of caution and grant too many applications in these technology areas, but this interpretation is perhaps better examined in the results on Type II errors.

In terms of factors increasing the likelihood of Type I error, decision year has a large effect. This indicates that there has been a positive trend over time in the probability of Type I errors. Several other factors were also found to have a statistically significant effect: Somewhat curiously, the presence of a US inventor also increased the likelihood of an incorrect rejection – a result which we find difficult to explain. Several technology areas were found to have higher Type I error rates *ceteris paribus*: ICT, communications, electronics, automobile. Revealed research advantage and number of claims were not statistically significant.

5.2.2 Type II Errors

The second column in Table 5 presents the determinants of a Type II error. The first point to note about these results is that they are not a perfect mirror image of the results presented above on Type I errors. Although there are some variables – such as examination duration and number of past applications – whose influence is significant and the same sign as above, there are others whose effects are in opposing directions. One example of this type of variable is years-in-force: here, an increase in the number of years actually increases the probability of the office making a Type II error. If our conjecture is correct that applicants have private (but imperfect) information about the potential *ex post* commercial value of the invention, our result may simply reflect the fact applicants with valuable inventions are more persistent in their negotiations with the patent office and it is well-known that examiners often face perverse incentives to grant patents to persistent applicants. Once again, the welfare implications are complex, but this would seem to be a welfare-reducing outcome since such patents may have genuine commercial value, but they may also have strategic value in the sense that they are used in cross-licensing negotiations. The fact that the patent has limited inventiveness is difficult for third parties to establish and thus the incorrectly-granted patent may create unjustified bargaining power for its owner in such cross-licensing arrangements.

Two additional variables whose influence differs across the two types of misclassification are the speed of technology cycle and decision year. The result that rapidly-changing technologies are more likely to experience Type II errors is perhaps a function of the fact that examiners err in the applicant's favour when the optimal size of the inventive step has not sufficiently crystallised. While this may provide some assistance to these areas of rapid change (which may require some nurturing due to the immature stage of development), it may also have serious welfare implications since an over-supply of patents in periods rapid technological change may limit the freedom to operate of colleague scientists (Binenbaum *et al.* 2003). The other interesting comparison with the Type I results is that decision year is actually negative for Type II errors – that is, there is a decreasing trend in the number of Type II errors made, *ceteris paribus*. This implies that the recent (and ongoing) furore over the number of "bad" patents granted may be confined to the US.

Some puzzles remain unanswered: for instance, the presence of a local inventor raised the probability of a Type II error but the presence of a US inventor lowered the probability of a Type II error. Perhaps the former result can be explained by the fact that locals push their domestic office to convince the patent office to grant a patent, but the latter result is a mystery. Over and above these effects, only the communications and electronics technology areas were found to have a significantly lower probability of an incorrect grant decision. Once again, revealed research advantage was not significant.

6. Conclusions

The paper has attempted to model misclassification in patent offices. Our findings on misclassification depend on two assumptions. First, we have implicitly assumed that different patent offices *should* make the same decisions regarding the patentability of a specific invention. While there are obvious differences in examination protocols across the offices, we argue that this is a plausible assumption since the fundamental principles of the examination process – that an invention is only patentable if it is novel, non-obvious and useful – are at the core of all patent office examinations. While there may be some arguments in favour of allowing patent offices to make different decisions regarding the same patent application, it comes at a cost since it no doubt introduces complexity into firms' investment decisions and makes their freedom to operate difficult to know.

Secondly, our notion of a correct decision rests on the legal meaning of validity (that is, novelty, non-obviousness and usefulness). From an economic perspective, however, whether or not an invention should be patentable depends on the relative net change to the incentive to invent and innovate, and, the deadweight monopoly losses. The latter includes strategic ways to construct undesirable patent thickets, build patent portfolios to extract additional bargaining power in cross-licensing arrangements or other rent-seeking activities. Our estimated size of misclassification effectively overlooks these issues. However, we can not rule out the possibility that the legal and economic interpretations of patent validity are correlated.

Notwithstanding these caveats, our analysis reveals that 6.1 and 9.8 per cent of patents are, respectively, incorrectly rejected and incorrectly granted. Offices are less likely to misclassify an application the longer the duration of examination and the more economically valuable the application. In other words, our results suggest that some factors, under the control of patent offices, are associated with misclassification. These are that allowing examiners to be swayed by applicant persistence may be increasing the incidence of Type II errors; and that a trade-off between examination duration and accuracy probably exists, as has been discovered in other literature.[23] Furthermore, in areas where the speed of technological change is fast, Type II errors are more likely to occur, but Type I errors are less likely to occur.

[23] See Popp, Juhl and Johnson (2004) and Regibeau and Rockett (2007) for more on this issue.

Appendix:

Data

Table A1 shows that the total number of patent applications filed in the trilateral patent offices was 190,583. Eliminating PCT and multiple-priority applications leaves 70,473 applications, of which 33,880 received a final patent examination decision (i.e. grant or reject) at both the EPO and JPO by the end of 2004. The patent applications are the focus of our study here since we are interested in using citation and renewal data at the USPTO to determine whether the correct decision was made in granting/rejecting a specific patent application. The remaining 36,593 applications were either still pending or had been withdrawn in at least one office.

TABLE A1

Summary of Complete Patent Applications in the Trilateral Offices, 1990-1995

Office of Application	Complete Patent Families
All USPTO applications	843 435
All EPO applications	433 186
All JPO applications	2 191 084
All Triadic Patent Families	190 583
• PCT families	18 488
• Non-PCT families	172 095
-single priority	70 473
(examination decision in all 3 offices)	*(33 880)*
-multiple priorities	101 622

We then match-merged the data for these 33,880 patent applications with the NBER patent database using the USPTO patent numbers (Hall, Jaffe and Trajtenberg 2002). This enabled us to collect more data on each patent application; data which is not available in the triadic patent family database such as application year, number and country of inventors, priority countries, number of claims, technology category, and the number of forward/backward citations. The last database provided us with information on whether the patent was renewed at the USPTO.

The construction of our sample may introduce three selection biases: a US-grant bias, a single-priority bias and a non-PCT bias. The US-grant bias occurs because we are not able to get information on applications that are rejected by the USPTO. This bias is however probably small since the proportion of all original patent applications granted by the USPTO is as high as 80-90 per cent (Quillen and Webster 2006).

The single-priority bias is potentially more substantial since 53 per cent of triadic family applications have multiple priorities. However, focusing on single-priority applications enables us to increase the certainty of the equivalence of the invention within a family. If multiple-priority applications were included, we would be less sure that differences in outcomes are due to discrepancies in the standard of examination rather than variation in the quality of the invention. Similar to almost all matched-observation studies, sample selection biases are only a concern if it affects the interaction between the variables under consideration (in our case the examination decision and citations). We have no clear reason to believe that this interaction will differ between our sample and the whole triadic population and therefore the potential bias is minimal.

The exclusion of PCT applications may lead to a sample selection bias problem since it is probable that PCT applications are more valuable than non-PCT applications (applicants only select the PCT route if they intend to apply for patents in four or more countries. Given the substantial application costs involved, this suggests the inventions also have considerable commercial potential). However, only 10 per cent of patent applications in the time period studied here used the PCT route.

Table A2
Variable Description and Summary Statistics

Variable	Description	Mean	Standard Deviation
Grant	Actual decision (1 if grant, 0 otherwise)	0.883	0.322
'True' grant	Predicted 'true' grant (1 if $\Pr(\tilde{y}_i = 1) > 0.92$)	0.860	0.347
Cite ratio	Number of citations received (forward) over number of citations made (backward), normalised with respect to the average ratio within technology area, US grant year and presence of US inventor.	1.089	1.360
Examination duration	Number of months lapsed between decision date and date of examination request	38.002	15.819
Years-in-force as a US patent	Number of years the patent has been maintained (renewal fees paid) at the USPTO, normalised with respect to the technology area.	1.001	0.314
Number of claims	Number of claims made in the US patent, normalised by the average number of claims made in that year.	12.425	8.539
Speed of technology cycle	The inverse of the mean age of backward citations on USPTO patent applications in each OST technology group from 1990-2001.	9.617	1.960
Revealed local research advantage	The expenditure in each industry as a proportion of the total expenditure across all industries in each jurisdiction (Europe, Japan) expressed as a ratio of R&D expenditure across all industries in each jurisdiction as a proportion of all R&D expenditure. The value is set to zero when there is no local inventor listed in the application.	0.396	0.614
Decision year	Time variable indicating the year the patent application is rejected or granted (1=1990)	11.028	2.611
Presence of a local inventor	Indicator with a value of 1 if at least one in the listed inventors of the US patent resides in the jurisdiction of the examining office.	0.351	0.477
Presence of a US inventor	Indicator with a value of 1 if at least one in the listed inventors of the US patent resides in the jurisdiction of the examining office.	0.292	0.455
Biotechnology	1 if the IPC codes in US patent include any of A01H (1/00, 4/00), A61K (38/00, 39/00, 48/00), C02F (3/34), C07G (11/00, 13/00, 15/00), C12M/N/P,Q,S, G01N (27/327, 33/53,54,55,57,68,74,76,78,88,92)	0.009	0.096
Drug	1 if the technological category in the NBER Patent Database[24] Drugs and Medicals (excludes those listed in Biotechnology)	0.050	0.217
Chemical	1 if the technological category in the NBER Patent Database is Chemical	0.210	0.407
Computer software[25]	1 if the IPC codes in US patent include any of G06F (3/&153/, 5/&165/, 7/&17/, 9/&19/&159/, 11/, 12/, 13/, 15/, 9/&19/, 15/, 9/&29/)	0.038	0.190
ICT	1 if the IPC codes in US patent include any of G06, G11, H04 (except those listed in Computer Software)	0.110	0.313
Communications	1 if the technological category in the NBER Patent	0.067	0.250

[24] Hall, B. H., A. B. Jaffe, and M. Tratjenberg (2001). "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools." NBER Working Paper 8498.
[25] This follows Graham and Mowery (2002).

	Database is Computers & Communications (exclude those in Computer Software and ICT above)		
Electronics	1 if the if the technological category in the NBER Patent Database is Electricals & Electronics	0.202	0.401
Automobile	1 if the technological subcategory in the NBER Patent Database is 53 or 55	0.060	0.238
Mechanical	1 if the technological category in the NBER Patent Database is Mechanical (exclude those identified as in Automobile above)	0.150	0.357
JPO as the examining office	Office indicator: JPO =1, EPO=0	0.500	0.500
Pooled-sample size	*49380*		

Table A3
Logit model of the probability of misclassification

Independent variables	Incorrect reject (Type I error)		Incorrect grant (Type II error)	
Examination duration	-0.003	(0.001)	-0.009	(0.003)
Years in force as a US patent	-1.697	(0.051)	1.730	(0.117)
Number of claims	-0.001	(0.002)	0.014	(0.006)
Speed of technology cycle	-3.944	(0.777)	3.788	(1.718)
Number of past applications	-0.100	(0.045)	-0.198	(0.097)
Revealed local research advantage	-0.078	(0.058)	0.190	(0.122)
Decision year	0.212	(0.007)	-0.215	(0.017)
Presence of a local inventor	-0.445	(0.079)	0.333	(0.170)
Presence of US inventor	0.248	(0.039)	-0.268	(0.115)
Constant	-3.796	(0.140)	4.178	(0.331)
Technology dummies	Yes		Yes	
Patent office dummy	Yes		Yes	
Sample size	42484		6896	
Proportion y=1	0.118		0.883	
Log likelihood	-12517		-1997	
Pseudo-R^2	0.186		0.197	

References

Alcacer, J. and Gittelman, M. (2006), "How do I know what you know? Patent examiners and the generation of patent citations" *Review of Economics and Statistics* 88(4):774-779.

Albert, M.B., Avery, D., Narin, F. and McAllister, P. (1991), "Direct validation of citation counts as indicators of industrially important patents", *Research Policy* 20, 251-59.

Allison, J., Lemley, M.A., Moore, K.A. and Trunkey, R.D. (2004), "Valuable patents", *Georgetown Law Journal* 92, 435-.

Artís, M., M. Ayuso, and M. Guillén (2002), "Detection of Automobile Insurance Fraud with Discrete Choice Models and Misclassified Claims, *The Journal of Risk and Insurance*, 69(3), 325-340.

Binenbaum, Eran, Carol Nottenburg, Philip G. Pardey, Brian D. Wright and Patricia Zambrano. 2003. "South-North Trade, Intellectual Property Jurisdictions, and Freedom to Operate in Agricultural Research on Staple Crops." *Economic Development and Cultural Change*, 51(2): 309-355.

Caudill, S.B. and F.G. Mixon, Jr. (2005), "Analysing Misleading Discrete Responses: A Logit Model Based on Misclassified Data", *Oxford Bulletin of Economics and Statistics*, 67(1), 105-113.

Cockburn, I.M., Kortum, S. and Stern, S. (2003), "Are all patent examiners equal? The impact of characteristics on patent statistics and litigation outcomes," NBER Working Paper 8980.

Dernis, H. and Khan, M. (2004) Triadic Patent Families Methodology. *OECD STI Working Paper.* Paris.

Dustmann, C. and A. van Soest (2001), "Language Fluency and Earnings: Estimation with Misclassified Language Indicators", *Review of Economics and Statistics*, 83(4), 663-674.

Farrell, J. and Merges, R.P. (2004), "Incentives to challenge and defend patents: Why litigation won't reliably fix patent office errors and why administrative patent review might help", *Berkeley Technology Law Journal* 19:943-70.

Gallini, N. (1992), "Patent policy and costly imitation", *RAND Journal of Economics* 23, 52-63.

Gilbert, R. and Shapiro, C. (1990), "Optimal patent length and breadth", *RAND Journal of Economics* 21, 106-12.

Graham, S.J.H., Hall, B.H., Harhoff, D., Mowery, D.C. (2003), "Post-issue patent 'quality control': a comparative study of U.S. patent re-examinations and European patent oppositions. In: Cohen, W.M., Merrill, S.A. (Eds.), *Patents in the Knowledge Based Economy.* The National Academic Press, Washington DC.

Graham, S.J.H. and Harhoff, D. (2006), "Can Post-Grant Reviews Improve Patent System Design? A Twin Study of US and European Patents", mimeo.

Guellec, D. & van Pottelsberghe, B. (2000) Applications, Grants and the Value of Patent. *Economics Letters*, 69, 109-114.

Hall, B. H., Jaffe, A. B. and Trajtenberg, M. (2002) The NBER Patent Citations Data File: Lessons, Insights, and Methodological Tools. IN Jaffe, A. B. & Trajtenberg, M.

(Eds.) *Patents, Citations, and Innovations: A Window on the Knowledge Economy.* Cambridge, Massachusetts, The MIT Press.

Hausman, J.A., Abrevaya, J. and Scott-Morton, F.M. (1998), "Misclassification of the dependent variable in a discrete-response setting", *Journal of Econometrics*, 87, 239-269.

Hegde, D. and Sampat, B.N. (2005), "Examiner citations, applicant citations and the private value of patents", mimeo, University of California Berkeley, dated 23rd November.

Hunt, R.M. (1999), "Non-obviousness and the incentive to innovate: An economic analysis of intellectual property reform", Federal Reserve Bank of Philadelphia Working Paper 99-3.

Jaffe, A.B and Lerner, J. (2004), *Innovation and its Discontents: How our Broken Patent System is Endangering Innovation and Progress and What to do About it*, Princeton University Press.

Jaffe, A.B., Trajtenberg, M. and Henderson, R. (1993), "Geographic localization of knowledge spillovers as evidenced by patent citations," *Quarterly Journal of Economics* 108(3), 577-98.

Karki, M.M.S. (1997), "Patent citation analysis: A policy analysis tool", *World Patent Information* 19(4), 269-72.

Kenkel, D.S., Lillard, D.R. and Mathios, A.D. (2004), "Accounting for misclassification error in retrospective smoking data", *Health Economics*, 13, 1031-1044.

Kesan, J.P. and Banik, M. (2000), "Patents as Incomplete Contracts: Aligning Incentives for R&D Investment with Incentives to Disclose Prior Art", *Journal of Law and Policy* 2, 23-54.

Lanjouw, J. O. & Shankerman, M. (1997) Stylized facts of patent litigation: Value, scope and ownership. National Bureau of Economic Research.

Lemley, M.A. (2001), "Rational ignorance at the patent office", *Northwestern University Law Review* 95, 1497-1532.

Merges, R.P. (1999), "As many as six impossible patents before breakfast: Property rights for business concepts and patent system reform", *Berkeley Technology Law Journal* 14, 577-615.

Merges, R.P. and Nelson, R.R. (1990), "On the complex economics of patent scope", *Columbia Law Review* 90(4), 839-916.

Michel, J., Bettels, B. (2001), "Patent citation analysis — A closer look at the basic input data from patent search reports", *Scientometrics* 51, 185-201.

Narin, F., Noma, E. and Perry, R. (1987), "Patents as indicators of corporate technological strength", *Research Policy* 16: 143-55.

National Academies of Science (2004), *A Patent System for the 21st Century*, The National Academies Press, Washington DC.

Popp, D., Juhl, T. and Johnson, D.K.N., 2004, Time in purgatory: Examining the grant lag for U.S. patent applications, *Topics in Economic Analysis & Policy* 4(1), article 29.

Quillen, C.D.J. and Webster, O.H. (2006) Continuing Patent Applications and Performance of the U.S. Patent Office – Updated. *Federal Circuit Bar Journal* 15**,** 635-677.

Ramalho, E. A. (2002), "Regression Models for Choice-Based Samples with Misclassification in the Response Variable", *Journal of Econometrics*, 106, 171-201.
Ramalho, E. A. (2007), "Binary Models with Misclassification in the Variable of Interest and Nonignorable Nonresponse", *Economics Letters*, 96, 70-76.
Regibeau, P. and Rockett, K., 2007, Are more important patents approved more slowly and should they be?, CEPR Discussion Paper 6178, March.
Sakakibara, M. & Branstetter, L. (2001) Do Stronger Patents Induce More Innovation? Evidence from the 1988 Japanese Patent Law Reforms. *RAND Journal of Economics,* 32**,** 77-100.
Sampat, B.N. (2005), "Determinants of patent quality", mimeo, Columbia University, dated September.
Shapiro, C. (2007), "Patent reform: Aligning reward and contribution", paper presented at the NBER Conference on Innovation Policy and the Economy, 12th April.
Thompson, P. (2006), "Patent citations and the geography of knowledge spillovers: Evidence from inventor- and examiner-added citations", *Review of Economics and Statistics*, 88(2), 383-389.
Trajtenberg, M. (1990), "A penny for your quotes: Patent citations and the value of innovations", *RAND Journal of Economics* 21(1), 172-87.
Wagner, R.P. (2002), "Reconsidering estoppel: Patent administration and the failure of Festo", *University of Pennsylvania Law Review*, Vol. 151.