Estimating the Patent Premium: Evidence from the Australian Inventor Survey*

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1 Introduction

Economists and policy makers have long understood that investment in innovation—the engine of long run productivity growth—is sub-optimal in a competitive market. For this reason, governments around the world employ an array of policies in order to stimulate and support innovation. Common policy approaches include funding R&D within government agencies, or the higher eduction sector, as well as R&D subsidies to private firms, grant programs and fiscal (tax) incentives. Across the OECD, governments typically fund between 10 and 20 percent of total business investment in R&D.[1] Legally enforceable intellectual property rights, and patent law in particular, also provide an implicit subsidy for innovative activities; that is, a transfer from technology consumers to technology owners.[2] In this paper, we take a closer look at the implicit subsidy provided to inventors by the Australian patent system, based on analysis of novel survey data on almost 1500 Australian inventions.

Existing estimates of the commercial and economic value of patents and the technology they protect has been predominantly based on analysis of patent renewal data (Gronqvist 2009; Deng 2007; Lanjouw 1998; Pakes 1986; Sampat and Ziedonis 2004; Schankerman 1998), or by considering the influence of patent ownership on firm value (or Tobin's Q) (Griliches 1981; Hall et al. 2005; Bessen 2007; Hall and MacGarvie 2007). A final approach relies on firm and inventor surveys to examine the value, distribution and importance of patent protection (Mansfield et al. 1981; Mansfield 1986; Taylor and Silberston 1973; Harhoff et al. 1999; Harhoff et al. 2003; Gambardella et al. 2008).

Our analysis uses data drawn from the Australian Inventor Survey 2007 (AIS-07), which surveyed all Australian patent applicants from 1986 to 2005. In the survey, inventors

[1] Figures for 2005 or nearest available year including both tax incentives and other direct subsidies, calculated from OECD (2008a, 2008b)

[2] Of course, the patent system also results in static deadweight loss as well as other positive and negative externalities, which we do not consider here.

were asked to estimate the monetary value generated by their inventions, *inter alia*. A major difference between our study and other inventor surveys (see Harhoff et al. 1999 and Gambardella et al. 2008) is that we survey *patent applicants* rather than *patentees*.[3] Since some patent applications were unsuccessful, we have information about the private value of both patented and unpatented inventions. Moreover, there is considerable variation in the commercialization outcomes—and therefore profit streams—across patented and unpatented inventions. This variation is the key to our empirical identification of the patent premium. In order to identify a 'pure' patent premium, we attempt to disentangle invention quality from returns to patent protection.[4] Since we do not have independent evaluations of invention quality (as in Moser 2007), we rely on information such as whether the inventor rated the invention as 'radical' or 'incremental' to control for systematic differences in the technological characteristics of patented and unpatented inventions.

In light of this, our paper makes a number of contributions to the existing literature. First we present estimates of the private (monetary) value of Australian inventions. These estimates contribute to the small number of existing studies on European and US invention values. Our second, and most important, contribution is to develop a unique empirical approach to identifying the patent premium and hence the implicit subsidy provided by the patent system. In doing so, we construct a counterfactual based on a sample of inventions drawn from the population of *potentially patentable* inventions, as indicated by the applicant's decision to apply for a patent. Since our estimated patent premium is conditional on a patent application being made, inventions for which it is optimal to appropriate returns via secrecy are not included in the analysis. Finally, our paper provides estimates of the heterogeneity of the patent premium across technology

[3] Another important difference is that the PatVal-EU survey used by Gambardella et al. (2008) is based on a large sample of inventors, while our survey was sent to the population of Australian patent applicants.

[4] An important qualification is that our 'pure' patent premium will capture returns to patent thickets and defensive patenting.

areas. Given that firms choose their intellectual property management strategies from a range of different appropriation mechanisms—which are well-known to vary in their effectiveness—an estimate of the patent premium has important implications for the strategic management of inventive activity.

Some caveats are appropriate. First, as with all survey data, it is possible that inventors systematically inflate the self-reported monetary value of their inventions. Our estimates of the patent premium would be biased if such optimism is more pronounced for successful patent applicants. Second, disentangling the value of the patent from the quality of the invention is difficult to do. Despite our best efforts, we recognize that we may have conflated invention value and the patent premium to some degree. Third, we focus solely on inventor and technological characteristics and not on complementary assets within the firm which are known to be important, particularly with regard to licensing issues (see, e.g., Arora and Ceccagnoli 2006). Similarly, we do not observe firms' willingness to enforce their patents, which is an important determinant of the private returns to patenting (see Lanjouw 1998; Lanjouw and Schankerman 2001 for discussion).[5]

2 Background

The patent system functions by enabling innovators exclusive control over their intellectual assets. Patent holders are able to charge above marginal cost and thereby accrue rents. However, patents are just one of many different appropriation mechanisms—including trademarking and branding, moving down the learning curve, and trade secrecy—that are available to firms trying to appropriate their investments in innovation. Since the pioneering work of Levin et al. (1987) and Cohen et al. (2000), it

[5]Since the cost of enforcing a patent right is borne by its owner, not by the state, the patentee must spend money to detect (and stop) infringement. The private returns to patent protection are therefore contingent on the credibility of the patentee's threat to take court action against the alleged infringer. This may be a function of firm size or patent portfolio size, both of which are unobserved.

has been well-known that the effectiveness of different appropriation mechanisms varies greatly across technology areas. This tends to suggest that patents may only be necessary for effective commercialization in a few technology areas including pharmaceuticals and chemicals, where the technology is highly codified (and therefore easy for rivals to replicate) (see Harabi 1995).

In order to understand returns to patenting, it is important to distinguish between the underlying value of an invention and the value of patent protection. The value of an invention is defined as the discounted flow of profits that it generates over the course of its economic life. This can be thought of as a function of the willingness to pay for an invention or the 'quality adjusted R&D' that went into its production (Bessen 2007). The value of patent protection are the returns over and above that which could have been generated by the second best means of appropriation (Schankerman 1998; Lanjouw 1998). This implies that, in the absence of patent protection, firms are able to generate some returns using alternative means of appropriation.[6] The value of patent protection can be defined as the *incremental* return (i.e., in dollar terms) or as the *proportional* return to patent protection (i.e., the value of the patent proportional to the value of the invention). The latter has been defined as the "patent premium" by Arora et al. (2008) and is analogous to Schankerman's (1998) "effective subsidy rate".

Existing approaches which estimate the value of patent protection can be divided into three streams. The first stream relates to surveys of firms and inventors, which have generally indicated that patenting ranks near the bottom of all appropriation mechanisms (see Levin et al. 1987; and Cohen et al. 2000). Similarly, Mansfield and collaborators (1981; 1986) found patent protection to be important in the commercialization of a minority of innovations (see also Taylor and Silberston 1973). Results from recent inventor surveys have generated estimates the value of patented inventions and have demon-

[6]In some instances firms may prefer secrecy (or other means of appropriation) to patenting. But if they choose to apply for a patent, we infer that patenting must be the best option for that particular invention since the option of using secrecy is foregone once disclosure occurs.

strated that the distribution of returns is highly skewed (for example, Gambardella et al. 2008).

A recent study by Arora et al. (2008) develops a model of innovation and patenting which enables them to directly estimate the patent premium and its impact on R&D investment based on the the Carnegie Mellon Survey data. They model the patent premium as consisting of a fixed firm component as well as an idiosyncratic component and then jointly estimate the firm's R&D productivity, patent propensity and patent premium. They show that the mean premium is positive in only a few industries, but that conditional on patenting, the premium is, on average, 0.5.

The second stream involves imputing the value or incentive effect of patents from the behavior of patent owners (patent renewal studies). In a seminal contribution, Schankerman and Pakes (1986) estimated the value of patent rights based on patterns of renewals (see also Sampat and Ziedonis 2004; Deng 2007; and Gronqvist 2009). The premise of this approach is that firms will only renew their patent if the value of patent protection, over the renewal period, is larger than the renewal fees. The method involves estimating parameters that describe the distribution of initial value of patented inventions as well as depreciation rates that best predict the observed patterns of renewals.[7] The resulting estimates reflect the incremental monetary value (rather than proportional increase) of patent protection. Additionally, it is generally acknowledged that the highly skewed distribution patent values make finite sample estimation unreliable (Bessen 2007). Schankerman (1998) generates an estimate of the effective subsidy rate by dividing his estimates of the value of patent protection by the the total R&D expenditure "used to produce those patents" (p.95). In practice, however, patent rights are simply divided by aggregate R&D expenditure in the previous year, giving an average estimated effective subsidy rate of 0.25.[8]

[7]Typically these estimates have assumed that depreciation rates are constant across all technology classes.

[8]See similar analysis by Lanjouw (1998) for West German patents.

The third stream infers the value of patent protection from the behavior of investors via the market value of firms and R&D investment. Examples of this approach include Griliches (1981); Hall et al. (2005); Hall and MacGarvie (2007); and Bosworth and Rogers (2001). This approach extracts estimates of the value of patented inventions based on firm values or Tobin's Q. Early efforts using this approach did not attempt to distinguish between the value of patent rights and the value of the patented invention. However, Bessen (2007) suggests that, in principle, the *incremental* value of patent rights can be isolated if we can control for the firm's total quality-adjusted technology stock.

3 Survey Data and Empirical Approach

Data for this study were drawn from the Australian Inventor Survey 2007 (AIS-07). The AIS-07 involved sending a questionnaire to every Australian inventor who a submitted patent application to the Australian Patent Office between 1986 and 2005.[9] [10] Given that some inventions have multiple inventors, and some inventors were involved in multiple inventions, the relationship between inventor and invention is many-to-many. To deal with this, surveys were sent to each listed inventor on a patent application.[11] Where an inventor had multiple inventions, the survey asked them questions regarding a maximum of five inventions. In order to increase the response rate, we conducted two separate mail-outs of the survey—those inventors who had not responded to the initial survey in July 2007 were re-sent the questionnaire in December 2007.

[9]As in the PatVal-EU survey, we sent the survey to the inventor rather than the owner of the invention. While it is possible that the inventor knows less than the owner about commercialization outcomes, Gambardella et al. (2008) compare the value estimates from a sample of French inventors and patent owners and find that the bias introduced is negligible. We have no reason to believe that such a bias is any larger in Australia.

[10]Since our sample was derived from an attempt to enumerate *all* inventions in the population, oversampling to provide more information with regard to the thin tail of highly valuable inventions (as per the PatVal-EU survey) is irrelevant. However, it is possible that successful inventors were more likely to respond to our survey than unsuccessful inventors. If this is true, there may be some non-response bias with regard to invention values.

[11]In most cases only one response was received per invention. Where multiple surveys were returned on the same invention, only one (randomly selected) response was included in the analysis.

The AIS-07 questionnaire included a comprehensive set of inventor- and technology-specific characteristics and a range of outcomes at different stages of commercialization including product development; make and sell; mass production; export; and licensing and spin-off. The inventors were asked a series of questions about the invention; for example, whether the invention was radical or incremental, the inventor's previous experience with patenting, whether the inventor was aware of any rivals trying to copy the invention, and the complexity of the final product (i.e. how many patents were required to produce the final product). Most importantly for this study, the AIS-07 included a set of questions relating to the private monetary value of the inventions. Answers to such questions capture the value of the invention, the returns to patenting and any returns to the construction of patent thickets.

In total, there were 43,200 inventor-application pairs in the population for which we had a complete address and inventor name. These applications related to 31,313 unique patent applications (i.e., inventions). On the basis of the number of surveys returned to us unopened (and a post-enumeration survey of non-respondents), we estimate that there were 5,446 inventions with valid addresses at the time of the mail-out.[12] We received completed questionnaires relating to 3,736 unique inventions.[13]

In total, the sample has 2,501 observations with non-missing invention values. A subset of 379 observations with missing information on other explanatory variables in our empirical model are excluded, leaving a total of 2,122 observations. A further 645 applications were pending at the time of survey, i.e., these applications were still under examination by the patent office. In deriving our main results, we removed these 645 observations from the sample because our primary focus here is on the identification of

[12]The low proportion of inventions with valid inventor addresses is a result of the fact that the survey included patent applications dating back to 1986. Since the administrative database at the Australian Patent Office does not have a mechanism that updates inventors' contact details in any systematic manner, we were not able to contact inventors whose contact address had changed for any reason (e.g. job change, retirement, or changes in personal circumstances. Moreover, some inventors had passed away since the patent application was made.

[13]For more details of the AIS-07, including estimated response rates, see Webster and Jensen (2009).

the premium associated with a patent grant.[14] This leaves us with a final sample size of 1,477 inventions.

Survey responses came from inventors in a wide range of employment arrangements: more than half were employed in companies (47.1 percent) or public sector research organizations (6.3 percent). The residual (46.7 percent) were individual inventors. The inventions in the sample of survey respondents covered a broad cross-section of different technology areas, which were classified using the OST-IPC technology concordance. The distribution by technology area suggests that our sample is broadly representative of the population of patent applications.

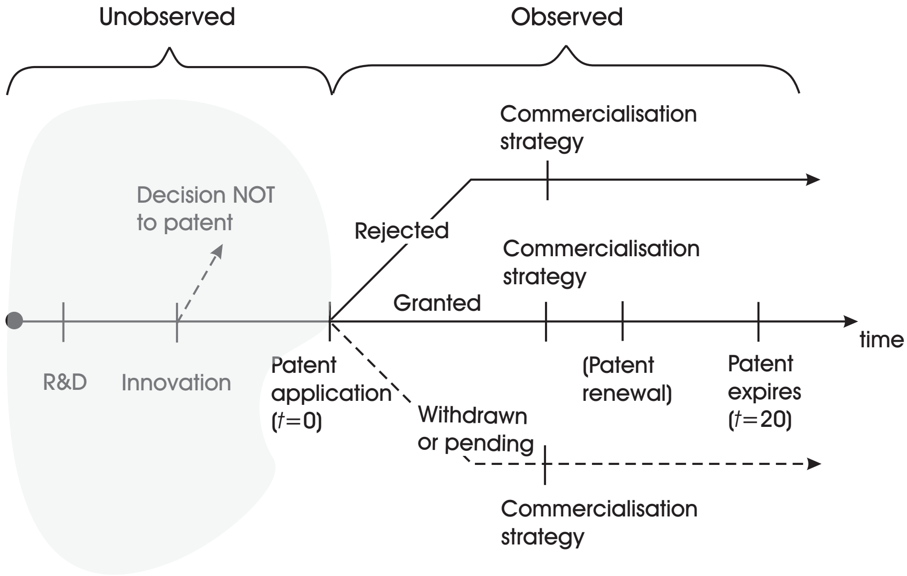
Since the AIS-07 was sent to the population of patent applicants, our sample of respondents includes a large number of inventors whose patent applications were ultimately unsuccessful. Thus, our data set includes a mix of inventions, some of which passed the novelty and non-obviousness tests imposed by the Australian Patent Office and some of which did not. By applying for a patent the inventor has signalled that, to the best of their knowledge, the qualitative nature of their technology meets the patentability criteria, i.e. it is *potentially patentable*.

In applying for a patent the inventor has disclosed details of their invention and thereby foregone the possibility of relying on secrecy to appropriate returns. This indicates that our sample only includes inventions for which patenting was considered to be the best option. If secrecy was the best option, the inventor would not have applied for the patent in the first place (Moser 2007). As a corollary, it suggests that our estimates are an upper bound of the *ex ante* value of patent protection since it may be harder to appropriate returns without patent protection once disclosure has occurred (Horstmann et al. 1985; Schankerman 1998).

[14] However, our results are not sensitive to the exclusion of pending applications. See the Appendix for details.

To illustrate our empirical approach to identification of the patent premium, consider the following stylized representation of the innovation timeline. Our period of analysis starts at the observed date of patent application ($t = 0$) which corresponds to the year of the first cohort of patent applications in 1986. Prior to this, the inventor has engaged in some R&D activity which resulted in the development of an innovation. However, we do not observe this activity, nor do we observe the inventor's decision about which innovations to patent.

Figure 1: Innovation Timeline



Following the patent application, we observe a range of patent examination outcomes: whether the patent was granted (and renewed), rejected, withdrawn or is still pending. We also observe the commercialization stages attempted by the inventor and the estimated value generated by the invention. Many of the inventions underlying the unsuccessful patent applications were, in fact, commercialized with varying degrees of success. Thus, we have variation in both patent grant outcome (grant/reject) and commercialization outcome (success/failure). The time period of our analysis, which ends in 2007, takes us to the end of the legal life of patents granted in 1986 and 1987 ($t = 20$).

In principle, an invention can continue to generate value *after* the end of the patent period. However, in most cases, the economic life of an invention is shorter than the legal life.[15]

4 Estimates of Invention Value

The value of an invention is defined as the discounted flow of profits that accrues to its owner over the course of its economic life. However, invention value is difficult to measure in practice. Economists would normally approach this problem using prices observed in market transactions, which reflect the expected value of the invention (adjusted for risk). The problem with this approach is that the vast majority of patents are not traded in an open market.[16] An increasingly popular alternative—and the one we adopt in this paper—is a survey instrument where inventors are asked to estimate the value of their invention.

One difficulty with the use of surveys to measure invention value arises because the flow of profits may occur over a long time horizon. What we observe in most inventor surveys, however, is simply a lump sum estimate of value (which is recalled *ex post*). We do not observe when the profit flow starts or stops, nor do we observe how (or whether) the inventor calculated the discounted value. Since most inventor surveys include a sample of inventions of different age and rates of depreciation, the estimates of value are quite noisy. The PatVal-EU approaches this problem by asking inventors to evaluate the expected future stream of profits "at the time the patent was issued". However, it could be difficult for a survey respondent to fully comprehend the meaning of expected

[15]More than half of the 1992 cohort of USPTO patents were not renewed to their full term (Hegde and Sampat 2007).

[16]Recent papers such as Serrano (2006), and Sneed and Johnson (2007) have examined patent transfers (via auctions) in order to understand the market for patents. Although Serrano (2007) shows that almost 20 percent of patents held by small firms in the United States are traded at least once in their life, this is still a very small proportion of all patents (since the vast majority of patents are taken out by large firms and are not traded).

future profit streams, let alone make the calculation accurately.

The approach we have employed is to separate historical returns (i.e. those returns generated up to the time of the survey in 2007) from the residual value (i.e. the discounted value of expected future profits after 2007) of the invention. This eases the computational burden imposed on the inventors and enables us to evaluate the sensitivity of our results to the limitations of the different measures of invention value. Specifically, we asked patent applicants the following three questions:

[i.] "To date, what is your estimate of sales revenue from products and processes using this invention?"

[ii.] "If this patent has been licensed, what is your best estimate of licensing revenues to date?"

[iii.] "If you were selling this patent or invention today, what price would you be willing to accept for it?"

In each case, the survey respondent had to select from six possible value ranges (all in Australian dollars): below \$100,000, \$100,001–\$500,000, \$500,001–\$1million, \$1–\$2 million, \$2–\$10 million, above \$10 million. To convert the responses to numerical values, we took the midpoint of each interval. Since the highest value category (above \$10 million) is unbounded, we imposed an upper bound of \$50 million.[17]

Question (i) is a backward-looking measure of sales revenue generated, which we assume is correlated with the profit stream generated by the invention. It may however be a weak measure of process (as opposed to product) invention value since processes are more likely to be used in-house and therefore do not generate easily attributable sales revenue. Moreover, process inventions are likely to affect cost (or productivity) rather

[17] Acknowledging a degree of arbitrariness in this upper bound, we also completed all results using values \$100m and \$200m. These variations did not change the estimation results reported in this paper.

than sales. Question (ii) is a backward-looking measure of licensing revenues. It will pick up the value of both product and process inventions since both types of invention are commonly licensed.[18]

Question (iii) is forward-looking and captures the expected residual value of the invention. That is, it captures that the inventor's expectation regarding the proportion of the total value still available at the time the survey was sent to the inventor (2007). Since inventions in the sample are a mix of ages, the inventions will be heterogeneous in the proportion of value lost already to depreciation and obsolescence. It is important to note that Question (iii) overcomes some of the computational burden imposed on inventors by simply asking them to estimate the selling price *at the time of the survey.* This also means that our forward-looking measure of value is in constant (2007) prices. In light of the difficulties in collecting invention value it is reassuring that responses to question (i) and question (iii) are positively correlated.[19]

To estimate invention value, we use information from responses to all three questions. Since Question (i) is revenue- rather than profit-based, we arbitrarily set the gross margin for goods and services produced using an invention to be 30 per cent.[20] We then add the three components of value together to construct the private invention value, which we denote *InvVal*.[21]

Figure 2 depicts the distribution of estimated private invention value in our sample (*InvVal*). Since recent patent applications are more likely to be in the "pending" cat-

[18]Questions (i) and (ii) may not be mutually exclusive.

[19]The raw correlation is 0.33. In a log on log regression model controlling for year of application (and therefore obsolescence), the coefficient on the (log) response to question (iii) is 0.5, with a t value above 25.

[20]We have also checked our results by taking the value of an invention at 100 per cent of the revenue of all goods and services sold. This variation produces essentially the same results.

[21]With regard to the licensing revenue component, we set the value to zero if the respondent did not answer the question on licensing or was unsure of the amount. Thus the licensing revenue is probably an understatement of the revenue from licensing. Also note that we ignore any issue associated with the transaction costs of licensing.

egory and their value is truncated, we exclude these observations from our analysis.[22] The distribution of value is highly skewed to the right; the mean and median invention values in our sample are \$6.3 million and \$800,000 respectively. The observed skewness of the distribution is consistent with other inventor surveys such as the PatVal-EU survey. In fact, the mean invention value in the PatVal-EU survey was 11 million euros, and the median value was 650,000 euros (see Gambardella et al. 2008).

Figure 2: Distribution of Private Invention Values in Australia

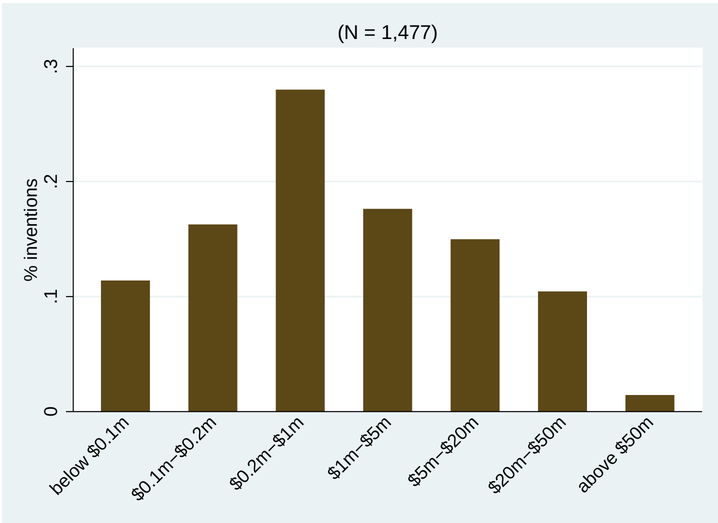


Table 1 shows that the distribution of invention values varies across different technology areas, which were classified using the UK Office of Science and Technology (OST) classification. Given the observed skewed distribution, the median values are more representative than the mean values. In terms of the median, the highest value technology area is metals and metallurgy (\$7.2 million), followed by information technology (\$6 million). The lowest value technology area is agriculture and food machinery which has a median value of \$340,000.

As a check on the consistency of our estimated invention values, Table 2 presents the distribution of invention values by commercialization stage. Recall that we asked in-

[22] As a robustness check, we also undertook the analysis on the full sample, including those categorized as pending. This did not change the results presented in the next section.

Table 1: Private Invention Values by Technology Area

OST	Median	Mean (A$'000)	Std. dev.	N
Electrical devices–electrical engineering	538	9,403	18,281	36
Audiovisual technology	815	7,459	14,027	19
Telecommunications	365	4,054	10,015	34
Information technology	6,071	17,401	20,485	50
Optics	3,706	13,431	19,354	14
Analysis, measurement, control	758	5,822	10,271	74
Medical engineering	800	5,922	12,439	65
Organic fine chemicals	765	741	619	7
Macromolecular chemistry, polymers	115	2,372	4,592	5
Pharmaceuticals, cosmetics	2,925	11,278	17,258	32
Biotechnology	365	3,135	7,791	17
Materials, metallurgy	7,200	11,232	14,622	11
Agriculture, food	1,565	10,777	14,987	21
General processes	1,670	9,260	15,452	68
Surfaces, coatings	2,550	10,963	13,237	9
Material processing	2,100	7,790	11,654	31
Thermal techniques	440	4,100	11,853	39
Basic chemical processing, petrol	1,345	6,526	11,873	28
Environment, pollution	3,350	9,735	13,458	21
Mechanical tools	815	4,671	8,645	38
Engines, pumps, turbines	1,658	11,377	14,608	44
Mechanical elements	820	3,506	6,867	62
Handling, printing	765	6,994	15,224	104
Agriculture/food machinery	340	3,278	7,299	104
Transport	500	4,946	9,899	113
Space technology, weapons	800	2,642	4,303	7
Consumer goods & equipment	470	5,269	12,622	172
Civil engineering, building, mining	765	4,501	10,336	252
All obs.	800	6,345	12,665	1,477

ventors to record which stage of commercialization was attempted. Although we do not use this information in our empirical analysis, one would expect that private value was increasing in the stage of commercialization attempted. That is, the value of an invention which has reached the mass production stage is expected to be higher than one which only made it to the development stage. This is exactly what we observe: Of the 1,467 inventions in our sample with non-missing commercialization stage and invention value information, 345 reached the export stage and had the highest median value of $1.95 million, while the 280 inventions that reached the mass production stage which had a median value of $765,000. This intuitively consistent pattern suggests that our invention value estimates appear to be logical in their ordinal ranking.

Table 2: Private Invention Values, by Commercialization Stage

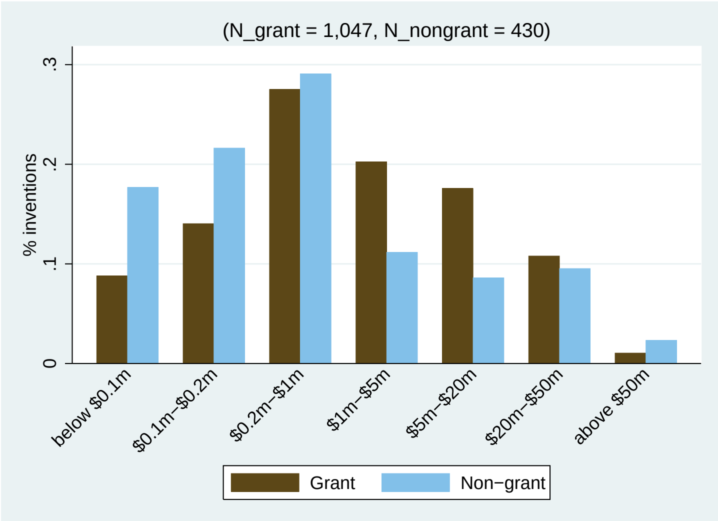
Commercialisation stage	Median	Mean	Std. dev.	N
	Invention values			
	A$'000			
No commercialisation attempt	345	5,691	15,065	74
Development attempted	365	6,410	13,680	197
Manufacturing attempted	690	5,507	11,817	571
Reached mass production	765	6,162	12,470	280
Products/services exported	1,950	7,865	12,860	345
Total	800	6,317	12,644	1,467

What is particularly interesting in our results is the difference in invention value by patent grant status, which is presented in Figure 3. Comparing inventions with and without a patent grant, it is clear that there are proportionately more valuable inventions (above $1 million) among those inventions which are protected by a patent. However, inventions not protected by patent are still highly valuable. The difference between the mean value of the patented and non-patented inventions is only 9.4 percent.[23] Therefore, we conclude that patented inventions are more valuable, but that unpatented inventions are far from worthless. This is somewhat surprising given the argument that inventions without patent protection are likely to be worth less once disclosure has occurred. This

[23]The mean values are $6.5 million and $5.9 million for patented and unpatented inventions respectively.

result clearly indicates that the second best means of appropriating returns are still quite effective.

Figure 3: Distribution of Private Invention Value, by Patent Grant Status



5 Empirical Model

Let V_{ij} denote the total private value of invention i in technology area j, $i = 1, \ldots, n_j$ and $j = 1, \ldots, J$. To capture the effect of patents on invention value, we specify a linear model where the value of an invention depends on whether a patent was granted (conditional on a patent application being made).

$$\ln V_{ij} = \alpha G_{ij} + X\beta + \delta_j + \varepsilon_{ij}, \tag{1}$$

where G_{ij} is a binary variable taking the value of unity if a patent has been granted and zero otherwise, X is vector of additional explanatory variables, δ_j is a technology-specific term, and ε_{ij} is the residual error term. We model the technology-specific term, δ_j, in two ways. In the 'fixed intercept' model, δ_j is modeled with a technology-specific dummy variable, which takes the value of unity if the invention is in technology area j, and zero otherwise. In a second specification, which we call the 'random-intercept' model, δ is assumed to be a random variable and follows an identical and independent normal distribution with mean zero and variance σ_{δ}^2.

One of the most difficult aspects of estimating the patent premium relates to the separation of the value of patent protection from the underlying characteristics of the technology. If inventions that are granted a patent generally have higher commercial value, our estimates of the patent premium would be biased. In determining whether an invention is patentable, the patent office considers whether the invention relates to patentable subject matter and whether it is useful, novel and non-obvious. Thus, the patent examiner evaluates the invention's technological merit, and does not take into consideration its expected economic value. Empirical evidence suggests that a large proportion of patented inventions have very low (or zero) commercial value (see Harhoff 1999; Gambardella 2008). Conversely, there are many examples of inventions with substantial commercial value that are not covered by a patent - an observation supported by the preceding results. However, it remains a possibility that there are other characteristics of the underlying technology which determine the value of the invention (and are associated with the patentability requirements).[24] [25]

While it is not necessarily the case that inventions which have the technological characteristics will be systematically more valuable than those deemed not patentable, it remains plausible that this may be the case. To investigate this issue further, we first employed a Heckman-type sample selection model. We estimated the first stage selection equation using maximum likelihood and the resulting estimates fail to reject the null hypothesis of no sample selection (the full results of which are included in the attached Appendix). However, the results of the selection equation are sensitive to the specification and the instruments used.

[24]Hegde and Sampat (2007), for instance, demonstrate that examiner-inserted citations (which proxy technological value) are a good predictor of renewal (which proxies economic value).

[25]One important feature of our empirical approach is that our sample only includes inventions that, in the view of the applicant, involve patentable subject matter and have the potential of passing the criteria of novelty and non-obviousness.

Taking these factors into account, we proceed using a reduced-form approach which includes additional variables to control for characteristics of the technology which may be correlated to invention value. First, we include a dummy variable, *Radical invention*, which relates to whether the inventor rated their invention as 'radical' or 'incremental' relative to the existing state of the art. Second, we construct a variable related to the number of products and processes for which the invention was used, which is denoted as *No. of uses*. This is expected to be be positively correlated with value because the more potential uses an invention has, the more licenses can be signed and the higher is the expected cumulative revenue. Although this is probably a noisy relationship (since there are many single-use inventions which have high commercial value), it seems reasonable to expect *a priori* that value is an increasing function of the generality of the invention, *ceteris paribus*.

Third, we include a variable *Other inventions used* to proxy for the complexity of the technology area. This variable is based on the survey question which asked the inventor how may other patents were used to develop the product. The expected sign of this variable is unclear since it could be the case that complex technologies are more valuable (i.e. there is a positive association with value) or it could be that transaction costs associated with negotiating with other patent owners in complex technology areas erodes the value of the invention (i.e. there is a negative association with value). The net effect of these two forces depends on who owns the other patents required to develop the product, something which we did not observe in our survey. In instances where the surveyed inventor also owns the other patents required to develop the product, transaction costs will be zero.

We also include a dummy variable, *PCT application*—whether the application was made through the Patent Cooperation Treaty (PCT). This accounts for the fact that the invention may have patent protection in other legal jurisdictions, even if the patent application was rejected by the Australian Patent Office.

For the dependent variable V_{ij}, we employ two alternative measures that capture different aspects of invention value. Our principal estimate of invention value is denoted by *InvVal* and was discussed previously. As an alternative, we consider a model based on the forward-looking profit-based measure of value (Question iii) as a dependent variable, which we denote as *FInvVal*. We do this in an attempt to ascertain the robustness of our previous result and the *ad hoc* assumption that costs are uniformly the same (70 percent) across all inventions. In particular, if the proportion of revenue which is profit varies systematically with patent protection, our use of a fixed proportion may downward bias our estimate of the patent premium. Each model includes patent application year dummies (equivalent to invention age). In the primary model, these dummy variables capture technology or business cycle effects. Using the alternative dependent variable, they also capture the effects of depreciation.

In the basic version of our model, the patent premium is captured by the coefficient α of the variable *Granted* in (1). This dummy variable equals one for patent applications that were granted, and equals zero if the application was refused, withdrawn, lapsed or revoked.[26] As such, the variable takes a broad definition of 'non-grants' in that it includes all patent applications that were either unsuccessful or were removed from the examination process by the patent office (or the applicant). The key point is that all the inventions categorized as 'granted' have patent protection and that all inventions categorized as 'non-grants' do not have patent protection. The size and sign of the coefficient of the variable *Granted* tells us whether the protection offered by a patent increases (and by how much) the inventor's returns, *ceteris paribus*. Given that the dependent variable is in logarithms, we interpret α as the proportional increase in invention value that is due to a patent grant. Table 3 lists the variables we used in the estimation, and some descriptive statistics.

[26]Pending applications are excluded from the analysis. However, we did run the model with pending applications included and the results did not change in any substantial way. See the Appendix for details.

The base model is extended in several ways by using different measures of invention values, the inclusion of pending applications, and by a different transformation of the dependent variable.[27] An important extension is to allow the effect of a patent grant to vary by technology area. This is an important consideration because the existing evidence tends to suggest that patents may be more effective in appropriating returns from inventive activity in highly codified technology areas (see Harabi 1995; Cohen et al. 2000).

For the fixed-intercept model, we introduce interaction terms between the two variables G_{ij} and OST technology area dummy d_j, so that (1) becomes:

$$\ln V_{ij} = \alpha G_{ij} + \alpha_j (G_{ij} \times d_j) + X\beta + \delta_j + \varepsilon_{ij}, \quad j = 1, \ldots, J-1. \tag{2}$$

Thus the effect of a patent grant on an invention in technology area j is given by $\alpha + \alpha_j$, which varies by technology area. The estimation results are discussed in the next section.

6 Results

In our base model (1), we estimate specifications with both fixed- and random-intercepts. The results from both of these models are reported in Table 4. In the fixed-intercept model, the main explanatory variable of interest is the dummy variable *Granted*. The main result is that, under the fixed-intercept estimation, inventions which are protected by a patent are 47 percent more valuable than inventions without a patent, *ceteris paribus*; whereas the patent premium is estimated to be 44 percent under the random-intercept model. This implies an average implicit subsidy of around \$2 million and that the equivalent subsidy to the median patented invention is \$256,000.[28] Since approximately 2000 patents are granted each year in Australia,[29] our result suggests that in 2005

[27] We report most of these results in the Appendix.

[28] Given by 0.47/(1+0.47)x (average/median patented invention value).

[29] This figure is estimated based on the 2645 applications in 2005, as reported in Jensen and Palangkaraya (2008) multiplied by the average proportion of applications that are ultimately granted

the patent system reflected an implicit subsidy to innovators of about \$4 billion. This is approximately 5 times larger than the combined value of the \$425 million contributed by the government through tax incentives (IA 2007) and the \$420 million via subsidies, grants and procurement (ABS Cat. 8104.0).

The coefficients of the other explanatory variables are consistent with *a priori* expectations. For example, the variables *Radical invention* and *PCT application* are both positively associated with value. In addition, the results support the notion that inventions which have many uses are positively correlated with higher value. The results from the random-intercept model are remarkably consistent with those from the fixed-intercept specification, so are not discussed in any detail.

We next extend the model by allowing the coefficient of grant status to vary by technology areas. For the fixed-intercept model, we include the interaction terms of patent grant status and technology areas in the estimating model. The corresponding extension of the random-intercept model is a random coefficient model in which a random term is included in the coefficient of grant status. The results are reported in Table 5. In each case we perform a statistical test of whether the effect of a patent grant varies by technology areas. For the fixed-intercept model with interaction terms, the joint test of all interaction terms gives an F test statistic of 0.94, which has a p-value of 0.55. In the case of the random coefficient model, we test the random coefficient model against the random intercept model by a likelihood ratio test. The χ^2 test statistic is 2.25, which at 2 degrees of freedom yields a p-value of 0.32.

Thus we find no evidence to suggest that the effect of a patent grant is different across technology areas. This is somewhat surprising given the empirical support in other studies that suggests patents are more valuable in pharmaceuticals and chemicals than

(0.8). Note that the number of patents applied for each year has been increasing over time, particularly in recent years. It is too early to tell if the increases in applications will result in a commensurate increase in the proportion of patent applications granted.

Table 3: List of Variables and Summary Statistics

Variable	Explanation	Mean	Std. dev.
ln(InvVal)	Private value of invention in logarithm	6.913	2.016
ln ln(InvVal)	Private value of invention in double logarithm	1.891	0.294
ln(FInvVal)	Forward private value of invention in logarithm	6.209	2.089
No. of uses	No. of products/processes for which invention was used	1.357	1.011
Other inventions used	No. of other inventions used in development	0.351	0.604
No. inventors	No. of inventors involved	1.238	0.707
Company affiliation	Proportion of inventors with company affiliation	0.396	0.489
Radical invention	dummy, (=1 if invention was radical relative to state of art)	0.641	0.480
PCT application	dummy, (=1 if PCT application)	0.318	0.466
Granted	dummy, (=1 if patent application granted)	0.709	0.454
Lapsed	dummy, (=1 if patent application lapsed)	0.278	0.448
Expired	dummy, (=1 if application expired or ceased)	0.243	0.429
RWR	dummy, (=1 if application revoked, withdrawn or refused)	0.013	0.113

Table 4: Estimation Results: Fixed- and Random-intercept Models

	Fixed intercept		Random intercept	
	Param. est.	Std. err.	Param. est.	Std. err.
Dep. variable:	ln(InvVal)			
No. of uses	0.4412**	0.0479	0.4402**	0.0471
Other inventions used	0.4728**	0.0799	0.4676**	0.0791
No. inventors in application	-0.0860	0.0733	-0.1153†	0.0686
Company affiliation	0.3339**	0.1030	0.3510**	0.1013
Radical invention	0.6495**	0.0995	0.6634**	0.0983
PCT application	0.6669**	0.1143	0.6681**	0.1112
Granted	0.4695**	0.1102	0.4404**	0.1089
Intercept	5.5537**	0.5974	5.4533**	0.5846
Log likelihood			-2,934.6	
Adjusted R^2	0.238			
Number observations	1,477			
Number technology areas	28			

Notes: (1) Included in both regression models are 19 year dummies, which denote the year in which the patent application was lodged.
(2) Included in the fixed-intercept model are 27 OST technology classification dummies.
Significance levels: †: 10% *: 5% **: 1%

other technology areas. However, we note that the existing literature does show some inconsistencies. For instance, analysis by Schankerman (1998) finds that the value of patent protection in pharmaceuticals is less than in the case of other technological fields. Nonetheless, we caution that this result is driven by the large variation within technology areas, which suggests that the coefficients of the interaction terms in the fixed-intercept model were estimated with little precision.[30]

As discussed above, a possible objection of using our estimates of total private value (*InvVal*) as the dependent variable in the regression is that if the proportion of revenue which is profit varies systematically with patent protection our use of a fixed proportion may downward bias our estimate of the patent premium. Therefore as a further robustness check, we also implement the same regression models with the forward-looking, profit-based measure of value *FInvVal* as the dependent variable. In this model, year of patent application dummy variables can be thought of as including a combination of technology (or business cycle) effects as well as depreciation. The results are reported in Table 6. The results are remarkably consistent with the previous set of results, suggesting that our results are not sensitive to the definition of invention value.

[30] In an attempt to improve the point estimates of technology area effects, we re-estimated the fixed-intercept model using six major OST technology areas rather than the 30 technology area classifications. In this model, we do find strong evidence that the value of a patent grant varies across technology areas. However, this is a much coarser (and heterogeneous) classification of technology areas. The results are presented in the Appendix.

Table 5: Estimation Results: Effect of Grant Varies by Technology Areas

Dep. variable: ln(InvVal)	Fixed inter. Param. est.	Fixed inter. Std. err.	Random coeff. Param. est.	Random coeff. Std. err.
No. of uses	0.4469**	0.0483	0.4391**	0.0471
Other inventions used	0.4736**	0.0803	0.4730**	0.0790
No. inventors in application	-0.0877	0.0741	-0.1150†	0.0682
Company affiliation	0.3447**	0.1039	0.3406**	0.1011
Radical invention	0.6608**	0.1009	0.6627**	0.0981
PCT application	0.6971**	0.1157	0.6813**	0.1105
Granted (G)	0.8605**	0.2650	0.4034**	0.1210
$G\times$Electrical devices–electrical engineering	-1.3109*	0.6596	–	
$G\times$Audiovisual technology	0.7779	1.0460	–	
$G\times$Telecommunications	-0.8375	0.8958	–	
$G\times$Information technology	-0.7908	0.5707	–	
$G\times$Optics	-0.3974	1.0836	–	
$G\times$Analysis, measurement, control	-0.2082	0.6049	–	
$G\times$Medical engineering	-0.2446	0.5273	–	
$G\times$Organic fine chemicals	-0.7806	1.5087	–	
$G\times$Pharmaceuticals, cosmetics	-0.2660	0.8500	–	
$G\times$Biotechnology	0.6946	1.0476	–	
$G\times$Materials, metallurgy	1.5170	1.8772	–	
$G\times$Agriculture, food	-0.6698	0.8405	–	
$G\times$General processes	-0.9385	0.5744	–	
$G\times$Surfaces, coatings	-1.0996	1.2868	–	
$G\times$Material processing	-1.7980*	0.7516	–	
$G\times$Thermal techniques	-0.5208	0.7018	–	
$G\times$Basic chemical processing, petrol	-0.7774	0.8173	–	
$G\times$Environment, pollution	-0.4468	0.8641	–	
$G\times$Mechanical tools	0.7789	0.6714	–	
$G\times$Engines, pumps, turbines	-0.1623	0.6144	–	
$G\times$Mechanical elements	-0.8273	0.6108	–	
$G\times$Handling, printing	-0.9313*	0.4712	–	
$G\times$Agriculture/food machinery	-0.5461	0.4442	–	
$G\times$Transport	-0.6393	0.4376	–	
$G\times$Space technology, weapons	0.1695	1.5087	–	
$G\times$Consumer goods & equipment	0.0207	0.3900	–	
Intercept	5.2882**	0.6268	5.4486**	0.5881
Log likelihood			-2,933.5	
Adjusted R^2	0.237			
Number observations	1,477			
Number technology areas	28			

Note: (1) Included in both regressions are 19 year dummies.
(2) Included in the fixed-intercept model are 27 OST technology classification
(3) The Omitted reference group for the interaction terms is "$G\times$Civil engineering, building, mining." Another interaction term "$G\times$Macromolecular chemistry, polymers" is omitted due to singularity.

Significance levels: †: 10% *: 5% **: 1%

Table 6: Estimation Results: Forward values as Dependent Variable

	Fixed intercept		Random intercept	
	Param. est.	Std. err.	Param. est.	Std. err.
Dep. variable:	ln(FInvVal)			
No. of uses	0.4127**	0.0497	0.4154**	0.0489
Other inventions used	0.4826**	0.0829	0.4859**	0.0820
No. inventors in application	-0.0592	0.0761	-0.0831	0.0710
Company affiliation	0.1449	0.1070	0.1609	0.1050
Radical invention	0.7356**	0.1033	0.7539**	0.1019
PCT application	0.6772**	0.1187	0.6767**	0.1153
Granted	0.5555**	0.1144	0.5349**	0.1129
Intercept	4.5050**	0.6204	4.2767**	0.6059
Log likelihood			-2,987.9	
Adjusted R^2	0.234			
Number observations	1,595			
Number technology areas	28			

Note: (1) Included in both regression models are 19 year dummies.
(2) Included in the fixed-intercept model are 27 OST technology classification
Significance levels: †: 10% *: 5% **: 1%

7 Conclusions

In this paper, we examine the implicit subsidy provided to innovators via the patent system using data from a comprehensive survey of inventors who applied for a patent in Australia between 1986 and 2005. We use the variation in patent examination outcomes to identify the magnitude of the patent premium. Our results provide strong and robust support for the existence of a patent premium. In fact, on average, the presence of a patent increases the returns to an invention by around 47 percent regardless of how we define "value". We estimate the total monetary value of this implicit subsidy to all inventions to be over $4 billion per year - much larger than the support provided to innovators via direct transfers from the government or fiscal incentives.

These estimates are of obvious importance relating to firm valuation, and technology management. Given that there are a range of different appropriation mechanisms—from trade secrecy right through to keeping ahead of your rivals—which are available to a firm as part of its intellectual property management strategy, it is not clear which mechanism should be used. Part of the answer to this depends on the relative effectiveness of the appropriation mechanisms across technology areas. In this regard, we provide new evidence on the effectiveness of patenting by technology area.

The welfare (policy) implications of our estimates of the patent premium are more complex. Carefully quantifying the magnitude of the benefit of the patent system to individual innovators is certainly a necessary component of policy evaluation, though it is far from sufficient. Importantly, the measure does not capture the social benefits of invention and patent protection (that do not accrue to the inventor). The auxiliary function of the patent system in facilitating the disclosure of technical details (see Denicolo and Franzoni 2004) and in facilitating gains from trade between inventors and developers (see for example, Gambardella et al. 2007) are well recognized. A complete welfare analysis should also consider a range of possible deleterious effects of the patent system. As well as the static deadweight loss resulting from monopoly pricing, recent research has highlighted additional concerns about unintended effects of patent protection including whether patents hinder innovation in complex, cumulative technologies (see Scotchmer 1991; Bessen and Maskin 2009), to the creation of patent thickets (see von Graevenitz et al. 2008; Shapiro 2000), or an anti-commons (Heller and Eisenberg 1998); and the publication of numerous "bad" patents resulting in costly dispute resolution downstream (Sampat 2005; Merges 1999).

This paper attempts to tackle a complex problem using a novel empirical approach. In doing so, we hope to have shed some new light on a fundamental issue frequently asked, but never definitively answered: what is the incremental increase in private value of holding a patent? In tackling such an issue, we acknowledge that there are many dimensions of the problem that we have addressed imperfectly. Foremost among these is that invention value is difficult to measure. We have relied on an increasingly common approach of using an inventor survey, but we are cognisant of the fact that self-reported evaluations of invention value can be problematic. However, in the absence of a perfectly-functioning market for technology (which may never exist), we believe we have made some valuable inroads into understanding how inventor surveys can be used to tackle the identification of the patent premium.

Finally, it is very difficult to disentangle invention quality from patent value. Rather than relying on self-reported proxies of invention quality such as whether the invention was radical (as we have done), it may be better to rely on independent evaluations of the inventions (such as in Moser 2007), although such data are difficult to come by. Future research on this issue might consider alternative ways in which the underlying technological characteristics may be measured.

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Appendix: Variations of the basic model

This Appendix discusses several variations of the basic model of invention value, in addition to the results from a Heckman selection model. We show that, in all variations, estimates of patent premium are remarkably consistent in both magnitude and statistical significance.

Heckman Selection Model

Patent grant decisions are made by patent examiners evaluation of the novelty, non-obviousness and utility of an application. In theory, the decision to grant a patent is based purely on the invention's technological merit, not the invention's expected commercial value. Nonetheless, it is plausible that an invention that greatly advances the state of the art is also likely to have higher commercial value. To test for such selection bias, we estimate a standard Heckman-type sample selection model using the same data as before.

Assume there exists a latent variable that measures the degree of technological merit of an invention according to the patent examination criteria. Let this latent variable be denoted G_{ij}^* and we assume

$$G_{ij}^* = Z\gamma + u_{ij}. \tag{A1}$$

We specify the invention value equation as before, except we assume that this relationship holds if $G_i^* > 0$. That is, for invention i in technological area j, its value is given as

$$\ln V_{ij} = X\beta + \delta_j + \varepsilon_{ij} \text{ if } G_{ij}^* > 0. \tag{A2}$$

We make the following distributional assumptions

A1 $u_{ij} \sim N(0, 1)$.

A2 $\varepsilon_{ij} \sim N(0, \sigma^2)$.

A3 $Cov(u_{ij}, \varepsilon_{ij}) = \sigma_{u\varepsilon}$.

Define ρ as the correlation coefficient between u_{ij} and ε_{ij}. Then a direct test of whether there is any selection effect can thus be formulated as a joint test of whether ρ is statistically different from zero.

We estimate the model using maximum likelihood. The selection equation is identified through four variables that are excluded from the value equation. They are (i) the proportion of public-sector affiliated inventors in a patent application, (ii) the aggregate experience, in years, of all inventors in a patent application, (iii) a time trend t, and (iv) t^2. The estimation results are presented in Table A1.

Table A1: Estimation Results: Sample Selection Model

	Value eq.		Selection eq.	
	Param. est.	Std. err.	Param. est.	Std. err.
No. of uses	0.4222**	0.0531	–	
Other inventions used	0.4301**	0.0873	–	
No. inventors in application	-0.1267	0.0797	-0.0058	0.0635
Company affiliation	0.2789*	0.1306	0.5707**	0.0799
Radical invention	0.5437**	0.1222	0.2762**	0.0747
PCT application	0.7459**	0.1234	–	
Public sector affiliation	–		1.1534**	0.2672
Aggregate experience	–		0.0148	0.0175
t	–		-0.0714	0.0465
t^2	–		-0.0008	0.0019
Intercept	6.4494**	0.5849	1.2183**	0.2826
$\hat{\sigma}$	1.7219			
	(0.0615)			
$\hat{\rho}$	-0.3634			
	(0.1623)			
LR test $H_0 : \rho = 0$	$\chi^2(1) = 2.51$, p-value = 0.11			
Log likelihood	-2,825.1			
Number observations	1,477			

Note: (1) Figures in parentheses are standard errors
(2) Included in the value equation are 19 year dummies and 27 technological area dummies.
Significance levels: †: 10% *: 5% **: 1%

It is worth noting that the likelihood ratio test of no sample selection (i.e., $\rho = 0$) fails to reject the null hypothesis at the usual levels of statistical significance. Thus we fail to find any evidence to suggest that sample selection is an issue in our estimation of invention values. It should, however, be cautioned that our results are sensitive to the specification of the selection equation and the instruments used.

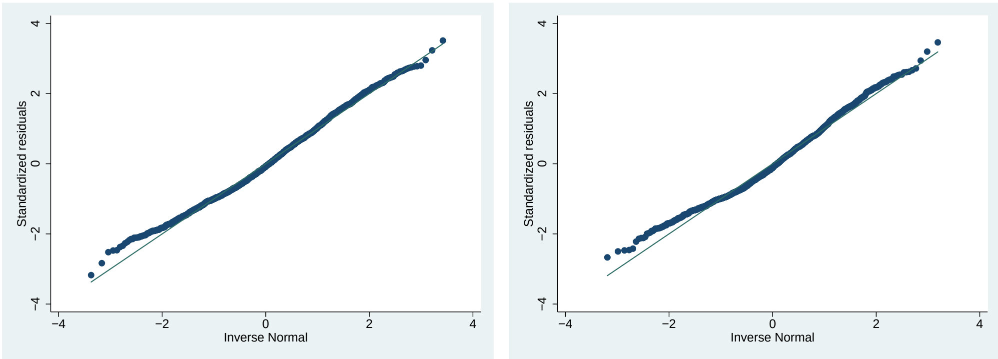
Double Logarithmic Transformation

Given that the distribution of private value is highly skewed, one concern with the basic model is that a simple logarithmic transformation of invention values may result in non-normal errors. We check for non-normal errors using a quantile-quantile plot

(Q-Q plot), which plots the quantiles of the standardized residuals against those of the normal distribution. The plots, as shown in Figure A1, reveal that although most points are on the 45-degree line, some slight departures occur at both tails. We address this

Figure A1: Q-Q plots—standardized residuals of basic models

(a) Fixed intercept residuals (b) Random intercept residuals



concern using a double logarithmic transformation of the dependent variable. That is, we estimate fixed and random intercept models of the following form:

$$\ln \ln V_{ij} = \alpha G_{ij} + X\beta + \delta_j + \varepsilon_{ij}. \tag{A3}$$

The estimation results are reported in Table A2. We note that the signs and statistical significance of the coefficients are unchanged. However, to estimate the effect of a patent grant on invention value, i.e., the patent premium, we note that:

$$\frac{\Delta(\ln V_{ij})}{\Delta G_{ij}} = \exp(\ln \ln V_{ij})\alpha. \tag{A4}$$

The premium is no longer a constant, it is now data dependent. We compute the patent premium for all observations in the sample and report the summary statistics in Table A3.

Table A3 shows that, on average, the presence of a patent grant increases the value of inventions by about 53 per cent and 50 per cent according to the fixed- and random-intercept models, respectively. These estimates are comparable to the corresponding patent premium estimates of 47 per cent and 44 per cent under the basic model.

Table A2: Log-log dependent variable estimation

	Fixed intercept		Random intercept	
	Param. est.	Std. err.	Param. est.	Std. err.
Dep. variable:	$\ln\ln$(InvVal)			
No. of uses	0.0611**	0.0070	0.0608**	0.0069
Other inventions used	0.0654**	0.0117	0.0645**	0.0115
No. inventors in application	-0.0090	0.0107	-0.0138	0.0100
Company affiliation	0.0497**	0.0150	0.0524**	0.0148
Radical invention	0.0959**	0.0145	0.0981**	0.0143
PCT application	0.0998**	0.0167	0.0996**	0.0162
Granted	0.0784**	0.0161	0.0742**	0.0159
Intercept	1.6858**	0.0872	1.6617**	0.0852
Log likelihood			-91.0	
Adjusted R^2	0.235			
Number observations	1,477			
Number technology areas	28			

Notes: (1) Included in both regression models are 19 year dummies.
(2) Included in the fixed-intercept model are 27 OST technology classification dummies.
(3) Significance levels: †: 10% *: 5% **: 1%

Table A3: Effect of patent grants on invention values

OST	Fixed intercept Mean	Fixed intercept Std. dev.	Random intercept Mean	Random intercept Std. dev.	N
Electrical devices–electrical engineering	0.528	0.097	0.504	0.093	36
Audiovisual technology	0.549	0.078	0.528	0.076	19
Telecommunications	0.486	0.054	0.477	0.053	34
Information technology	0.629	0.096	0.570	0.087	50
Optics	0.601	0.089	0.537	0.080	14
Analysis, measurement, control	0.532	0.070	0.508	0.066	74
Medical engineering	0.531	0.074	0.499	0.070	65
Organic fine chemicals	0.473	0.059	0.499	0.067	7
Macromolecular chemistry, polymers	0.443	0.089	0.565	0.107	5
Pharmaceuticals, cosmetics	0.590	0.089	0.540	0.082	32
Biotechnology	0.465	0.056	0.492	0.059	17
Materials, metallurgy	0.601	0.085	0.557	0.082	11
Agriculture, food	0.579	0.064	0.540	0.060	21
General processes	0.565	0.077	0.522	0.072	68
Surfaces, coatings	0.599	0.086	0.485	0.070	9
Material processing	0.585	0.081	0.537	0.073	31
Thermal techniques	0.487	0.061	0.476	0.060	39
Basic chemical processing, petrol	0.552	0.080	0.514	0.075	28
Environment, pollution	0.596	0.117	0.531	0.104	21
Mechanical tools	0.524	0.074	0.494	0.070	38
Engines, pumps, turbines	0.599	0.095	0.553	0.088	44
Mechanical elements	0.516	0.065	0.493	0.063	62
Handling, printing	0.520	0.069	0.492	0.065	104
Agriculture/food machinery	0.480	0.064	0.459	0.061	104
Transport	0.505	0.083	0.485	0.080	113
Space technology, weapons	0.495	0.085	0.490	0.084	7
Consumer goods & equipment	0.494	0.068	0.471	0.065	172
Civil engineering, building, mining	0.509	0.059	0.482	0.056	252
All obs.	0.525	0.083	0.497	0.074	1,477

Including Pending Applications

Recall that the results presented in Table 4 were obtained from a sample that excludes 563 pending applications. These applications were excluded on the ground that majority of them would subsequently be granted a patent, it is not appropriate to classify them as non-grants. In this variation we include these pending applications in the estimation and report the results in Table A4.

As shown in Table A4, the estimates for patent premium are now lower, from around 50 per cent to below 40 per cent. This decline is not surprising, given that we now include as non-grants 563 pending applications, majority of which would eventually be granted a patent.

Table A4: Estimation results including pending applications in sample

	Fixed intercept		Random intercept	
	Param. est.	Std. err.	Param. est.	Std. err.
Dep. variable:	ln(InvVal)			
No. of uses	0.4328**	0.0413	0.4310**	0.0408
Other inventions used	0.4462**	0.0672	0.4507**	0.0666
No. inventors in application	-0.0833	0.0682	-0.0915	0.0656
Company affiliation	0.2974**	0.0868	0.3149**	0.0856
Radical invention	0.7484**	0.0848	0.7551**	0.0840
PCT application	0.6578**	0.0954	0.6605**	0.0931
Granted	0.3861**	0.1004	0.3723**	0.0995
Intercept	5.5208**	0.5981	5.4637**	0.5893
Log likelihood			-4,084.9	
Adjusted R^2	0.233			
Number observations	2,040			
Number technology areas	28			

Notes: (1) Included in both regression models are 19 year dummies.
(2) Included in the fixed-intercept model are 27 OST technology dummies.
(3) Significance levels: †: 10% *: 5% **: 1%

Alternative Definitions of Invention Value

In constructing the invention value in the text, we assumed that the profit margin of the sales revenue from products and processes using an invention is 30 per cent. Here, we do not assume a profit margin, rather we include all sales revenue as part of the invention value. which we refer to as the gross invention value. The fixed- and random-intercept models are re-estimated using this gross invention value. The estimation results are presented in Table A5.

We note that the coefficient estimates reported in Table A5 do not differ much from those reported in Table 4 in the text. In particular, the estimates of patent premium from the fixed- and random-intercept models are respectively 49 per cent and 45 per cent, which compares well with the corresponding estimates of 47 per cent and 44 per cent reported in Table 4.

Table A5: Estimation results using gross invention values

	Fixed intercept		Random intercept	
	Param. est.	Std. err.	Param. est.	Std. err.
Dep. variable:	ln(InvVal)			
No. of uses	0.4405**	0.0486	0.4402**	0.0478
Other inventions used	0.4195**	0.0811	0.4118**	0.0803
No. inventors in application	0.0707	0.0744	-0.1128	0.0693
Company affiliation	0.4723**	0.1046	0.4898**	0.1027
Radical invention	0.6238**	0.1010	0.6379**	0.0998
PCT application	0.6786**	0.1161	0.6750**	0.1127
Granted	0.4861**	0.1119	0.4545**	0.1105
Intercept	5.9606**	0.6066	5.8681**	0.5925
Log likelihood			-2,956.0	
Adjusted R^2	0.230			
Number observations	1,477			
Number technology areas	28			

Notes: (1) Included in both regression models are 19 year dummies. (2) Included in the fixed-intercept model are 27 OST technology dummies.
(3) Significance levels: †: 10% *: 5% **: 1%

Alternative Technology Classifications

The sample contains three different ways of classifying technology areas; i.e., from coarse to fine, OST Major, OST, and OST subclasses. There are six OST major classes, 30 OST classes and 413 OST subclasses. The estimation results presented in Table 4 make use of

30 OST classes. In this variation we introduce a coarser classification in the estimation of the fixed-intercept model, and a finer classification for the random-intercept model.

Fixed-intercept model with a coarser classification

In this variation we re-estimated the fixed-intercept model with patent grant and technology interaction terms using a coarser classification of technology areas, i.e., the six OST major technology classes. The estimation results are reported in Table A6.

Table A6: Fixed-intercept model with major technology areas and interactions

Dep. variable: ln(InvVal)	Param. est.	Std. err.
No. of uses	0.4583**	0.0477
Other inventions used	0.4632**	0.0802
No. inventors in application	-0.1149	0.0704
Company affiliation	0.3372**	0.1021
Radical invention	0.6706**	0.0997
PCT application	0.7357**	0.1131
Granted (G)	0.9048**	0.1977
$G\times$Electricity, Electronics	-1.0816**	0.3778
$G\times$Instruments	-0.3599	0.3822
$G\times$Chemicals, pharmaceuticals	-0.3076	0.4866
$G\times$Process engineering	-1.0637**	0.3467
$G\times$Mechanical engineering	-0.5471*	0.2632
Intercept	4.8737**	0.6025
Adjusted R^2	0.223	
Number observations	1,477	
Number major technology areas	6	

Note: (1) Included in the regression are 19 year dummies and 5 major OST technology dummies.
(2) The Omitted reference group for the interaction terms is "$G\times$Other technologies"
(4) Significance levels: †: 10% *: 5% **: 1%

Recall that with 28 OST technology classes, most coefficient estimates of the interaction terms are not statistically significant, as shown in Table 5. However, with only six major technology classes, Table A6 shows that three out of five coefficient estimates of the interaction terms are statistically significant. Moreover, the joint test that all coefficients of the interaction terms are no different from zero yields a F test statistic of 2.8, which at 5 and 1,440 degrees of freedom, has a p-value of 0.0159. That is, we can reject the null hypothesis that all interaction terms have zero coefficient at the usual 5 per cent level of significance.

Contrasting these results with those reported in Table 5, we think the significance of the interaction terms are related to the number of technology classes. With 28 classes, the number of inventions in each class is relatively small, which reduces the precision of the coefficients of the interaction terms. Table A6 shows that once the number of classes are reduced, the precision of the coefficient estimates improves so that statistically significance results obtain.

Random intercept model using a finer classification

Recall that, in order to maintain parity with the fixed-intercept model, we estimate the random-intercept model in the text with 28 technology classes. However, we have at our disposal a finer classification in the form of OST subclasses, which contain more than 400 technology areas. We make use of these finer classification in our estimation of the random-intercept model and report the results in Table A7. All coefficient estimates are similar to those for the basic model with 28 technology classes given in Table 4. In particular, the estimate of patent premium is 42 per cent, the magnitude of which is comparable to the estimate of 44 per cent under the basic model.

Table A7: Random-intercept Model with OST subclasses

Dep. variable: ln(InvVal)	Param. est.	Std. err.
No. of uses	0.4284**	0.0471
Other inventions used	0.4714**	0.0791
No. inventors in application	-0.1018	0.0683
Company affiliation	0.3499**	0.1007
Radical invention	0.6521**	0.0981
PCT application	0.7125**	0.1100
Granted	0.4228**	0.1085
Intercept	5.3861**	0.5786
Log likelihood	-2,930.9	
Number observations	1,477	
Number technology areas	323	

Note: Included in the regression are 19 year dummies.
(4) Significance levels: †: 10% *: 5% **: 1%