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Patent protection and the erosion of profits: Econometric evidence

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Abstract

This paper presents estimates of the R&D depreciation rate using survey data on Australian inventions. Its novelty is twofold. First, it relies on direct observation of the revenue streams of inventions. This is in sharp contrast with previous studies which all rely on models based on indirect observation and require strong identifying assumptions. Second, it presents estimates of the effect of patent protection on the depreciation rate. We find that the yearly depreciation rate varies between 1 and 5 per cent, although as much as 15 per cent of the decline in value occurs within the first two years. We further find that patent protection slows down the erosion of profits by about 1?2 percentage points

Jelcodes:O32,O34

Patent protection and the erosion of profits: Econometric evidence

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1. Introduction

Intangible assets are attracting major academic and policy interest in today's knowledge economies. Intangible assets are assets that are not physical in nature, such as knowledge generated through investment in research and development (R&D), yet deliver concrete economic benefits. Since the seminal work by Solow (1956), research has established that intangible assets account for a significant proportion of firms' value and are an important driver of productivity growth (Adams 1990; Coe and Helpman 1995; Lev and Sougiannis 1996; Crépon et al. 1998; Webster 2000). However, our understanding of intangible assets is still limited and many open questions remain.

One such question is the speed at which these assets depreciate. This paper focuses on the private rate of depreciation of R&D assets, defined as the rate of decay of appropriable revenues that these assets generate (Pakes and Schankerman 1984). The depreciation rate of R&D is a key economic parameter. It provides information about the speed of technological change and is essential for estimating the returns to R&D investments (Pakes and Schankerman 1984; Esposti and Pierani 2003; Hall et al. 2010). In this regard, Hall (2005:342) argues that measurement of the depreciation of R&D assets is the 'central unsolved problem in the measurement of the returns to R&D'. The 'depreciation problem' arises from the difficulty in reconciling depreciation rates obtained using different methodologies (see also Griliches 1998). In addition, because the R&D depreciation rate is endogenous to R&D investments, it is also central to the understanding of industry dynamics (Caballero and Jaffe 1993; Jovanovic and Nyarko 1998; Pacheco-de-Almeida 2010). Finally, it is also of practical relevance in other fields such as growth accounting studies, where it is used to build R&D capital stock and to compute the rental price of R&D capital (Nadiri and Prucha, 1996; Fraumeni and Okubo, 2005; Corrado and Hulten 2010).

Within this context, this paper presents novel estimates of the R&D depreciation rate using data from the Australian Inventor Survey (AIS). The sample contains information on 2259 patent applications filed at the Australian patent office (IP Australia) between 1986 and 2005. Only a handful of studies have estimated the R&D depreciation rate and all of them rely on indirect inference and strong identifying assumptions. By contrast, the approach proposed in this paper relies on direct observation of inventors' estimates of the revenue streams generated by inventions and is thus genuinely different from existing approaches. This paper also presents estimates of the effect of patent protection on the depreciation rate. To the best of our knowledge, this study is the first of its kind: existing estimates do not differentiate between patented and unpatented inventions. Yet, since the very purpose of patent protection is to slow down the erosion of profit, the depreciation rate of unpatented inventions should be higher than that of patented inventions. Because not all the patent applications in the AIS were granted, the dataset allows us to study how patent protection affects the depreciation rate. Understanding the magnitude of the difference in the depreciation rate between patented and unpatented inventions may help resolve observed discrepancies in previous estimates and will provide novel insights into the economic effects of the patent system.

To anticipate the results, we find that the depreciation rate is in the lower range of existing estimates and varies between 1 and 5 per cent depending on model specifications. However, we also find that as much as 15 per cent of the decline in value occurs within the first two years. Industry-specific depreciation rates exhibit little heterogeneity. The decline in value that occurs in the early life of an invention is largest in the radio, television and communication equipment industry (up to 20 per cent). Inventions in the pharmaceuticals and medicinal chemicals industry exhibit the lowest depreciation rate and the smallest early decline in value. We further find that patent protection mitigates the depreciation rate. Inventions protected with a patent enjoy a reduction in their depreciation rate by about 1–2 percentage points, thereby providing evidence that patent protection increases the returns to R&D. However this effect is only observed for 'strong' patents, i.e. patents which provide effective legal protection from copying of the invention.

The rest of the paper is organised as follows. The next section provides background information on R&D depreciation. Section 3 presents the econometric framework and the data, and section 4 presents the results. Finally, section 5 discusses the implications of the findings and concludes.

2. R&D depreciation rate and the patent system

This section first discusses the concept of R&D depreciation. It then presents the main approaches that have been proposed in the literature for estimating the R&D depreciation rate (a longer literature review is presented in Mead 2007). The overview serves to emphasise the originality of the method proposed in this paper, as well as report available estimates of R&D depreciation rates for comparison purposes. It also serves to illustrate our point that existing empirical studies do not account for the effect of patent protection on the R&D depreciation rate. Finally, this section discusses the effect of patenting on R&D depreciation.

2.1. Defining R&D depreciation

The concept of R&D depreciation is multifaceted. The knowledge created by R&D investments has both a commercial value and a technological value. It can be embodied in products and processes to deliver an economic benefit, and it can also create opportunities for follow-on innovations. Both commercial and technological value decline over time, suggesting the existence of two distinct depreciation rates. We refer to the decline of appropriable revenues simply as the *depreciation rate of R&D* (our focus in this paper), and the decline in the usefulness of the invention in creating new knowledge as the *obsolescence rate of R&D*. These two objects somehow echo the concepts of exchange value and use value in classical economic theory. The textbook example of this is the wheel. While the wheel has revolutionised transportation systems, has led to innumerable follow-on innovations and is still widely used today (high use value), no one can extract a profit from the use of the invention (no exchange value).

A further definitional refinement relates to the type of the R&D considered: R&D input versus R&D output. These two quantities differ because not all R&D input will be converted into an economically valuable output. A research project may fail to deliver a concrete inventive output or may lead to an inventive output that has no economic value. This distinction matters because it directly affects the nature of the phenomenon being studied. While studies that look at R&D investments (input) inform about the overall *returns to R&D*, studies that focus on inventions (output) informs more specifically about the *returns to technological innovation* (i.e. successful R&D). If anything, the depreciation rate obtained using R&D input measures should be higher than the rate obtained using invention-level data because of the fact that some R&D projects fail. This distinction is a key dividing line in the empirical literature, although few scholars have emphasised this point. The methodology presented in this paper falls within the latter category as it relates to inventive output that was advanced enough to warrant a patent application.

2.2. Available estimates

A handful of studies have sought to estimate the depreciation rate of R&D. A first formal attempt is that of Pakes and Schankerman (1984), who use patent data (output). The authors exploit the fact that the owner of a patent must pay yearly renewal fees in order to maintain a patent in force. They develop a model of the patent renewal decision in which revenues from a patented invention decline deterministically and a patent is renewed for an additional year if the annual revenue at least covers the cost of the renewal fee. They then impose distributional assumptions on invention value and calibrate their model using aggregate data to infer the decay rate of appropriable revenues. This methodology has been refined in a number of ways, in particular by using individual patent data and by accounting for the stochastic nature of the flow of revenues using real option models (Pakes 1986; Lanjouw 1998; Baudry and Dumont 2006; Deng 2007; Bessen 2008).

Other attempts, which rely on R&D expenditures (input) rather than patent data, have also been proposed. Studies in this group are of two main types. A first approach, predominant in the field of accounting studies, relies on firms' financial performance measures. Hirschey and Weygandt (1985) show that R&D expenditures have a positive effect on the market value of firms controlling for the replacement cost of tangible assets. Although the focus of their paper is on the need to capitalise R&D expenditures for accurate accounting, they are able to interpret their model parameters in terms of depreciation rates (or 'amortisation rate' in accounting jargon), but at the cost of identifying assumptions. In particular, they need to assume that R&D investments grow at the equilibrium rate, which is a strong assumption for firm-level studies. Related works include Hall (2005), who also uses firm market value, and Lev and Sougiannis (1996) and Ballester et al. (2003), who use firm earnings.

A second approach that relies on R&D expenditure estimates production models of the economy. Nadiri and Prucha (1996) specify a model of factor demand for the United States manufacturing sector with static price expectations and non-capital input decisions. The depreciation rate of R&D capital is one of the parameters of their model. Other production models include Bernstein and Mamuneas (2006) and Huang and Diewert (2011). Models in this second group are estimated from industry-level data and are therefore not directly comparable with firm-level estimates. The depreciation rate obtained reflects the contribution of R&D investments to the productivity of both the firm conducting the research, and all the other firms in the same industry. Table 1 summarizes the main estimates of R&D depreciation rates. The estimates vary greatly, ranging from almost no depreciation to almost 50 per cent.

Table 1. Overview of R&D depreciation rate

Article	Key data	Model	Unit	Rate
Pakes and Schankerman (1984)	Granted patents	Patent renewal	Invention	0.25
Pakes (1986)	Granted patents	Patent renewal	Invention	0.11–0.19
Lanjouw (1998)	Granted patents	Patent renewal	Invention	0.02–0.06
Deng (2007)	Granted patents	Patent renewal	Invention	0.06–0.11
Bessen (2008)	Granted patents	Patent renewal	Invention	0.13–0.27
Hirschey and Weygandt (1985)	R&D expenditures	Accounting	Firm	0.02–0.17
Lev and Sougiannis (1996)	R&D expenditures	Accounting	Firm	0.11–0.20
Ballester et al. (2003)	R&D expenditures	Accounting	Firm	0.02–0.46
Hall (2005)	R&D expenditures	Accounting/ Production function	Firm	-0.06–0.28
Nadiri and Prucha (1996)	R&D expenditures	Production function	Industry	0.12
Bernstein and Mamuneas (2006)	R&D expenditures	Production function	Industry	0.18–0.29
Huang and Diewert (2011)	R&D expenditures	Production function	Industry	0.01–0.29

Notes: Point estimates of depreciation rates reported. The depreciation rates in Lev and Sougiannis (1996) are computed as the average values of the parameters δ_k in Table 3.

Note that it is also possible to estimate depreciation rates from the 'service life' of R&D projects. This approach involves asking R&D managers about the number of years an R&D asset will be used and dates back at least to Schott (1976). It has been adopted by statistical offices in their efforts to capitalise R&D expenditures in national account systems (Peleg 2008; Ker 2013). One strength of this approach is that it produces service lives for the different components of R&D (basic research, applied research, and development). Weaknesses include the fact that it relies on a stated service life (as opposed to a revealed service life), and that service life is expressed in years and is, therefore, not directly comparable with the literature on R&D depreciation.

Although existing studies differ widely in their scope and methodology, one common trait is that they rely on indirect inference to estimate the depreciation rate. By contrast, the methodology adopted in this paper relies on direct inference. Our data on inventor estimates of invention revenue streams lend themselves to estimating the depreciation rate in a way that allows for using weak identifying assumptions.[1] In addition, no previous research has explicitly studied the effect of patent protection on the depreciation rate. While estimates that rely on granted patents are only informative about the decay rate of revenues from patented inventions, estimates that rely on R&D expenditures mix both patented and unpatented inventions (as well as successful and unsuccessful R&D projects). Estimating the effect of patent protection on the depreciation rate is thus a step forward in bringing these two sets of estimates closer to each other.

2.3. Effect of patent protection on the depreciation rate

As Griliches (1979:101) observes, the depreciation rate of revenues accruing to the innovator derives from two related points regarding the market valuation of the invention: the loss in specificity of the knowledge as it leaks to other firms in the industry ('imitation effect'); and the development of better products and processes which displace the original innovation ('displacement effect'). This observation immediately suggests two ways in which patent protection may reduce the depreciation rate. First, patent protection reduces the imitation effect as it confers the right to exclude others from making, using, selling and importing the invention. Second, patent protection also slows down or blocks follow-on research by competitors (Scotchmer 1991; Bessen and Maskin 2009), thereby mitigating the displacement effect.

The literature is equivocal about both of these effects. On the one hand, scholars have shown that patent protection increases the value of inventions (Arora et al. 2008; Jensen et al. 2011) or the value of the patenting firm (Ceccagnoli 2009), thereby providing evidence that patenting strengthens firms' appropriability conditions. On the other hand, patent protection is an imperfect appropriability mechanism, for two reasons. First, patent rights are costly to enforce. While it is well recognised that many firms apply for patents to protect against imitation (Cohen et al. 2000; Blind et al. 2006; de Rassenfosse 2012), the actual effectiveness of patent protection has been questioned. Enforcing a patent requires considerable resources, either financial resources to defend the validity of a patent in court or other resources such as a large patent portfolio to increase negotiation power and settle before trial (Hall and Ziedonis 2001; Farrell and Merges 2004; Weatherall and Webster forthcoming). Second,

[1] Of course there are also limitations associated with our approach, in particular regarding the fact that we use the inventor's estimate of the revenue stream. We discuss the caveats in sections 3 and 4. Note that, in contrast to service lives estimates, our approach relies on a revealed-approach for estimating the depreciation rate (a stated-approach would involve asking respondents directly about the depreciation rate).

patent protection is ineffective against imitators inventing around an innovation (Mansfield et al., 1981; Gallini 1992). To protect themselves against substitute technologies, firms sometimes resort to a 'patent fencing' strategy which involves filing multiple patents per innovation (Reitzig, 2004). As these concerns have the potential to undermine the benefit of patent protection, the empirical analysis shall touch upon these issues.

There is, however, one important proviso to our approach to bear in mind. Patent protection is a costly and substitutable good and firms self-select into the patent system. The cost is both monetary (actual cost of patenting) and non-monetary (disclosure requirement in patent law) and authors have shown that it affects the patenting decision (Horstmann et al. 1985; Zaby 2010; de Rassenfosse and van Pottelsberghe, 2013). The substitutability of patent protection arises from the alternative appropriation mechanisms such as lead time and the availability of complementary assets (Teece 1986; Cohen et al. 2000; Arora and Ceccagnoli 2006). Therefore, under some conditions it might well be that inventions kept secret enjoy a lower depreciation rate than inventions submitted to the patent office. The Coca-Cola formula is the archetypal example of an innovation that would have depreciated at a much faster pace if it were patented. In this paper the effect of patent grant is estimated for firms that self-select into the patent system, i.e. no secrecy in the sample.

3. Framework and data

3.1 Empirical framework

There is no unique pattern in the evolution over time of the revenue streams of inventions. While some inventions may produce most revenue in their early life, others may deliver no return until late. We call $V(a)$ the amount of appropriable revenues remaining at age a (that is, from $a \to \infty$). Invention value is subject to high uncertainty and is consequently very difficult to predict.[2] However, it is necessarily the case that, ex post, $V(a)$ is a declining function of age. We follow previous convention and model invention value at age a using an exponential decay function:

$$V(a) = V(0)e^{-\delta a} \tag{1}$$

[2] We discuss this issue in greater detail in section 4.3.

where δ is the depreciation parameter. The model assumes a constant depreciation rate over time, and we show in section 4.2 that our data supports that assumption. Dividing equation (1) by $V(0)$ and taking to the log, the empirical counterpart of equation (1) can be written as:

$$\ln \frac{V_{ia}}{V_{i0}} = -\delta a + \varepsilon_{ia} \quad (2)$$

where i denotes an invention and δ is the parameter to be estimated.[3] We do not observe the full sequence of invention values $\{V_{ia}\}\ \forall\, i, a$. We observe invention value at age 0 and the residual invention value at the time of the survey. Heterogeneity comes from that fact that inventions belong to cohorts of different vintages. Thus, we observe $\{V_{ia}: a = 0, a_i; a_i \neq 0\}$.

Note that, in its initial form, equation (2) does not include a constant term – an intercept c different from 0 would imply that $\mathrm{E}[\ln(V_{i0}/V_{io})] = c$, which cannot be true. However, given that the youngest inventions in the sample are two years old, a constant term different from 0 can be interpreted as the decline in value that occurs within the first two years. We model variations in the depreciation rate δ as a linear function of covariates such that equation (2) can be written as (including a constant term):

$$\ln \frac{V_{ia}}{V_{io}} = c - (\boldsymbol{x}_i'\boldsymbol{\beta})a + \varepsilon_{ia} \quad (3)$$

where $\boldsymbol{x}_i'\boldsymbol{\beta}$ is the inner product between the vector of covariates $\boldsymbol{x}_i$ and the vector of parameters $\boldsymbol{\beta}$, and the error-term $\varepsilon_{ia} \sim N(0, \sigma_a^2)$ in the baseline specification. It is clear from equation (3) that all the explanatory variables must be interacted with the age variable. Equation (3) will be estimated with OLS as well as with alternative regression models. We will use a generalised linear model to account for the fact that the dependent variable is not normally distributed as well as robust regression models to account for a difference in the trustworthiness of estimates across vintages.

Note that we rely on conservative evidence thresholds for the declaration of significant coefficients (p-values of 0.01 and 0.005). We follow Johnson (2013) who shows that commonly-used levels of significance represent only weak evidence in favour of hypothesised effects.[4]

[3] We explain in section 4.2 that the regression equation (2) also encompasses the class of declining balance models and is, therefore, quite general.

[4] Johnson (2013) recommends using reference p-value thresholds of 0.005 and 0.001 instead of the usual 0.10, 0.05 and 0.01. We adopt weaker thresholds than recommended (0.01 and 0.005) due to the relatively low number of observations in our sample for such stringent thresholds.

3.2 Data sources

The empirical analysis combines data from four sources. The main data source is the AIS and it is complemented with information from patent databases.

3.2.1 Australian Inventor Survey (AIS)

In 2007 the Melbourne Institute at the University of Melbourne has conducted a survey of patent applications by Australian inventors submitted to IP Australia, the Australian Patent Office, from 1986 to 2005. Each surveyed inventor was asked questions related to the characteristics of the invention, including questions about invention value. A complete description of the survey methodology is provided in Webster and Jensen (2011). There are 3862 inventions in the database and information on value is available for 2558 of them. Non-response biases for the dependent variable are investigated in section 4.1.

3.2.2 IP Australia's AusPat database

The AusPat database from IP Australia is used to get information on the priority date of the patent application as well as their grant status. The priority date is the date of the first filing of an application for a patent. It is used to compute the age of the invention. Approximately two-thirds of inventions with non-missing invention value were eventually granted patent protection. Two patent applications were still pending at the time of the study.

3.2.3 Patstat

The European Patent Office worldwide patent statistical database Patstat is used to get information on the family size and the IPC codes of each patent application. The family size is defined as the number of jurisdictions in which patent protection was sought. We adopt the extended INPADOC family definition, which groups together applications that are directly or indirectly linked through priorities (see Martinez 2011 for more information on patent families). International Patent Classification (IPC codes) codes represent the different areas of technology to which the patents pertain. They are assigned by examiners at the patent office and are thus homogeneous across patents.

3.2.4 IPC-ISIC Concordance Table

Patents have been assigned to the appropriate industries using the empirical concordance table between IPC and International Standard Industrial Classification (ISIC) codes provided by Schmoch et al. (2003). The concordance table was built by investigating the patenting activity in technology-based fields (IPC) of more than 3000 firms classified by industrial sector (ISIC codes). When a patent contains more than one IPC code, the industry allocation is performed on a fractional basis.

3.3 Dependent variable

The dependent variable is the log of the proportion of invention value remaining at the time of the survey ($\ln V_{ia}/V_{i0}$). It is constructed from the following three survey items:

- *G1. To date, what is your estimate of sales revenue from products and processes using this invention?*
- *G2. If you were selling this patent or invention today, what price would you be willing to accept for it?*
- *G3. If this patent has been licensed, what is your best estimate of the licensing revenues to date?*

Each item is measured on a 7-point Likert scale with categories: 0 < $100,000; $100,000 to $500,000; $500,000 to $1m; $1m to $2m; $2m to $10m; > $10m; and unsure. A total of 1627 observations from respondents who selected 'unsure' for any of the questions were dropped from the sample (474 observations dropped with G1, an additional 610 observations dropped with G2 and a final 543 observations dropped with G3). The values are expressed in 2007 Australian dollars.

Since question G1 is revenue-based – rather than profit-based – we set the gross profit margin m at 30 per cent for goods and services produced using an invention following Jensen et al. (2011). (We investigate the sensitivity of estimates to the parameter m in section 4.3.) The variable V_{ia} is the residual value for patents of age a and corresponds to question G2. The variable V_{i0} is the total value at $a = 0$. It can be computed as (m*G1 + G3) + G2. Since the data is ordinal, the dependent variable was constructed from the mid-point value of each category (the last category was arbitrarily assigned a value of $15m), although we note that alternative methodologies for converting categories into actual dollars will be tested.

Contrary to the existing approaches outlined in section 2, which rely on indirect inference to determine appropriable revenues, the dependent variable used in this paper is a direct measure of revenues. Although there may be a bias in inventors' evaluation of the value of their inventions, such bias is mitigated by the use of ordinal variables (at the cost of precision, however). Another potential source of bias relates to the fact that inventions belong to cohorts of different ages. The remaining value (forward-looking question G2) is subject to a greater deal of uncertainty for younger cohorts, and respondents may experience greater difficulty in recollecting revenues earned for older inventions (backward-looking questions G1 and G3). This issue will be dealt with in the empirical analysis.

3.4 Covariates

Age of the patent (a). Computed as the number of years elapsed between the year of the priority patent application and the year of the survey (2007).

Grant status of the patent (grant). Dummy variable takes the value 1 if the invention was granted patent protection and 0 otherwise. Australia's patent law decrees that a patent right should be granted only for inventions that have a high degree of inventive merit over existing knowledge. The decision to grant a patent is done after a thorough examination of international prior art conducted by specialist patent examiners within IP Australia. It is therefore an exogenous event based on technological merit, not commercial value.

Private companies (private). Dummy variable takes the value 1 if the invention belongs to a private company and 0 if it belongs to a public research organisation or an individual inventor.

Strength of patent protection (weak). Dummy variable takes the value 1 if respondents reported a lack of confidence in legal protection from copying of invention. It is obtained from the highest scores (6 and 7) of a Likert-scale question in the AIS and is only available for inventions with a granted patent.

International protection (intl protection). Dummy variable takes the value 1 if the invention is protected in at least one other country, that is if the INPADOC family covers at least two jurisdictions. Seeking international expansion for a patent is a complex and expensive process that requires a certain level of commitment from its owner. We use this variable to capture the ability of the owner to defend the patent in court in case of infringement.

Other patents involved (other patents). The AIS contains information on the number of patents that were also used to develop the product. It is an ordinal variable with five categories [none; 1 to 5; 6 to 10; 11 to 20; 20+]. For the purpose of the analysis, the variable 'other patents' is a dummy variable that takes the value 1 if at least one other patent is used to develop the product. Without using the terms ‘patent fences’ and ‘patent thickets’, the presence of other patents suggests that it becomes more difficult for competitors to invent around a technology. Similarly, patent protection may matter less for technologies that involve several patented components. Even if patent protection is not obtained for one component, another component may enjoy patent protection thereby providing effective protection for the whole technology.

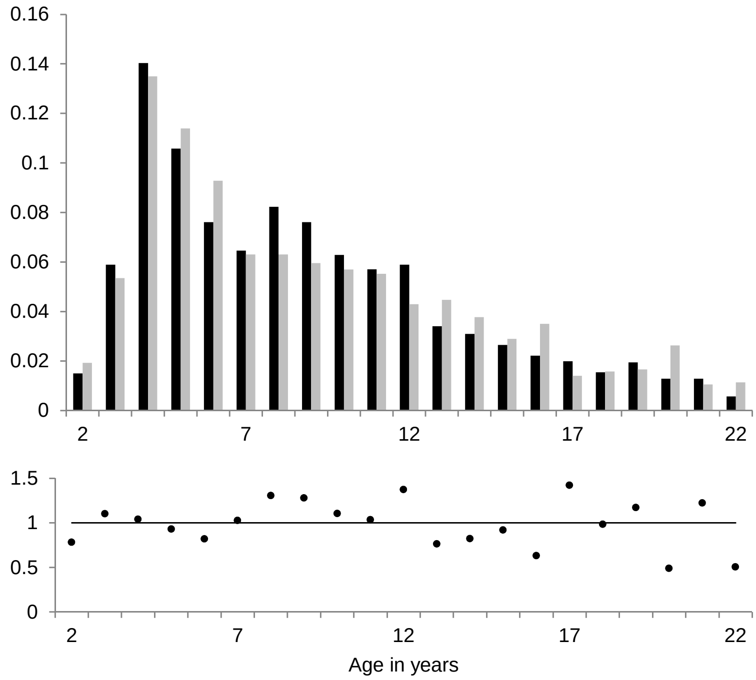
Industry dummies. Dummies corresponding to the main ISIC code of the patent.

4. Results

4.1 Descriptive statistics

There were 3862 inventions surveyed in the AIS and information on value is available for 2558 of them. Among these, 2259 inventions (88 per cent) are matched to the Patstat database. We did not find evidence of bias in the reporting of invention value. Such a bias can be investigated along two dimensions that are available from external sources (Patstat and AusPat databases): the number of jurisdictions in which patent protection is sought (the family size) and the age of inventions. The average family size is 3.34 for inventions for which information on value is provided (N=2259), 3.23 for inventions with no information on value (N=1141), and the difference is not statistically significant (p-value of 0.38). Similarly, the average age is 8.82 years for inventions with information on value and 9.06 years for inventions lacking information on value, and the difference is not statistically significant (p-value of 0.18). The age profile of inventions is presented in the upper panel of Figure 1 for the series of inventions with information on value (black bars) and missing information on value (grey bars). The ratio of frequencies between the two series, depicted in the lower panel, oscillates around 1 and does not suggest the presence of bias.

Figure 1. Histogram of invention ages and ratio of missing to non-missing value information



Notes: Upper panel: histograms of invention ages by availability of value information (black: available, grey: missing). Lower panel: ratio of frequencies between the two series.

Table 2 presents descriptive statistics of the sample used. Since the dependent variable is the logarithm of the ratio of values, it is always negative. The mean of the dependent variable is -0.63 and the median is -0.26 (not reported). The skewness of the dependent variable is explained by the predominance of more recent inventions in the sample. Inventions in the sample are older than two years and the average age is 8.82 years. There are 47 per cent of observations from private entities, and the overall grant rate is 67 per cent. About 17 per cent of granted patents are considered weak, 52 per cent of inventions are part of an international patent family, and 35 per cent of inventions come with at least one other patent application. The correlation structure of variables indicates that there are no collinearity issues.

Table 2. Descriptive statistics

	Min	Mean	Max	Std. Dev	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $ln\, V_{ia}/V_{i0}$	-5.97	-0.63	-0.00	0.78	1.00						
(2) *a*	2	8.82	24	4.74	-0.16	1.00					
(3) *grant*	0	0.67	1	-	-0.05	-0.10	1.00				
(4) *private*	0	0.47	1	-	0.01	0.27	0.13	1.00			
(5) *weak*	0	0.17	1	-	0.00	0.02	-	-0.05	1.00		
(6) *intl protection*	0	0.52	1	-	0.02	-0.03	0.13	0.06	-0.04	1.00	
(7) *other patents*	0	0.35	1	-	0.07	-0.07	0.24	0.27	-0.08	0.20	1.00

Notes: N = 2259. Variable 'weak' only available for granted patents (N=1502). Right panel: correlation coefficients.

4.2 Estimates of depreciation rates

Table 3 presents baseline estimates of equation (4). Results using an OLS regression model without a constant in column (1) suggest that appropriable revenues decrease at a rate of 6 per cent annually. However, this model violates the basic OLS assumption that the mean of residuals be equal to zero, which typically calls for the inclusion of a constant term. Allowing for a constant term *c* in column (2) reduces the depreciation parameter to 2.6 per cent. The estimated value for the earliest observations available is $\mathrm{E}[\ln(V_{i2}/V_{io})] = c + \delta * 2$, and the constant term *c* can therefore be interpreted as the early decline in value that is not accounted for by the depreciation parameter. In other words, the OLS regression model suggests that 33 per cent $(= 1 - e^{c})$ of the decline in value occurs within the first two years. Figure 2 depicts the model fit. It suggests that the linearity assumption of the depreciation rate holds (at least locally, when $a \geq 2$).[5] A close look at the residuals suggests the presence of heteroscedasticity (the variance of residuals increases with age, not reported). Although standard errors are clustered by cohort, a more appropriate distributional assumption or a more appropriate treatment of likely outliers could improve estimation. We investigate these two issues in turn.

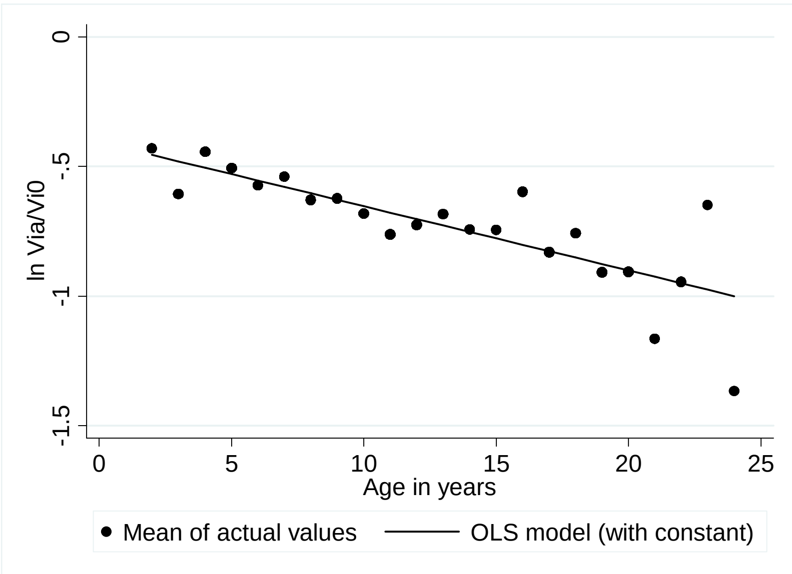
[5] More flexible specifications of the decay function (up to the third-order polynomial of age) were considered but did not perform better in terms of the Akaike and Bayesian information criteria (AIC and BIC) than the linear model. For instance, the BIC is 5236 for the linear model, 5244 for the second-order polynomial model and 5250 for the third-order polynomial model.

Table 3. Depreciation parameter with various estimation methods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Method:	OLS	OLS	GLM	Quantile	MM	Quantile	MM
a	-0.061**	-0.026**	-0.055**	-0.023**	-0.015**	-0.013**	-0.010**
	(0.004)	(0.004)	(0.009)	(0.002)	(0.002)	(0.003)	(0.003)
$a \times private$						-0.013**	-0.007**
						(0.002)	(0.002)
$a \times industry\ dummies$						Y**	Y
Constant		-0.403**	2.132**	-0.147**	-0.152**	-0.133**	-0.138**
		(0.044)	(0.133)	(0.025)	(0.019)	(0.023)	(0.019)
Observations	2259	2259	2259	2259	2259	2259	2259
R^2	0.024	0.024	0.024	0.024	0.024	0.035	0.033

Notes: R^2 is the square of the correlation coefficient between the predicted values of the dependent variables and their actual values. Standard errors in parentheses. Standard errors clustered by cohort in columns (1), (2), and (3). ** p<0.005, * p<0.01

Figure 2. Actual and predicted ratio of values (to the logarithm), by age cohort



Notes: Series for the OLS model is obtained from column (2) of Table 3.

The OLS regression model requires the dependent variable to be normally distributed. The dependent variable actually takes its value on the interval $[0, -\infty)$ such that the normality assumption is violated. In column (3) we assume that the dependent variable conditional on the covariates follows a Gamma distribution and we estimate a generalized linear model (GLM).[6] The estimated coefficient is -0.055 and corresponds to a marginal effect at mean of

[6] The dependent variable is transformed to $-\ln(V_{ia}/V_{i0})$ so that it takes its value on the interval $[0, +\infty)$.

2.3 per cent, which is very close to the OLS estimate. However, the residuals still exhibit heteroscedasticity. Heteroscedasticity is probably a consequence of the fact that inventions belong to cohorts of different vintages, such that the level of trustworthiness of estimates varies. A quantile regression model is presented in column (4). The quantile regression model estimates the effects of covariates on the median of the dependent variable rather than on its mean and is one way of accounting for potential outliers (Koenker and Bassett 1978). The estimated depreciation rate is remarkably similar to previous estimates (2.3 per cent) but we note that the constant term is much lower (-0.147). The constant term suggests that approximately 14 per cent of the decline in value occurs within the first two years. Results of a robust regression model that down-weights potential outliers is reported in column (5). We adopt the MM-estimator by Yohai (1987) and implemented in Stata by Verardi and Croux (2009). The depreciation parameter is slightly lower, at 1.5 per cent, and the constant term is closer to zero as compared with column (2). The last two regression models lead to greater model fit than OLS and GLM and are our preferred specifications.

Although the framework adopted is that of an exponential decay model, the parameter can also be interpreted in terms of a declining balance model. Such a model takes the form $V_{ia} = V_{i0}(1-\delta)^a$ and can be rewritten as $\ln V_{ia}/V_{i0} = \ln(1-\delta)\, a = \beta a$. Thus, the declining balance depreciation rate can easily be recovered from the estimated parameter β. It corresponds to $\delta = 1 - e^{\beta}$. Note that for β small, $\delta \cong \beta$ such that both models give sensibly similar results.

Regressions presented in the last two columns allow for a differentiated effect for private companies. Inventions by private companies depreciate by about one percentage points more than inventions by public research organisations and individuals, probably owing to greater competitive pressure. The regressions also include dummies for seven industries that have at least 100 observations each. These seven industries account for more than 80 per cent of inventions and the corresponding dummies are jointly significant when the quantile estimator is used (but not when the MM estimator is used). Industry-specific estimates of the R&D depreciation rate are presented in Table 8 in Appendix A for the selected industries. We briefly discuss industry-specific results for reader convenience. Point estimates vary in the range between 1 and 4 per cent. The depreciation rate is lowest in the pharmaceuticals and medicinal chemicals industry (in the range 0.6–1.7 per cent) and highest in the machinery and equipment industry (in the range 2.1–4.0 per cent). The decline in value that occurs in the early life of an invention is smaller than the reference group in the pharmaceuticals and medicinal chemicals industry (in the range 5–9 per cent) and larger than the reference group in the radio, television and communication equipment industry (with approximately 19 per cent of the value disappearing within the first two years).

The next sets of results presented in Table 4 estimate the effect of patent protection on the depreciation rate using both the quantile and the MM-estimators. The grant effect, associated with the variable '$a \times grant$', is straightforward to interpret. It corresponds to the percentage points reduction in the depreciation rate. For instance, the value of 0.014 in column (1) suggests that inventions that enjoy patent protection have a depreciation rate that is on average 1.4 per cent lower than that of unpatented inventions. The corresponding rate for the MM-estimate in column (5) is 1.2 per cent. One must be careful when interpreting the grant effect because of the limited information available. Ideally one would observe the full sequence of values together with the grant and lapse events to estimate the effect of one additional year of protection on the depreciation rate. Unfortunately, however, the full sequence of value is not observed in the AIS such that the correct interpretation of the grant effect is the yearly reduction in the depreciation rate over the life of inventions, given an average length of protection of eleven years (which is the average length of protection at IP Australia as indicated in Sutton 2009).

Mitigating factors for the grant effect are investigated in columns (2)–(4) and (6)–(8). In particular, the strength of patent protection may affect the returns to patenting. We break down grant patents into patents for which holders are confident about the quality of their intellectual property rights (*weak* = 0) and for which they are not (*weak* = 1). We find that only patents in the former group effectively reduce the depreciation rate. Point estimates are not statistically different from zero when patent protection is considered weak (and in any case are lower than when patent protection is considered strong). Similarly, the ability to defend the patent in court may matter more than the actual grant and may drive some of the effect. We use the variable 'intl protection' as a proxy variable and we break down the grant effect into two groups: patent holders that have applied for international patent protection (they may have deeper pockets and/or be more willing to enforce their patent rights), and patent holders that have not. The corresponding parameters in columns (3) and (7) suggest that inventions having an international patent protection have a lower depreciation rate than inventions with only a domestic protection by about half a percentage point. A third concern that may affect the estimated parameter is that patent protection may matter less for technologies that involve several patented components. Even if patent protection is not obtained for one component, another component may enjoy patent protection thereby providing effective protection for the whole technology. This issue is investigated in columns (4) and (8) with the variable 'other patents'. The presence of other patents does not seem to further slow the erosion of profits.

Table 4. Effect of patent grant on depreciation rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Quantile estimator				MM-estimator			
x:		*weak*	*intl protection*			*weak*	*intl protection*	
a	-0.026**	-0.027**	-0.023**	-0.028**	-0.021**	-0.021**	-0.020**	-0.021**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
$a \times grant$	0.014**			0.013**	0.012**			0.012**
	(0.004)			(0.004)	(0.003)			(0.003)
$a \times grant \times (x = 0)$		0.015**	0.010			0.013**	0.010*	
		(0.004)	(0.004)			(0.003)	(0.004)	
$a \times grant \times (x = 1)$		0.012	0.015**			0.008	0.014**	
		(0.005)	(0.004)			(0.004)	(0.003)	
$a \times other\ patents$				0.007				0.003
				(0.003)				(0.002)
$a \times private$	-0.016**	-0.016**	-0.017**	-0.016**	-0.009**	-0.009**	-0.009**	-0.009**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
$a \times industry\ dummies$	Y**	Y**	Y**	Y**	Y	Y	Y	Y
Constant	-0.099**	-0.100**	-0.111**	-0.099**	-0.116**	-0.114**	-0.118**	-0.116**
	(0.032)	(0.033)	(0.031)	(0.031)	(0.019)	(0.018)	(0.019)	(0.019)
Observations	2259	2259	2259	2259	2259	2259	2259	2259
R^2	0.037	0.039	0.038	0.037	0.035	0.035	0.036	0.035

Notes: R^2 is the square of the correlation coefficient between the predicted values of the dependent variables and their actual values. Standard errors in parentheses. ** p<0.005, * p<0.01

4.3 Sensitivity analysis

Table 5 presents a series of robustness tests aimed at assessing the validity of the results. A first concern relates to the fact that observations in the sample belong to cohorts of different vintages. While future revenues are more uncertain for younger cohorts (question G2), past revenues may be more difficult to estimate accurately for older cohorts (questions G1 and G3), leading to a dependent variable that may be inconsistently measured across cohorts. Figure 4 and Figure 5 in Appendix B depict the variable V_0 by cohort. There is no noticeable systematic difference in the mean of invention value across cohorts (except at age 24, Figure 4), and the variable varies widely within cohorts as shown by the box plot in Figure 5. However, a linear regression of V_0 against the age variable suggests that the reported value declines slightly with age (not reported). This effect could be due either to an underestimation of the past revenues (which would affect older inventions) or an overestimation of the future revenues (which would affect younger inventions). While the robust regression models adopted already account for greater variance in the dependent variable, we report an additional test. The sample used in column (1) is restricted to inventions in a narrow age range. It includes inventions that are between five and 12 years old. This selection criterion filters out approximately the 20 per cent youngest inventions and the 20 per cent oldest inventions. Results presented in the upper panel of Table 5 must be compared with those in column (1) of Table 4, while results in the lower panel must be compared with those in column (5) of Table 4. Quantile estimates suggest that the yearly depreciation rate is about 5 per cent while the grant effect is 2.2 per cent. MM-estimates suggest that the yearly depreciation rate is about 3 per cent while the grant effect is 1.4 per cent. In other words, figures presented in Table 4 can be seen as conservative estimates.

Second, we were careful to explain in the previous section that the correct interpretation of the grant effect is 'the yearly reduction in depreciation rate over the life of inventions, given an average length of protection of eleven years'. We are left with this interpretation because the structure of the data does not allow us to associate the grant and lapse events to revenue stream estimates. However, it is possible to obtain a more precise picture of the grant effect by focusing on the youngest inventions, which are more likely to enjoy patent protection. The results in column (2) are estimated on the sample of inventions with a maximum age of eight years, capturing roughly half of the inventions. Doing this leads to an estimate of the grant effect that is essentially unchanged.

A third concern relates to the fact that some inventions in the sample were transferred or sold to a third-party, casting doubt on the accuracy of the revenue stream estimates. Regression results presented in column (3) of Table 5 are performed on a sample that excludes 539 such inventions.[7] The results remain largely unchanged.

[7] We exclude inventions for which the following questions were answered positively: 'Has there been any attempt to license or sell this patent to a third party?' and 'Has there been any attempt to transfer this patent to a spin-off company?' Therefore, we are not able to differentiate between inventions that were sold from inventions that were licensed and the sample used in column (3) also excludes the latter.

Fourth, we were not able to match twelve per cent of the observations to the Patstat database (see section 4.1). Including these observations in the regression leaves the results unchanged, as shown in column (4).

A final concern relates to the fact that we have arbitrarily taken the mid-point value of each category of the ordinal variables to construct the dependent variable. In columns (5) and (6) we test whether the results are robust to alternative imputation methods. In column (5) we assume that observations are uniformly distributed in the range covered by their category (0 to $100,000, $100,000 to $500,000, etc.), while in column (6) we assume that observations are distributed according to a Beta distribution that is skewed to the left. The quantile regression model leads to a slightly higher depreciation rate and grant effect, while the MM-estimator leads to a slightly lower depreciation rate and grant effect. Notice that the result depends on the actual draw.

Table 5. Robustness tests

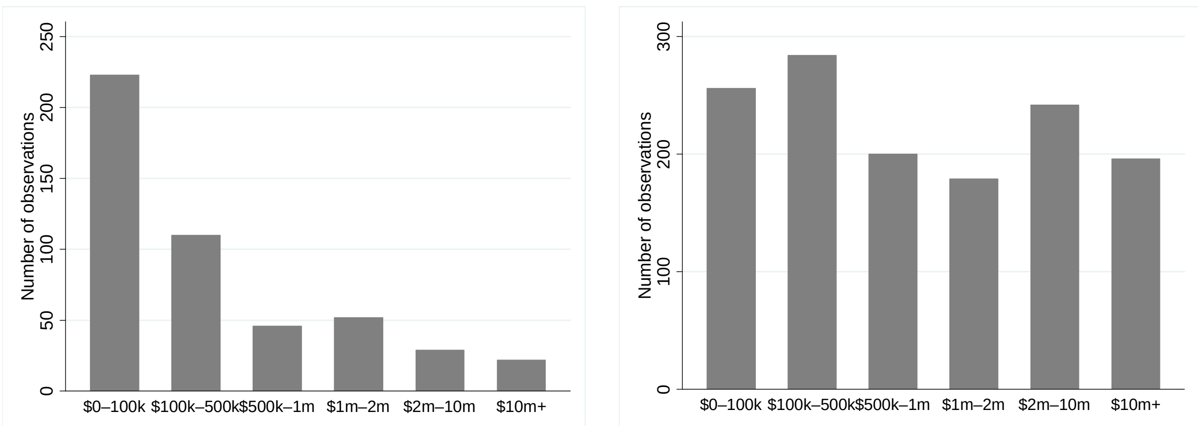
	(1) Y5–Y12	(2) ≤ Y8	(3) No transfer	(4) All obs.	(5) Uniform	(6) Beta
Quantile estimator						
a	-0.051**	-0.028**	-0.023**	-0.025**	-0.034**	-0.029**
	(0.010)	(0.009)	(0.006)	(0.005)	(0.006)	(0.007)
$a \times grant$	0.022**	0.017**	0.013**	0.009*	0.019**	0.019**
	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)
Constant	0.063	-0.123**	-0.126**	-0.108**	-0.055	-0.052
	(0.070)	(0.037)	(0.034)	(0.029)	(0.032)	(0.040)
MM-estimator						
a	-0.029**	-0.010	-0.019**	-0.023**	-0.009*	-0.011**
	(0.008)	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)
$a \times grant$	0.014**	0.010**	0.011**	0.011**	0.007*	0.007*
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)
Constant	-0.063	-0.103**	-0.128**	-0.127**	-0.120**	-0.102**
	(0.042)	(0.023)	(0.023)	(0.019)	(0.017)	(0.016)
Observations	1319	1227	1721	2556	2259	2259

Notes: The regressions control for industry dummies and the 'private' dummy. Standard errors in parentheses. ** p<0.005, * p<0.01.

A potential data limitation relates to the fact that we do not observe the moment at which invention value exhausts. The survey was conducted in 2007 and we have assumed so far that all inventions in our sample have lived up to at least 2007. In addition, we have assumed so far a residual value of $50,000 for inventions that were allocated to the lowest residual value category. Approximately 30 per cent of inventions have a residual value between $0 and $100,000 and are thus at risk of having their residual value artificially inflated to $50,000 and their life artificially stretched to 2007.

We rely on patent renewal data to gauge the severity of the bias. In particular, we collected lapse (or expiry) date of granted patents from the AusPat database to improve the measurement of variables age and G2. Roughly a quarter of granted patents were already lapsed at the time of the survey. Interestingly, however, not all of the lapsed patents have a residual value in the lowest value category. The left hand side panel of Figure 3 shows that, while a large proportion of inventions have indeed the lowest residual value, 54 per cent of inventions have a residual value greater than $100,000 even though the patent right has expired. As emphasized by various scholars, the value of a patent differs from the value of the underlying inventions (e.g., Harhoff et al. 2003; Arora et al. 2008) and Figure 3 provides direct evidence to that claim. The right hand side panel of Figure 3 depicts the distribution of residual value for inventions that obtained patent protection and patent protection was still valid at the time of the survey for comparison purposes.

Figure 3. Distribution of residual invention value (patent expired vs. patent still valid)



Notes: Inventions with a granted patent only. Left panel: inventions with a lapsed patent at the time of the survey. Right panel: inventions with a valid patent at the time of the survey.

In light of the above evidence, we have used lapse events to adapt the age and G2 variables in the following way. If the patent had lapsed at the time of the survey and the residual value of the invention is comprised between 0 and $100,000, the age variable was reduced to coincide with the expiry date of the patent and the residual value was set to $1 (instead of $0 due to the logarithm transformation of the dependent variable). For example, an invention with priority year 2000 which lapsed in 2004 and had the lowest residual value G2 now has an age of 4 years (down from 7 years) and a residual value of $1 (down from $50,000). A total of 189 observations, or 12 per cent of the sample, are affected by this adjustment.

We expect the depreciation rate to increase with the inclusion of lapse data. Because the age of inventions is either reduced or remained constant and the residual value is either reduced or remained constant, it must be that invention value declines more rapidly. Another reason relates to attenuation bias, i.e. the fact that measurement error in an explanatory variable drives regression coefficients down to zero. Since the adjustment increases the accuracy of our dependent variable, it should logically reinforce the depreciation rate.

Table 6. Using information on renewals

	(1)	(2)	(3)	(4)
Renewal information used:	No	Yes	No	Yes
Estimator:	Quantile estimator		MM-estimator	
a	-0.033**	-0.033**	-0.016**	-0.011**
	(0.004)	(0.004)	(0.003)	(0.003)
Constant	-0.029	-0.097	-0.100**	-0.168**
	(0.038)	(0.038)	(0.022)	(0.023)
Observations	1525	1525	1525	1525
R^2	0.041	0.025	0.041	0.025

Notes: Sample restricted to inventions with a granted patent. R^2 is the square of the correlation coefficient between the predicted values of the dependent variables and their actual values. Standard errors in parentheses. ** p<0.005, * p<0.01.

The sensitivity of the results is analysed in Table 6, which compares estimates of the depreciation rate when information from patent renewal is taken into account and when it is not. Lapse events are only available for inventions with a granted patent such that regressions are performed on this subsample. Taking renewal information into account does not affect estimates obtained with the quantile regression model from column (1) to column (2) and only slightly affects results obtained with the MM-estimator from column (3) to column (4). In particular, the depreciation rate seems to be slightly lower whereas the early decline in value is higher (15.5 per cent versus 9.5 per cent). In short, the inclusion of lapse event data leaves the depreciation parameter roughly unchanged and increases the early decline in value. We can also interpret these results in light of the attenuation bias and conclude that the robust regression models adopted preserve us from the attenuation bias since the coefficient associated with the age variable remains constant or decreases. (By contrast, the coefficient obtained with the OLS regression models increases from 3.15 per cent to 4.53 per cent, not reported.)

Another potential limitation relates to the assumption of a 30-per cent gross profit margin m for question G1 (past revenues). The sensitivity of the results to the chosen m is assessed in Table 7, which reports estimates of the depreciation rate and the grant effect for values of m comprised between 0.20 and 0.40. The coefficients are largely insensitive to gross profit margin used, for both the quantile estimator and the MM-estimator. The only noticeable difference is that the grant effect is not significantly different from 0 under our strict statistical threshold with m = 0.20 when the MM-estimator is used (p-value of 0.047).

Table 7. Sensitivity to varying the gross profit margin (parameter m)

	(1)	(2)	(3)	(4)	(5)
m =	0.20	0.25	0.30	0.35	0.40
Quantile-estimator					
a	-0.021**	-0.023**	-0.026**	-0.026**	-0.029**
	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)
$a \times grant$	0.010**	0.012**	0.014**	0.014**	0.015**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Constant	-0.061	-0.081**	-0.099**	-0.127**	-0.140**
	(0.024)	(0.026)	(0.032)	(0.036)	(0.041)
MM-estimator					
a	-0.011**	-0.018**	-0.021**	-0.022**	-0.022**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$a \times grant$	0.006	0.010**	0.012**	0.013**	0.014**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	-0.067**	-0.085**	-0.116**	-0.145**	-0.169**
	(0.016)	(0.018)	(0.019)	(0.020)	(0.021)
Observations	2,259	2,259	2,259	2,259	2,259

Notes: Standard errors in parentheses. ** p<0.005, * p<0.01

We have assumed so far that the age of the invention corresponds to the age of the patent (computed from the priority filing date). It should be kept in mind that patent age is necessarily a lower bound estimate of invention age – a patent application can only be filed if an invention exists. Yet, we do not expect much difference between the two measures. For example, Hall et al. (1986) report econometric evidence on a strong contemporaneous relationship between R&D expenditures and patenting at the firm level.

Additional robustness tests were performed but are not reported. First, we checked that the results obtained for the 'intl protection' variable are not affected by our choice of a dummy variable rather than the actual family size. We have interacted the 'grant' variable with the family size and the results did not change. Second, we made sure that our interpretation of the 'other patents' variable, which takes the value of 1 if at least one other patent was used to develop the product, is correct. While we implicitly assume that these other patents belong to the same firm, the possibility exists that they belong to other firms. We have no way of ruling out this possibility with certainty. To hint towards an answer, we exploit that fact that inventors should be listed in more than one patent if they reported that the focal patent involves other patents. We find that such inventors were 2.5 more likely to have filed another patent at IP Australia than inventors who did not mention that other patents were involved. This finding is consistent with our assumption that the other patents belong to the same firm. We have also estimated the regression model on a sample that excludes inventions that involve more than five other patents and inventions that were licensed. The possibility that patents from other firms are involved is indeed more likely when a large number of patents is concerned (as in the case in complex products industries) or when the focal patent was licensed (a sign that cross-licensing may have occurred). Doing this leads to coefficients that remain similar. Third, we have performed the estimations on a sample that exclude patents describing process inventions. Such inventions are less likely to generate sales revenue such that the value estimates might be underestimated. The depreciation rate is approximately 2 per cent and the grant effect 1 per cent, for both the quantile and MM estimators.

5. Discussion and concluding remarks

5.1 Contributions

This paper contributes to the literature in two ways: it presents a new methodological approach for estimating R&D depreciation rate and it addresses a new research question. First, we take a fresh look at an old question. To the best of our knowledge, this study is the first to estimate the R&D depreciation rate from direct observation of the revenue streams of inventions. This feature of the data allows us to estimate the R&D depreciation rate in a very natural way that permits the use of weak identifying assumptions. This approach is in stark contrast with previous studies which all rely on indirect inference. We find that the yearly depreciation rate for R&D is in the lower range of existing estimates and varies in a range between 1 and 5 per cent, depending on model specifications. However, we also find that about 15 per cent of the decline in value occurs within the first two years. We find surprisingly little variation across industries. The depreciation rate is lower than the average by 0.5–1.0 percentage point in the pharmaceuticals and medicinal chemicals industry. Meanwhile the decline in value that occurs in the early life of an invention is smaller than the average in the pharmaceuticals and medicinal chemicals industry, and larger than the average in the radio, television and communication equipment industry (up to 20 per cent).

Second, we look at a new question, namely the extent to which patent protection slows the erosion of profits. Because not all patent applications in the AIS were granted, the data allow us to study the effect of patent protection on the depreciation rate. However, we observe invention value at two points in time such that we are not able to study the effect of patent protection in detail (that is, as a function of the length of patent protection). Rather, the grant effect reflects an average length of protection of eleven years (which is the mean patent life at IP Australia). We find that patent protection reduces the depreciation rate by 1–2 percentage points. Interestingly this result seems to be valid only for 'strong' patents. The grant effect indeed vanishes when patent protection is reported as weak.

We can now apply insights from this paper to briefly reflect on the 'depreciation problem' mentioned in Griliches (1998) and Hall (2005). The depreciation problem arises from the difficulty in reconciling depreciation rates obtained using different methodologies. We have emphasised a key dividing line in the empirical literature, with studies that rely on R&D input data (expenditures) on the one hand and studies that rely on R&D output data (patents) on the other hand. We logically expect a lower depreciation rate for studies that rely on R&D output data – such as ours – due to the fact that only successful R&D is observed. We have also highlighted an important limitation of studies that use patent renewal data. These studies assume that the depreciation rate is exogenous to patent protection. That is, the optimal renewal period is chosen given an intrinsic depreciation rate. This assumption is counterintuitive since the very purpose of patent protection is to slow the erosion of profits. One might think that studies based on patent renewal data would therefore lead to estimates that are downwardly biased. We caution against such a conclusion for two reasons. First, we have shown that the majority of inventions that were granted patent protection still had a residual value greater than $100,000 even though the patent had lapsed. Second, inventions for which no patent is filed and that are successfully kept secret may well enjoy a much lower depreciation rate than inventions protected by a patent.

A potential limitation of our study relates to the lack of R&D expenditure data. Although the theoretical literature has long established the endogenous nature of R&D investment and R&D depreciation (Caballero and Jaffe 1993; Jovanovic and Nyarko 1998; Pacheco-de-Almeida 2010), existing empirical research has not been able to account for the effect of R&D investment on the depreciation rate. This paper is no exception. Future research showing how R&D depreciation and R&D investment affect each other and how this relationship is mitigated, e.g. by the strength of competition or by the strength of intellectual property rights, would be particularly welcome.

5.2 Implications

Our results have implications that extend beyond academic interest. First, estimates of R&D depreciation rates are of immediate relevance to statistical offices around the world in their ongoing efforts to capitalise R&D investments in their national account systems (OECD 2010). The assumption of a constant depreciation rate is validated by our data, at least after two years. More flexible polynomial specifications did not improve results obtained with the simple linear regression model. As far as the early life of inventions is concerned we find a strong decline in value, suggesting that researchers and practitioners at statistical offices should adopt a truncated depreciation function where a large proportion of the value is depreciated in the first few years. This approach is particularly recommended for analyses that rely on R&D input data, given the failure rate of R&D projects. Finally, we find little industry-level variation in the depreciation rate, which validates the current practice of adopting a single depreciation rate across industries.

Second, existence of a grant effect is open to various economic interpretations. It is evidence that patent protection slows down the process of creative destruction (Caballero and Jaffe 1993); increases the private returns to R&D (Hall 2005); and is associated with a premium (Arora et al. 2008; Jensen et al. 2011).[8] These different interpretations all relate to

[8] It is important to emphasize that the present results are conditional on the existence of an inventive output. The overall effect of patent protection is to encourage technological progress and, therefore, to stimulate creative destruction.

the same phenomenon, namely the fact that patent protection assures greater appropriability. However, the grant effect is statistically significant only when patent protection is strong. We know from previous studies that owners of weak patents may be able to abusively extract a profit from their intellectual property rights due to the public-good nature of challenging a patent (Farrell and Shapiro 2008). This paper shows that such patents have a higher depreciation rate than patents considered as strong, suggesting that imitation occurs faster for weak patents. The stronger erosion of profits partially mitigates the social cost of these weak patents.

Third, at a more practical level, our estimates are also relevant to the growing number of financial institutions that take patents as collateral for loans (Mann 2005; Amable et al. 2010). Because a large proportion of the decline in value occurs early in the life of a patent, lenders are well advised to wait for technological uncertainty to dissipate before accepting a patent as collateral.

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Appendix A. Industry-specific depreciation rates

Table 8. Industry-specific depreciation rates

	(1)	(2)	(3)	(4)
	Quantile estimator		MM estimator	
Depreciation rate (a)				
Reference group	-0.020**	-0.019**	-0.012**	-0.015**
Chemicals and chemical products	-0.023**	-0.017	-0.016**	-0.009
Pharmaceuticals and medicinal chemicals	-0.011	-0.017	-0.006	-0.011
Basic metals and fabricated metal products	-0.023**	-0.020	-0.012**	-0.012
Machinery and equipment n.e.c.	-0.035**	-0.040**	-0.021**	-0.022*
Radio, television, and communication equipment	-0.023**	-0.013	-0.014**	-0.008
Motor vehicles, trailers and semi-trailers	-0.036**	-0.037**	-0.014**	-0.009
Furniture and n.e.c.	-0.027**	-0.027**	-0.016**	-0.022**
Early drop in value (constant term)				
Reference group	-0.125**	-0.128	-0.148**	-0.117**
Chemicals and chemical products	-0.125**	-0.192	-0.148**	-0.227**
Pharmaceuticals and medicinal chemicals	-0.125**	-0.052	-0.148**	-0.099
Basic metals and fabricated metal products	-0.125**	-0.156	-0.148**	0.147**
Machinery and equipment n.e.c.	-0.125**	-0.077	-0.148**	-0.138
Radio, television, and communication equipment	-0.125**	-0.209**	-0.148**	-0.215**
Motor vehicles, trailers and semi-trailers	-0.125**	-0.114	-0.148**	-0.213*
Furniture and n.e.c.	-0.125**	-0.125	-0.148**	-0.082

Notes: N = 2259. Reference group is all other industries. ** $p<0.005$, * $p<0.01$.

Appendix B. Bias in the reporting of invention value

Figure 4. Mean of initial value (V_0) by cohort

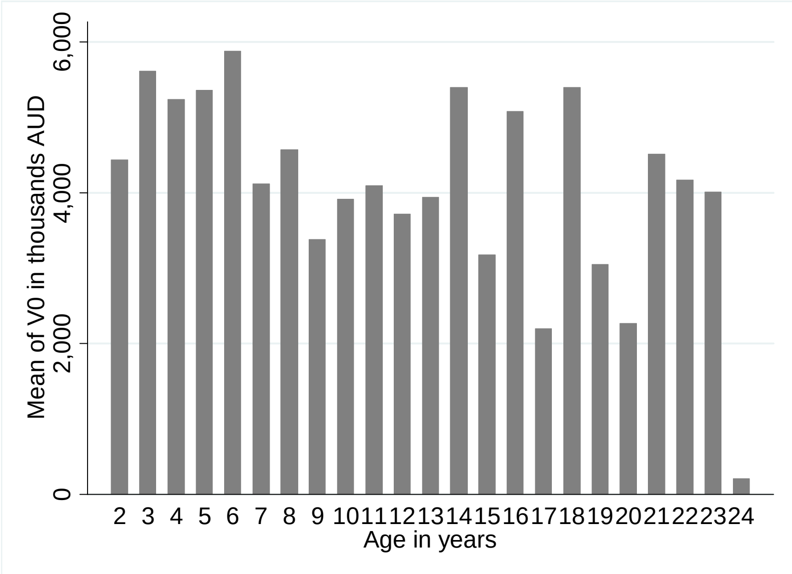

Figure 5. Box plot of initial value (V_0) by cohort