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Econometric evidence on the depreciation of innovations

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Abstract

This paper presents estimates of the depreciation rate of innovations using survey data on revenues associated with Australian patents. 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. Results suggest that the depreciation rate is in the 2–7 per cent range. Inventions for which a patent is granted are associated with a 1–2 percentage point reduction in the depreciation rate.

Keywords: appropriability, intangible asset, obsolescence, depreciation, returns to R&D, weak patent

JEL Codes: M41, O32, O33, O34

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1. Introduction

Intangible assets are attracting major academic and policy interest in today's knowledge economies. Intangible assets, such as knowledge generated through investment in research and development (R&D), are assets that are not physical in nature yet deliver concrete economic benefits. Research has established that intangible assets account for a significant proportion of firms' value (Lev and Sougiannis 1996; Crépon et al. 1998; Webster 2000) and are an important driver of productivity growth (Adams 1990; Coe and Helpman 1995; Corrado et al. 2009). Although our understanding of intangible assets has progressed significantly, 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 innovations, defined as the rate of decay of appropriable revenues from innovations (Pakes and Schankerman 1984). The depreciation rate of technological knowledge is a key economic parameter. It provides information about the speed of technological change and is essential for estimating the private returns to R&D investments (Pakes and Schankerman 1984; Esposti and Pierani 2003; Hall et al. 2010; Li and Hall 2016). 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). Furthermore, the rate of depreciation of technology in different industries and different countries serves also as an indicator of the rate of advance of technology in those different contexts that is not subject to the measurement problems that plague inter-industry and international comparisons of productivity growth (Li 2016). Finally, 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).

Within this context, this paper presents novel estimates of the depreciation rate of innovations 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. The empirical analysis comes with two distinguishing features. First, the estimation strategy departs from existing methods. Only a handful of studies have estimated the depreciation rate of technological knowledge and all of them rely on indirect inference. By contrast, the approach proposed in this paper relies on direct observation of

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inventors' estimates of the revenue streams generated by inventions. It is thus genuinely different from existing approaches.[1]

Second, the very purpose of patent protection is to slow down the erosion of profit, so the depreciation rate of innovations for which patent protection is granted should be slower than that for innovations for which patent protection was sought but not granted. Although our sample consists entirely of innovations for which patent protection was sought, not all of the patent applications in the AIS were granted, allowing us to study how patent protection affects the depreciation rate. The magnitude of the difference in the depreciation rate generated by successful patent application may help resolve discrepancies in previous estimates. It will also provide novel insights into economic aspects of the patent system.

The results suggest that the depreciation rate is in the lower range of existing estimates and varies between 2 to 7 per cent depending on model specifications and assumptions about the macroeconomic environment. The results further indicate that the depreciation rate is lower for inventions that are protected with a patent. Inventions protected with a patent enjoy a reduction in their depreciation rates of about 1–2 percentage points.

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

2. Definition(s) and estimates of technological depreciation rate

This section first discusses the concept of depreciation of technological knowledge. It then presents the main approaches that have been proposed in the literature, which focus mainly on depreciation of the value of accumulated R&D expenditure (a longer literature review is presented in Mead 2007). Subsequently, it discusses how our estimate of depreciation of the value of innovations relates to R&D depreciation. Finally, this section considers the effect of patenting on depreciation.

[1] Because patent law requires 'unity of invention', meaning that a patent shall relate to one invention or one inventive concept only, we use the terms 'invention' and 'patent application' interchangeably.

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2.1. Defining R&D depreciation

Depreciation of the asset represented by technological knowledge is often considered as analogous to the depreciation of tangible assets. But of course intangible assets do not physically degrade; the forces that cause their value to decline with time are subtler. The knowledge created by investment in R&D or other aspects of innovation can be embodied in products and processes to deliver a commercial benefit, and it can also create a technological benefit in the form of spillovers that facilitate subsequent inventions. For a specific invention, both commercial and technological benefit can either rise or fall after it is first created, as new information arrives about the effectiveness or uses of the invention. But there are generic forces that tend to cause value to decline on average over time. First, a successful invention will tend to invite imitation, which reduces the commercial value to the owner of the invention. Second, because technological improvement is on-going, the development of other new ideas will tend to partially or wholly supersede a given idea. This process of obsolescence will tend to reduce the commercial value, as new products compete with existing ones in the process that Schumpeter dubbed *creative destruction*. Obsolescence also tends to reduce the technological value of an invention over time, as each successive round of invention builds on the most recent knowledge and depends less on older knowledge.

Both commercial and technological values are subject to spillovers, so there may be a gap between the value captured by the party that made the investment (private return) and the overall social value. Given this gap, the private and social rates of depreciation may differ, as imitation and obsolescence may operate differently on the private and social values. For example, imitation may greatly erode the private value while not affecting the social value.[2] Obsolescence will generally reduce the social value, but may have relatively little impact on the private value, as the market for the products incorporating the invention may or may not be impacted by subsequent technologically-dependent inventions, and those subsequent inventions may or may not be monetized by the original inventor.

In this paper we focus on *private* depreciation rate of innovation capital, which we characterize as the average rate of decline in revenues that are appropriable by the original invention owner. The private depreciation that we observe results from some unknown combination of imitation and obsolescence. Our estimates do not speak directly to the social

[2] Indeed, imitation could increase the social value of an invention, if it has the effect of making the invention available to more users.

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depreciation rate, although the fact that imitation depreciates private but not social value suggests that, in general, the depreciation rate of social value should be slower than the private rate.

2.2. Available estimates

The most prominent approach to estimating depreciation of technological knowledge is to use investment expenditure—typically in the form of R&D—as a measure of the initially created asset, and then compare the benefits that flow from this asset over time to its initial value. 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 based on R&D expenditure estimates production models with the stock of R&D as an input along with labour and tangible capital. 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). Because these models are estimated at the economy or industry level, the returns to R&D implicitly include some degree of spillovers beyond the R&D-performing firm, and hence reflect to some degree the social rather than the private depreciation rate.

Another line of research focuses on the value of patents following Pakes and Schankerman (1984). This research exploits the fact that the owner of a patent must pay yearly renewal fees in order to maintain a patent in force. Pakes and Schankerman (1984) 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 approach 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).[3] Interestingly, studies that use patent renewal data usually assume that the depreciation rate is exogenous to patent protection. That is, the optimal renewal period is chosen given an intrinsic depreciation rate that is expected to be the same whether or not the patent is renewed. This assumption is counterintuitive since the very purpose of patent protection is to slow the erosion of profits.

There is a conceptual difference between estimates of depreciation based on input expenditures such as R&D, and estimates that look at the value over time of successfully created inventions. If a company spends money on research and comes up with nothing (or derives limited learning whose initial value is much less than the expenditure from which it was derived), no asset was created (or an asset was created worth much less than was spent to create it). The possibility of such failure of R&D is, presumably, anticipated by firms and factored into the expected return to R&D investment, but it does not represent depreciation. Yet, if we estimate depreciation rates by looking at performance (however measured) subsequent to investment (including money spent on unsuccessful investments), the loss of value flowing from failed research is likely to appear as depreciation. This suggests that estimates of depreciation based on R&D expenditures need to be interpreted as combining the effects of some average failure rate and depreciation of assets successfully created. On the other hand, if depreciation rates are inferred by looking at the decline in value of inventions once created, we are not including any effect due to R&D failure. Thus, conceptually, the R&D depreciation rate should be higher than the depreciation rate of innovations.

Table 1 summarises the main estimates. They vary greatly, ranging from almost no depreciation to almost 50 per cent, and there is not, in fact, a clear tendency for the estimates based on granted patents to be lower than those based on R&D expenditures, nor for industry-level estimates to be lower than those at the firm level. This wide variation illustrates the ‘depreciation problem’ raised by Zvi Griliches and Bronwyn Hall.

[3] Another approach that uses patent data involves modelling the evolution of the number of citations received by patents over time. As a piece of knowledge gradually becomes less useful in generating new knowledge, the number of citations received by a patent should decline (Jaffe and Trajtenberg 1996). It is however unclear that citation data inform about the decay of appropriable revenues. It more likely captures the technological obsolescence of inventions.

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Table 1. Overview of estimated R&D depreciation rates

Article	Key data	Model	Unit	Rate
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
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

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.

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, i.e. the estimates derive directly from how the revenue streams from specific inventions have changed over time.[4] In addition, no previous research has explicitly studied the difference in depreciation rates between inventions that are protected with a patent and inventions that are not. Whereas studies that rely on granted patents are only informative about the decay rate of revenues from patented inventions, studies that rely on R&D expenditures mix both patented and unpatented inventions. Estimating the depreciation rate for both groups separately is thus a step forward in bringing these two sets of studies closer to each other.

2.3. Depreciation and the patent system

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’, related to obsolescence as discussed above). 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 may

[4] Of course there are also limitations associated with this approach, in particular regarding the fact that it relies on the inventor’s estimate of the revenue stream. Sections 3 and 4 discuss the caveats.

inhibit follow-on research by competitors, or yield licensing revenue if subsequent products rely also on the earlier invention (Scotchmer 1991; Bessen and Maskin 2009), thereby mitigating the revenue loss due to displacement.

The literature is equivocal about both mechanisms. 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 2014). Second, patent protection is ineffective against imitators inventing around an innovation (Mansfield et al. 1981; Gallini 1992).

There is 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 costs are both monetary (actual cost of patenting) and non-monetary (disclosure requirement in patent law), and authors have shown that these costs affect 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 likely 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, and so we cannot say anything about depreciation of inventions that are protected by trade secrets.

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3. Framework and data

3.1 Empirical framework

The present value at time 0 of an invention that brings a revenue *X(t)* to its owner at time *t* is simply:

$$V(0) = \int_0^\infty X(t)e^{-rt}dt$$

where *r* is the nominal interest rate. The revenue *X(t)* expands with time due to demand growth and contracts with time due to depreciation (commanding lower price and/or capturing a smaller market share). We follow previous convention and model *X(t)* in an exponential growth framework:

$$V(0) = \int_0^\infty X(0)e^{-(r+\delta-g)t}dt$$

where g captures demand growth and δ is the depreciation rate.[5] The model assumes a constant depreciation rate over time, and section 4.2 shows that the data support that assumption. We are interested in the log of the proportion of value that remains to be appropriated at time *a*. It is easy to show that:

$$\ln\frac{V(a)}{V(0)} = -(r+\delta-g)a \tag{1}$$

Letting *i* denote an invention, the empirical counterpart of equation (1) is given by:

$$\ln\frac{V_{a,i}}{V_{0,i}} = c - \beta a_i + \varepsilon_{ia} \tag{2}$$

where the error-term $\varepsilon_{ia} \sim N(0, \sigma_a^2)$ in the baseline specification and is assumed to be orthogonal to the coefficient β.[6] Note the introduction of a constant term *c*, which we interpret as capturing the effect of innovation diffusion in early years. In short, *c* could capture the extent to which the invention has spread in the market and is appropriated by the firm. (See Appendix A for a discussion and alternative interpretations.)

[5] One could also conceive of depreciation in terms of the decline in the annual revenues, but another virtue of the exponential model is that the depreciation rate is the same whether conceived relative to the stock or the annual flow.

[6] As explained in section 4.2 the regression equation (2) also encompasses the class of declining balance models and is, therefore, quite general.

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The data do not contain information on the full sequence of values $\{V_{a,i}\}\ \forall\ i, a$. Two quantities are observed: invention value at age 0; and the residual invention value at the time of the survey (that is, at age a_i). Heterogeneity in the data comes from the fact that inventions belong to cohorts of different vintages. Thus, the parameter β is estimated from a mix of within variations in value and between variations in value. Equation (2) will be estimated with OLS as well as with alternative regression models: a generalised linear model, to account for the fact that the dependent variable is not normally distributed, and a robust regression model, to account for potential difference in the trustworthiness of estimates across vintages.

It is clear from the regression model that the parameter β that we are estimating is equal to $\delta + r - g$. We will return to this observation when discussing the regression results. It suffices to say now that the composition of the parameter β may provide insights into some of the discrepancy in the depreciation rate observed in the literature. Studies based on the production function approach (using R&D expenditure data) usually propose a comprehensive model of the economy that results in estimating directly the depreciation parameter δ (although, sometimes, the social rate of depreciation when industry-level R&D expenditure data are used). By contrast, studies based on patent renewal data typically do not control for demand growth. For instance, the 'depreciation' reported by Bessen (2008) using patent renewal data is purged from r (labelled s in his model) but not from g.

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 conducted a survey of patent applications by Australian inventors that were submitted from 1986 to 2005 to IP Australia, the Australian patent office. 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). The initial target population was composed of 31,313 patent applications but valid addresses were found for about 5446 addresses. There are 3862 inventions in the final database and information on value is available for 2558 of them.

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There are two selection effects at play: selection into taking part in the survey and selection into reporting information on value. The former selection results because we could not reach the original inventors (unknown addresses) or the inventors chose to not take part in the survey. We note that the participation rate is lower for older inventions (Webster and Jensen 2011:449). Our results will be underestimated to the extent that these older non-reachable and non-participating inventions exhibit a larger depreciation rate. Regarding the latter selection effect, section 4.1 provides evidence that non-respondents are unlikely to bias the results.

3.2.2 IP Australia's AusPat database

The online AusPat database from IP Australia is used to obtain information on the grant status of patent applications as well as their priority and expiry dates. 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.

3.2.3 PATSTAT

The European Patent Office (EPO) worldwide patent statistical database PATSTAT is used to obtain 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. This paper adopts 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 represent the different areas of technology to which a patent pertains. They are assigned by examiners at the patent office and are thus homogeneous across patents. Technical details on the construction of the variables are provided in de Rassenfosse et al. (2014).

3.2.4 IPC-ISIC Concordance Table

Patents are 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.

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3.3 Dependent variable

The dependent variable is the log of the proportion of invention value remaining at the time of the survey ($\ln V_{a,i}/V_{0,i}$). 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). (Section 4.3 investigates the sensitivity of estimates to the parameter *m*.) The variable $V_{a,i}$ is the residual value for patent *i* of age *a* and corresponds to question G2. The variable $V_{0,i}$ is the total value at age 0. It can be computed as (*m**G1 + G3) + G2. Since the data are 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 alternative methods 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, it is clear now that the dependent variable used in this paper is a direct measure of revenues. This approach, of course, introduces its own interpretation issues and possible bias. Inventors may systematically overvalue their innovations, particularly when forecasting their future value. Another potential source of bias relates to the fact that inventions belong to cohorts of different ages. Future value is subject to a greater deal of uncertainty for younger cohorts, and respondents may experience greater difficulty in recollecting revenues earned for older inventions. These issues will be explored 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 not based in any direct way on the commercial value of the invention, though we cannot rule out some degree of correlation. We will thus refrain from asserting a causal relationship running from patent grant to reduced depreciation.

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.

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.[7] There is no 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

[7] In theory, all the observations should be matched to the PATSTAT database. There are, however, coverage problems in the PATSTAT database for patents filed at IP Australia. Section 4.3 investigates the effect of a potential selection bias.

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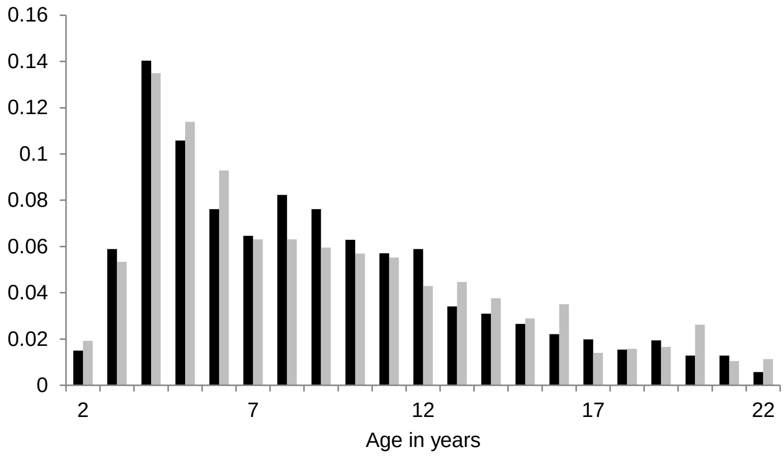
value (N=1141), and the difference is not statistically significant (p-value of 0.38). Similarly, the average age is 8.82 years for inventions with information on value and 9.06 years for inventions lacking information on value, and the difference is not statistically significant (p-value of 0.18). The age profile of inventions is presented in Figure 1 for the series of inventions with information on value (black bars) and missing information on value (grey bars).

Figure 1. Histogram of invention ages by availability of value information



Notes: Black bars: information available; Grey bars: information missing.

Table 2 presents descriptive statistics of the sample used. Note that the dependent variable is the logarithm of a ratio whose numerator is G2 and whose denominator is G2 plus the revenue numbers (G1 and G3). Hence the ratio never exceeds one and its logarithm is always negative. The mean of the dependent variable is -0.63 and the median (not in the table) is -0.26. These figures correspond to ratios of 53 per cent and 77 per cent, respectively. The skewness of the dependent variable is explained by the predominance of more recent inventions in the sample (as shown in Figure 1). 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. The correlation structure of variables indicates that there are no collinearity issues.

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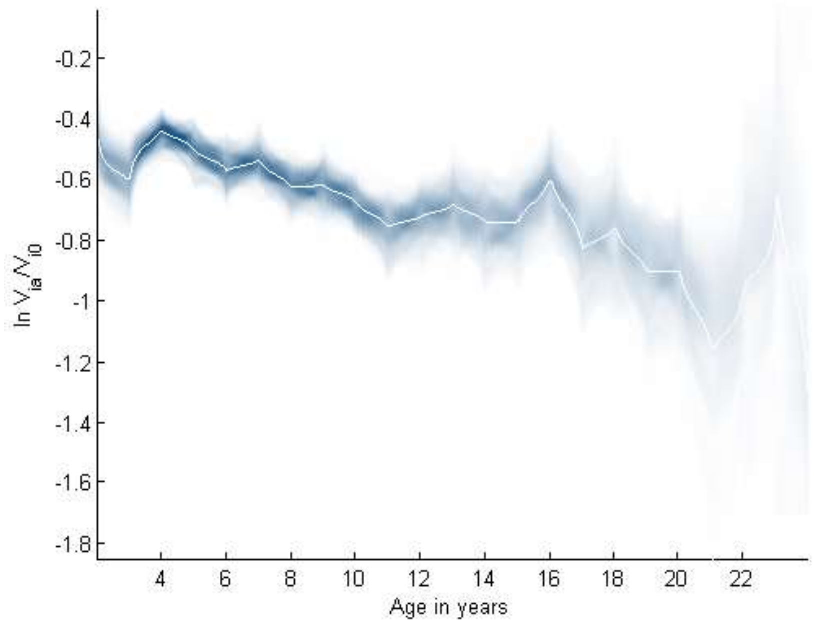
Table 2. Data descriptives

	Summary Statistics				Correlation coefficients			
	Min	Mean	Max	Std. Dev	(1)	(2)	(3)	(4)
(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	-	0.01	0.27	1.00	
(4) *private*	0	0.47	1	-	-0.05	-0.10	0.13	1.00

Notes: N = 2259.

Figure 2 provides an overview of the revenue function. It depicts the conditional mean of the dependent variable $ln\,V_{a,i}/V_{0,i}$ computed using a kernel-weighted moving average. The confidence interval is 'visually weighted' using the method proposed by Hsiang (2013). The intuition behind these visual weights is that regions with more statistical certainty are given darker colours. Econometric estimates presented in section 4.2 below aim at evaluating the slope of this function.

Figure 2. Overview of the depreciation function



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4.2 Econometric estimates

Baseline results

Table 3 presents baseline estimates of equation (2). Results using an OLS regression model without a constant in column (1) suggest a value for β of 6.1 per cent. However, this model violates the 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 in column (2) reduces the parameter β to 2.6 per cent and leads to a good model fit, as depicted in Figure 3.[8] We refrain from putting too much emphasis on the constant term but we note that it may adequately capture the presence of a diffusion process (Appendix A). A close look at the residuals suggests the presence of heteroscedasticity (the variance of residuals increases with age, not reported), and we have clustered standard errors by age cohort. Columns (3) and (4) investigate whether a more appropriate distributional assumption or a more appropriate treatment of likely outliers improves estimation.

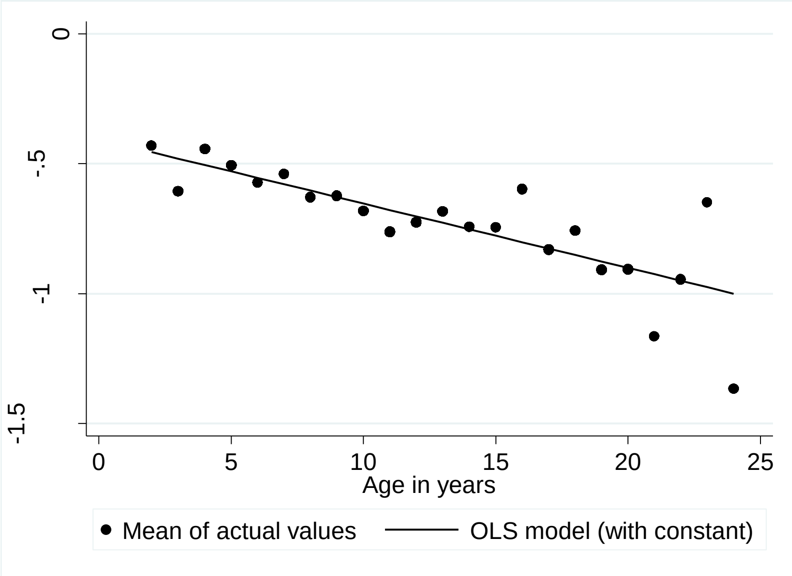
Table 3. Estimates of parameter β with various regression models

	(1)	(2)	(3)	(4)	(5)
Method:	OLS	OLS	GLM	MM	MM
a	-0.061**	-0.026**	-0.055**	-0.015**	-0.011*
	(0.004)	(0.004)	(0.009)	(0.002)	(0.004)
Constant		-0.403**	2.132**	-0.152**	-0.107**
		(0.044)	(0.133)	(0.019)	(0.021)
Observations	2259	2259	2259	2259	1399
R^2	0.024	0.024	0.024	0.024	0.024

Notes: The sample for column (5) is composed of inventions 9 or less years old. 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 age cohort in columns (1)–(3). ** p<0.005, * p<0.01.

[8] 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.

Figure 3. 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. The method used in column (3) assumes that the dependent variable conditional on the covariates follows a Gamma distribution by estimating a generalized linear model (GLM).[9] The estimated coefficient is -0.055 and corresponds to a marginal effect at mean of 2.3 per cent, which is very close to the OLS estimate of column (2). Column (4) reports the results of a robust regression model that down-weights potential outliers. The estimator is the MM estimator by Yohai (1987) as implemented in Stata by Verardi and Croux (2009). The parameter β is slightly lower, at 1.5 per cent.

Overall, estimates suggest a value for β in the range 1.5–2.6 per cent. To obtain a range of values for the depreciation rate, one needs to purge β from the effect of the macroeconomic variables g and r. Table B.1 in Appendix B presents values for g and r over the time period covered by the sample. Two time periods seem to emerge: 1989–1998 with large variations in both g and r, and 1999–2007 with more stable values for g and r. In the second period, $g - r$ is in the range 0.42–3.32 per cent and averages 1.64 per cent.

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

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To test for the sensitivity of the parameter β to variations in the macroeconomic variables, column (5) of Table 3 presents estimates obtained on inventions that fall in the second period (1999–2007), which contains the majority of observations. The estimated value for β is 1.1 per cent, i.e. a mere 0.4-percentage point lower than the value obtained using the full sample. Thus, it seems that the variability of macroeconomic environment in the 1990s only marginally affects the overall estimates. We will continue working with the full sample in the remainder of the analysis to maximise the number of observations.

Taken together, the results collected thus far inform us about the depreciation rate. Assuming a value for β comprised in the lower range of estimates, say 1–2 per cent, and considering a range of values for $r - g$ of 1–3 per cent, we obtain a depreciation rate in the range 2–5 per cent.

As a side note, 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 $V_{a,i} = V_{0,i}(1-\mu)^{a}$ and can be rewritten as $\ln V_{a,i}/V_{0,i} = \ln(1-\mu)\, a = \beta a$. Thus, the declining balance depreciation rate can easily be recovered from the estimated parameter β. It corresponds to $\mu = 1 - e^{\beta}$. Note that for β small, $\mu \cong \beta$ such that both models give sensibly similar results.

Estimates by patent grant status

The next sets of results, presented in Table 4, estimate the decline in revenue for inventions that were granted patent protection and inventions that were not. The estimates are obtained using the robust (MM) estimator. The specification in column (1) estimates the grant effect with the interaction variable 'a×*grant'*, which captures the percentage-points reduction in the depreciation rate. The value of 0.011 suggests that inventions that enjoy patent protection depreciate more slowly than inventions for which a patent was not granted—about 1.1-percentage point more slowly on average. The second specification (column 2) estimates the grant effect with the dummy variable '*grant*', which can be thought of as measuring the extent to which patent protection slows down/hastens diffusion. The positive coefficient suggests that inventions that enjoy patent protection diffuse more slowly.

The regression model in column (3) estimates both variables (‘*grant*’ and ‘$a \times grant$’) jointly. The point estimates and the statistical significances drop, owing to the strong correlation between both variables (correlation coefficient of 0.76). However, the F-test leads to a rejection of the null hypothesis that both coefficients are jointly equal to zero. We obtain a similar conclusion when including industry fixed effects in column (4) and when restricting the sample to inventions by private companies in column (5). (Table C.1 in Appendix C provides industry-specific estimates of the parameter β for inventions by private firms.) Note that excluding the variable ‘$a \times grant$’ from the model in column (5) produces a coefficient of 0.088 (*t*-stat of 2.78) associated with the variable ‘*grant*’ (not reported). Excluding the variable ‘*grant*’ from the model in column (5) produces a coefficient of 0.016 (*t*-stat of 2.36) associated with the variable ‘$a \times grant$’ (not reported).

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). Note also that we are careful not to insist on the causality of the result. On the one hand, the decision to grant a patent is based on technological rather than economic factors, and the very purpose of patent protection is to slow down the erosion of profits. So it seems likely that the granting of a patent does indeed slow depreciation. But we certainly cannot rule out that technological attributes of an invention that make it more likely to be granted patent protection also convey a degree of intrinsic protection against depreciation. So we cannot interpret our estimate as a measure of the causal impact of the patent grant on depreciation. Estimates of the magnitude of the difference between protected and unprotected innovations are interesting in their own right independent of the issue of causality.

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Table 4. Effect of patent grant on the decline in revenue

	(1)	(2)	(3)	(4)	(5)
Sample:	All	All	All	All	Firms
a	-0.026**	-0.017**	-0.019**	-0.018*	-0.047*
	(0.004)	(0.002)	(0.006)	(0.007)	(0.017)
a×grant	0.011**		0.002	0.001	0.017
	(0.003)		(0.007)	(0.007)	(0.017)
grant		0.098**	0.080	0.087	-0.008
		(0.021)	(0.044)	(0.044)	(0.088)
F-test (p-value) (grant=0 & a×grant=0)			0.000	0.000	0.024
Industry effects	No	No	No	Yes	Yes
Constant	-0.132**	-0.199**	-0.186**	-0.150**	-0.027
	(0.019)	(0.023)	(0.039)	(0.046)	(0.091)
Observations	2259	2259	2259	2259	1057
R^2	0.022	0.026	0.025	0.029	0.026

Notes: The sample in column (5) includes inventions from private companies only. R^2 is the square of the correlation coefficient between the predicted values of the dependent variables and their actual values. MM estimator. 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. On the one hand future revenues are more uncertain for younger cohorts (question G2), but on the other hand 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 D.1 and Figure D.2. in Appendix D 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 D.1), and the variable varies widely within cohorts as shown by the box plot in Figure D.2. 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). Although the robust regression model adopted already accounts for greater variance in the dependent variable, an additional test is performed. 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 Table 5

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must be compared with those in column (1) of Table 4. The coefficient associated with the age variable is about 4 per cent and the grant effect is 1.3 per cent. In other words, figures presented in Table 4 can be seen as conservative estimates.

A second 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 (2) of Table 5 are performed on a sample that excludes 539 such inventions.[10] The results remain unchanged.

Third, twelve per cent of the observations were not matched to the PATSTAT database (see section 4.1). Including these observations in the regression leaves the results unchanged, as shown in column (3).

Fourth, we have arbitrarily taken the mid-point value of each category of the ordinal variables to construct the dependent variable. Columns (4) test whether the results are robust to an alternative imputation method. Specifically, we assume that observations are uniformly distributed in the range covered by their category (0 to $100,000; $100,000 to $500,000; etc.). The results remain largely unchanged, although, of course they now depend on the actual draw.

Next, it is possible that the results are affected by a fundamental difference in inventors' answers to forward-looking and backward-looking questions. We estimate the decline in revenue off of the relative magnitude of the inventor's forward-looking valuation of the invention and their estimate of revenues already accrued; our finding of relatively slow depreciation corresponds to the stated reservation prices for sale of the invention (assumed to represent future revenues) being generally high relative to the revenues already received. While the revenue estimates are subject to error, it does not seem that they would be biased in a particular direction. But the future-looking valuation may well be biased upward: it has been observed in a variety of contexts that people have a tendency to over-value goods in possession, particularly if they are self-created (Kahneman et al. 1990, Buccafusco and Sprigman 2011). We cannot, of course, analyse the consequences for our estimates of arbitrarily large upward bias in the estimates, as might be obtained if inventors were so enamoured of their own inventions that they effectively would not sell at any price. But it is

[10] The sample excludes 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 (2) also excludes the latter.

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perhaps illuminating to test the consequences for the findings of quantified upward bias. If, for example, the reported sale values represent a systematic 50 per cent over-valuation of the true future value, the estimated parameter β would be pushed to around 3.4 per cent (column 5). While we cannot put a specific upper bound on this bias, this suggests that even if the reservation sales price is significantly inflated, the corrected depreciation rate remains at the low end of estimates available in the literature. Conversely, the reported residual value may not reflect the value for the best potential buyer, who may be willing to pay more than the residual value for the current owner. Assuming on average a systematic 50 per cent under-valuation lowers the key parameter to 1.8 per cent (column 6).

Next, we have performed the estimations on a sample that excludes patents describing process inventions (column 7). These inventions are less likely to generate sales revenue such that the value estimates might be underestimated. The parameter β reaches 2.4 per cent and the grant effect 1 per cent.

Finally, we have implicitly assumed that respondents have discounted past cash flows with the nominal interest rate, but we cannot rule out that they provided a simple sum of flows, which would underestimate the value of older revenues. In order to test the sensitivity of the estimates to this issue, we have adjusted past revenues with a discount rate proportional to the patent's age (using values for r presented in Appendix B). Results presented in column (8) show a depreciation rate of 4 per cent.

Table 5. Robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Y5–Y12	No transfer	All obs.	Uniform	Over-valuation	Under-valuation	Product only	Discount factor
a	-0.037**	-0.025**	-0.025**	-0.022**	-0.034**	-0.018**	-0.024**	-0.039**
	(0.008)	(0.005)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.007)
$a \times grant$	0.013**	0.011**	0.011**	0.009**	0.014**	0.008**	0.010*	0.016**
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)
Constant	-0.067	-0.139**	-0.137**	-0.134**	-0.209**	-0.081**	-0.126**	-0.142**
	(0.042)	(0.024)	(0.019)	(0.017)	(0.026)	(0.014)	(0.021)	(0.029)
Observations	1319	1721	2556	2259	2259	2259	2259	2259

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

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Including information on the 'legal life' of patents

Exponential decay implies that patent value goes to zero asymptotically. This is an approximation; in reality, an invention may lose all value in finite time. The survey was conducted in 2007 and the methodology has implicitly assumed so far that all inventions in the sample have lived up to at least 2007. In addition, inventions that were allocated to the lowest residual value category were given an arbitrary residual value of $50,000. Approximately 30 per cent of inventions have a residual value in the range $0–100,000 and are thus at risk of having their residual value artificially inflated to $50,000 and their life artificially stretched to 2007.

Patent renewal data can help 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 panel of Figure 4 shows that a large proportion of inventions associated with a lapsed patent have the lowest residual value. However, 54 per cent of inventions have a residual value greater than $100,000 even though the patent right has expired. As emphasised by various scholars, the value of a patent differs from the value of the underlying invention (e.g., Harhoff et al. 2003; Arora et al. 2008) and Figure 4 provides direct evidence supporting that claim. The right panel of Figure 4 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.

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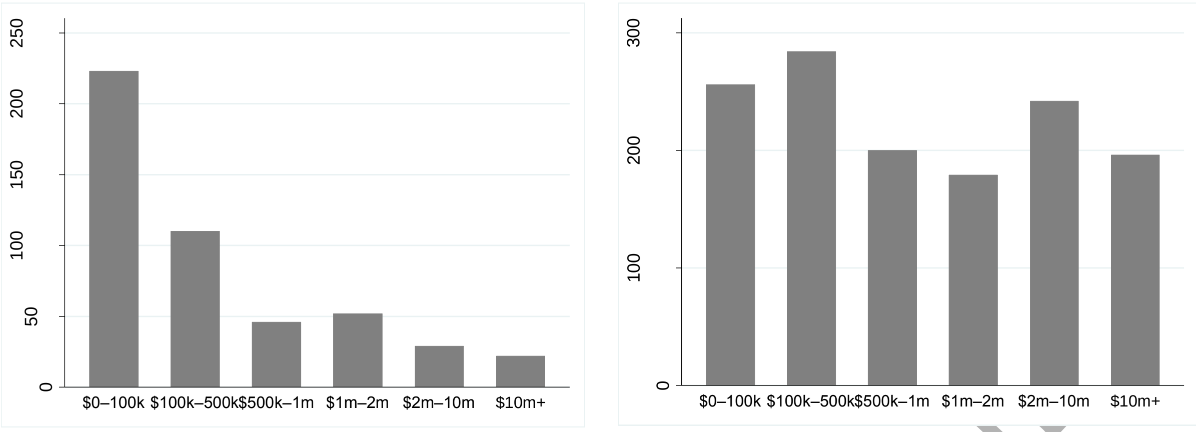
Figure 4. Distribution of residual invention value G2 (patent expired vs. patent still valid)



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 falls in the lowest value category (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. This adjustment is quite extreme, because we know from Figure 4 that inventions associated with a lapsed patent may still have a residual value. However, it gives us am overview of the potential bias associated with the fact that we do not observe when residual invention value became null (if at all). Taking renewal information into account slightly affects regression results: the parameter loses 0.5-percentage points (not reported).

Sensitivity to the profit margin parameter

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 Panel A of Table 6, which reports estimates of the key parameter and the grant effect for values of *m* comprised between 0.15 and 0.40. The coefficients gradually increase with the gross profit margin used but are stable for *m* in the range 0.25–0.35.

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Table 6. Sensitivity to varying the gross profit margin (parameter *m*)

	(1)	(2)	(3)	(4)	(5)	(6)
m =	0.15	0.20	0.25	0.30	0.35	0.40
Panel A: Full Sample (N = 2,259)						
a	-0.005**	-0.014**	-0.022**	-0.026**	-0.027**	-0.028**
	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
a × grant	0.000	0.005	0.010*	0.011**	0.012**	0.012**
	(0.001)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Constant	-0.083**	-0.082**	-0.102**	-0.132**	-0.160**	-0.185**
	(0.007)	(0.014)	(0.018)	(0.019)	(0.021)	(0.021)
Panel B: No other patent used (N=1,471)						
a	-0.006**	-0.019**	-0.025**	-0.027**	-0.029**	-0.030**
	(0.002)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)
a × grant	0.001	0.008	0.012*	0.013**	0.013**	0.013**
	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-0.077**	-0.076**	-0.107**	-0.142**	-0.172**	-0.197**
	(0.010)	(0.020)	(0.023)	(0.025)	(0.026)	(0.027)

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

Another related issue concerns the allocation of revenues to the focal patent. Whereas questions G2 and G3 pertain directly to the patent, question G1 covers any product and processes that use the invention, which is a broader concept than simply pricing the patent. 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+]. Panel B of Table 6 presents estimates obtained on a sample of patents that are not used in conjunction with other patents. As such, we are able to allocate more directly the revenues to the focal patent. The estimates for the parameter β are 0.1- to 0.4-percentage points higher than corresponding estimates in Panel A (the grant effect remains essentially unchanged).

Age of the patent vs. age of the invention

The data provide information on the age of the patent and is silent on the age of the invention. 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. Tentative evidence suggests that there is not much difference between the two measures. Figure E.1 in Appendix E shows that patents are usually filed shortly after initial R&D expenditure and, therefore, shortly after actual invention date. It relies on 497 observations obtained from an international survey of patent applicants at the EPO conducted in 2006 (see de Rassenfosse 2012). Roughly 80 per

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cent of patents in this sample are filed within one year of the start of the R&D project. This result confirms earlier econometric evidence by Hall et al. (1986) related to the strong contemporaneous relationship between R&D expenditures and patenting at the firm level.

5. Discussion

The contribution of this paper is twofold. First, it takes a fresh look at an old, but still open, question. As far as we can ascertain, this study is the first to estimate the depreciation rate of technological knowledge from direct observation of the revenue streams of inventions. This feature of the data allows estimating the depreciation rate in a natural way that provides an interesting and valuable contrast with previous studies, which all rely on indirect inference. Second, this paper provides the first empirical estimates of the extent to which patent protection is associated with a slower erosion of profits.

Assuming a value for the quantity $r - g$ between 1 and 3 per cent, and observing that the yearly decline in revenue obtained from the numerous specifications is in the range from 1 to 4 per cent, we come to the conclusion that the depreciation rate of innovations is in the range between 2 and 7 per cent. We further observe that inventions for which a patent is granted are associated with a 1–2 percentage point reduction in the depreciation rate.

We are careful not to attach a causal interpretation to the association between patent protection and the slower erosion of profits. Yet the negative correlation between grant status and depreciation rate is an instructive finding, making the pattern that patent-renewal-derived depreciation estimates in previous studies are not lower than those derived from R&D expenditures quite puzzling.

Figures presented in this paper are in the lower range of previous estimates owing, we believe, to four main factors. First, previous estimates mainly deal with the depreciation of R&D expenditure. Our focus on inventions submitted to the patent system excludes apparent depreciation associated with unsuccessful R&D. Second, as already discussed, patent protection itself may slow depreciation, further widening the gap with estimates based on R&D expenditure. Third, the data clearly show a drop of value in early years that is not consistent with the subsequent rate of exponential depreciation. We explain that this pattern is consistent with the presence of a diffusion process, though we acknowledge that there are alternative possible mechanisms. Whatever its source, if this qualitative time pattern is common, estimating an overall average depreciation rate ignoring this early-year behaviour will produce a higher estimated overall rate. In our data, accounting for this early drop in value has led to a reduction of the yearly depreciation rate by 3.5 percentage points. Fourth, we cannot exclude the possibility that non-respondents affect our results. We show that companies responding to the survey but not reporting invention value do not affect the results, but we cannot comment on the larger group of companies not responding in the first place.

Although the present study pushes the frontier by including inventions for which patents were sought but not granted, a potential limitation relates to the fact that it observes inventions that self-selected into the patent system. This selection excludes both inventions judged to be unpatentable and those for which secrecy is chosen over patenting. This makes our estimates conceptually closest to those that infer depreciation from patent renewal decisions rather than relating firm performance over time to R&D expenditures.

Finally, this paper also has implications for the development of accounting principles. First, under current accounting principles R&D expenditures are immediately expensed, despite the fact that they produce a stream of future benefits. Hirschey and Weygandt (1985) and Lev and Sougiannis (1996) have emphasised the 'value-relevance' of R&D expenses and argue that they should be capitalised. This paper provides additional evidence that patents, most of which result from internal R&D activities, contribute to future profits and should be amortizable. Second. only externally-acquired patents can be amortized under current accounting principles, and over a period not exceeding their legal lives. Yet, we find that the useful life is longer than the legal life, i.e., many patents that have lapsed still produce economic benefits to their owners.

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Appendix A. Adding a diffusion process to *X(t)*

One can give several explanations for the early drop in value that we observe in Figure 2. It may reflect the presence of a learning/diffusion process, a genuinely greater depreciation rate in earlier years, the effect of uncertainty about valuation of new inventions (e.g., Gneezy et al. 2006), or a combination of these factors. We do not have time series of revenues per invention, such that we cannot possibly differentiate between these explanations.

However, for the sake of argument, let us consider the addition of a diffusion process to the revenue function *X(t)*. We model *X(t)* as a combination of an exponential decay process and an innovation diffusion process following Caballero and Jaffe (1993). Assuming constant demand for clarity of exposition (g = 0), we can write *X(t)* as

$$X(t) = X(0)e^{-\delta t}(1 - e^{-\gamma t})$$

where γ is the diffusion parameter (note that γ can equally well capture the resolution of uncertainty over time) and t > 0. Using patent citation data, Caballero and Jaffe (1993:39) observe a diffusion process that is quite fast. They estimate the value for γ at about 0.8. This finding is consistent with Mansfield (1985), who found that 70 per cent of product innovations were known and understood by rivals within 12 months of the innovation, and only 17 per cent took longer than 18 months.

A diffusion parameter of 0.8 would suggest that 90 per cent of the diffusion has occurred in year 3, that is, when we start observing data. A parameter of 1.2, corresponding to Mansfield's estimate of 70 per cent diffusion in the first year, would imply that 97 per cent of the diffusion has occurred in year 3.

Figure A.1 illustrates how the dependent variable $\ln(V_{a,i}/V_{0,i})$ changes if we consider a diffusion process, in addition to an exponential decay function.

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Figure A.1. Dependent variable $\ln(V_{a,i}/V_{0,i})$ under different speeds of diffusion.

Note: A parameter γ = ∞ corresponds to an instantaneous diffusion. The parameter δ is set at 5 per cent.

Our data are too crude to provide an estimate for γ. However, under a scenario in which most of the diffusion has occurred in the early years, the simulation provided in Figure A.1 suggests that the outcome of the diffusion process can be captured in a satisfactory manner with the inclusion of a constant term in the regression model. The constant term accounts for the shift in the depreciation function induced by the diffusion.

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Appendix B. Values for *g* and *r*

As a guide for reading the econometric estimates of the parameter β in regression model (2) and its relation to the depreciation rate, this section provides values for variables *g* and *r* for different time periods. The variable *g* is defined as the year-on-year growth rate of the gross domestic product (expenditure approach) in current Australian dollars. Data come from the OECD National Accounts Database.

The variable *r* is the long-term interest rate (per cent per annum), measured as secondary market yields of 10-year bonds. Data come from the Monthly Monetary and Financial Statistics (MEI) dataset of OECD Finance Database.

Table B.1 Reference values for variables *g* and *r*.

Year	*g*	*r*	*g – r*
1987	13.40%	13.19%	0.21%
1988	13.50%	12.10%	1.40%
1989	9.87%	13.41%	-3.54%
1990	2.66%	13.18%	-10.52%
1991	1.94%	10.69%	-8.75%
1992	4.98%	9.22%	-4.24%
1993	5.09%	7.28%	-2.19%
1994	6.19%	9.04%	-2.85%
1995	6.74%	9.21%	-2.47%
1996	5.22%	8.21%	-2.99%
1997	5.77%	6.95%	-1.19%
1998	5.36%	5.49%	-0.13%
1999	6.52%	6.01%	0.51%
2000	6.73%	6.31%	0.42%
2001	6.82%	5.62%	1.21%
2002	6.28%	5.84%	0.44%
2003	7.56%	5.37%	2.20%
2004	7.03%	5.59%	1.44%
2005	8.19%	5.34%	2.85%
2006	8.91%	5.59%	3.32%
2007	8.40%	5.99%	2.41%

Notes: See main text for data sources.

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Appendix C. Industry-specific estimates

Table C.1. Industry-specific estimates

	OLS		MM		MM		
	Single regression		Single regression		Industry-specific regression		
	c	β	*c*	β	*c*	β	Mean of β
2401	-0.134	-0.053	-0.16	-0.018	-0.158	-0.018	-0.030
	(0.184)	(0.020)	(0.047)	(0.008)	(0.086)	(0.009)	
2423	-0.160	-0.042	-0.089	-0.011	-0.048	-0.007	-0.020
	(0.094)	(0.014)	(0.073)	(0.011)	(0.034)	(0.005)	
2728	-0.590	-0.020	-0.223	-0.014	-0.271	-0.013	-0.016
	(0.283)	(0.024)	(0.073)	(0.006)	(0.083)	(0.007)	
2900	-0.287	-0.046	-0.122	-0.026	-0.129	-0.027	-0.033
	(0.094)	(0.011)	(0.075)	(0.013)	(0.070)	(0.012)	
3200	-0.459	-0.029	-0.248	-0.009	-0.278	-0.010	-0.016
	(0.103)	(0.013)	(0.082)	(0.010)	(0.078)	(0.010)	
3400	-0.402	-0.053	-0.091	-0.035	-0.127	-0.037	-0.042
	(0.339)	(0.030)	(0.122)	(0.009)	(0.132)	(0.013)	
3600	-0.341	-0.047	-0.004	-0.038	-0.056	-0.036	-0.040
	(0.141)	(0.018)	(0.081)	(0.010)	(0.099)	(0.010)	

Notes: N = 1057 (sample of inventions by private firms).
Reference group is all other industries in the single regression.
Robust standard errors in parenthesis (clustered by age for OLS).
2401: Chemicals and chemical products; 2423: Pharmaceuticals and medicinal chemicals; 2728: Basic metals and fabricated metal products; 2900: Machinery and equipment n.e.c.; 3200: Radio, television, and communication equipment; 3400: Motor vehicles, trailers and semi-trailers; 3600: Furniture and n.e.c..

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Appendix D. Bias in the reporting of invention value

Figure D.1. Mean of initial value (V_0) by cohort

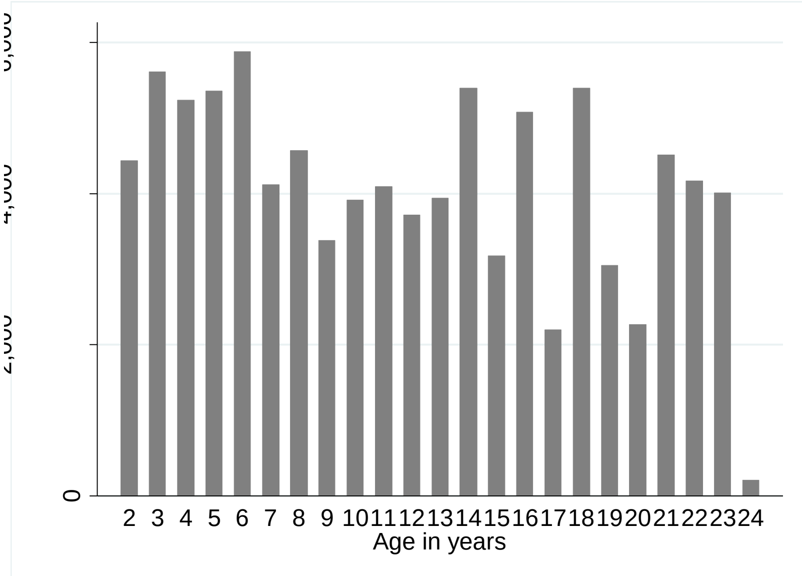
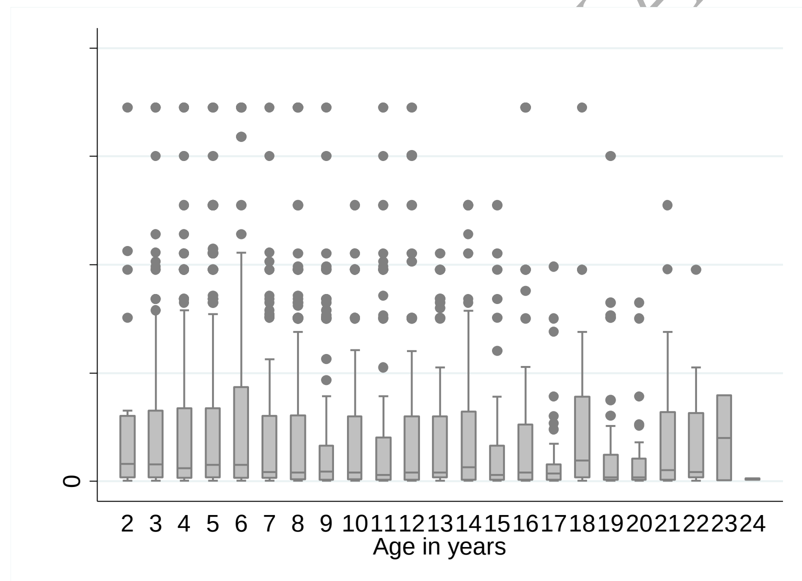


Figure D.2. Box plot of initial value (V_0) by cohort



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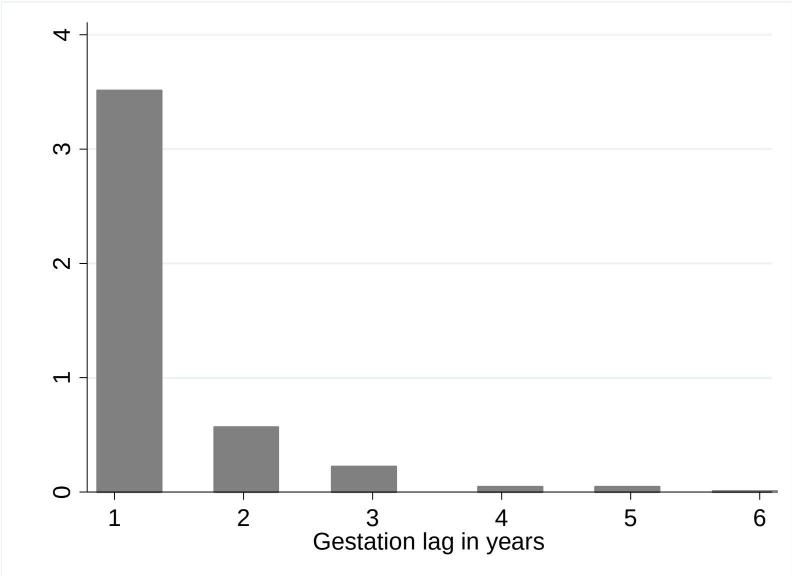
Appendix E. Evidence on the gestation lag

Figure E.1. Average time between initial expenditure on R&D and first patent filing



Notes: N = 497.

Sources: Based on unpublished data from the 2006 European Patent Office Applicant Survey. See de Rassenfosse (2012) for details.

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