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Gaétan de Rassenfosse  
Adam B. Jaffe

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Econometric Evidence on the R&D Depreciation Rate  
Gaétan de Rassenfosse and Adam B. Jaffe  
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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. Results suggest that the yearly depreciation rate varies in a range of 1 to 5 per cent, although the depreciation rate is stronger in the first two years of inventions averaging 8–9 per cent. Patent protection slows down the erosion of profits by about 1–2 percentage points.

Gaétan de Rassenfosse  
EPFL - CDM - ITPP - IIPP  
Odyssea Station 5  
CH-1015 Lausanne  
gaetan.derassenfosse@epfl.ch

Adam B. Jaffe  
Motu Economic and Public Policy Research  
PO Box 24390  
Wellington 6142  
New Zealand  
and Queensland University of Technology  
and also NBER  
adam.jaffe@motu.org.nz

## 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 R&D assets, defined as the rate of decay of appropriable revenues that these assets generate (Pakes and Schankerman 1984).<sup>1</sup> 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 private 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 policy relevance in fields such as growth accounting, 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).<sup>2</sup> The importance of, and difficulties associated with, the measurement of R&D depreciation are well captured by a quote from the U.S. Bureau of Economic Analysis (2012):

"Research and development (R&D) depreciation rates are critical to calculating the rates of return to R&D investments and capital service costs,

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<sup>1</sup> R&D assets account for a large proportion of intangible assets. For example, they account for approximately 50 per cent of intangible assets in the United States (Corrado et al. 2009:676).

<sup>2</sup> The rental price is the user cost of R&D capital. It is used in national account systems to estimate R&D capital services. It includes: the opportunity cost of investing elsewhere; the loss in market value of the good due to ageing (i.e. depreciation); the capital gains or losses due to asset price inflation/deflation; and adjustments for differential tax treatment across assets.

both of which are important for capitalizing R&D investments in the national income and product accounts. Although important, measuring R&D depreciation rates is extremely difficult because both the price and output of R&D capital are generally unobservable” (Li 2012: 2).

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. The empirical analysis comes with two innovations. First, the estimation strategy departs from existing methods. Only a handful of studies have estimated the R&D depreciation rate and all of them rely on indirect inference. By contrast, the approach proposed in this paper relies on direct observation of inventors’ estimates of the revenue streams generated by inventions. It is thus genuinely different from existing approaches.<sup>3</sup> Second, this paper estimates the depreciation rate for both patented and not patented inventions. To the best of our knowledge, this study is the first of its kind: existing estimates either rely entirely on patented inventions or 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 of 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 discrepancies in previous estimates. It will also provide novel insights into the economic effects of the patent system.

The results suggest that the depreciation rate is in the lower range of existing estimates and varies in a range of 1 to 5 per cent (depending on model specifications) after the first few years of an inventions life. There is, however, more rapid decline of 10 to 15 per cent in value in the first two years after patent application. 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. 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

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<sup>3</sup> 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.

by about 1–2 percentage points. However this effect is only observed for ‘strong’ patents, i.e. patents which were reported to 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 findings and explains their relevance for the fields of industrial organization and accounting, as well as for statistical offices.

## **2. Definition(s) and estimates of R&D depreciation rate**

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. Finally, this section discusses the effect of patenting on R&D depreciation.

### ***2.1. Defining R&D depreciation***

From an accounting perspective, R&D depreciation looks much like 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 R&D investments 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.<sup>4</sup> 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 R&D, 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 depreciation rate of R&D, although the fact that imitation depreciates private but not social value suggests that, in general, the depreciation rate of social value should be less than the private rate.

## ***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).<sup>5</sup> 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

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<sup>4</sup> Indeed, imitation could increase the social value of an invention, if it has the effect of making the invention available to more users.

<sup>5</sup> Although we use the term ‘depreciation rate of R&D’ when patent data is used, we are aware that there is not a one-to-one relationship between R&D output and patents. First, not all inventions are patented let alone patentable. Second, not all patents originate from R&D activities.

2006; Deng 2007; Bessen 2008).<sup>6</sup> 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. This assumption is counterintuitive since the very purpose of patent protection is to slow the erosion of profits.

Other attempts, which rely on R&D expenditures (input) rather than patent data, have also been undertaken. 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 with the stock of R&D as an input along with labor 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. Table 1 summarizes the main estimates of R&D depreciation rate. The estimates vary greatly, ranging from almost no depreciation to almost 50 per cent, and there is not, in fact, a clear tendency for the industry-level estimates to be lower than those at the invention or firm level. This wide variation illustrates the 'depreciation problem' raised by Zvi Griliches and Bronwyn Hall.

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<sup>6</sup> 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.

**Table 1.** Overview of estimated R&D depreciation rates

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  $\delta_k$  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.<sup>7</sup>

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. The data on inventor estimates of invention revenue streams lends itself to estimating the depreciation rate in a straightforward manner.<sup>8</sup> 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

<sup>7</sup> Median service lives across all industries presented in Ker (2013) are 6 years (unweighted) and 10 years (weighted by R&D expenditures). Assuming a linear depreciation leads to a depreciation rate of 16.7 per cent and 10 per cent, respectively. Additional assumptions are needed to convert these figures into an exponentially declining depreciation function.

<sup>8</sup> 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.



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. R&D 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 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 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 2013). Second, 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 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.

### 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  $a \rightarrow \infty$ ). Invention value is subject to high uncertainty and is therefore difficult to predict. However, it is necessarily the case that, ex post,  $V(a)$  is a declining function of age. This paper follows previous convention and models invention value at age  $a$  using an exponential decay function:

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

where  $\delta$  is the depreciation parameter.<sup>9</sup> The model assumes a constant depreciation rate over time, and section 4.2 shows that the data supports that assumption beyond the first few years of an invention's life. Dividing equation (1) by  $V(0)$  and taking logs, the empirical counterpart of equation (1) can be written as:

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<sup>9</sup> 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.

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

where  $i$  denotes an invention and  $\delta$  is the parameter to be estimated.<sup>10</sup> The data do not contain information on the full sequence of invention values  $\{V_{ia}\} \forall i, a$ . Two quantities are observed: 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, the information set is  $\{V_{ia}: a = 0, a_i; a_i \neq 0\}$ , and the depreciation rate is estimated from a mix of within variations in invention value and between variations in value.

Note that, in its initial form, equation (2) does not include a constant term – an intercept  $c$  different from 0 would imply that  $E[\ln(V_{i0}/V_{i0})] = c$ , 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. Variations in the depreciation rate  $\delta$  are modelled as a linear function of covariates such that equation (2) can be written as (including a constant term):

$$\ln \frac{V_{ia}}{V_{i0}} = c - (\mathbf{x}_i \boldsymbol{\beta}) a + \varepsilon_{ia} \quad (3)$$

where  $\mathbf{x}_i \boldsymbol{\beta}$  is the inner product between the vector of covariates  $\mathbf{x}_i$  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: a generalised linear model, to account for the fact that the dependent variable is not normally distributed, and robust regression models, to account for potential difference in the trustworthiness of estimates across vintages.

Note that this paper relies on conservative evidence thresholds for the declaration of significant coefficients (p-values of 0.01 and 0.005). We follow Johnson (2013) who shows

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<sup>10</sup> As explained in section 4.2 the regression equation (2) also encompasses the class of declining balance models and is, therefore, quite general.

that commonly-used levels of significance represent only weak evidence in favour of hypothesised effects.<sup>11</sup>

### **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. Section 4.1 provides evidence that non-respondents do not bias the results.

#### *3.2.2 IP Australia's AusPat database*

The online AusPat database from IP Australia is used to get 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 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. 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) 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. Technical details on the construction of the variables are provided in de Rassenfosse et al. (2014).

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<sup>11</sup> 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.

### 3.2.4 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.

### 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.<sup>12</sup>

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  $V_{ia}$  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  $(m \cdot G1 + G3) + G2$ . Since the data is ordinal, the dependent variable was constructed from the mid-point value of each

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<sup>12</sup> An implicit assumption is that the backward value measures (G1 and G3) represent discounted cash flows. Section 4.3 explains that the depreciation rate would be about 0.5 percentage point below the ‘true’ rate should the backward value measures in fact represent undiscounted cash flows.

category (the last category was arbitrarily assigned a value of \$15m), although 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 the respondents reported a "lack of confidence in legal protection from copying of the 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. This variable is a proxy for 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**

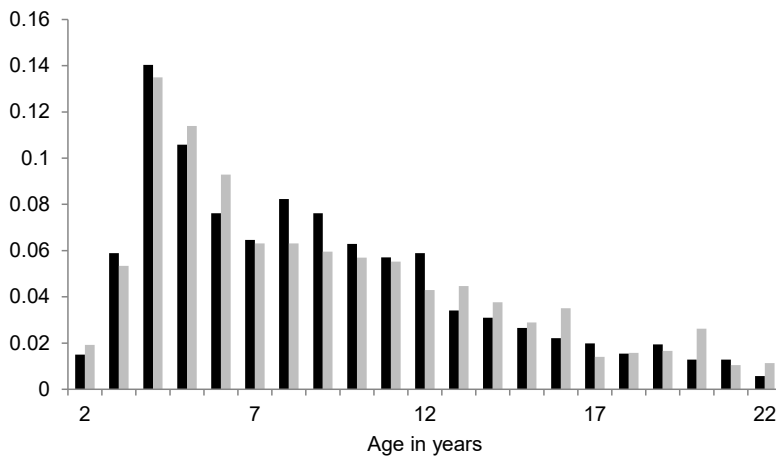
### ***4.1 Descriptive statistics***

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.<sup>13</sup> 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 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).

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<sup>13</sup> 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.

**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. 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. About 17 per cent of granted patents are considered weak by inventors, 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.

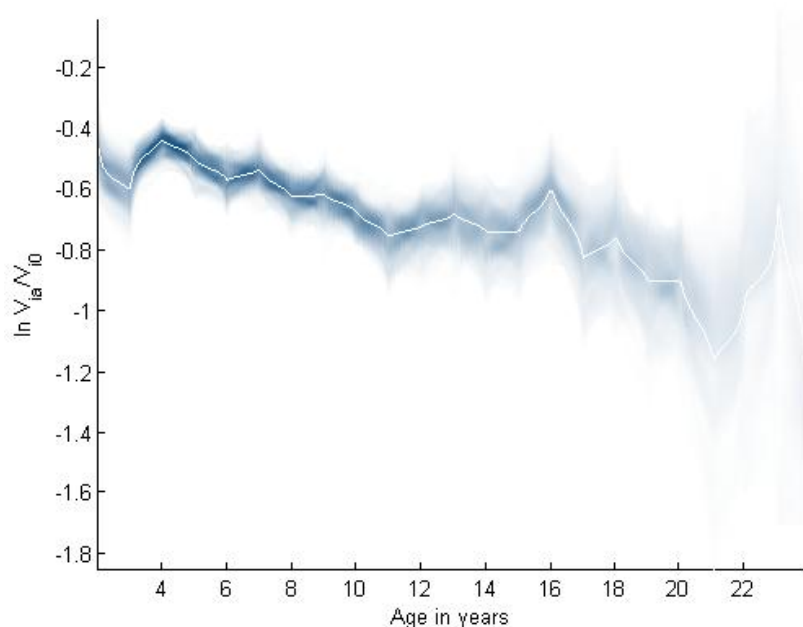


**Table 2.** Data descriptives

	Summary Statistics				Correlation coefficients							
	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) <i>grant</i>	0	0.67	1	-	-0.05	-0.10	1.00					
(4) <i>private</i>	0	0.47	1	-	0.01	0.27	0.13	1.00				
(5) <i>weak</i>	0	0.17	1	-	0.00	0.02	n.a.	-0.05	1.00			
(6) <i>intl protection</i>	0	0.52	1	-	0.02	-0.03	0.13	0.06	-0.04	1.00		
(7) <i>other patents</i>	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).

Figure 2 provides an overview of the depreciation function. It depicts the conditional mean of the dependent variable  $\ln V_{ia}/V_{i0}$  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 the depreciation function.

**Figure 2.** Overview of the depreciation function

#### 4.2 Econometric estimates of the R&D depreciation rate

##### Baseline estimates

Table 3 presents baseline estimates of equation (3). 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  $E[\ln(V_{i2}/V_{i0})] = c + \delta * 2$ , 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 the average depreciation rate in the first two years is about 18 per cent ( $=[1-\exp(c+\delta*2)]/2$ ). Figure 3 depicts the model fit. It suggests that the linearity assumption of the depreciation rate holds (at least locally, when  $a \geq 2$ ).<sup>14</sup> A close look at the residuals suggests the presence of heteroscedasticity (the variance of residuals increases with age, not reported), and standard errors are therefore clustered by age cohort. Columns (3)–(5) investigate whether a more appropriate distributional assumption or a more appropriate treatment of likely outliers improves estimation.

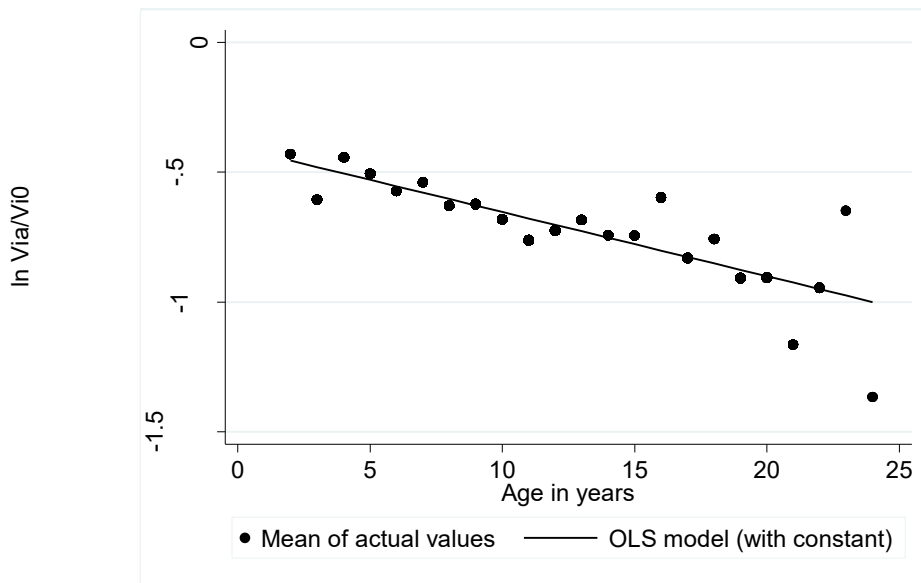
**Table 3.** Depreciation parameter with various estimation methods

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

Notes: R<sup>2</sup> 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

<sup>14</sup> 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  $[0, -)$  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).<sup>15</sup> 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). However, the residuals still exhibit heteroscedasticity. Heteroscedasticity may be 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 the constant term is much lower (-0.147). The constant term suggests that the average depreciation rate in the first two years is about 9 per cent. Results of a robust regression model that down-weights potential outliers is reported in column (5). The estimator is the MM estimator by Yohai (1987) as implemented in Stata by Verardi and Croux (2009). The depreciation parameter is slightly lower, at 1.5 per cent, and the constant

<sup>15</sup> The dependent variable is transformed to  $-\ln(V_{ia}/V_{i0})$  so that it takes its value on the interval  $[0, +\infty)$ .

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.

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  $V_{ia} = V_{i0}(1 - \delta)^a$  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  $\beta$ . It corresponds to  $\delta = 1 - e^\beta$ . Note that for  $\beta$  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 A.1 and Figure A.1 in Appendix A for the selected industries and briefly discussed here. Point estimates vary in the range between 1 and 4 per cent. The depreciation rate is lowest in the pharmaceuticals and medicinal chemicals industry (point estimates in the range 0.6–1.7 per cent) and highest in the machinery and equipment industry (point estimates in the range 2.1–4.0 per cent). The depreciation rate in the early life of an invention is smaller than the reference group in the pharmaceuticals and medicinal chemicals industry (in the range 4–5 per cent) and larger than the reference group in the radio, television and communication equipment industry (about 10 per cent).

#### *Estimates by patent grant status*

The next sets of results, presented in Table 4, estimate the depreciation rate for inventions that were granted patent protection and inventions that were not. The estimates are obtained using both the quantile estimator (left panel) and the MM estimator (right panel). 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). 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 exogenous to the firm, and based mainly on the technical merit of the invention (not its economic potential). In addition the very purpose of patent protection is to slow down the erosion of profits. Thus the causal interpretation seems a priori valid. On the other hand, one cannot exclude the possibility of reverse causality. The invention may be refused patent protection because a similar technology may already exist, such that the technology is bound to depreciate at a faster pace. Estimates of the magnitude of the grant effect are interesting in their own rights independently of the direction of causality.

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. The group of granted patents is broken down into patents for which respondents are confident about the quality of their intellectual property rights (*weak* = 0) and for which they are not (*weak* = 1). Results indicate 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.<sup>16</sup> 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			
<i>x</i> :	<i>weak</i>	<i>intl protection</i>			<i>weak</i>	<i>intl protection</i>		
<i>a</i>	-0.026** (0.006)	-0.027** (0.006)	-0.023** (0.005)	-0.028** (0.005)	-0.021** (0.004)	-0.021** (0.004)	-0.020** (0.004)	-0.021** (0.004)
<i>a</i> × <i>grant</i>	0.014** (0.004)			0.013** (0.004)	0.012** (0.003)			0.012** (0.003)
<i>a</i> × <i>grant</i> × ( <i>x</i> = 0)		0.015** (0.004)	0.010 (0.004)			0.013** (0.003)	0.010* (0.004)	
<i>a</i> × <i>grant</i> × ( <i>x</i> = 1)		0.012 (0.005)	0.015** (0.004)			0.008 (0.004)	0.014** (0.003)	
<i>a</i> × <i>other patents</i>				0.007 (0.003)				0.003 (0.002)
<i>a</i> × <i>private</i>	-0.016** (0.003)	-0.016** (0.003)	-0.017** (0.003)	-0.016** (0.003)	-0.009** (0.002)	-0.009** (0.002)	-0.009** (0.002)	-0.009** (0.002)
<i>a</i> × <i>industry dummies</i>	Y**	Y**	Y**	Y**	Y	Y	Y	Y
Constant	-0.099** (0.032)	-0.100** (0.033)	-0.111** (0.031)	-0.099** (0.031)	-0.116** (0.019)	-0.114** (0.018)	-0.118** (0.019)	-0.116** (0.019)
Observations	2259	2259	2259	2259	2259	2259	2259	2259
R <sup>2</sup>	0.037	0.039	0.038	0.037	0.035	0.035	0.036	0.035

Notes: R<sup>2</sup> 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

<sup>16</sup> 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.

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 B.1 and Figure B.2. 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 B.1), and the variable varies widely within cohorts as shown by the box plot in Figure B.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 models adopted already account 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 the upper panel of Table 5 must be compared with those in column (1) of Table 4, and 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 of the depreciation rate.

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.<sup>17</sup> The results remain largely 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).

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<sup>17</sup> 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.

Fourth, we have arbitrarily taken the mid-point value of each category of the ordinal variables to construct the dependent variable. Columns (4)–(5) test whether the results are robust to alternative imputation methods. We assume that observations are uniformly distributed in the range covered by their category (0 to \$100,000, \$100,000 to \$500,000, etc.) in column (4), and that they are distributed according to a Beta distribution that is skewed to the left in column (5). The quantile regression model leads to slightly higher depreciation rate and grant effect than the baseline case, whereas the MM estimator leads to slightly lower depreciation rate and grant effect. Notice that the result depends on the actual draw.

Finally, it is possible that the results are affected by a fundamental difference in inventors' answers to forward-looking and backward-looking questions. Fundamentally, we estimate the depreciation rate 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).<sup>18</sup> If, for example, the reported sale values represent a 50 per cent over-valuation of the true future value, the estimated depreciation rate would be pushed to around 2.6–3.7 per cent in our preferred models (columns 3 and 4 of Table 3). 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 (after the first two years) remains at the low end of previous estimates.

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<sup>18</sup> Alternatively (and indistinguishably), inventors' reservation price for sale may include an option value associated with unknown and uncertain new uses for the invention. This would not be a bias from a cognitive perspective, but it would artificially depress the estimated depreciation rate when set against the actual realized revenues in the past.



**Table 5.** Robustness tests

	(1)	(2)	(3)	(4)	(5)
	Y5–Y12	No transfer	All obs.	Uniform	Beta
Quantile estimator					
<i>a</i>	-0.051** (0.010)	-0.023** (0.006)	-0.025** (0.005)	-0.034** (0.006)	-0.029** (0.007)
<i>a</i> × <i>grant</i>	0.022** (0.005)	0.013** (0.004)	0.009* (0.003)	0.019** (0.004)	0.019** (0.005)
Constant	0.063 (0.070)	-0.126** (0.034)	-0.108** (0.029)	-0.055 (0.032)	-0.052 (0.040)
MM estimator					
<i>a</i>	-0.029** (0.008)	-0.019** (0.005)	-0.023** (0.004)	-0.009* (0.004)	-0.011** (0.003)
<i>a</i> × <i>grant</i>	0.014** (0.004)	0.011** (0.004)	0.011** (0.003)	0.007* (0.003)	0.007* (0.002)
Constant	-0.063 (0.042)	-0.128** (0.023)	-0.127** (0.019)	-0.120** (0.017)	-0.102** (0.016)
Observations	1319	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.

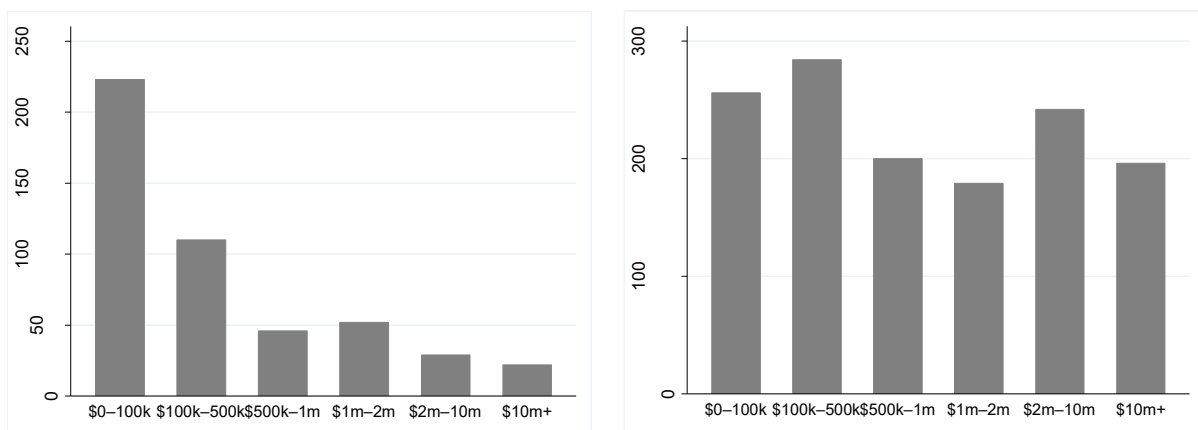
### *Including information on the ‘legal life’ of patents*

Exponential depreciation implies that patent value goes to zero only 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 hand side 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 emphasized 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 hand side 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.

**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 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.

**Table 6.** Using information on renewals

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

Notes: Sample restricted to inventions with a granted patent. R<sup>2</sup> 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. In short, the inclusion of lapse event data leaves the depreciation parameter roughly unchanged and increases the early decline in value.

#### *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 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 and the MM estimators. The only noticeable difference is that the grant effect is not significantly different from 0 under the strict statistical threshold adopted 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
<b>Quantile estimator</b>					
$a$	-0.021** (0.004)	-0.023** (0.005)	-0.026** (0.006)	-0.026** (0.006)	-0.029** (0.007)
$a \times grant$	0.010** (0.003)	0.012** (0.003)	0.014** (0.004)	0.014** (0.004)	0.015** (0.005)
Constant	-0.061 (0.024)	-0.081** (0.026)	-0.099** (0.032)	-0.127** (0.036)	-0.140** (0.041)
<b>MM estimator</b>					
$a$	-0.011** (0.004)	-0.018** (0.004)	-0.021** (0.004)	-0.022** (0.004)	-0.022** (0.004)
$a \times grant$	0.006 (0.003)	0.010** (0.003)	0.012** (0.003)	0.013** (0.003)	0.014** (0.003)
Constant	-0.067** (0.016)	-0.085** (0.018)	-0.116** (0.019)	-0.145** (0.020)	-0.169** (0.021)
Observations	2,259	2,259	2,259	2,259	2,259

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

### *Age of the patent vs. age of the invention*

The data provides 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 C.1 in Appendix C 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 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.

### *Additional considerations*

Additional robustness tests were performed but are not reported. First, 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 the 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. Second, we have performed the estimations on a sample that excludes patents describing process inventions. These 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. Third, we checked the sensitivity of the estimates with respect to the implicit assumption that the backward value measures (G1 and G3) are discounted cash flows. It is easy to show that the assumption that the figures are discounted when in fact they are undiscounted leads to an underestimation of the depreciation rate. We collected historic data on inflation rate from the Reserve Bank of Australia in order to investigate the magnitude of the potential bias. Discounting the backward value measures leads to a point estimate of the depreciation rate that is about 0.5 percentage points higher than the baseline case. The point estimate of the grant effect is about 0.2 percentage points higher.

## **5. Discussion**

### ***5.1 Contributions***

The contribution of this paper is twofold. First, it takes a fresh look at an old question. As far as we can ascertain, 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 estimating the R&D depreciation rate in a natural way that provides an interesting and valuable contrast with previous studies, which all rely on indirect inference. The results suggest that the yearly depreciation rate for R&D is in the lower range of existing estimates, between 1 and 5 per cent, depending on model specifications. However, the depreciation rate is higher in the first two years, averaging about 8 to 9 per cent. Regarding industry estimates, the depreciation rate is lower than the average by 0.5–1.0 percentage point in the pharmaceuticals and medicinal

chemicals industry. The decline in value that occurs in the early life of an invention is also smaller than the average in the pharmaceuticals and medicinal chemicals industry (in the range 4–5 per cent). In fact most of the heterogeneity of the depreciation rate across industries comes from heterogeneity in the early decline in value.

Second, this paper looks at a new question, namely the extent to which patent protection is associated with a slower erosion of profits. Inventions that are protected with a patent exhibit a depreciation rate that is 1–2 percentage points below that of inventions that have no patent protection. Interestingly this result is valid only for ‘strong’ patents. The grant effect indeed vanishes when patent protection is reported as weak. We are nevertheless careful not to attach a causal interpretation to the grant effect observed – we do not interpret our results as evidence of a ‘patent premium’. Yet the negative correlation between grant status and depreciation rate is an instructive finding. It contributes to reconciling estimates using different methodologies. It suggests that estimates of the R&D depreciation rate obtained using patent renewal data are a lower bound of the actual depreciation rate.

A potential limitation of this study relates to the fact that it observes inventions that self-selected into the patent system (i.e., no secrecy in the sample). This limitation naturally applies to all studies that estimate the depreciation rate using patent data. The present study pushes the frontier, however, by including inventions that were refused patent protection. An alternative way of estimating the depreciation rate involves looking at R&D expenditures. This approach provides information on inventions kept secret, but it also misses some inventive output since not all patentable inventions originate from R&D activities (Nagaoka and Walsh 2009). In fact, scholars have proposed a wide variety of methods for estimating the depreciation rate and this paper has discussed at length the differences between the various methods. A key dividing line in the empirical literature can be drawn between 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.

## ***5.2 Implications***

The 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 the data, at least after a period of two years. A strong decline in value occurs during the early life of inventions,

suggesting that researchers and practitioners at statistical offices should consider the implications of a kinked depreciation function where a large proportion of the value is depreciated in the first few years. The results also show that there is little industry-level variation in the depreciation rate, which validates the current practice of adopting a single depreciation rate across industries. Inventions in the pharmaceuticals industry are a notable exception, with a depreciation rate well below the average.

Second, the finding that the grant effect is statistically significant only when patent protection is strong has implications for the industrial organisation and management literature. Farrell and Shapiro (2008) have shown 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. 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. This conclusion holds regardless of the causality of the grant effect (indeed weak and strong patents are both granted).

Third, this paper also has implications for the development of accounting principles. 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.

We should also caution against a misinterpretation of the results. Whereas accounting principles state that patents must be amortised over a period not exceeding their legal lives, we find that many patents that have lapsed still produce economic benefits to their owners (i.e., the useful life is longer than the legal life). But this finding does not challenge the accounting principles. Only *externally-acquired* patents are currently allowed to be amortised, and the cost of acquiring patents cannot exceed the benefits they will bring during the remaining of their legal lives (since patents that have lapsed have no exchange value). However, the finding suggests that allowing the amortisation of internally-developed patented technologies will not totally solve the problem of the misreporting of R&D.

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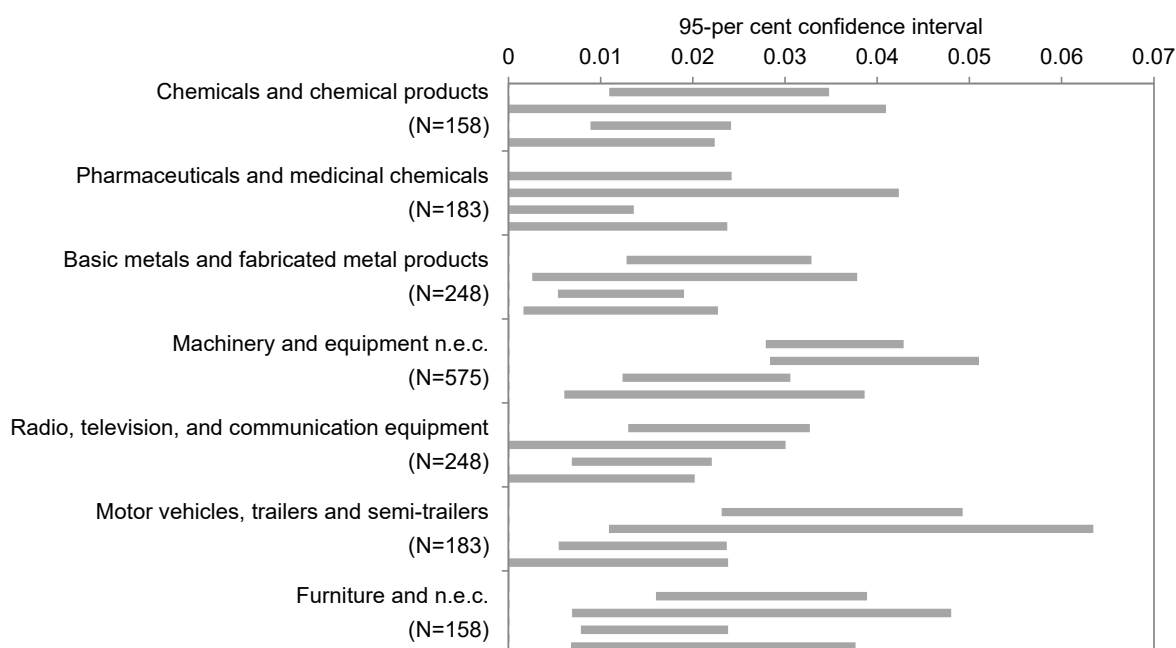
## Appendix A. Industry-specific depreciation rates

**Table A.1.** Industry-specific depreciation rates

	(1)	(2)	(3)	(4)
	Quantile estimator		MM estimator	
<i>Depreciation rate (a)</i>				
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**
<i>Early drop in value (constant term)</i>				
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.

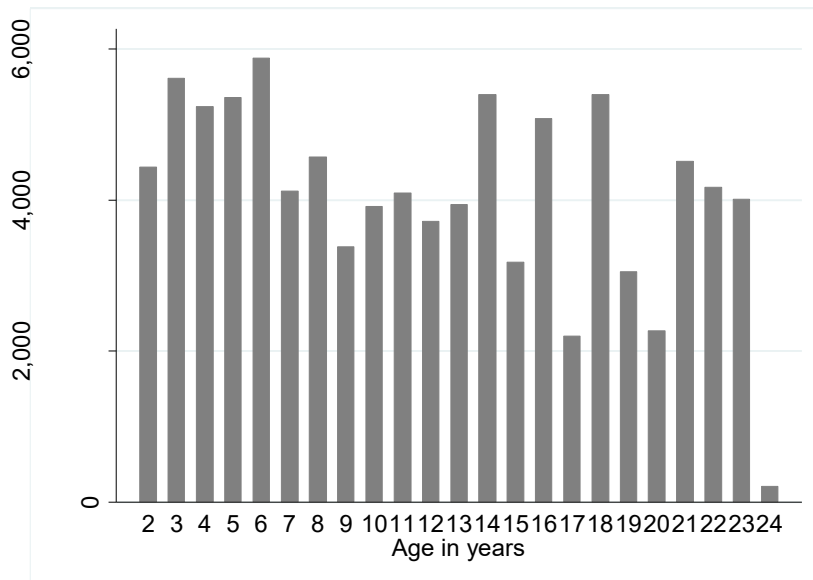
**Figure A.1.** Ninety-five-per cent confidence interval of the depreciation rate



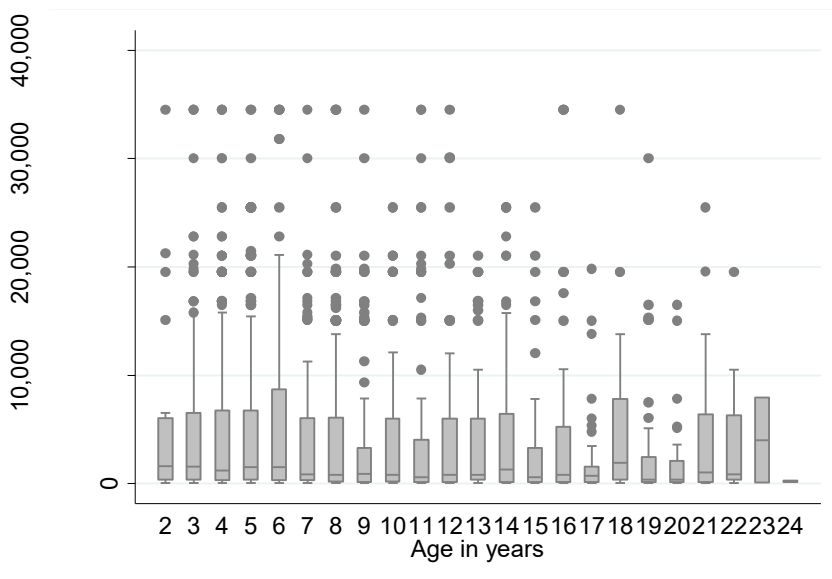
Notes: Based on estimates in Table A, from column (1) for the first set of bars to column (4) for the last set.

## Appendix B. Bias in the reporting of invention value

**Figure B.1.** Mean of initial value ( $V_0$ ) by cohort

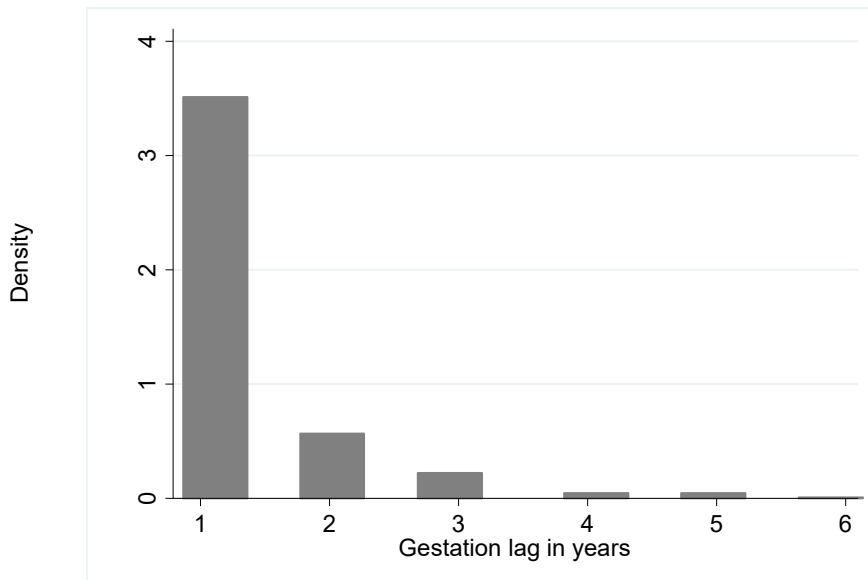


**Figure B.2.** Box plot of initial value ( $V_0$ ) by cohort



## Appendix C. Evidence on the gestation lag

**Figure C.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.